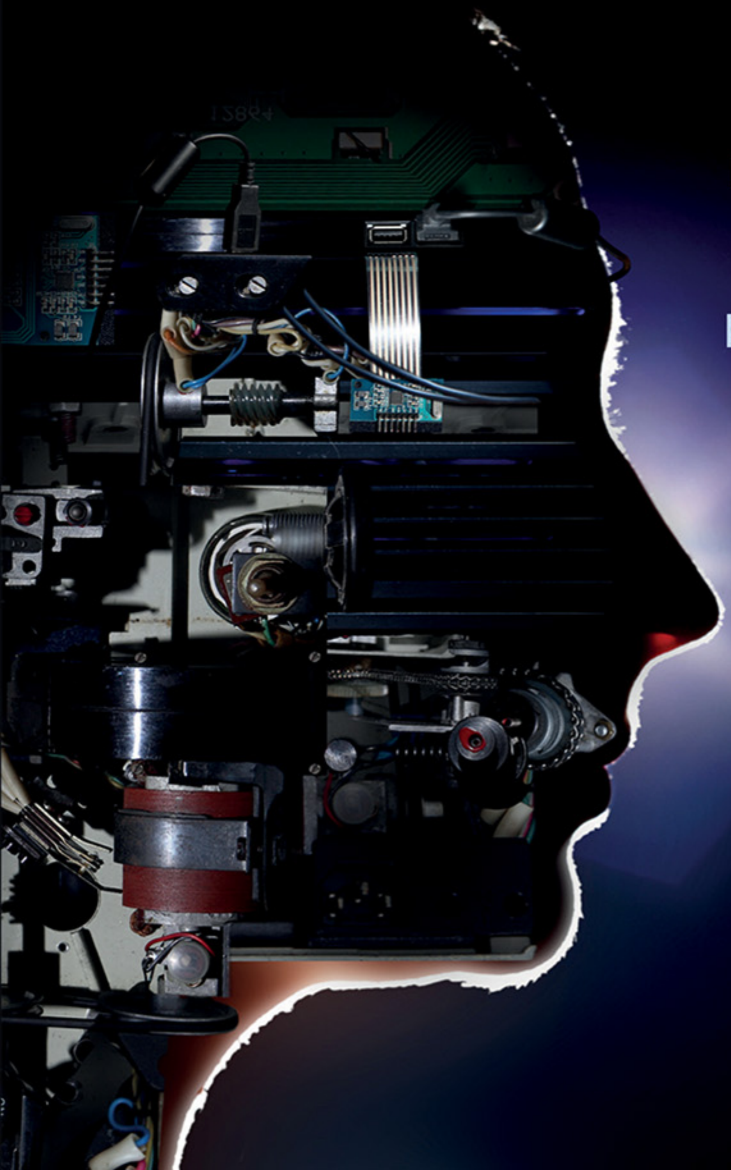
DIGITAL TWIN FOR SMART MANUFACTURING



Edited by
Rajesh Kumar Dhanaraj
Ali Kashif Bashir
Rajasekar Vani
Balamurugan Balusamy
Pooja Malik

Digital Twin for Smart Manufacturing

This page intentionally left blank

Digital Twin for Smart Manufacturing

Edited by

RAJESH KUMAR DHANARAJ
Symbiosis International (Deemed University), Pune, Maharashtra, India

ALI KASHIF BASHIR
Department of Computing and Mathematics, Manchester Metropolitan University, Manchester, United Kingdom

VANI RAJASEKAR
Department of CSE, Kongu Engineering College, Tamil Nadu, India

BALAMURUGAN BALUSAMY
Associate Dean-Student Engagement Shiv Nadar Institution of Eminence, Delhi, India

POOJA MALIK
Department of Computer Science and Engineering, Shiv Nadar University, Greater Noida, India

ELSEVIER

ACADEMIC PRESS
An imprint of Elsevier

Academic Press is an imprint of Elsevier
125 London Wall, London EC2Y 5AS, United Kingdom
525 B Street, Suite 1650, San Diego, CA 92101, United States
50 Hampshire Street, 5th Floor, Cambridge, MA 02139, United States
The Boulevard, Langford Lane, Kidlington, Oxford OX5 1GB, United Kingdom

ISBN: 978-0-323-99205-3

For Information on all Academic Press publications
visit our website at https://www.elsevier.com/books-and-journals

Publisher: Matthew Deans
Acquisitions Editor: Sophie Harrison
Editorial Project Manager: Rafael G. Trombaco
Production Project Manager: Prasanna Kalyanaraman
Cover Designer: Mark Rogers

Typeset by MPS Limited, Chennai, India

Contents

List of contributors

Md. Akkas Ali
School of Computing Science and Engineering, Galgotias University, Greater Noida, Uttar Pradesh, India

K. Arun Kumar
IT, Rathinam College of Arts and Science, Coimbatore, Tamil Nadu, India

Balamurugan Balusamy
Shiv Nadar Institution of Eminence, Delhi, India

K. Balasamy
Bannari Amman Institute of Technology, Erode, Tamil Nadu, India

M.R. Bharathkumar
EIE, Sri Sairam Engineering College, Chennai, Tamil Nadu, India

Amir Ahmad Dar
Department of Mathematics, Lovely Professional University, Punjab, India

Rajesh Kumar Dhanaraj
Symbiosis International (Deemed University), Pune, Maharashtra, India

V. Dhanashree
EIE, Sri Sairam Engineering College, Chennai, Tamil Nadu, India

Pankaj Dhumane
Sardar Patel College, Chandrapur, Maharashtra, India

N.R. Gayathiri
Department of Artificial Intelligence and Data Science, Bannari Amman Institute of Technology, Erode, Tamil Nadu, India

Apurva Gupta
School of Computer Science, University of Petroleum and Energy Studies, Dehradun, Uttarakhand, India

R. Indrakumari
School of Computing Science and Engineering, Galgotias University, Greater Noida, Uttar Pradesh, India

B. Persis Urbana Ivy
Department of Computer Science and Engineering, Bharath Institute of Higher Education and Research, Chennai, Tamil Nadu, India

G.K. Kamalam
Department of Information Technology, Kongu Engineering College, Perundurai, Tamil Nadu, India

A. Kavitha
Dr. N.G.P. Institute of Technology, Coimbatore, Tamil Nadu, India

R. Keerthivasan
EIE, Sri Sairam Engineering College, Chennai, Tamil Nadu, India

D. Kalaskar Keshao
Dr. Ambedkar College, Chandrapur, Maharashtra, India

Ankit Khare
School of Computer Science, University of Petroleum and Energy Studies, Dehradun, Uttarakhand, India

A. Kodieswari
Department of Information Technology, Bannari Amman Institute of Technology, Erode, Tamil Nadu, India

A. Malini
Thiagarajar College of Engineering, Madurai, Tamil Nadu, India

M. Nalini
EIE, Sri Sairam Engineering College, Chennai, Tamil Nadu, India

P. Nancy
Department of Computing Technologies, SRM Institute of Science and Technology, Kattankulathur Campus, Chennai, Tamil Nadu, India

N. Nithyashree
EIE, Sri Sairam Engineering College, Chennai, Tamil Nadu, India

T. Poongodi
School of Computing Science and Engineering, Galgotias University, Greater Noida, Uttar Pradesh, India

S. Prabu
Department of Computer Science and Engineering, Karpaga Vinayaga College of Engineering and Technology, Madhuranthakam, Tamil Nadu, India

Vani Rajasekar
Department of CSE, Kongu Engineering College, Tamil Nadu, India

Umamaheswari Rajasekaran
Thiagarajar College of Engineering, Madurai, Tamil Nadu, India

A. Rajendran
ECE, Karpagam College of Engineering, Coimbatore, Tamil Nadu, India

P. Ramyavarshini
Thiagarajar College of Engineering, Madurai, Tamil Nadu, India

Rahul Rawat
School of Computer Science, University of Petroleum and Energy Studies, Dehradun, Uttarakhand, India

K.R. Sabarmathi
Bannari Amman Institute of Technology, Erode, Tamil Nadu, India

Shrddha Sagar
School of Computing Science and Engineering, Galgotias University, Greater Noida, Uttar Pradesh, India

Aradhna Saini
Department of Computer Science and Engineering, Noida Institute of Engineering and Technology, Greater Noida, Uttar Pradesh, India

S. Salini
Department of Computer Science and Engineering, Bharath Institute of Higher Education and Research, Chennai, Tamil Nadu, India

Prithi Samuel
Department of Computational Intelligence, SRM Institute of Science and Technology, Kattankulathur Campus, Chennai, Tamil Nadu, India

M. Saravanakumar
IT, Rathinam College of Arts and Science, Coimbatore, Tamil Nadu, India

V. Satheeswaran
Nehru Institute of Technology, Coimbatore, Tamil Nadu, India

K. Sathya
Department of CT/UG, Kongu Engineering College, Erode, Tamil Nadu, India

D. Shamia
V.S.B. College of Engineering Technical Campus, Coimbatore, Tamil Nadu, India

Vandana Sharma
School of Computing Science and Engineering, Galgotias University, Greater Noida, Uttar Pradesh, India

A. Shobanadevi
Department of Data Science and Business Systems, School of Computing, SRM Institute of Science and Technology, Kattankulathur, Chennai, Tamil Nadu, India

B. Shuriya
CSE, PPG Institute of Technology, Coimbatore, Tamil Nadu, India

Anamika Singh
School of Computing Science and Engineering, Galgotias University, Greater Noida, Uttar Pradesh, India

P. Sivaprakash
IT, Rathinam College of Arts and Science, Coimbatore, Tamil Nadu, India

G.K. Sriram
Thiagarajar College of Engineering, Madurai, Tamil Nadu, India

S. Suganyadevi
KPR Institute of Engineering and Technology, Coimbatore, Tamil Nadu, India

T. Veeramakali
Department of Data Science and Business Systems, School of Computing, SRM Institute of Science and Technology, Kattankulathur, Chennai, Tamil Nadu, India

Vijayalakshmi
Department of Data Science CHRIST (deemed to be University), Lavasa, Maharashtra, India

Shipra Yadav
IICC, RTM Nagpur University, Nagpur, Maharashtra, India

CHAPTER 1

Digital twin and digital twin–driven manufacturing

Apurva Gupta, Ankit Khare and Rahul Rawat
School of Computer Science, University of Petroleum and Energy Studies, Dehradun, Uttarakhand, India

1.1 Origin of digital twin

This study focuses on the overall progress of the digital twin from the year 2002 when Dr. Michael Grieves coined the term digital twin to when NASA in the year 2010 gave the detailed definition of digital twin [1]. For instance, a windmill is equipped with several sensing elements (sensors) that are related to essential regions of effectiveness. Sensing elements assemble data for various aspects of the performance of the substantial object, such as power production, temperature, and more. These data are transmitted to a system where transmitted data get processed and applied virtually. NASA was the first to use digital twin technology for the space vehicle named Apollo 13. It helps minimize human efforts and financial losses for betterment of the society. Let us start with its definition and try to understand digital twin in a simple language.

1.1.1 Definition of digital twin

It is a virtual representation of a real-life entity. Nonstop data transfer allows the virtual object to occur at the same time as the real one, allowing for a continuous digital representation of a real-world subject. The miniaturization and the decline in prices allow the consolidation of information, communication, and integration of sensors into practically all products. The products can feel their own circumstances and their surroundings. The ability to integrate the process of the product with the captured data from the sensors of the product, allows the creation of a digital twin. It is a complete characterization of a source product that will help in digitalizing the lifecycle of the product [2]. The idea of the digital twin was initially introduced by David Gelernter in his book MIRROR WORLD in 1991 and then in the year 2002 Dr. Michael Grieves at the Institute of Technology, Florida coined the term digital twin and applied

Digital Twin For Smart Manufacturing
DOI: https://doi.org/10.1016/B978-0-323-99205-3.00006-7

it to manufacturing. Back in 2002, there were only three-dimensional conceptual frameworks that included physical objects, virtual counterparts, and connections without any solid evidence and explanation. However, NASA, in the year 2010, gave the detailed definition of digital twin. As mentioned by NASA, it is a multi-physics integrated simulation, a numerical imitation of a spacecraft vehicle or it is the integrated structure that uses the finest physical patterns, sensor updates, fleet history, and more, to reflect the life of correspondent spaced vehicle twin model. NASA was the first to use digital twin technology in its space vehicle [3].

It is used to establish a connection between the real and virtual worlds. Digital twins collect actual data from the established sensors. The data is circulated regionally or stored in the cloud. The collected data is applied to the real asset, which helps in optimizing the performance of real assets [4].

Dr. Grieves introduced digital twin in 2002. In the initial phases, it was three-dimensional, which included a physical entity, virtual counterparts, and connections that tie both parts together (Fig. 1.1).

1.1.2 History

However, in the year 2005, another idea was put forward by Dr. Grieves that classified digital twin into three subtypes: digital twin prototypes, digital twin instance, and digital aggregate [5].

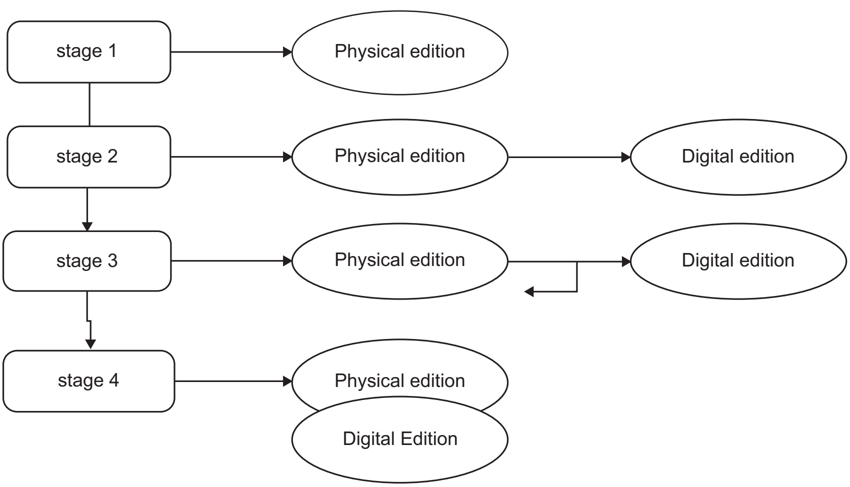


Figure 1.1 Various stages of digital twin.

NASA, in the year 2010, gave the detailed definition of digital twin in Roadmap Report 2010 [6]. NASA was the first to use digital twin technology in its space vehicle. The concept was used to evaluate space capsules and ships using digital models. In the early stage, it was used on the ground as a reflector, which is helpful in recognizing the issues in orbit, which eventually gave way to full digital simulation [7]. In the year 2012, NASA and the U.S. together published the paper after exploring the application of digital twin and stated that it will be the key technology in the future for vehicles subsequently in the year 2014. Digital twin was introduced in different fields, such as the aerospace industry, automotive, oil and gas, healthcare, and medicines [8] (Fig. 1.2).

1.1.3 Development in digital twin

Until the 20th century, physical space played a key role in the industry. In this era, humans used to organize physical assets and were kept close in distance. Also, humans were only responsible for drawing and manufacturing tasks. Anyhow, humans were not able to draw high-efficiency functional equipment due to the limited access and the geographical limitation.

As time progressed, advancements in technologies have helped humans with computers, simulations tools, wireless networks, and more to overcome geographical limitations enabling one to control the physical assets remotely [7].

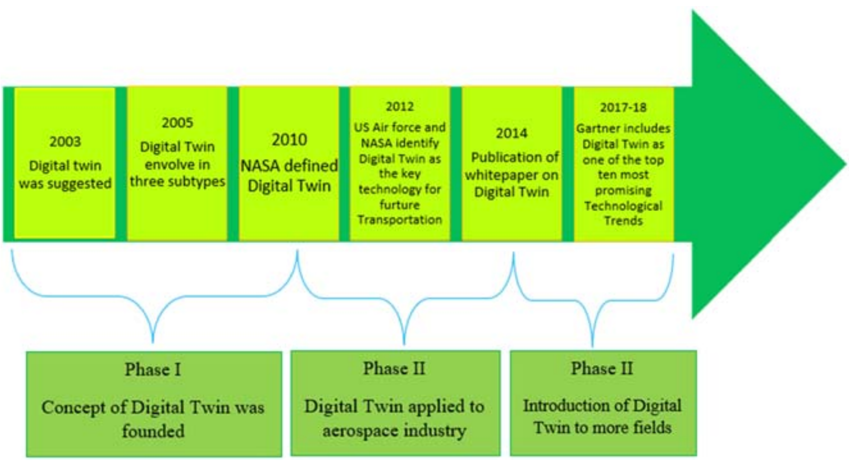


Figure 1.2 History of digital twin.

With the help of modern technology, it became easier to perform, conduct, plan, and execute models more efficiently and effectively. It has also been noticed that the building of such new models promotes the development of new era technical knowledge, for instance, the Internet of Things (IoT), mesh computing, blockchain, mobile computing, and more. The interaction between the physical model and virtual models is more active and also rapidly increasing day by day. It is becoming an unavoidable trend that is improving the potential of technologies like digital twin in various fields, such as aerospace, manufacturing, etc. A digital twin can be simple and complicated depending upon their need or the requirement for the data.

1.1.4 Challenges solved with the help of digital twin?

It exhibited several positive results in industrial areas as it could easily evaluate the process without making heavy investments and increase or boost the output by solving all the barriers without any risk.

It has already been utilized to tackle or resolve several barriers in a wide range of areas from manufacturing to medical and energy plants.

1.1.5 Designing of a digital twin

There is research on physical and operational objectives of a physical system, which include the properties, parking, work behavior in different conditions, positions, and more. It can be created in two different ways. One way is to design a system framework of the physical object. Another way is to create a data framework that will organize and link sensor data and other information. Cooperation with other assets helps develop a mathematical framework that will simulate the original [9].

1.1.5.1 Data-based digital twin

With this approach, the data of the physical object is structured to certain models. A common approach is to order by different functionalities or assemblies of the physical object. In this way, using a digital twin, a simple structured root cause analysis can be provided, which makes it possible to quickly obtain an overview of the object's performance [10].

1.1.5.2 System-based digital twin

In contrast, the system-based digital twin focuses on the actual physical object. Multiple models are integrated to obtain the most feasible, accurate, and realistic representation of real object. The system model represents the single source that has comprehensive information between logical, physical components, and functional stages. To create a digital twin of the object, knowledge of all the technical details is required [10].

Addition data of the individual components are present in the software and the electronic components used. A sketch is required for creating, which is enriched with more models and data to generate a large model that includes all information and properties. The digital twin allows the exchange of data between several models and systems.

After collecting all the data, they are synthesized with the help of AI algorithms and analytics software, which help the developers develop a mathematical model that accurately identify all the important parameters of real-world entity. The model will have an identical appearance to the corresponding object. It may include all minor to major details and functions in the same way as the original physical entity.

Finally, we have to integrate the physical object with its digital model to examine its continuous monitoring in real world. To achieve this, the virtual model should keep on receive the feedback from the sensors that collect data from the real-world entity of the product, which help the digital version to mimic and observe the behavior of the original version in real time.

The result will be a virtual mirror model for each physical model that has the capability of analyzing, evaluating, optimizing, and predicting. The basic component of digital twin architecture comprises various sensors, IoT, AI, and measurement technologies. From a computational perspective, the key method to develop a digital twin is the integration of data and information that accelerates the flow of information from raw sensory data (IoT devices) to high-level understanding and important finding. The building mechanism of the model can be complex or simple depending upon the variety and quantity of the data. Also, mechanism of the model decides how accurately it will behave in comparison with real-world physical version. It can be used with a prototype to provide feedback of the actual product as it is developed or can even act as a prototype in its own right to model what could occur with a physical entity when developed.

1.1.6 Digital twin functions

In general, the digital twins version can be used to observe the behavior of the prototype, analyze the abnormalities, and optimize the performance of physical prototypes based on advanced data analytics. Therefore, based on their functionality, we can group them into three distinguish groups:

1. **To see**

   The basic-level of digital twins technology is used to perform monitoring by the data obtained from different sensors, devices, and a software program that visualizes the situation.

2. **To think**

   The middle-level digital twins technology is equipped to perform operational modification in the existing system to find the best asset or process configuration.

3. **To-do**

   The advanced digital twins technology can be used to integrate intelligent algorithms with collected data to find out the issues and their most appropriate solution.

The focus of this study is to show the possibilities of new concepts of the digital twin in various fields and how it is helping in the technology to grow human society and minimize human efforts with the ability to change the industrial ecosystem. The main focus of the study will be on covering the basics of digital twin, including its history, applications, benefits, and challenges.

1.1.7 Application of the digital twin

In modern times, digital twin is being introduced to more fields due to its efficiency and effectiveness. Digital twin technology determining the best course of action to service critical physical assets by eliminating the guesswork. Its application includes aerospace, healthcare, manufacture, smart cities, and automobiles.

1.1.7.1 Application of digital twin in aerospace

As we know, due to the rapid increase in the intricacy of the aerospace system, the complexity of rapidly growing aerospace systems has significantly exceeded conventional development techniques as a result of the greater complexity of such systems, and the costs associated with traditional aerospace activities, such as physical prototyping, testing, and periodic maintenance, will continue to increase. One of those virtual capabilities is that of the digital twin, which can simulate with increasing levels of fidelity, speed, granularity, and reduce the costs [11] (Fig. 1.3).

It has increased the intricacy of such a system, due to which the estimated cost of traditional aerospace activities, such as prototyping, physical

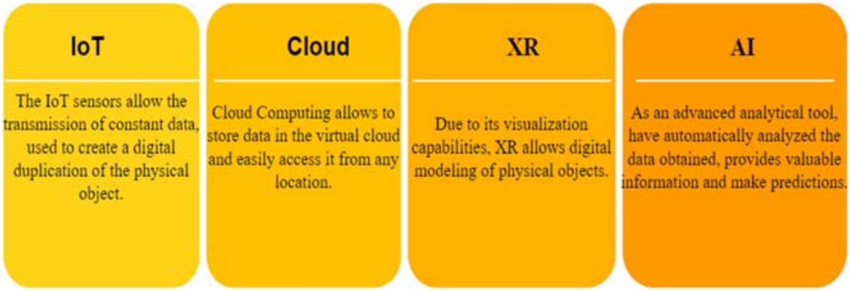


Figure 1.3 Use of digital twin in aerospace.

testing, and maintenance will increase. The virtual capability of the digital twin to imitate the physical circumstances that lead to significant decrease in the cost and the resources needed to design, produce, and keep aerospace assets up and running.

Due to the lack of understanding and communication between the different departments in the designing process, digital twin in the intelligent design of the spacecraft aims to build a physical design simulation system, shorten the design cycle, and meet the requirement for the faster, best, and most reliable spacecraft.

The design of the spacecraft is generally based on the conceptual requirements that have been proposed in the general design and the theoretical knowledge to transform the conceptual design into a specific structure as per the parameters (Fig. 1.4).

1.1.7.2 Application of digital twin in healthcare

The efficacy of a digital twin is significantly increasing in the field of healthcare in modern times. A digital twin can be used to monitor a patient's conditions virtually to acknowledge the overall condition and to give right treatment to patients by continuously capturing data from them individually.

Rightly implemented digital twin for a particular patient helps regulate the right treatment, predict the outcome of the prescribed medication by using the historical data of the patient. Let us assume the scenario of a patient who suffers from heart failure and needs Cardiac Resynchronization Therapy (CRT) by installing a pacemaker. The placement of the pacemaker must be precise to avoid future risks [12]. In such a case, with the digital twin, a virtual representation can be created that helps cardiologists define the position for the placement of the pacemaker before intervention surgery, which will minimize the risk to the patients' life (Fig. 1.5).

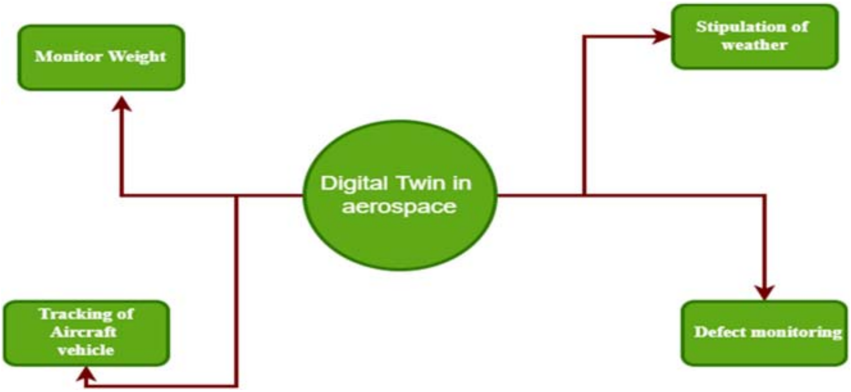


Figure 1.4 Digital twin in aerospace.

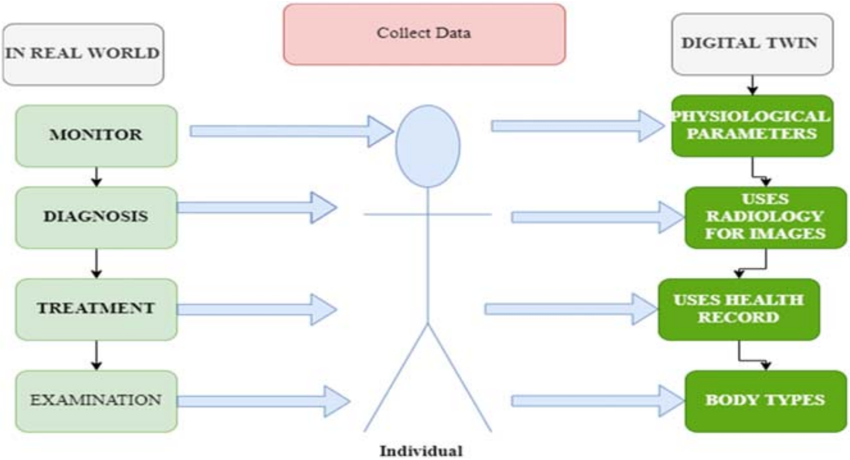


Figure 1.5 Digital twin in healthcare.

Unlearn AI

Unlearn AI is the advancing technique that boosts clinical trials of Alzheimer's disease and various other complex diseases with the help of historical datasets and diseases fed in machine learning models. It helps doctors generate the virtual picture of a patient's baseline present in the clinical studies. This leverages the trial power and confidence, also accelerating the proceedings.

With the help of machine learning for forecasting Alzheimer's disease progression, machine learning can only predict an endpoint. Its ability to simultaneously simulate large numbers of patients' characteristics could also be an essential step toward personalized medicine for Alzheimer's disease [13].

1.1.7.2.1 Digital twin objective in healthcare

(Fig. 1.6)

1. **Predictive result**: Attention to the patient evolves toward preventive care. Information about a person's genetic, biochemical, physiological, and behavioral aspects are captured to create a personalized digital twin. A person's digital replica can predict and analyze health outcomes to generate custom ideas, which would help implement preventive strategies, which will reduce the costs of medical care. Digital twins can reduce the time used by hospital staff in patient flow management and optimize inventories when predicting the patient's specific results, as well as the maintenance of the programming team [14].
2. **Personalized medicine**: Personalized medicine is one of the fields growing rapidly in the field of medicine. This aims to solve the problem by providing treatments of diseases and intervening in prevention and treatment. It aims to customize accurately because it adapts to the variables, for example, environmental, genetic factors, and lifestyle factors that make each patient unique. The ability to model individual patients with different physiological characteristics and mechanistic differences, therefore, is a natural strategy for implementing custom medication. The digital twins of a patient can be useful for customizing treatment schemes for an individual, without having long waiting times for detection/diagnostic results.
3. **Medical education and training**: The usage of digital twin in combination with virtual reality is increasing rapidly, which helps meet the

Figure 1.6 Objective in healthcare.

training and education needs of health professionals. Many companies have simulated medical anatomy and surgical procedures to minimize the use of corpses and inspire interactive learning.

4. **Surgical planning**: The patient's virtual replica allows surgeons to better plan surgical procedures and identify the risks associated with surgery. In some cases, modeling can help mitigate the need for surgery completely. The National Institute of Health develops digital twin models for athletes to accurately predict trauma-related trauma of brain injuries throughout their careers. In case of injury, this data will be an advantage in the acceleration of surgical procedures and recovery plans.

1.1.7.2.2 Application of digital twin in automobiles

There are several challenges faced by automobile manufacturers that are ensuring improved vehicle design for the past few decades. The key for the automotive industry to drive profit was to mass produce products, its adoption, and globalization. The use of digital twin in the automobile industry has helped turn the tables around [15] (Fig. 1.7).

The digital twin has the potential to input multiple challenges being faced by the automotive industry and offer solutions. Nowadays, the automotive industry is quickly adopting the digital twin. As it saves the industry time in all aspects [16] using traditional development techniques, the vehicle development process used to take around a decade to design and launch the vehicle, whereas with the adoption of digital twin now it can be done with more perfection by investing lesser time [17].

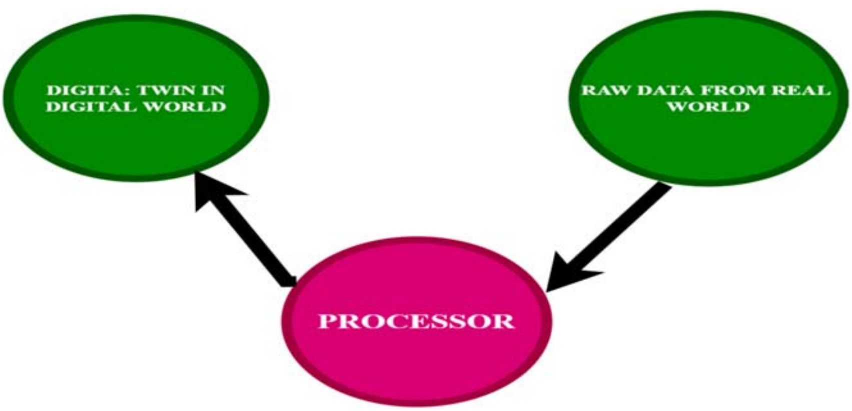


Figure 1.7 Digital twin in automobile.

It has caused changes in the automotive industry and led to the development of automatic vehicles. To overcome traffic and environmental problems, automatic automobiles use a series of sensors to navigate, as well as a navigation system and control mechanical systems and computers to process the data [18].

1. **Product tests**

   Digital twin helps determine product quality and performance by experimenting virtually with different raw materials to improve the design and optimize product performance. For example, a virtual model of a new tire can be tested for different climatic and optimized final results as needed [19].

2. **Increasing manufacturing capacity**

   Companies can take advantage of digital twins to simulate the impact and benefits of the new machine in production capacity before installation. The virtual model should consider the characteristics of the company's product, which includes material, the data of the production time and the machine required, and more, and then provides information on how the new machine can increase the production.

3. **Employee training**

   Companies can configure a factory infrastructure using a digital twin and train workers remotely without the use of physical equipment. For example, a manufacturing company in China can train its employees in India to facilitate the process of contracting and understanding the training needs of new hires [19].

4. **Predictive maintenance**

Digital twins of machines and manufacturing equipment can be used to determine when there is a need for maintenance and can be used to improve the health of production lines of factories. In this case, digital twins take advantage of real-time data extracted from IoT devices and sensors in the manufacturing process to detect the repetition of faults and the causes [19].

1.1.7.3 Role of digital twin in smart city

Digital twins are considered the new starting point for smart city construction. The use and potential of digital twins to be effective within an intelligent city are increasing day by day because of the developments in IoT. Within a growing number of developed smart cities, the most connected communities use more digital twins. A large amount of data collected by the IoT sensors is embedded in main services within a city, but will also pave the way for research aimed at the creation of advanced AI algorithms [20]. The development of digital twin cities will stimulate new ideas and procedures in urban planning, management, and services. It will also help realize the goal of intelligent city development [21].

As part of the digital transformation, manufacturers are developing digital twins to aid in the design and development of products and machines. They are also taking a step closer to building smart cities by gathering and analyzing single pieces of infrastructure [22].

Cities all around the world are already using digital twin technology. This concept is being expanded to include the idea of national twins, which would connect various urban areas onto a national platform.

Companies can create a digital twin of a company's foundation and teach workers virtually without having to actually install the technology. For example, a manufacturing business in Russia may teach its employees in Mexico on a digital twin of the facility even before the complete technology or structure is installed in Mexico, making the recruiting process easier and allowing new recruits to grasp their training requirements.

The creation of smart cities has been a large area of focus of governments in recent years. However, the concept of intelligent city must evolve sequentially with changes that affect the ecosystems in the city. The cities usually have three main features that make them smart.

1. **Awareness**: Intelligent cities have real-time awareness of the conditions that change rapidly, such as their environment, traffic, and public changing slowly and periodically.
2. **Response**: Large levels of consciousness, along with rapid response times, make a city truly intelligent. In the operations of the city, efficient responses can prevent dangerous situations that increase safety, avoid disasters, and save lives.
3. **Prediction**: The ability to predict and respond proactively to events is integral to smart cities; however, with the amount of data captured and supported by today's artificial intelligence algorithms, we are closer to becoming a reality (Fig. 1.8).

1.1.7.3.1 Objective of digital twin in smart city

1. **Smart city operation brain**

   The concept of a Smart City Operation Brain is a smart twin city that adopts the digital twin city model. The operation brain will be responsible for planning, organizing, and monitoring the various tasks and activities of the city. The smart city operation center is the core of

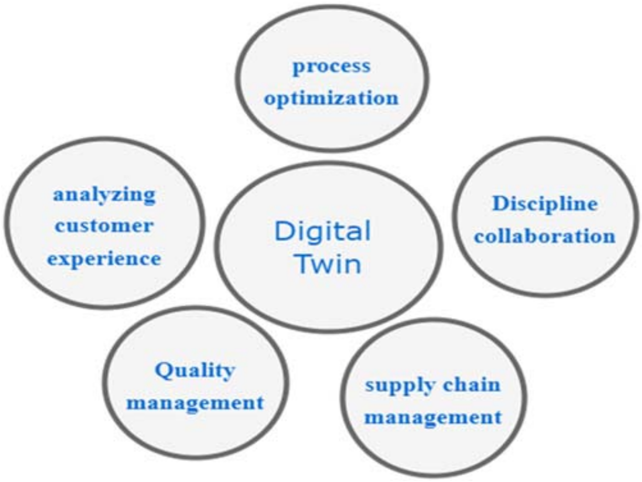


Figure 1.8 Digital twin in manufacturing.

the smart city. It coordinates the various departments, organizations in the city, and monitors the operations of the city [23].

2. **Smart city traffic brain**

   Wuhan Smart City Traffic Brain is a project that uses digital twin technology to collect and analyze big data on travel trajectories in cities. Through the use of mobile platforms and sensors, the data collected by Wuhan Smart City Traffic System can be analyzed and integrated with various emergency platforms [23]. The system uses big data collected by real-time traffic flow data. It combines various data such as traffic data, vehicle speeds, and historical congestion data to develop a congestion index evaluation algorithm. It can then inform traffic officials about the current state of road congestion and provide them with a better understanding of road conditions.

   With the use of smart transportation computing and GIS calculation, all of these activities include a decision process to support traffic departments in reducing and clearing traffic issues.

3. **Smart city public epidemic services**

   The database can be connected to an enterprise cloud platform to be used for an analysis model that uses AI and other technologies to detect and predict the occurrence of an epidemic. The system connects various government agencies and employers to take some actions. It provides the users with a reference for prevention and control. It informs them about the various services available to them [23].

4. Flood monitoring and flood situation services

In the lifecycle of a flood disaster, monitoring and forecasting of flood events can be performed in real time, which can be used for disaster assessment and reconstruction. The smart city flood monitoring system mainly consists of three parts, namely the digital twin, the flood knowledge map, and the flood service application. The main component of the system is flooded big data monitoring, which is mainly focused on the real-time collection of flood data.

This project aims to collect, analyze water conditions and rain conditions in urban areas and lakes using ground-based sensors, and satellite remote sensing technology.

1.1.8 Digital twin–driven manufacturing

The digital twin is the virtual representation of the entity, which is a synchronized instance of a digital model or a template that represents an entity throughout its lifecycle, and it is sufficient to meet the requirement of a very specific use case that the digital twin is meant to address. It can create information construct for a physical asset. It was intended to reduce the complexity by creating a digital version of any physical assets and their operating condition [24].

There are several challenges faced by the industry in product designing, process optimization, quality management, supply chain management, discipline collaboration, and analyzing customer experience.

1.1.8.1 Product design

Digital twin creates a framework between the physical and virtual assets. It creates virtual representations, prototypes, or templates during the designing phase with the help of these different simulations. The designs can be tested before investing in actual prototypes, which saves time and money by reducing the number of duplications required to get the product into production [25].

1.1.8.2 Process optimization

The manufacturers of the processing industry must strategize how to improve their operations to meet increasing demands. This operational improvement will require more up-to-date devices, systems, and processes, which in turn will require a more complex approach to measure the performance and objectives.

Increasingly, the industry must use digital twin digital technology to create predictive analysis of asset performance. Digital twins provide real-time data analysis that can be applied in multiple forms throughout the supply chain of the industry.

It should be used to improve decision-making, safety, and to increase profitability. It can process and analyze important performance indicators with the help of sensors. The digital twin can identify different ways to optimize production, with the help of root cause analysis [24].

1.1.8.3 Quality management

The digital twin operator responds from the IoT sensors at the time of production, which maintains the quality and reduces the work. It analyzes every part of the production and analyzes the variances so that better material can be used [24]. By analyzing all product-related data virtually, it tries to maintain the quality of the product.

1.1.8.4 Supply chain management

With the help of the digital twin, the distribution firm can analyze performance. The performances include packaging, route, efficiency, understanding the dynamic behavior of the supply chain, discovery of bottlenecks, development of supply chain design, monitoring of risks and testing various incidents, transport planning, inventory optimization, etc. [26]. A digital twin is useful for optimizing just in time or just in sequence and distribution route. The quality of model-based decision support depends largely on data, integrity, fullness, validity, and rapid availability. These data requirements are of particular importance in the risk management of the supply chain to predict interruptions and react. A combination of simulation, optimization, and analysis of data constitutes a digital twin a new vision driven by data from the risk management of the supply chain [27]. A digital twin of the supply chain is a model that can represent the status of the network for the given time and allow full visibility of the end-to-end supply chain to improve resilience and test emergency plans.

It uses live information sources, such as incoming shipping schedules, vehicle locations, and inventory levels, to evaluate the current status of the supply chain and provide updated forecasts.

It offers programmable notifications or alerts to inform abnormal situations, such as the levels of services below the thresholds. It provides triggers that can use to program custom actions that will be carried out automatically when selected events occur, such as possible remains.

It allows developing action plans to help address abnormal situations and try those plans to ensure that they are effective. A twin digital supply chain is a part of a bigger picture as the simulation model is being integrated with the surrounding IT environment of databases and business intelligence tools.

1. **Improved design testing of the supply chain process**

   Digital twins in the supply chain measure the risks of business and transformation before they occur. For example, a company generates models for several structures, which include data related to manufacturing, inventory, and product distribution.

2. **Monitoring of risk and testing**

   Digital twin allows companies to try and discover the best emergency action, and try different scenarios in a virtual environment, for the supply chain.

3. **Transportation plan and facilities**

   It can evaluate changes in demand and supply that affect the physical locations of the supply chain. By taking advantage of data in real time, digital twins can allow the management of the supply chain for better-planned transportation.

4. **Optimizing the inventory**

   It involves putting the right products in the right place at the correct price. Most companies also face a continuous inventory challenge to determine how much to maintain and where. Meanwhile, they have to maximize customer service at the lowest possible total cost and such calculation is a difficult task.

   In addition, greater unpredictability in demand requires more inventory. This increase in inventory is necessary to comply with the required levels of service. A digital twin is suitable in this regard. It can help optimize the inventory in a single store and throughout the network. It allows taking into account the demand forecasts. In addition, a digital twin also improves replacement policies and changes inventory levels. Digital twin does this according to the demand to avoid stocks while minimizing the cost [28].

5. **Predicting the performance of packaging materials**

When applied to packaging, digital twins can simulate packet forms and packaging material to test defects before usage, which not only decreases the financial cost but also the environmental cost [29] (Fig. 1.9).

6. **Analyzing the customer experience**

   Digital twin can be used to collect data over time from customer experience to know the product performance and the end-user

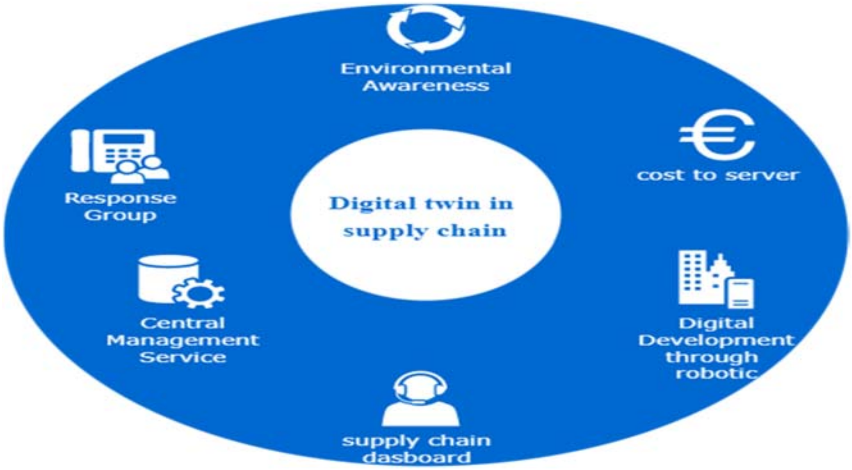


Figure 1.9 Role of digital twin in supply chain.

experience. This data can be used to help engineers and designers improve the manufactured product by the customer experience.

7. **Foresight maintenance**

 Digital twins can be used to identify variations that indicate the need for forecasting or maintenance repairs before a series of serious problems occurs for individual equipment or manufacturing processes. The digital twin also helps optimize load levels, tool calibration, and cycle times [29].

8. **Cross-discipline collaboration**

The availability of operating data of digital twins facilitates the participation of disciplines, which allows collaboration, improved communication, and faster decision-making. The production, sales, and marketing teams can work together, using the same data, to make more decisions [24].

1.1.9 Advantages of digital twin

1. It can be used for the creation of prototypes before manufacturing, which can reduce the defects of the product and the reduction of time for the market.
2. It can be used to monitor the constant transmission of use and performance of data in real time.
3. It can be used for improvements in the process that include the monitoring of the levels of the workforce against the production or

alignment of a supply chain with manufacturing or maintenance requirements.
4. It can be used to reduce the risk of accidents and unplanned inactivity time through failure.
5. It can be used to reduce maintenance costs when predicting failure before it occurs.
6. It can be used to ensure that the production goals are not affected by the maintenance, repair, and order of the spare parts.
7. It can be used to combine the lifecycle data of assets or end-to-end products in digital threads.
8. Industries can use them to support new products as a service business model.
9. It can be used to accelerate medical innovation, as they are useful in the investigation of numerous and the development of new drugs.

1.1.10 Disadvantages of digital twin

1. Digital twins are not satisfactory in all situations, it can elevate complications.
2. Digital twin is dependent on the Internet; therefore, its probability of success is directly dependent on the stability of the Internet connectivity.
3. As it accumulates data and intellectual capital required to be confidential, it can bring harm to the industry due to which security is always at risk.
4. They will be required across entire supply chains.
5. The concept of digital twins is based on 3D CAD models and not on 2D drawings.
6. The digital twin will be required in all supply chains.

Experts are required for digital twins as we need their experience for the availability and the evolution and governance of this technology.

References

[1] About the importance of autonomy and digital twins for the future of manufacturing [J]. IFAC-Papers on Line 48 (3) (2015) 567–572.
[2] S. Haag, R. Andrel, Digital twin—Proof of concept, Manufact. Lett. 15 (2018) 64–66.
[3] C. Miskinis, The history and creation of the digital twin concept, 2019, Challenge Advisory, https://www.challenge.org/insights/digital-twin-history/.
[4] F. Tao, et al., Digital Twin Driven Smart Manufacturing, Elsevier Science, Netherlands, 2019.
[5] Digital twin driven smart manufacturing. United Kingdom: ElsevierScience.
[6] https://www.twi-global.com/technical-knowledge/faqs/what-is-digital-twin.

[7] F. Tao, M. Zhang, A.Y.C. Nee, Digital twin driven smart manufacturing, Elsevier Science, United Kingdom, 2019.
[8] I.D. Network, Shark Tank Event. Indiana Defense Network. https://perma.cc/F47K-4GAM, 2020.
[9] S. Mathupriya, S. SairaBanu, S. Sridhar, B. Arthi, Materials today: proceedings.
[10] S. Kunnen, D. Adamenko, R. Pluhnau, A. Loibl, A. Nagarajah.
[11] E.M. Kraft, The air force digital thread/digital twin-life cycle integration and use of computational and experimental knowledge. In: 54th AIAA aerospace sciences meeting. 2016, p. 0897.
[12] V. Soni, Digital Twin – Top Use Cases in Healthcare, eInfochips, 2022. Available from: https://www.einfochips.com/blog/digital-twin-top-use-cases-in-healthcare.
[13] D.A. Garcia, J. Roseman, How Digital Twin Technology is Disrupting Healthcare, PLUGANDPLAY, 2021.
[14] LifeSciences, Digital Twin Simulating the Bright Future of Healthcare, 2021, FutureBridge, https://www.futurebridge.com/digital-twin-simulating-the-bright-future-of-healthcare/.
[15] https://www.tcs.com/content/dam/tcs/pdf/Industries/manufacturing/abstract/industry-4-0-and-digital-twin.pdf.
[16] CNBC, Automaker is quickly getting ready to debut a sedan and a SUV, □CNBC, Vietnam's rst-automaker, Sep 2018. https://www.cnbc.com/2018/09/10/is-fast-fastenough-for-vinfast-vietnams- (accessed Dec 2018).
[17] Warranty Week, Automotive OEM Warranty Report, Apr 2018. https://www.warrantyweek.com/archive/ww20180405.html. (accessed Dec 2018).
[18] R. Sell, E. Coatanéa, F. Christophe, Important aspects of early design in mechatronic. In: 6th International DAAAMBalt. Conference on industrial engineering., April 2008.
[19] H. Simsek, Top 5 Use Cases of Digital Twin in Automotive Industry in 2022, 2022, AI Multiple. https://research.aimultiple.com/digital-twin-automotive/.
[20] N. Mohammadi, J.E. Taylor, Smart city digital twins. In: Proc. IEEE Symp. Ser. Comput. Intell. (SSCI), Nov. 2017, pp. 1–5.
[21] L. Deren, Y. Wenbo, S. Zhenfeng, Smart city based on digital twins, Computational Urban Science 1 (2021) 1–11. Available from: https://link.springer.com/article/10.1007/s43762-021-00005-y#Sec3.
[22] J. Kosowatz, Smart Cities Look for Digital Twins, 2021, The American Society of Mechanical Engineers. https://www.asme.org/topics-resources/content/smart-cities-look-for-digital-twins.
[23] L. Deren, Y. Wenbo, S. Zhenfeng, Smart city based on digital twins, Computational Urban Science 1 (2021) 1–11.
[24] M. Crawford, Digital Twin Applications for Manufacturing, 7, The American Society of Mechanical Engineers, 2021. Available from: https://www.asme.org/topics-resources/content/7-digital-twin-applications-for-manufacturing
[25] F. Tao, J. Cheng, Q. Qi, M. Zhang, H. Zhang, F. Sui, Digital twin-driven product design, manufacturing and service with big data, The International Journal of Advanced Manufacturing Technology 94 (2018) 3563–3576.
[26] EN, Supply Chain Digital Twins, 2021, AnyLogistic, https://www.anylogistix.com/supply-chain-digital-twins/.
[27] I.M. Cavalcantea, E.M. Frazzon, F.A. Forcellinia, D. Ivanov, 2019. A supervised machine learning approach to data-driven simulation of resilient supplier selection in digital manufacturing.
[28] EN, Supply Chain Digital Twins, 2022, AnyLogistic, https://www.anylogistix.com/features/supply-chain-digital-twins/.
[29] H. Simsek, Top 5 Ways Digital Twins Transform Supply Chains in 2022, AI Multiple, 2022. Available from: https://research.aimultiple.com/digital-twin-supply-chain/.

This page intentionally left blank

CHAPTER 2

Knowledge-Driven Digital Twin Manufacturing

T. Veeramakali[1], A. Shobanadevi[1] and S. Prabu[2]
[1]Department of Data Science and Business Systems, School of Computing, SRM Institute of Science and Technology, Kattankulathur, Chennai, Tamil Nadu, India
[2]Department of Computer Science and Engineering, Karpaga Vinayaga College of Engineering and Technology, Madhuranthakam, Tamil Nadu, India

2.1 Introduction

Industry 4.0 recommended next-generation smart manufacture, such as upgrades for the industrial sectors to achieve high adaptability, quick design modifications, digital information technology, and more adaptable skilled workforce training. Cyber-physical systems [1,2], Internet of Things (IoT) [3], and cloud computing [4,5] are examples of technologies used in manufacturing. The concept of "intelligent manufacturing" is used to describe how manufacturing companies might gain a competitive edge in a fast-paced, international market [6,7]. One may say that the current interest in the Fourth Industrial Revolution has led to the idolization of intelligence that is built into actual production systems. Being absolutely aware of the technological advancements within the Industry 4.0 era is the real idea of an ubiquitous factory [8] characterized by computational technology that "recesses into the backdrop of our lives" [9]. A fresh approach to data-driven product design has recently been developed. The widespread use of digital design tools demonstrates that the design process is becoming more digital than before (e.g., CAD, FEA, CAE, CAM, etc.). Data are directly collected from smart items that use the IoT, transferred in real-time toward the "cloud," and then evaluated through big data analytics.

The intelligent manufacturing system (IMS) leverages the deep incorporation of new generation information technologies, such as Industrial IoT, big data analytics, digital twin, and knowledge engineering, to achieve a versatile, smart, and fully independent production process to optimize product quality control and efficiency while lowering the costs [10,11]. As a result, setting up IMS is crucial for industrial businesses to

Digital Twin For Smart Manufacturing
DOI: https://doi.org/10.1016/B978-0-323-99205-3.00005-5

move toward Industry 4.0. To support fully independent operations as well as self-optimization of IMS during production process, IMS configuration is not only needs the establishment of ubiquitous connections for manufacturing devices (MDs) to the cyber system but also needs to bring together the software-defined functional nodes, such as data analytics tools and knowledge-based systems, within the cyber system [12].

To finish manufacturing duties, intelligent manufacturing should take sustainability into account [13], and intelligent manufacturing tools like computer-based numerical control (CNC) machine tools and industrial robots [14–17] should be much more intelligent. This will enable better integration of these tools further into the closed-loop system of intelligent manufacturing. A variety of intelligent manufacturing systems are emerging, and as more of them are being created for particular purposes and used in real production, the level of intellect is rising considerably [10,18–22]. The sustainable collaborative manufacturing system platform connects customers, experts, and businesses and offers them individualized services as well as allows exploration and improvements in new services for intelligent manufacturing [23–30].

There is no longer a single authoritative source of statistics in the current state of the manufacturing system. The ability to automatically rearrange themselves (via actuators) enables the flexible creation of a variety of products. Smart objects include sensors, machinery, equipment, products, etc. that have embedded localized intelligence and many are invisibly interconnected (through the cloud) [31]. The idea of digital twin (or cyber twin) of a manufacturing system has materialized as a result of its growing autonomy. The idea of a "system that duplicates the life of its flying twin," was first proposed by Dr. Grieves in 2003, which has already been embraced in the realm of aviation [32]. The "twinning" procedures, which involves creating a digital replica of an actual system, has recently been proposed at various stages of the product lifecycle as an interconnected collection of pertinent digital artifacts via various simulation techniques [33–35].

The term "Digital Twin" refers to a comprehensive physical and functional representation of a part, a product, or a system [36], which contains a plethora of data that may be helpful at various stages of the project's lifecycle [37]. While digital twins are emerging as the key enablers in prognostics and health management as well as in smart maintenance, repair, and modernization activities, smart objects also bring opportunities for production methods' self-regulation and real-time simulation-based enhancement of goods and manufacturing process [38–40]. The integration, reuse, creation, and management of information produced from sensory data processed by intelligent algorithms are demonstrated by digital twins, as well as by scientific publications and industrial uses. However, since human workers are not a core component of the 4.0 revolution, simplified knowledge access and fruition is a factor that is sometimes disregarded during the design process of the digital twin.

This study concentrates on the interaction between a pair of virtual and physical products against such a backdrop. To visualize product structure, simulate product behavior, and improve product efficiency, products are built in laboratories for such virtual environment. When goods are used by end customers in the physical environment, their performance, behaviors, and interactions with the consumers are recorded by sensors and managed by actuators. Virtual and physical products are often developed, evaluated, and upgraded in some way apart from one another. A fresh framework is needed in light of a data-driven product design to efficiently converge, integrate, as well as sync the ever-growing "larger" data pertaining to the virtual product, the physical product, and their back-and-forth exchanges.

As the minimum implementation unit for intelligent manufacturing, autonomous and self-optimizing manufacturing cells are proposed as new requirements, including learning and cognitive capabilities. Cellular manufacturing is wherein the idea of a manufacturing cell comes from [41]. By bringing together all the machine tools engaged in the sequence of operations of a product's natural flow and grouping them close to one another, distinct from other groups, it tries to construct short, focused channels in concentrated real space to save cost and maintain flexibility. Many frameworks have already been established recently to give an understanding of the intelligent manufacturing paradigms, including cloud manufacturing [42] and smart manufacturing [43]. At the same time, certain implementation strategies for intelligent manufacturing have been put forth, including production data analysis as well as gathering [44], RFID-based production monitoring [45], as well as digital twin-based cyber-physical fusion [46]. The aforementioned groundbreaking works advance both the comprehension and use of intelligent manufacturing. However, the development of an autonomous manufacturing cell—which is also essential for manufacturing enterprises to put intelligent manufacturing into practice—has received relatively less attention. An autonomous production cell is one that can function independently from human control across most situations (Fig. 2.1).

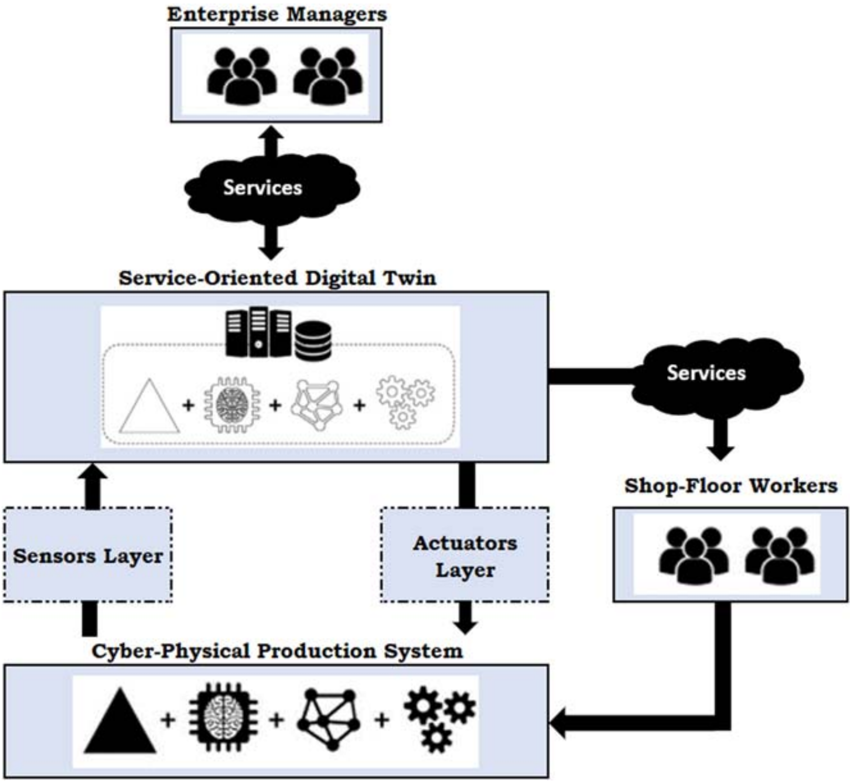


Figure 2.1 An Industrial Internet service-oriented model.

2.2 A service-oriented model for the Industrial Internet

Through data gathering and analysis, physical manufacturing resources could be virtually represented (i.e., in their Digital Twin), and their status and behavior can be dynamically monitored, supervised, and changed by a manufacturing staff (both enterprise supervisors and shop-floor operators), thanks to a set of apps and services that can be accessed at any time and from any location through the cloud. Fig. 2.2 presents a service-oriented implementation model for the Industrial Internet pyramid.

Each physical production resource (such as materials, machine tools, machining centers, robots, products, software resources, etc.) has a sensor layer that continuously gathers data. This data includes basic attributes, real-time status, process parameters, processing progress, maintenance records, operation data of products, as well as demands data, user behavior data, as well as transaction data. The foundation of the knowledge about

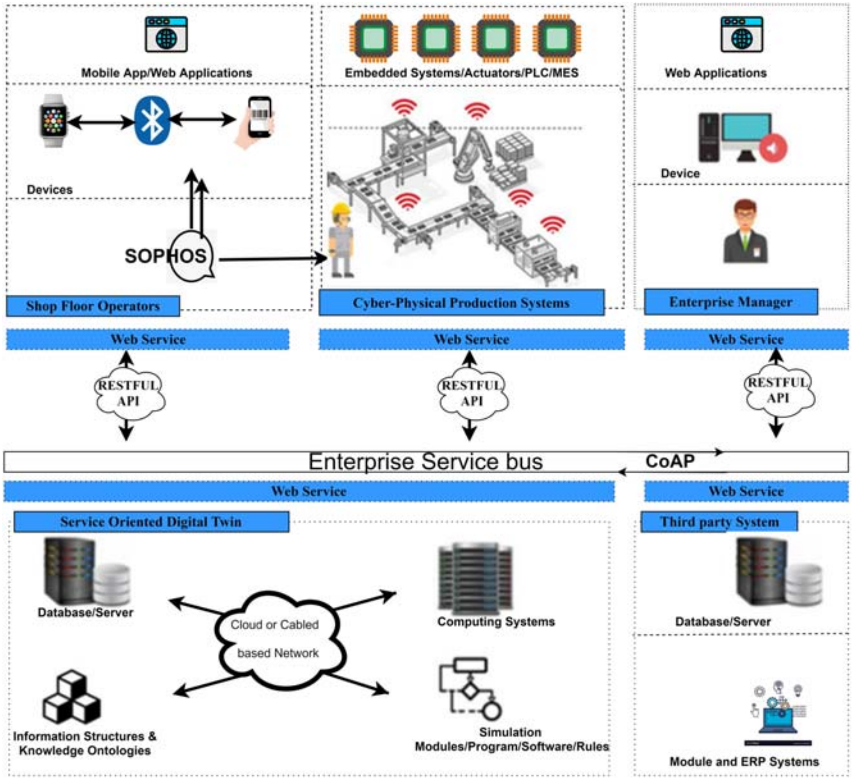


Figure 2.2 A technological architecture of a service-oriented digital twin application.

the CPPS comprises these components as well as a few documents (such as robot manuals and work plans) that can also be linked to resources and categorized by system for subsequent usage by users.

The entire process of decision-making and control is covered by the services provided by the service-oriented digital twin. Knowledge-empowered supervisors would make better decisions because they would watch and engage with the CPPS's real-time updated digital twin rather than directly monitoring or acting upon it. The current model offers the following four services to manufacturing managers:

Depends on the sensed as well as processed data, the Fault Detection and State Monitoring Service identifies the real-time status, the history and scheduled operations as well as potential sources of ongoing faults of the manufacturing resources, giving managers a useful tool to comprehend and assess the state and health situation of the CPPS.

The Prognostics and the Scenario Optimization Service forecasts a possible production scenario's performance in the future based on the CPPS's real-time state, current and forecasted production data, simulation models, rules, optimization algorithms, etc., as well as user-defined parameters, offering a way to confirm production capability and capacity, reduce the likelihood of costly failure and downtime, identify maintenance priorities, and more.

The Manufacturing Scenario Execution Service gives the manager a mechanism to quickly and concretely apply new work plans, maintenance schedules, or production schedules by converting potential production scenarios into low-level parameters for the CPPS and instructions for the actuators layer.

If the CPPS exhibits an unusual state or behavior, the Notification Service notifies the production management so that they can act before failure. A proactive variant of the fault diagnosis and state monitoring service alerts the manager about any unexpected or risky behavior directly from the service-oriented digital twin [47].

2.3 A technological architecture of a service-oriented digital twin

A distributed system of networked elements, such as computing systems and devices, storage systems, as well as smart devices (such as smartphones, tablets, and smartwatches), known as remote terminals, is the technical solution that best matches the previously proposed service-oriented model Remote Terminal Units (RTUs). Remote terminal units (RTUs) will serve as knowledge gateways because they provide factory workers access to services that enable cross-layer integration between the CPPS, the service-oriented digital twin, and the workers. The exchange of all the messages contained inside RESTful web services allows all the systems in the network to coordinate their movements and other aspects of their behavior (WS). Representational State Transfer (REST) architectural style has been used due to its increased popularity [48], as well as the fact that it makes use of common Internet standards and takes advantage of a system's web-based nature [49]. Additionally, the use of RESTful WS enables simple integration with CPPS management tools (e.g., a third-party ERP system or MES). Constrained application protocol (CoAP), which is frequently used for the IoT domain, is used to incorporate a WS mapping into an Enterprise Service Bus incorporated into a central server because the service-oriented digital twin is a distributed network of computing systems that provides or consumes web services. Its responsibility is to obtain the service ticket, direct it to the appropriate producer (the system providing the service), and give the completed result back to the customer (the RTU requesting the service). Clients access these resources using platforms like GET, PUT, POST, and DELETE after the server makes resources (the architectural components) available through a URL. CoAP resembles HTTP a lot from a developer's perspective. The process is quite similar to getting a value from a Web API if the manufacturing staff wants to use the mobile application to get data from a sensor in the CPPS. The URL http://www.digital-twin/api/getMachine/000X/getStatus, which would return a JSON file with all the details about machine state, is used to request particular resource. 000X is the identification number of the machine we wish to study.

Fig. 2.3 depicts the technical layout of the service-oriented digital twin application that is presented here. It consists of four main components and an additional component that represents a generic third-party system (such as a particular manufacturing control module or ERP system) that can be used to offer manufacturing employees value-added services (such as interaction only with CPPS) or to the stakeholders of the enterprise (such as delivery period of the "mass-customized" product based on the real-time status of the plant, use of ERP data for testing with the digital twin) [47].

2.4 A flexible ontology-based knowledge structure

The functionality of the service-oriented digital twin can be jeopardized by the lack of an adaptable knowledge structure that can be reused for various manufacturing processes and CPPS configurations and also is resilient to modifications in the CPPS over time. This issue is addressed in this architecture. A flexible and configurable ontology-based knowledge structure is designed to map all the raw and processed data generated by the CPPS or by the service-oriented digital twin, making it possible for users without programming experience to add new data streams toward the knowledge structure or change the knowledge structure to suit their needs. Fig. 2.4 presents an extracted piece of a knowledge structure depends on an ontology. The "Item" class in this ontology represents a general industrial asset or manufacturing resource whose status at a given moment is specified as a concatenation of the following:

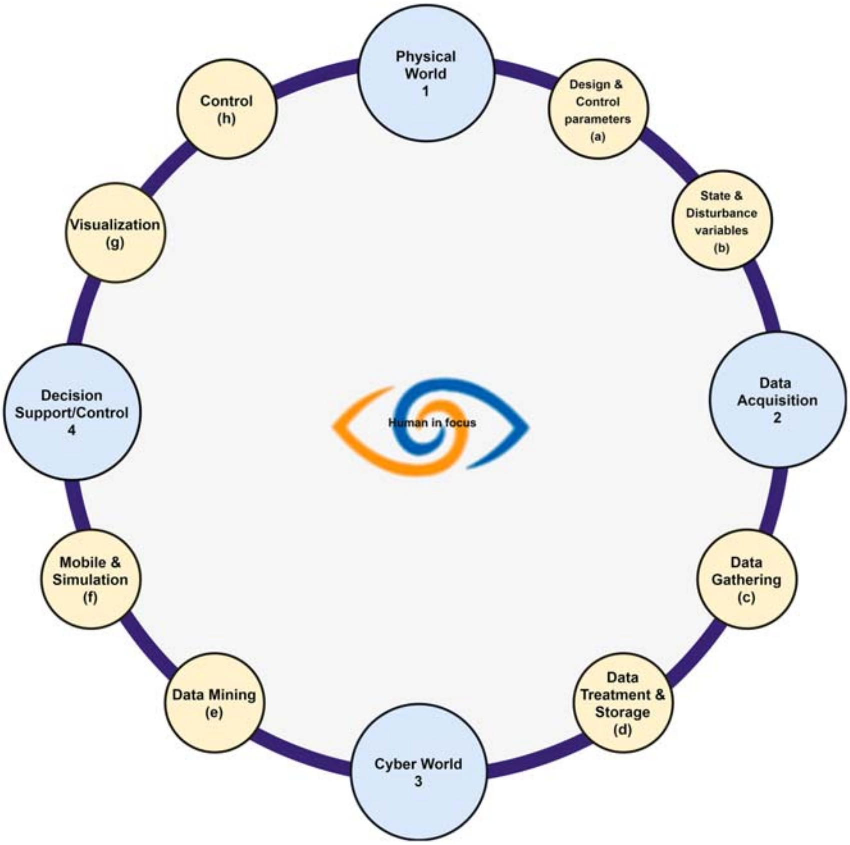


Figure 2.3 A CPPS process.

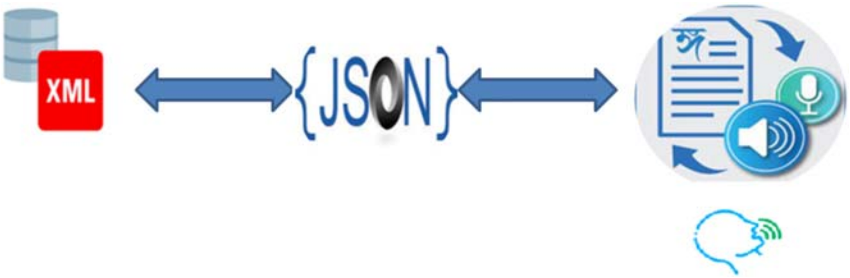


Figure 2.4 A technological structure for an advanced ubiquitous knowledge fruition.

- A predetermined set of fixed attributes that remain constant over time (unless changed by the system administrator), including a unique ID, name, description, category, the collection of objects in such a previous

state, multimedia files like images, videos, or audio, or generic files (like PDF), 3D models, more information, and the time since the last update.
- A variety of dynamic custom characteristics that may be coupled to data streams originating from sensors in the CPPS and generated using a GUI depending on the kind of asset. Examples include a band saw's "cut angle," a lathe's "speed," an electric engine's "oscillation," and "operating temperature." [47]

2.5 A technological solution for advanced ubiquitous knowledge fruition

Utilizing the technology framework shown in Fig. 2.4, the application prototype for the shop-floor operators has been created to convey information quickly and effectively. It has been created as an Android application that can read QR codes and allow users to either touch on the screen or speak to the device to make a service request. The request would result in a JSON response, which the smart device will analyze and translate into a useable format (e.g., text, images, audio, video, 3D models). Additionally, the server is fitted with Apache Solr (a java-based open source platform for full text-based search, hit highlighting, faceted search, dynamic grouping database integration, and rich documents—.doc, .docx, and .pdf—management) and the plug-in Lucene (an open source high-performance and java-based search engine that provides APIs to retrieve information based on inverted index-based algorithms), allowing them to offer an intelligent "4.0 knowledge navigation" (as already proposed and tested in Longo, Nicoletti, & Padovano, 2017). Searches are much faster and more effective with Solr and Lucene than with conventional object-relational mapping since they are based on "key-value" non-relational databases. This design approach is based on the Text-To-Speech (TTS) and Speech-To-Text (STT) features of Android, which have been shown to be reliable and solid systems with an average response time of 2 seconds and a 95% accuracy rate. As a result, the system would be able to correctly respond to simple questions using keyword recognition and complex questions using sentence semantic analysis [47].

2.6 Conclusions and further research

In the context of an Industry 4.0 that is more focused on people, the Industrial Internet pyramid put forth in this study makes the case that an organization will change from an Automated Factory to a Smart Factory when there is no longer any information asymmetry within and among technology, processes, and people, resulting in a fully (or nearly fully) coupled human-machine interaction. The difficulty of this transformation is not only due to the paucity of structured information and clear implementation guidelines in the literature, but also due to the difficulty of empowering and persuading businesses and operators—who are more accustomed to legacy systems and conventional practices—to quickly and effectively use this knowledge.

In fact, industrial production environments have demonstrated that they cannot function without the human intervention, which is now changing from traditional blue-collar workers to knowledge-empowered workers. This is because, as businesses ascend the Industrial Internet pyramid to the top and Industry 4.0 initiatives are supported by a ubiquitous knowledge, there will be no information asymmetry between CPPS and manufacturing employees. The two case studies demonstrated how the current technology-driven Industry 4.0 initiatives' potential has not yet been fully realized due to a lack of ubiquitous knowledge-oriented propensity in manufacturing enterprises and because simple technological change is easily replicable by competitors and does not give the company any value addition or competitive advantage globally.

By presenting the Industrial Internet pyramid and creating a prototype of a service-oriented digital twin that greatly supports the manufacturing employees' daily jobs on the shop floor of two enterprises, this chapter seeks to advance the concept of Smart Factory. While the bottom of the Industrial Internet pyramid (which involves bridging the production system and employees through a seamless bidirectional information stream) can be easily calculated in cases where new technologies, innovative robots, or automated smart machines are purchased and deployed in a production line, businesses are hesitant to invest money and effort because the return on investment is frequently uncertain.

Instead, the encouraging findings of this application research demonstrate how production and business performance may be improved in a statistically meaningful way, providing optimism for any sort of firm. Research is currently being done to increase the intelligent vocal assistant's capacity to understand and accurately respond to a variety of other instructions or requests. Additionally, research is being done on the statistical correlation between an enterprise's performance and its knowledge management initiatives, as well as on how long it will take to see a meaningful return on investment.

Given this, one area of applicability is for managing and operating industrial assets. Numerous new knowledge-driven business opportunities may arise as a result of the service-oriented digital twin. To implement a complete organizational-wide transformational change or to offer cutting-edge services to the customers in the context of a mass customization production strategy, this knowledge can also be conveniently shared with the enterprise's stakeholders, such as customers, suppliers, partners, etc. Sales orders can be coupled with production scheduling or maintenance tasks in a smart factory so that the manufacturing staff can plan or reschedule specific tasks in real-time in accordance with the revised production timeline and levels. When outsourcing tactics are used in maintenance operations, this element becomes even more important.

It is common for third-party companies who offer maintenance services to be keenly interested in learning in an understandable and timely manner whether it is possible to perform maintenance operations on a machine (or set of machines) based on the anticipated output levels. The implementation of the Industrial Internet pyramid outside of the industrial environment in a more thorough manner across the company and organizational levels may be an intriguing expansion of the current work. Service-oriented digital twins with intelligent verbal assistants may act as the hinges between a supplier and a client, streamlining and improving the supply process, if we expand the concept of eliminating information asymmetry also among the stakeholders of a supply chain. In this regard, the integration of digital twins with reliable data-sharing technologies (like blockchain) may usher in a new era of supply chain research.

In a time when knowledge must be safeguarded against potential cyberattacks, this final feature of trusted data-sharing technology is very important. Cyberattackers may target IT industrial systems more frequently as more industrial smart assets connect to the internet and service-oriented digital twins gain popularity. They may do this by using virtual tools to steal organizational knowledge, conduct industrial espionage or extortion, or even take control of the physical systems. To provide proper, robust cybersecurity measures and activities to promote knowledge resiliency, considerable research efforts and practices must be taken into account.

References

[1] S. Waschull, J.A.C. Bokhorst, E. Molleman, et al., Work design in future industrial production: transforming towards cyber-physical systems, Comput. Ind. Eng. 139 (2020) 105679.

[2] Y. Javed, M. Felemban, T. Shawly et al., A partition-driven integrated security architecture for cyber-physical systems. arXiv:190103018[csSY], 2019.
[3] A. Van Der Zeeuw, A.J. Van Deursen, G. Jansen, Inequalities in the social use of the internet of things: a capital and skills perspective, N. Media Soc. 21 (6) (2019) 1344−1361.
[4] M. Habibi, M. Fazli, A. Movaghar, Efficient distribution of requests in federated cloud computing environments utilizing statistical multiplexing, Future Gener. Comput. Syst. 90 (2019) 451−460.
[5] H. Yan, P. Yu, D. Long, Study on deep unsupervised learning optimization algorithm based on cloud computing. In: 2019 international conference on intelligent transportation, Big data & smart city (ICITBS), 2019, pp 679−681.
[6] X. Chen, S. Zhang, J.M.P. Geraedts, Guest editorial focused section on sensing and perception systems for intelligent manufacturing (SPIM), IEEE/ASME Trans. Mechatron. 23 (3) (2018) 983−985.
[7] G. Xue, Y. Xia, A flexible logistics system for intelligent manufacturing workshop. In: Proc. IEEE ICMIMT, Cape Town, South Africa, 2019, pp. 133−137.
[8] J.S. Yoon, S.J. Shin, S.H. Suh, A conceptual framework for the ubiquitous factory, Int. J. Prod. Res. 50 (8) (2012) 2174−2189.
[9] M. Weiser, The computer for the 21st century, Sci. Am. 265 (3) (1991) 94−105.
[10] R.Y. Zhong, X. Xu, E. Klotz, S.T. Newman, Intelligent manufacturing in the context of industry 4.0: a review, Engineering 3 (5) (2017) 616−630.
[11] K. Ding, F.T.S. Chan, X. Zhang, G. Zhou, F. Zhang, Defining a digital twin-based cyber-physical production system for autonomous manufacturing in smart shop floors, Int. J. Prod. Res. 57 (20) (2019) 6315−6334.
[12] J. Leng, et al., Digital twin-driven rapid reconfiguration of the automated manufacturing system via an open architecture model, Robot. Comput. Int. Manuf. 63 (2020). Art. no. 101895.
[13] B. He, Q.J. Pan, Z.Q. Deng, Product carbon footprint for product life cycle under uncertainty, J. Clean. Prod. 187 (2018) 459−472.
[14] H. Radhi, Multi-objective optimization of turning process during machining of AISI 1025 on CNC machine using multiobjective particle swarm optimization, Univ. Thi-Qar J. Eng. Sci. 10 (1) (2019) 65−70.
[15] B. He, X.Y. Cao, Z.C. Gu, Kinematics of underactuated robotics for product carbon footprint, J. Clean. Prod. 257 (2020) 120491.
[16] S. Chiaverini, B. Siciliano, O. Egeland, Review of the damped least-squares inverse kinematics with experiments on an industrial robot manipulator, IEEE Trans. Control. Syst. Technol. 2 (2) (1994) 123−134.
[17] Y. Altintas, J. Yang, Z.M. Kilic, Virtual prediction and constraint of contour errors induced by cutting force disturbances on multi-axis CNC machine tools, CIRP Ann. 68 (1) (2019) 377−380.
[18] P. Zheng, H.H. Wang, Z.Q. Sang, et al., Smart manufacturing systems for Industry 4.0: conceptual framework, scenarios, and future perspectives, Front. Mech. Eng. 13 (2) (2018) 137−150.
[19] F. Tao, Q.L. Qi, A. Liu, et al., Data-driven smart manufacturing, J. Manuf. Syst. 48 (2018) 157−169.
[20] A. Yadav, S.C. Jayswal, Modelling of flexible manufacturing system: a review, Int. J. Prod. Res. 56 (7) (2017) 2464−2487.
[21] B.H. Li, B.C. Hou, W.T. Yu, et al., Applications of artificial intelligence in intelligent manufacturing: a review, Front. InfTechnol Electron. Eng. 18 (1) (2017) 86−96.
[22] A. Kusiak, Smart manufacturing, Int. J. Prod. Res. 56 (1/2) (2017) 508−517.

[23] B. He, Y.C. Hua, Feature-based integrated product model for low-carbon conceptual design, J. Eng. Des. 28 (6) (2017) 408−432.
[24] H. Bouzary, F. Frank Chen, Service optimal selection and composition in cloud manufacturing: a comprehensive survey, Int. J. Adv. Manuf. Technol. 97 (1/4) (2018) 795−808.
[25] H. Bouzary, F.F. Chen, K. Krishnaiyer, Service matching and selection in cloud manufacturing: a state-of-the-art review, Procedia Manuf. 26 (2018) 1128−1136.
[26] D. Bauer, D. Stock, T. Bauernhansl, Movement towards service-orientation and app-orientation in manufacturing it, Procedia CIRP 62 (2017) 199−204.
[27] A. Giret, E. Garcia, V. Botti, An engineering framework for service-oriented intelligent manufacturing systems, Comput. Ind. 81 (2016) 116−127.
[28] Y. Cao, S.L. Wang, L. Kang, et al., Study on machining service modes and resource selection strategies in cloud manufacturing, Int. J. Adv. Manuf. Technol. 81 (1/4) (2015) 597−613.
[29] B. He, D. Zhang, Z.C. Gu, et al., Skeleton model-based product low carbon design optimization, J. Clean. Prod. (2020). Available from: https://doi.org/10.1016/j.jclepro.2020.121687.
[30] I.E. Grossmann, Optimization and management in manufacturing engineering: resource collaborative optimization and management through the internet of things, Optim. Methods Softw 34 (1) (2019) 220−223.
[31] S. Wang, J. Wan, D. Li, C. Zhang, Implementing smart factory of industry 4.0: an outlook, Int. J. Distrib. Sens. Netw. 12 (1) (2016) 3159805.
[32] M. Shafto, M. Conroy, R. Doyle, E. Glaessgen, C. Kemp, J. LeMoigne, et al., Modeling, simulation, information technology & processing roadmap. Technology Area, 11. National Aeronautics and Space Administration, 2010.
[33] R. Rosen, G. von Wichert, G. Lo, K.D. Bettenhausen, About the importance of autonomy and Digital Twins for the future of manufacturing, IFAC-PapersOnLine 48 (3) (2015) 567−572.
[34] B. Schleich, N. Anwer, L. Mathieu, S. Wartzack, Shaping the Digital Twin for design and production engineering, CIRP Ann. 66 (1) (2017) 141−144.
[35] S. Boschert, R. Rosen, Digital twin − the simulation aspect, in: P. Hehen berger, D. Bradley (Eds.), Mechatronic Futures: Challenges and Solutions for Mechatronic Systems and Their Designers, Springer International Publishing, 2016, pp. 59−74.
[36] E.J. Tuegel, A.R. Ingraffea, T.G. Eason, S.M. Spottswood, Reengineering aircraft structural life prediction using a Digital Twin, Int. J. Aerosp. Eng. (2011) 2011.
[37] A. Cerrone, J. Hochhalter, G. Heber, A. Ingraffea, On the effects of modeling as-manufactured geometry: toward Digital Twin, Int. J. Aerosp. Eng. (2014) 10. Available from: https://doi.org/10.1155/2014/439278. Article ID 439278.
[38] R. Stark, S. Kind, S. Neumeyer, Innovations in digital modelling for next generation manufacturing system design, CIRP Annals-Manufacturing Technol. 66 (1) (2017) 169−172.
[39] J. Lee, B. Bagheri, H.A. Kao, A cyber-physical systems architecture for industry 4.0-based manufacturing systems, Manuf. Lett. 3 (2015) 18−23.
[40] Q. Qi, F. Tao, Y. Zuo, D. Zhao, Digital Twin service towards smart manufacturing, Procedia CIRP 72 (1) (2018) 237−242.
[41] E. Ostrosi, A.-J. Fougères, Intelligent virtual manufacturing cell formation in cloud-based design and manufacturing, Eng. Appl. Artif. Intell. 76 (2018) 80−95. Available from: https://doi.org/10.1016/j.engappai.2018.08.012.
[42] G. Adamson, L. Wang, M. Holm, P. Moore, Cloud manufacturing − a critical review of recent development and future trends, Int. J. Comput. Integr. Manuf. 30 (4−5) (2017) 347−380. Available from: https://doi.org/10.1080/0951192X.2015.1031704.

[43] A. Kusiak, Smart manufacturing, Int. J. Prod. Res. 56 (1–2) (2018) 508–517. Available from: https://doi.org/10.1080/00207543.2017.1351644.
[44] K. Ding, P. Jiang, S. Su, RFID-enabled social manufacturing system for inter-enterprise monitoring and dispatching of integrated production and transportation tasks, Robot. And. Comput.-Integr. Manuf. 49 (2018) 120–133. Available from: https://doi.org/10.1016/j.rcim.2017.06.009.
[45] Z.X. Guo, E.W.T. Ngai, C. Yang, X. Liang, An RFID-based intelligent decision support system architecture for production monitoring and scheduling in a distributed manufacturing environment, Int. J. Prod. Econ. 159 (2015) 16–28. Available from: https://doi.org/10.1016/j.ijpe.2014.09.004.
[46] K. Ding, T.S.C. Felix, X. Zhang, G. Zhou, F. Zhang, Defining a digital twin-based cyber-physical production system for autonomous manufacturing in smart shop floors, Int. J. Prod. Res. (2019) 1–20. Available from: https://doi.org/10.1080/00207543.2019.1566661.
[47] F. Longo, L. Nicoletti, A. Padovano, Ubiquitous knowledge empowers the Smart Factory: the impacts of a service-oriented digital twin on enterprises' performance, Annu. Rev. Control. 47 (2019) 221–236.
[48] Khan M, Silva B.N, Han K, A web of things-based emerging sensor network architecture for smart control systems, Sensors 17 (2) (2017) 332. Available from: https://doi.org/10.3390/s17020332.
[49] Iarovyi S., Mohammed W.M., Lobov A., Ferrer B.R., Lastra J.L.M., Cyber–Physical Systems for Open-Knowledge-Driven Manufacturing Execution Systems, Proceedings of the IEEE 104 (5) (2016) 1142–1154. Available from: https://doi.org/10.1109/JPROC.2015.2509498.

CHAPTER 3

Digital twin and artificial intelligence in industries

S. Salini and B. Persis Urbana Ivy
Department of Computer Science and Engineering, Bharath Institute of Higher Education and Research, Chennai, Tamil Nadu, India

3.1 Introduction

The present paradigm for manufacturing calls for a significant increase in product diversity, production in lot sizes of one, even when demand is unknown, and stringent delivery deadlines. Future factories will need more adaptability and reconfigurability so that they can quickly react to changes in demand and unanticipated circumstances. Additionally, these plants will need to be able to perform high-level activities without complex (re)programming or human involvement. As a direct consequence, the implementation of cutting-edge digital technology and industrial processes must now take place. In this regard, the collection of technologies known as digital manufacturing has been deemed to be one of the most promising in terms of meeting the growing need for individualized production [1]. Even if it will take more time and a cultural shift on the part of the industry as a whole, businesses can take advantage of this opportunity to place an even higher emphasis on data analytics to enhance both the quality of their services and their cost-effectiveness. And as a result of this, Off will need to consider how it can most effectively integrate this potential into its approach to regulation to facilitate improved market results for customers. New developments in the Internet of Things (IoT) and Artificial Intelligence (AI) are providing the impetus for the emerging trend known as Industry 4.0, which may be seen in the field of advanced manufacturing [2]. Integrating and interacting with equipment to collect data is made possible via the IoT. AI-based solutions analyze machine data, and the combination of these basic technologies yields high-value information in the form of suggestions or judgments that boost manufacturing productivity, cut down on unexpected maintenance costs, and ensure product uniformity [3,4]. Industry 4.0 applications are helping

Digital Twin For Smart Manufacturing
DOI: https://doi.org/10.1016/B978-0-323-99205-3.00014-6

the digital industrial transformation. Applying statistical approaches to previously collected study data to determine how AI is progressing at the frontier of its field is the purpose of our research. In light of the aforementioned, the primary emphasis of our study was placed on the incorporation of AI into "cyber-psychical systems" (CPS), which link human and computer interactions. Our study focused on developing a conceptualization of AI assimilation in CPS "digital twins" (DT) that is acceptable to the general public, complies with security norms, and can withstand legal examination. This study expands upon prior studies of cyber risk in I4.0 [5–8], focusing instead on the statistical biometrical analysis of massive datasets and qualitative empirical analysis of the most prominent national frameworks for I4.0. "Industry 4.0" (I4.0) stands for the digitalization of manufacturing processes; IoT is a network that connects everyday objects. This study bridges the gap between AI and cyber-physical systems, as well as the broader issue of "Industry 4.0," or the digitization of manufacturing processes. For the sake of this paper's research goals, cyber-physical systems and AI are combined (Fig. 3.1).

Mining the implicit link between each data item in the database is what we mean when we talk about relational data topic mining at big data (BD). Mining frequent item sets of transaction sets in a database is both a necessary step and the ultimate goal of association rules (the most fundamental pattern is an itemized, which refers to a collection of several

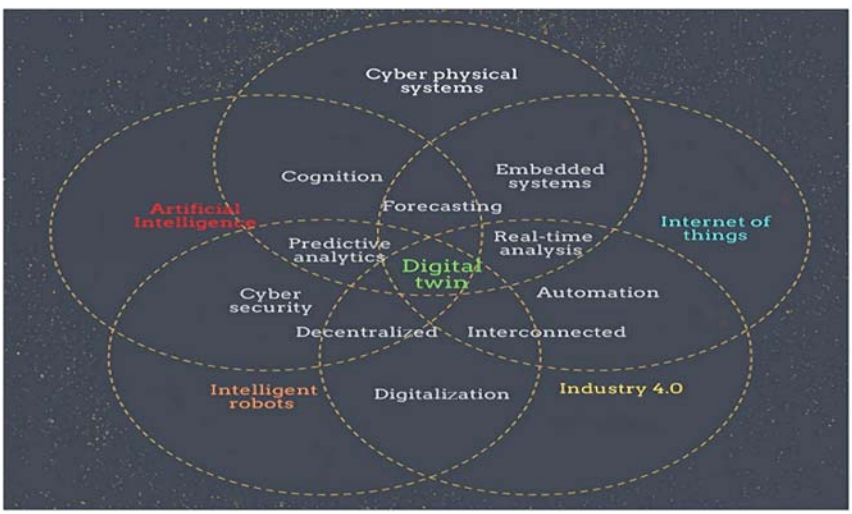


Figure 3.1 Research (mind-map) plan.

items; frequent patterns refer to item sets, sequences, or substructures that frequently appear in a dataset; frequent item sets refer to sets with support greater than or equal to the minimum support). Mining association rules provide for a clear expression of the link between each data item in the database, which makes the relationship easier for humans to comprehend. Utilizing our system to mine the significance of BD is a strategy that is both effective and economical. Static algorithms are only able to process data that conforms to certain standards. Static algorithms are plainly not sufficient to fulfill the needs for some locations, such as sites that require emergency processing and significant hazards, such as emergency fire monitoring, cabin gas monitoring, and other similar places. Even if the currently available dynamic algorithms are able to exert control on the data in real time, these algorithms still need more improvement and optimization to compute the data with a higher degree of precision and a smaller margin for error.

In addition, the production side of things is only partially covered by Industrial Internet of Things (IIoT) (meaning that only some of the information is gathered from the equipment). In terms of DTs, the sole method of data input is manual. There are prospects for the use of AI as a result of the widespread adoption of IIoT in industry and the associated growth in data processing. The goal of the study is to concentrate on the conception, structure, and application of DT in manufacturing through the use of AI and IIoT, as well as to demonstrate the possibility of utilizing the formal model to ensure the possibility of conducting an in-depth analysis of the current state and future development of the landscape. The notion of manufacturing posits that there are three primary components involved in the process: procedures, employees, and equipment. Every piece of information collected by these units is sent on to the manufacturing model (DT) and the decision support system (AI) [9] examines the commonly recognized notions of enterprise security and safety management by integrating these two interrelated tasks into a single concept. This is done to make the administration of business security and safety more efficient. DTs are highly detailed computer simulations of real-world systems that may communicate with their counterparts in the actual world via the use of sensors and other IoT-enabled devices.

The sensors that are used for environment realization and precise functional representation of the physical system in a meaningful virtual representation are where the majority of the complexities may be found. This is often done for more sophisticated control and simulation. In the past 10 years, there has been a significant expansion of the DT technology, which seeks to enable methods for exercising control over physically complicated systems. When it comes to the core of virtual and augmented reality, it is a natural progression and the fusion of many different developing technologies, such as IoT, wireless networks, sensor integration, machine learning (ML), AI, big data, and data visualization. Without a doubt, it is one of the cornerstones of Industry 4.0 in the direction of accomplishing holistic control and communication between management, machines, and workers. A representation of a manufacturing process or service in the digital world that is regulated by specified qualities and circumstances is referred to as a DT. This concept may be interpreted as follows: Processes and products from the physical world, together with their environments, may be digitally transported to the context of the cyber world and described there. In this manner, a DT may be applied to study and better comprehend an item or process, leading to its optimization without investing the resources that are necessary in a trial and error mode of operation that takes place in the actual world.

In this special issue, we investigate the numerous industries in which DT technology has been used and how it has been implemented. We welcome authors to submit high-quality, unique research that incorporates sensors used DT systems. In 2011, the Association of Industrial Automation of Ukraine (APPAU) was founded to serve as a driver of the trend toward Industry 4.0. The use of AI in manufacturing paves the way for a wide variety of options to create value, including the optimization of processes and the creation of new business models (Fig. 3.2), as can be shown below.

The objective of APPAU is to cultivate the local market via the growth of business and the formation of professional standards in the technical area. The following are the primary activities and responsibilities of APPAU [10,11] that will be of interest to the European community of industrial automation: The national movement, Industry 4.0, in Ukraine was established by APPAU and the Association for Innovative Development of Ukraine [12,13]. The humans and the equipment (such as robots, AGVs, machines tools, and so on) that make up the shop floor also make up the physical shop. Workers who are physically present on the factory floor are able to help in the completion of difficult production operations and make quick responses to emergency circumstances [14]. The actual shop-shape, floor's data relationships, and internal mechanism are all described by a virtual shop floor that is driven by real-time data

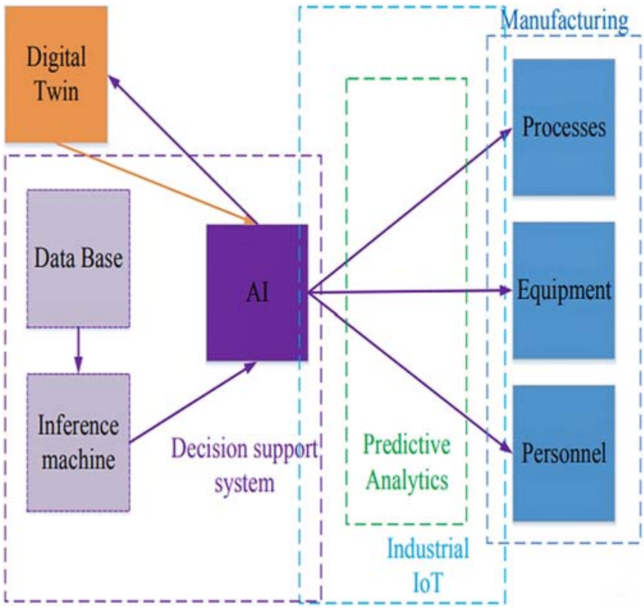


Figure 3.2 Artificial intelligence in manufacturing.

[15–18]. Data in DTS includes the simulation and operating data of the virtual model, as well as the information and knowledge of the shop floor that is recorded in the service system [19–21]. The physical data were obtained from the shop floor. The service system is responsible for providing a variety of applications, including scheduling [22–24]. ML learning strategies, such as supervised Artificial Neural Networks, are confronted with two primary obstacles: (1) the availability of datasets of adequate quality and quantity, and (2) the labeling of datasets for the purpose of training an ML model.

When training a ML model, there are primarily three types of data that are employed: [25] (1) in vivo data, which is data taken from natural, unaltered environments; (2) in vitro data, which is data acquired using physical sensors in a controlled laboratory setting; and (3) synthetic data, which is data produced by software simulations. Although manufacturing companies often have a large amount of in vivo data, the process of obtaining the data and cleaning them might be complex. In addition, the data that are utilized for training have to give knowledge across all of the states that the model has to take into consideration, such as normal and abnormal operating situations. In addition, while thinking about supervised ML, one major restriction is the input that is often needed from humans to manually label the enormous quantity of unique data. Manual labeling requires a lot of time and effort, and it also has the potential to make mistakes. This is particularly true in dynamic industrial settings, where items and procedures are often altered. Because of these restrictions, the creation of effective AI applications may be prevented in numerous industrial scenarios, as the amount of time and money necessary to generate such models may become an impediment.

3.2 Methodology

In this chapter, we present a framework that integrates DT technology with ML and TL with the purpose of incorporating AI applications in manufacturing CPSs. This is a step toward making the transition from traditional automation to smart manufacturing and flexible production systems. Fig. 3.3 illustrates the suggested framework for data-driven ML to be used in industrial AI applications.

The RAMI4.0 Reference Architecture [26] has been used as the basis for the layered architecture that has been followed in the construction of the framework that is being provided in [27]. This architecture has been modified such that it can accurately represent the following primary entities: the CPS that creates a digital thread between the physical world and

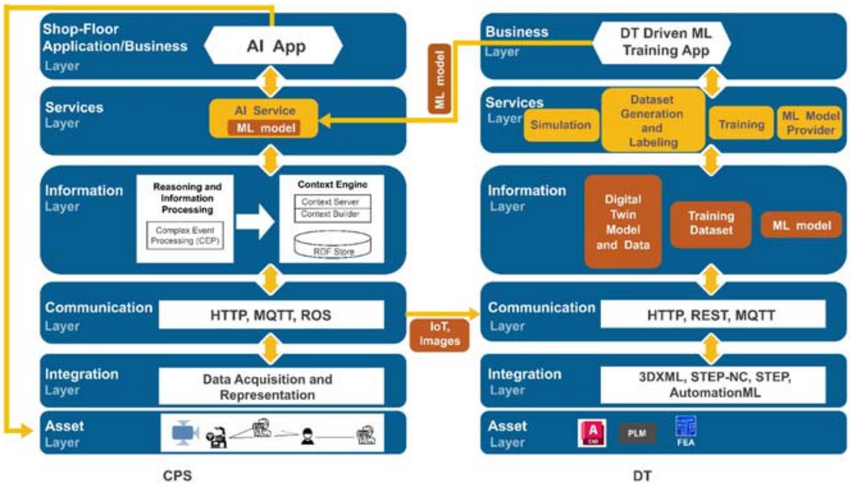


Figure 3.3. Usage of the digital twin for the development of ML-based applications for smart manufacturing.

the cyber world, such as a machine or a robot on the production floor, to connect the physical world to the cyber world.

Imagine a future in which each water company creates its own "DT," which is a virtual data-driven replica of the company that is supplemented with enormous amounts of granular data from multiple sources to replicate the environment in which the company operates as shown in Fig. 3.4. This would be a future in which water companies would develop their own "DTs" in the future.

Companies will need to make investments in a variety of sensor-like technologies to map and collect readings of its infrastructure, and will also need to augment this data with data drawn in from other sources to construct a DT. This is always going to be a changing goal, and as more the data becomes accessible, the twin will need constant updating. A DT will provide businesses with a once-in-a-lifetime chance to perform highly accurate and precise statistical analysis of correlations between variables. It

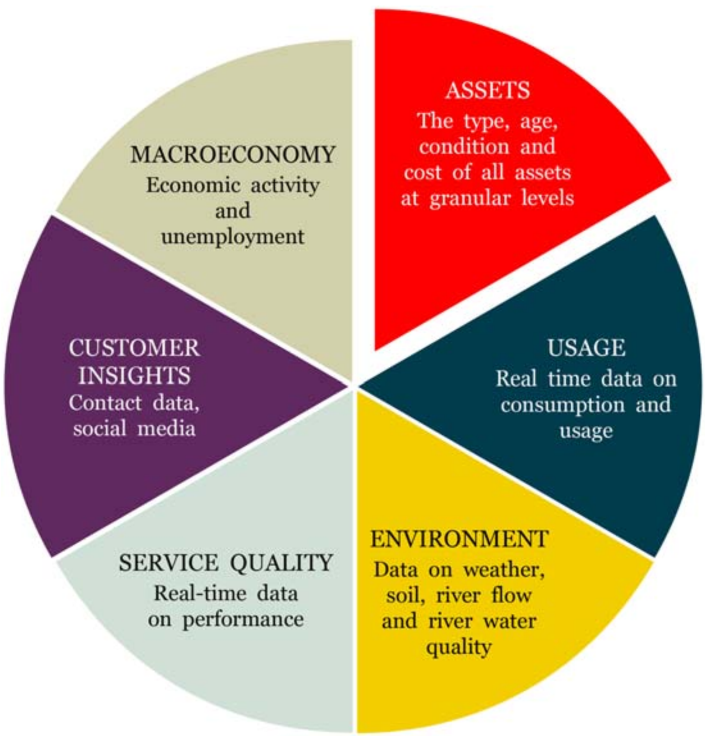


Figure 3.4 Types of data required to develop a digital twin.

is heartening to see that some businesses are already hard at work creating their own identical twins.

3.2.1 Digital twins and digital twin–based industry 4.0 application development

DTs, digital models (DM), and digital shadows (DS) are all examples of DT variations that have been suggested as a result of previous research (DTs). These varieties are distinguished from one another by the degree of data integration that exists between the real-world object and the virtual object that corresponds to it (i.e., the digital representation) [28]. Digital representations (DMs) are simulations of real-world objects that do not involve any mechanical data transmission from their physical counterparts. A DS features automatic, unidirectional dataflow from the real world to its digital counterpart. As a result, the virtual object is able to accurately reflect any changes that occur to the state of the corresponding physical item. The term "digital twin" refers to a digital representation of a real thing. There is a dataflow in both directions between "DTs" (processes or systems) and the physical things that correspond to them, and DTs closely mirror the state and behavior of the physical objects that they represent. DTs are increasingly being utilized to represent industrial equipment and to deliver smart data-driven solutions in manufacturing facilities in the framework of Industry 4.0 [28]. Predictive maintenance, monitoring of product quality, and optimization of manufacturing processes are all possible applications for these technologies [24,29–32]. However, there are limits in present DTs and their capacity to enable the creation, testing, updating, and porting of applications for Industry 4.0 in an efficient and cost-effective manner. In the automotive sector, the creation of a virtual model of a connected car is accomplished with the use of DTs. The technology is used by firms in the automotive industry to develop the best possible automobile product even before manufacturing begins. A DT is a virtual representation that mimics a real item or process throughout its existence. This technology allows you to remotely monitor and operate equipment and systems by bridging the gap between the digital and physical worlds in almost real time, making it possible for you to do so. A virtual representation of the as-designed, as-built, and as-maintained physical product is what the term "digital twin" refers to in the context of manufacturing. Accurate configurations of the actual product, production processes, or equipment are used to provide real-time process data and analytics that enhance this depiction. One of the aspects of Industry 4.0 that is expanding at the quickest rate is the notion of the DT. A DT is, to put it in the simplest words possible, a virtual counterpart of an item that exists in the real world that is operated in a simulation environment to verify its performance and effectiveness. Currently, we are in the midst of the fourth industrial revolution, which is also known as Industry 4.0. The value chain is characterized by increased automation as well as the use of smart machines and smart factories. Informed data contributes to the production of items that are produced in a manner that is more productive and efficient.

Because the purpose of our research was to analyze the connection between these systems, we chose to work with a more limited data set consisting of just 436 records. As may be seen in Fig. 3.5 below.

This conclusion was reached on the basis of our logic, which was to study the connection between the aforementioned issues, and not the research conducted on each of these topics separately. We did not include AI in the search for the data records because we intended to explore the implicit development of AI in these interconnected systems. Instead, the focus of our inquiry was on determining whether or not ideas linked to AI are present in the data records. We were interested in finding out whether or not AI is developing organically as a consequence of the connections between all of these different systems. Statistical approaches using R studio and the "bibliometrix" package (Aria and Cuccurullo 2017), as

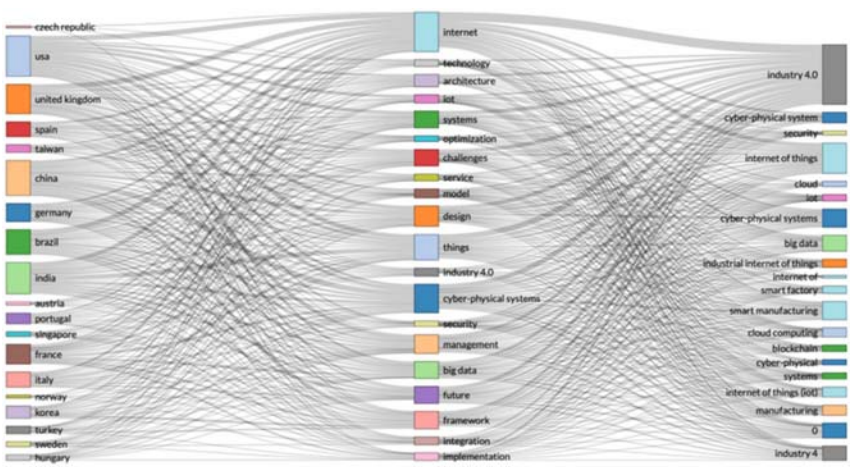


Figure 3.5 Bibliometric analysis of 436 data records—three-fields plot.

demonstrated in the preceding figure (Fig. 3.5), were used on the data records so that they could be analyzed.

3.2.2 Digital twin and industrial internet of things implementation

The Joint Stock Company "FED" makes active use of the DT technology that is being considered for the simulation of actual company manufacturing for the purpose of staff training and modeling activities that assist enhance business performance. Development of a DT for a manufacturer's logistics system is being aided by the usage of NET programming technologies. Turning machines, circle grinders, gear hobbers, and high-speed vertical milling machining centers are just some of the machines shown in the pictograms used to explain the tools of the trade in the manufacturing industry. It was developed with the intention of determining the most effective placement of manufacturing facilities as well as the most efficient routes for transporting finished goods to ensure maximum output. The software enables the creation of a digital business model, which can then be used to plan the optimal location for manufacturing facilities and generate an optimal manufacturing strategy. The following are some of the functions that are carried out by the application:

1. generating the necessary quantity of necessary equipment
2. establishing the required number of routes for the transportation of industrial units
3. capability to make changes to the system as it is being designed
4. computation of the amount of time and resources required for the manufacture and shipment of a single item.

The lifecycle of a product consists of several phases, including the stage of design, the stage of production, and the stage of service. DTs undergo all of these stages. It finds widespread use in the processes of model design as well as simulation and virtual debugging. During the process of digital transformation, the use of DTs has become more common. It is anticipated that by the year 2024, more than 25% of the newly developed DTs would be used as the binding function of the newly developed IoT. Industrial manufacturing and civil engineering may utilize DTs to anticipate the development track of equipment and systems because of the DT's ability to assess the virtual area and digitally map the interaction with things. As a result, it has the potential to significantly enhance the situational awareness of enterprises. In addition, it will help businesses improve the quality of their decision-making. For instance, companies that have this advantage may have a more appropriate amount of time set aside for maintenance and a more effective strategy for scheduling production.

An overview of the DTs application technology has been provided above; this technology will infuse the environmental management system at the scenic place with a greater degree of fresh energy. In the future, based on this technology, a virtual digital environment will be constructed to accomplish the smooth switching of numerous applications of the environmental management system of the scenic site. As a result of the evolution of the technologies that are associated to it, the IoT in industry may now function as DTs communication system. Real-time, intelligent independent access, as well as the efficient gathering and analysis of process, service information, and product data, are all facilitated by the use of this technology in the real-world industrial setting. Multiple types of communication software are used to link devices in the IIoT. This foundation allows it to perform all necessary tasks at the equipment layer and throughout the equipment layer network, including monitoring, exchanging, collecting, and analyzing data. The reality is that organizations may employ several forms of technology, such as sensors, software, and ML, to the task of collecting and analyzing data pertaining to physical items and associated big dataflows. A variety of technological methods may achieve this goal. As shown in Fig. 3.6, after the data gathering and analysis phases are complete, the data may be managed and put to use.

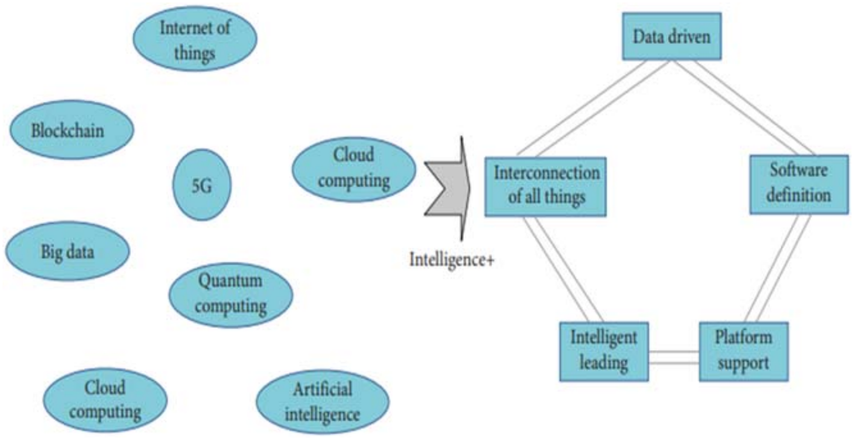


Figure 3.6 Concept map of digital twins technology.

The vision sensor may record video of the whole scene, and the data can then be analyzed by the system. This concept uses single-view imaging, which has the advantage of producing a picture that is indistinguishable from the original regardless of where in the scene the observer is standing, and of assuring that the whole procedure is consistent with the imaging principle. If this is the case, then having knowledge of the pertinent characteristics of the omnidirectional vision sensor is sufficient for practical purposes. On the basis of this information, the inverse operation may be used to determine the incidence angle information for each point in the scene. The following two facets are the primary foci of the investigation: With the addition of the omnidirectional vision sensor and the panoramic color structured light generator, this state-of-the-art visual sensing technology can be advanced toward the visual perception of body structure. Moreover, (2) through continued study, the accuracy of color recognition of projected light in the environment can be further improved, leading to the realization of the panoramic vision sensor with scene depth correlating to color. Studies show that this significantly enhances the visual experience of visual sensing technology, opening new possibilities for its use in the production of environmental art in scenic locations.

3.2.3 Estimating the costs of industry 4.0 application update

To determine how much it would cost to modernize an application, we devised a hypothetical scenario in which the value of m1 shifted and a1 had to be reintegrated for a new pickup vehicle (m3). We came to the conclusion that the models of both m1 and m3 were comparable and produced results that were comparable to those of the machine. To update the application, it was necessary to identify data from m3 (mo3 1) and integrate m3 and mo3 1 with that suggested in Section 4. The degree of a1 adaptability was determined by using the factor of 2.4. The following were considered to be the evaluation's assumptions: The costs associated with bringing a1 up to date using Azure IoT (first row) and CTs (second row) are broken down and summarized in Table 3.1. It demonstrates the NoQs that were run and the NoCs that were applied to identify the data coming from m3, the SloCs that were added or modified, the NoCs that were applied to integrate m3 and its data with a1, as well as the NoCs that were applied and the SloCs that were added or modified to develop the functionality of a1 and test it, as shown in the table below.

Table 3.1 Cost of updating the pickup monitoring application using the Internet of Things platform and CTs.

Industry 4.0 application	Identify (NoQ)	Identify (NoC)	Integration (NoC)	Integration (SloC)	Dev and test (NoC)	Dev and test (SloC)	Total cost ($)
IoT platform	0	1	0	2	3	0	90.00
CTs	0	1	1	0	0	0	36.00

3.2.4 Industrial use case study

An industrial camera has been included in the robotic system so that it can identify certain characteristics of the component that has to be handled. In the next stage, an advanced rendering simulation will be used in the DT model to generate a synthetic dataset that is appropriate for training a Convolution Neural Network (CNN)-based ML model for the classification of photographs. Blender, an open-source rendering tool, has been used for the purpose of producing more complex renderings of the DT model. The rendering specialist will first set up the 3D environment in such a way that the 3D STL model of the component will be correctly superimposed on the photograph of the actual environment that will be used as the backdrop. Model quality is increased by simulating real-world lighting circumstances and adding the right material attribute to the 3D component. To increase the accuracy of the model and the rendering simulation, we do this step. The following sequence of events will be covered in detail in this analysis: A 3D printer creates a new plastic component, which is then conveyed by conveyor belt to a robotic arm, which is tasked with choosing the part and placing it in a packing bin; the picking strategy of the robot is dependent on the orientation of the part. A 3D printer produces a new plastic component, which is then sent via a belt to a robotic arm (it may be faced up or down). The robotic system in this situation will have to operate unfamiliar components, which it has never seen before (e.g., a first small batch production of a new product during the ramp-up phase). With the use of AI, plant managers can use the DT to unlock hidden value in their plant data, which can then be used to optimize a wide range of processes. The DT produces virtual duplicates of physical locations, plant processes, business processes, and assets. A 3D model of the novel part to be handled by the robot will be created by a product designer using computer-aided design software. The model is then saved by the designer in STL geometry format.

To facilitate 3D printing an STL file is created; this file is then reused in the DT file's settings. As it helps ensure that the simulation is carried out correctly, the Level of Detail of the models used in the simulation is an essential component. The development of such a model typically involves taking a number of photographs of the actual component while it is being used in its natural setting, manually labeling those photographs, and then teaching a supervised ML model, such as a CNN, to identify the component [33]. A method such as this, on the other hand, necessitates the expenditure of time and effort to both capture the dataset and label the dataset to train the supervised CNN. In some circumstances, such as when there is a one-of-a-kind manufacture of 3D-printed components, for instance, the actual part simply does not exist, and as a result, it is not feasible to make use of this strategy. However, such constraints may be circumvented by tailoring and putting into practice the architecture that is given in the following figure. Fig. 3.7 is an illustration of the modified and customized solution that was developed for this particular industrial use case.

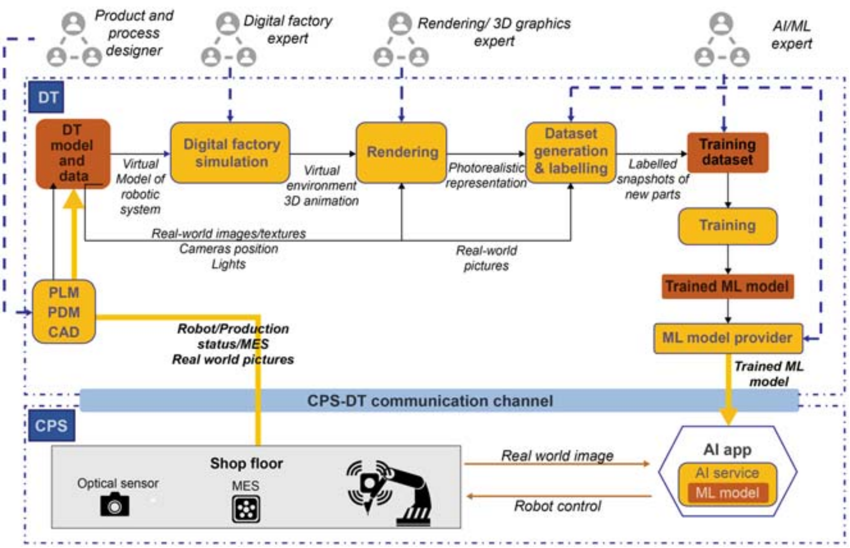


Figure 3.7 Digital twin–driven machine learning for self-adaptable handling of product variations by an industrial robot.

The simulation environment is equipped with a particular viewport that is analogous to the field of view of the actual camera. As a result, it is possible to take virtual images (snapshots) of the virtual portion that is located inside the planar region that is in front of the robot. After these stages have been performed, the rendering simulation system is now able to create synthetic, photorealistic photographs of the actual location, as seen in Fig. 3.8.

3.2.5 Taxonomy of digital twins

The next part presents a literature-based taxonomy of DTs [34] and lays the groundwork for the first cluster analysis. The taxonomy needed a total of four different design revisions. In all, we uncovered 11 relevant dimensions, each of which had a number of attributes. The dimensions are organized into meta-dimensions for easier comprehension. These meta-dimensions are organized in a manner that corresponds to the flow of data via a DT; specifically, the acquisition of data, the management and dissemination of data, and the conceptual scope of the data. The fourth iteration of the design of the taxonomy is now incorporated in a qualitative interview study with the intention of achieving the aim of incorporating qualitative data from industry experts into the taxonomy. We sent the taxonomy from the third iteration [34] to each of the experts and gave them the opportunity to make any necessary adjustments and provide examples of archetypical arrangements. Even if all of the experts agreed

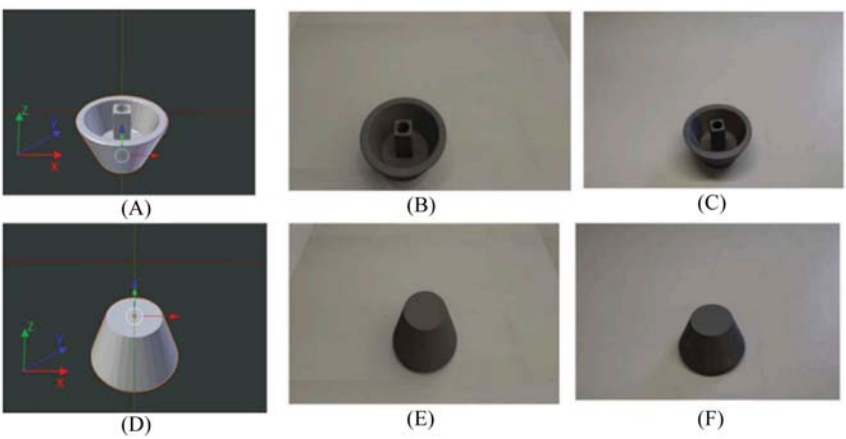


Figure 3.8 Virtual and real images of the part (A) 3D model of the part facing up, (B) realistic rendering of the virtual part facing up, (C) picture of the real part in the real environment, (D) 3D model of the part facing down, (E) realistic rendering of the virtual part facing down, (F) picture of the real part in the real environment.

that the proportions and attributes were accurate, there is still a wide variety of archetypical designs since each expert has their own distinct point of view. After that, the taxonomy that was produced needs to represent the design features and dimensions that are essential to archetype design.

3.2.6 Meta-dimension: conceptual scope

In conclusion, other three dimensions are included in the conceptual scope of the meta-dimension. Accuracy, the intellectual aspects, as well as the time of production, are all included inside this meta-dimension. The model component of a DT is where accuracy comes into play. We are shooting for the breadth of the model with this particular dimension. We distinguished exactness into two categories: Identical and partial. The difference between identical accuracy and partial accuracy is that identical accuracy describes a physical asset in its whole whereas partial accuracy describes a physical asset in its essential components only. However, the dimension accuracy contains the same idealized characteristic, which defines a perfect digital reproduction of actual objects. This helps ensure that the dimensions are as accurate as possible. The interviewees argued that there is no use in further evaluating this quality since complete model correctness is a condition that is likely not possible. This line of reasoning was presented in light of the fact that full model accuracy is likely not attainable. In this dimension, conceptual elements are separated into those that are physically autonomous and those that are bound. The former simply discusses the DT's virtual depiction, but the latter also discusses the DT's physical manifestation. This aspect places an emphasis on the definition that is used throughout a publication. As a result of the fact that it does not have any impact on either the relationship between the physical asset and the DT or the existence of a physical asset, it is not relevant to the process of developing the archetypes. In, the Beginning of Everything the last dimension is made up of three aspects that cannot coexist: digital-first, simultaneous, and physical-first. These aspects are incompatible with one another. They provide a description of the instant in time at which the DT is produced. Due to the fact that the production of an artifact is a process, it is impossible to pinpoint a certain instant in time. The commissioning of the formed thing, on the other hand, is the moment at which we consider the original creative process to have reached its conclusion. At this point in time, the DT is being brought into existence for the first time. When performing this analysis, we determine if the digital representation or the real asset was produced and, as a result, commissioned. It was a rare occurrence that both artifacts were commissioned at the same time. When an item is finished being created, that moment in time is referred to as the time of creation. It displays the remaining attributes graphically, along with their interrelationships with one another. The graphic places a particular emphasis on the distinction between the input of raw data and pre-processed data. A digital representation, the dataflow, the internal processing, and the internal repository are the constituent parts of the twin in terms of its underlying architecture.

3.2.7 Industrial artificial intelligence

It directs research efforts toward the use of AI in practically every aspect of the manufacturing process. Focusing on problem-solving from an industrial point of view, including replacing human interaction with intelligent machines, increasing productivity through the incorporation of AI concepts into engineering systems, and finding new insights through the use of ML and data mining techniques. Industrial artificial intelligence (IAI)'s goals are to facilitate productive communications between AI researchers and the industrial community, to drive real-world applications of intelligent machines in industries, and to provide solutions that are both effective and efficient for problem-solving emerging challenges associated with Industry 4.0. IAI will allow the submission of research papers and promote debates based on the usage of AI approaches, including both established and cutting-edge technologies, to either optimize or beneficially disrupt existing industrial procedures. The journal will be one of the first to give a focused scientific method that is peer reviewed to systematically hypothesize and apply fresh synergies of AI and ML to nearly every aspect of industrial chains.

3.2.8 Cyber twins

CTs are essentially digital representations of machinery in the real world. In this section, we would like to point out that the article solely discusses the applications of Industry 4.0 (such as preventative maintenance and product quality improvement), and the primary physical entities that are involved in Industry 4.0 are industrial equipment. As a result, CTs provide them with digital representations to help in the development of Industry 4.0 applications. Communication in both directions is supported by the

CTs between the physical machine and themselves. The state of the physical machine is mirrored in a CT, and any modifications made to the state of the CT are reflected, in a manner similar to that of current DTs, on the state of the physical machine. In addition, computer terminals (CTs) include an emulator or simulator of the machine, which allows them to closely mirror the operation of the original machine.

By using the machine semantic descriptions, CTs may be automatically constructed in a cost-efficient manner. Additionally, CTs themselves include semantic descriptions of both the machines and themselves. Additionally, CTs are readily updatable, which enables them to handle machine improvements as well as replacements. In addition, a CT is able to support a range of applications for Industry 4.0 and offers the following services to enable the development of these applications: Inquire about the semantic description of the machine that the CT is representing; the ontology may be used to describe both basic machines, which only have one sensor and one actuator, as well as sophisticated machines, which have a large number of sensors, actuators, and machine automation components. It is possible to capture the connection information of a machine, thanks to the notions of Communication Protocol and Endpoint that it includes. It recycles concepts such as sensor, actuator, system, and platform from previously developed SSN [43]/SOSA [52] ontologies; in Fig. 3.9, they are prefixed with "sosa" and "ssn." Fig. 3.9 is a visual representation of the concepts and connections that are offered by the CT ontology to capture machines and the data they produce.

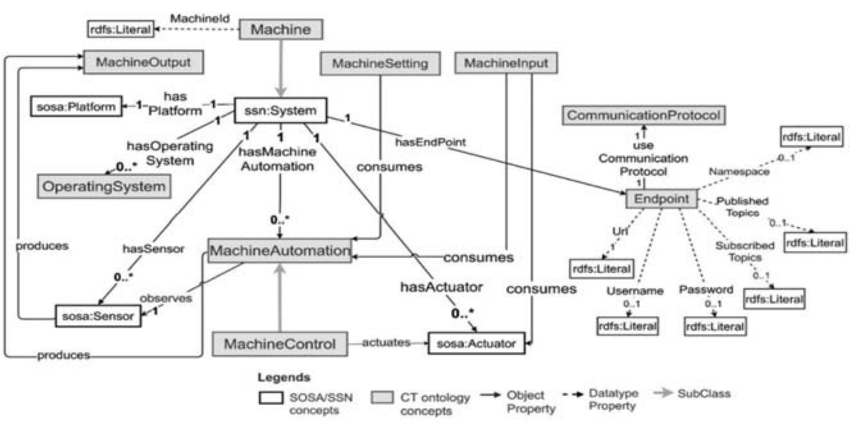


Figure 3.9 The CT ontology for modeling machines.

The ideas of sensors, actuators, systems, and platforms are recycled from the SOSA/SSN ontology into the CT ontology, along with the notions of machines, operating systems, machine automation, machine control, and machine monitoring (Fig. 3.1). The CT ontology is used for modeling many types of machines. The concepts of a sensor, actuator, system, and platform are recycled from the SOSA/SSN ontology into the CT ontology. Additionally, the CT ontology introduces the concepts of a machine, operating system, machine automation, machine control, communication protocol, and endpoint to model machines and the components that make up a machine. In addition, it allows for the modeling of machine data by making use of machine inputs, machine outputs, and machine settings.

3.3 Conclusion

In this article, archetypes were established based on the features of DTs. These traits were drawn from a solid literature basis and were expanded via interviews with industry professionals. We were able to construct clusters of DTs by using this database (RO1). Each cluster is distinguished by a unique combination of defining qualities. We were able to distinguish seven clusters, each of which had a unique pattern in the way that it was configured. We were able to determine the properties that each cluster had by using these patterns as a guide (RO2). Some of the early required qualities that we've identified in a DT include automated data collecting, various data sources, the application of data governance rules, a data processing and repository, and raw data input. These characteristics are noted as follows: The interview series offered some illuminating and fascinating perspectives. The majority of the qualities could be verified. However, several new facets emerged, such as the semi-manual data collecting and the dimension interoperability. Both of these features are discussed more below.

According to the examination of the configurations carried out by the specialists, there are additional essential qualities. A synchronization between the DT and the physical asset, as well as a data connection that can transmit data in both directions, are the other requirements. In addition, we were able to discover six other features that were optional. Because of this, we can now recognize five distinct archetypes of DTs (RO3). These archetypes expand and deepen upon one another. Every archetype has the required pieces, but the optional parts may be configured in a variety of different ways, from an Assistance Twin to an Exhaustive Twin.

The primary objective of this work is to discuss about the benefits of introducing a framework for enabling supervised ML-based AI application in manufacturing that can benefit from DT applications being developed in parallel in several industrial cases. To create and train new ML models, a strategy like this makes extensive use of cutting-edge computer infrastructure as well as cutting-edge simulation tools. In this article, we propose a methodical approach for building DT-driven ML-based AI applications in manufacturing. The suggested architecture provides support for cognitive applications by establishing a connection between a CPS and its DT in the form of a closed-loop system that shares data as well as models. In addition, one industrially relevant use case is shown, which demonstrates the prospects for applying DT-driven ML and discusses the advantages that emerge when the idea is used in industrial practise. This use case is offered as part of the presentation. The primary purpose of this body of work is to have a conversation about the benefits of introducing a framework to enable supervised ML-based AI application in manufacturing that can benefit from DT applications being developed in parallel in several industrial cases.

To create and train new ML models, a strategy like this makes extensive use of cutting-edge computer infrastructure as well as cutting-edge simulation tools. In this article, we propose a methodical approach for building DT-driven ML-based AI applications in manufacturing. The suggested architecture provides support for cognitive applications by establishing a connection between a CPS and its DT in the form of a closed-loop system that shares data as well as models. Furthermore, one industrially relevant use case is shown, showcasing the potential for DT-driven ML, and the benefits of using this concept in industry are discussed. This use case also highlights the opportunities for utilizing DT-driven ML. In addition, the suggested paradigm transfers the effort away from hard and tedious labeling jobs and toward DT-driven automated procedures and value-adding tasks conducted by specialists.

To prove the efficacy of data-driven ML development, future work may involve concrete implementations of the aforementioned use cases, and new use cases will be investigated and constructed. However, use case-driven research needs to be carried out in tandem with technology enablers, such as data acquisition technologies that make available fine-grained information, simulation technologies, and platform technologies that will enable DT-driven ML models in different layers of the production systems hierarchy (i.e., device, station, line, and plant). This kind of research should be carried out in order to maximize the benefits that can be reaped from the application of these technologies. Using factorial analysis, we were able to identify the primary national clusters of study on how AI is developing in IoT systems and cyber-physical systems. These clusters of research were found throughout the country.

According to the findings of our investigation, it is abundantly obvious that despite the political upheavals, the United States and China are strongly linked in the research partnership network. Moreover, the United Kingdom and Germany, the two leading European nations in this research, are not closely engaged in research collaborations on the topics of IoT, cyber-physical systems, and Industry 4.0, despite political and economic collaborations that even include a shared research budget. This research also came up with other findings, such as an up-to-date review of current and upcoming improvements in the field of I4.0, which was gleaned from academic literature and government efforts. This incorporates previous research to develop a common core language and strategy, as well as to consolidate previous standards into a new conceptual framework for embedding AI into the IoT and Industry 4.0. Cyber-physical systems are characterized as the research's linking systems for human-computer interactions. The primary focus of our investigation was on AI that is acceptable to the general public, complies with established security protocols, and can withstand close judicial examination.

This technology's simulation capabilities are particularly promising since they increase our ability to foresee failures, refine our service strategies, and implement lasting quality enhancements. These are all areas in which the industry is very interested. In the future, research might be focused on the development and implementation of DT-AI-IoT decisions for manufacturing, particularly in the areas of aircraft and engine construction, nuclear power plant instrumentation and control systems, and other related areas. It is also intended to develop a dynamical LS model and a dedicated tool for analyzing the spread of Industry 4.0 throughout the Kharkiv area, Ukraine, and beyond. This will allow for the evaluation and comparison of key metrics, as well as the support of decision-making for the development of this industry in a way that is successful and sustainable. After this, we provide a strategy for incorporating AI into DTS interactions and outline the necessary infrastructure. When combined with AI, DTS is able to build control plans and perform accurate evaluations of the entire situation on the actual shop floor. AI-enhanced DTS is a powerful tool that ensures synchronization between the state perception and the control execution processes. In addition, the three facets discussed above are used to present the technology that make interaction in DTS possible. It is important to point out that the present work does have a few restrictions attached to it. This article focuses on how AI may be used to improve DTS. However, there is need for more research into the dependability of the data provided by neural networks at this time since the basic logic of the behavior of neural networks is not entirely clear. Additionally, the challenge of ensuring that the control system in AI-enhanced DTS is as strong as possible is another one that requires additional focus. The work that will be done in the future will concentrate on the following aspects: (1) DT applications in certain manufacturing scenes that are based on AI; (2) specialized assessment techniques in AI-enhanced DTS; and (3) control concerns and interaction methods in AI-enhanced DTS. We used the proposed cost model to calculate how much it would cost to create an app utilizing the CTs and (indirectly) an IoT platform, for each of the possible use cases. The results of this comparison are shown below.

This evaluation found that CT-based application development is less expensive than the IoT platform-based alternative when the same CTs are used to develop multiple Industry 4.0 applications, as is typical in all settings requiring efficiency, preventative maintenance, and product consistency management and improvement. In the work that we plan to do in the future, we want to expand our experimental analysis so that it includes an approach that is based on statistics. By doing so, we can confirm that the suggested CTs-based strategy significantly reduces the cost of creating the Industry 4.0 application, and that it is also more flexible than options based on IoT platforms. One of our aims is to improve the CTs, CT management framework, and cost model so that they can sustain complicated machinery. These machines will have automation that will determine the actuation of the machine as well as the data that the machine will generate as a result of the automation. In particular, one of our goals is to investigate potential expansions to the CT model that might be beneficial to the automation of complicated equipment.

References

[1] G. Chryssolouris, D. Mavrikios, N. Papakostas, D. Mourtzis, G. Michalos, K. Georgoulias, Digital manufacturing: history, perspectives, and outlook. proceedings of the institution of mechanical engineers, Part B: J. Eng. Manuf. 223 (5) (2009) 451−462.

[2] D. Georgakopoulos, M. Fazia, M. Villari, R. Rajiv, Internet of things and edge cloud computing roadmap for manufacturing, IEEE Cloud Comput. 3 (2016) 66−73 [CrossRef].
[3] R. Ranjan, C.H. Hsu, L.Y. Chen, D. Georgakopoulos, Holistic technologies for managing internet of things services, IEEE Trans. Serv. Comput. 13 (2020) 597−601 [CrossRef].
[4] M. Milojevic, Digital Industrial Transformation with the Internet of Things, CXP Group, Glasgow, UK, 2017.
[5] P. Radanliev, D. De Roure, J.R.C. Nurse, R. Mantilla Montalvo, S. Cannady, O. Santos, et al., Future developments in standardisation of cyber risk in the Internet of Things (IoT), SN Appl. Sci. 2 (2) (2020) 1−16. Available from: https://doi.org/10.1007/s42452-019-1931-0.
[6] P. Radanliev, D. De Roure, M. Van Kleek, O. Santos, U. Ani, Artifcial intelligence in cyber physical systems, AI Soc. 1 (2020) 1−14. Available from: https://doi.org/10.1007/s00146-020-01049-0.
[7] P. Radanliev, D. De Roure, R. Walton, M. Van Kleek, R.M.R.M. Montalvo, L.L. T. Maddox, et al., Artifcial intelligence and machine learning in dynamic cyber risk analytics at the edge, SN Appl. Sci. 2 (11) (2020) 1−8. Available from: https://doi.org/10.1007/s42452-020-03559-4.
[8] P. Radanliev, D.D. Roure, K. Page, J.R.C. Nurse, R.M. Montalvo, O. Santos, et al., Cyber risk at the edge: current and future trends on cyber risk analytics and artifcial intelligence in the industrial internet of things and industry 4.0 supply chains, Cybersecur. Springer Nat. 3 (13) (2020) 1−21. Available from: https://doi.org/10.1186/s42400-020-00052-8.
[9] V. Kharchenko, S. Dotsenko, O. Illiashenko, S. Kamenskyi, Integrated cyber safety and security management system: industry 4.0 issue. In: Proc. of the 10th IEEE Dependable Systems, Services and Technologies Conference, DESSERT, Leeds, UK, 2019, pp. 197−201.
[10] Lesya Sobolevska, Landscape Industry 4.0 in Ukraine [Online] 2020. Available from: https://industry4-0-ukraine.com.ua/landscape/#firstPage.
[11] Internet of Things for Industry and Human Application. Volume 3. Assessment and Implementation [Online]. Available from: https://aliot.eu.org/wp-content/uploads/2020/01/ALIOT_MultiBook_Volume3_web.pdf.
[12] The Fourth Industrial Revolution [Online]. Available from: https://www.leapaust.com.au/industry-4-0/.
[13] Industry 4.0 [Online]. Available from: https://www.it.ua/ru/knowledgebase/technology-innovation/industry-4.
[14] F. Tao, M. Zhang, Digital twin shop-floor: a new shop-floor paradigm towards smart manufacturing, IEEE Access (2017) 20418−20427.
[15] J. Vachálek, L. Bartalský, O. Rovný, D. Šišmišová, M. Morháč, M. Lokšík, "The digital twin of an industrial production line within the industry 4.0 concept," 2017 21st International Conference on Process Control (PC), Strbske Pleso, Slovakia, 2017, pp. 258−262. Available from: https://doi.org/10.1109/PC.2017.7976223.
[16] F. Pires, A. Cachada, J. Barbosa, A.P. Moreira, P. Leitão, "Digital Twin in Industry 4.0: Technologies, Applications and Challenges," 2019 IEEE 17th International Conference on Industrial Informatics (INDIN), Helsinki, Finland, 2019, pp. 721−726. Available from: https://doi.org/10.1109/INDIN41052.2019.8972134.
[17] M. Singh, E. Fuenmayor, E.P. Hinchy, Y. Qiao, N. Murray, D. Devine, Digital Twin: Origin to Future. Applied System Innovation 4 (2) (2021) 36. Available from: https://doi.org/10.3390/asi4020036.
[18] X. Ma, F. Tao, M. Zhang, et al., Digital twin enhanced human-machine interaction in product lifecycle, Procedia CIRP 83 (2019) 789−793.

[19] Q. Qi, F. Tao, T. Hu, et al., Enabling technologies and tools for digital twin, J. Manuf. Syst. 58 (2021) 3−31. Available from: https://doi.org/10.1016/j.jmsy.2019.10.001.
[20] Y. Fang, C. Peng, P. Lou, et al., Digital-Twin based job shop scheduling towards smart manufacturing, IEEE Trans. Indust. Inform. 15 (2019) 6425−6435.
[21] M. Zhang, F. Tao, A.Y.C. Nee, Digital twin enhanced dynamic job-shop scheduling, J. Manuf. Syst. 58 (2020) 146−156.
[22] J. Vachálek, L. Bartalský, O. Rovný, et al. The digital twin of an industrial production line within the industry 4.0 concept. In: 2017 21st International Conference on Process Control (PC) IEEE, 2017.
[23] F. Biesinger, D. Meike, B. Kraß, et al., A digital twin for production planning based on cyber-physical systems: a case study for a cyber-physical system-based creation of a digital twin, Procedia CIRP 79 (2019) 355−360.
[24] J. Wang, L. Ye, R.X. Gao, C. Li, L. Zhang, Digital twin for rotating machinery fault diagnosis in smart manufacturing, Int. J. Prod. Res. 57 (2019) 3920−3934.
[25] T. Dahmen, P. Trampert, F. Boughorbel, J. Sprenger, M. Klusch, K. Fischer, et al., Digital reality: a model-based approach to supervised learning from synthetic data, AI Perspect. 1 (1) (2019) 2. Available from: https://doi.org/10.1186/s42467-019-0002-0.
[26] L. Monostori, Cyber-physical production systems: roots, expectations and R&D challenges. In: 47th CIRP Conference on Manufacturing Systems (CMS 2014), Windsor Canada, April, 2014.
[27] K. Alexopoulos, K. Sipsas, E. Xanthakis, S. Makris, D. Mourtzis, An industrial internet of things based platform for context-aware information services in manufacturing, Int. J. Comput. Integ. Manuf. 31 (11) (2018) 1111−1123. Available from: https://doi.org/10.1080/0951192X.2018.1500716.
[28] M.G. Juarez, V.J. Botti, A.S. Giret, Digital twins: review and challenges, J. Comput. Inf. Sci. Eng. 21 (2021) 030802 [CrossRef].
[29] F. Tao, H. Zhang, A. Liu, A.Y.C. Nee, Digital twin in industry: state-of-the-art, IEEE Trans. Ind. Inform. 15 (2019) 2405−2415 [CrossRef].
[30] Q. Qiao, J. Wang, L. Ye, R.X. Gao, Digital twin for machining tool condition prediction, Procedia CIRP 81 (2019) 1388−1393 [CrossRef].
[31] C. Liu, H. Vengayil, R.Y. Zhong, X. Xu, A systematic development method for cyber-physical machine tools, J. Manuf. Syst. 48 (2018) 13−24 [CrossRef] International Conference on Process Control, StrbskePleso, Slovakia, 6−9 June 2017; pp. 258−262.
[32] J. Vachalek, L. Bartalsky, O. Rovny, D. Sismisova, M. Morhac, M. Loksik, The digital twin of an industrial production line within the industry 4.0 concept. In Proceedings of the 2017 21st International Conference on Process Control, StrbskePleso, Slovakia, 6−9 June 2017, pp. 258−262.
[33] P. Aivaliotis, A. Zampetis, G. Michalos, S. Makris, A machine learning approach for visual recognition of complex parts in robotic manipulation. In: 27th International Conference on Flexible Automation and Intelligent Manufacturing, (FAIM2017), 11 423−430, Modena, Italy, June 27−30, 2017.
[34] H. van der Valk, H. Haße, F. Möller, M. Arbter, B. Otto, A taxonomy of digital twins. In: AMCIS 2020 proceedings. AIS, Salt Lake City, 2020.

CHAPTER 4

Artificial intelligence—driven digital twins in Industry 4.0

Prithi Samuel[1], Aradhna Saini[2], T. Poongodi[3] and P. Nancy[4]
[1]Department of Computational Intelligence, SRM Institute of Science and Technology, Kattankulathur Campus, Chennai, Tamil Nadu, India
[2]Department of Computer Science and Engineering, Noida Institute of Engineering and Technology, Greater Noida, Uttar Pradesh, India
[3]School of Computing Science and Engineering, Galgotias University, Greater Noida, Uttar Pradesh, India
[4]Department of Computing Technologies, SRM Institute of Science and Technology, Kattankulathur Campus, Chennai, Tamil Nadu, India

4.1 Introduction

Artificial intelligence (AI) and digital twin (DT) technologies both have experienced significant growth in recent years and now are regarded as two of the main drivers of Industry 4.0 by both academic and industrial sectors. The technology and information serve as the foundation of DT, the algorithms and prototype serve as the core, and programming and services serve as the application. The comprehensive and systematic blending of application competence becomes even more crucial to the establishment of DT and AI in industrial sectors. The traditional model-based strategies to multi-objective challenges are predicted to be adjusted by AI-powered DT technology to the changing constraints and to give a demand-oriented, real-time competent assessment foundation. One of the new, very technological developments in Industry 4.0 is the digital twin. This intelligent computing offers a visual replica of almost any physical entity in a digital format to help discover mistakes and possibilities for development, as it benefits numerous sectors. With a CAGR of 58%, the worldwide economy for DTs is predicted to grow to US$48.2 billion by 2026. Perhaps, more so than before, the complete and structured incorporation of domain-specific knowledge is essential for the foundation of DT and AI. A thorough industry-focused analysis of AI and DT technologies and the development of sustainable and industrial ecology is currently lacking. This chapter aims to fill this research gap by addressing recent advancements in DTs from such a domain-specific approach, examining applied AI techniques in each subfield, classifying their contribution to

Digital Twin For Smart Manufacturing
DOI: https://doi.org/10.1016/B978-0-323-99205-3.00002-X

sustainable development, and compiling practical difficulties in numerous application sectors.

4.1.1 Artificial intelligence and digital twins in Industry 4.0

A DT is a depiction of an entity that is either currently real or might someday be introduced into the real world. DT is outfitted with detectors and functional components required to imitate the object's behavior as though it were actually physically present. These include the various aspects of the conceptual object's actual existence at the moment, including its energy levels, climate, environment, and effectiveness. After it has been created, the DT could be used to create models, examine levels of productivity, and determine what changes could be made to the actual entity. The main lesson you would learn from DTs is their capacity to offer some insightful data. DTs and AI are expected to shift the global game wherein every industry will strive to maximize profits. AI and DTs have reciprocal relationships because they both help each other grow. Corporations can obtain experimental results with the use of DTs, which can help with the development of AI models. Additionally, DTs can build a setting for testing machine learning (ML). AI can, however, be useful for DTs. Businesses can create DTs and extract a lot of data from them using deep learning and AI algorithms.

DT technology is being used to train staff, enhance operational effectiveness, and test items before they are released to identify and rectify any problems. In addition to using DTs for deep learning, AI is now being utilized to analyze operational models, regardless of where the product and its associated equipment are located. Real-time data provided by the DT can help prevent service problems and improve industrial output. Through effective forecasting and prospective prediction, they have the power to lower costs, but they often facilitate speedy decision-making. Such characteristics are necessary for helping humans efficiently in any industry and simplifying their lifestyles down to the minute.

4.1.2 Opportunities of artificial intelligence and digital twin in Industry 4.0

A practical and methodological framework with several applications, including those in product development, instrument production, healthcare analysis, aircraft, and other sectors, AI in DTs is highly favorable.

4.1.2.1 Smart manufacturing

Smart manufacturing has been facilitated by the development of advanced and sophisticated information technology, including big data, AI, Internet of Things, edge computing, etc. The autonomous and active self-optimization of smart manufacturing is its most important characteristic. Zhou et al. [1] conducted research and put forward a knowledge-driven framework for the modernization of DT manufacturing sites into smart manufacturing, which could also proactively detect, replicate, comprehend, anticipate, and control. It can increase the quality of the product while simultaneously lowering production costs. For traditional manufacturers, smart manufacturing is more of an opportunity than a challenge. A DT driving system was developed by Li et al. [2] to construct a global sustainability assessment DT mobility system for smart manufacturing initiatives. Smart manufacturing focused on cyber-physical systems (CPS) has emerged as the primary tendency in the growth of the manufacturing sector as sensing technologies and data processing have undergone advancements.

4.1.2.2 Automotive autonomous driving

As massive data analysis and deep learning techniques evolve, AI applications are emerging swiftly. It is essential to apply AI algorithms to create automated driving systems as one of them. Real-world applications of autonomous driving technology include fewer traffic fatalities, more effective use of time, space, and other resources, and even improved driving accessibility for people with disabilities. But because autonomous driving has such strong technological demands, using DTs to replicate traveling in a virtual world has become a necessary step. The integration of increasingly more AI and automated techniques in the transportation and distribution processes is made possible by the technology revolution sparked by the digital workplace age, according to Almeaibed, et al. [3]. The benefits brought about by the digital age have been used in the era of DTs in self-driving cars. Additionally, maintaining the security of self-driving vehicles can significantly lower the frequency of traffic accidents.

4.1.2.3 Intelligent urban transportation

The idea behind DTs is to merely map persons, things, connections, and activities from the current world to the virtual one. By reviewing and interpreting the DT in the virtual environment, one may perform an investigation on real-world objects. The study by Gao and Cai [4] demonstrates that the development program of urban functional departments is optimized and examined in accordance with big data and Geographic Information System. Urban functional area management's main objective is to restrict or control the appropriate use of resources and lay the groundwork for the effective use of urban space. The primary foundation for urban planning consists of pertinent indicators, including the available capacity of the region's ecosystem and biodiversity, the density data of the present infrastructure investment, and the areas for regional growth. The goal of traffic composition control is to optimize traffic control techniques using assessment and interpretation. DT technology can be utilized to mimic urban traffic patterns. This is a crucial use case for DTs in enabling smart transportation.

4.1.3 Challenges and research directions in Industry 4.0

It is increasingly clear that DT technology coexists with AI and IoT, giving rise to similar problems. Identifying the challenges is the first step toward addressing the problems.

4.1.3.1 Infrastructure

To support the algorithms' execution, high-performance infrastructure in terms of modern computer systems is required to keep up with AI's explosive growth. Costs associated with setting up and maintaining these systems are the current infrastructure-related challenge. For example, the prices of high-performance graphics processing units (GPUs) that can execute machine and deep learning techniques range from $1000 to $10,000. To run such devices successfully, the infrastructure must also have modernized hardware and software. The use of GPUs "as a service," which offers on-demand GPUs at a cost through the cloud, is considered as a solution to this problem.

4.1.3.2 Data

From a data perspective, it is critical to make sure the data is of high quality. To ensure that AI algorithms are given the highest quality data possible, data need to be processed and cleaned.

4.1.3.3 Security and privacy

Regulation is one way to guarantee the protection of personal data, and ML, a distributed platform for model training, is another. It addresses privacy and security concerns when adopting business intelligence within a

DT by allowing clients' data in a learning approach to remain localized without sharing data. This emphasizes the issues with managing the data when constructing AI algorithms, but besides being an encompassing rule regarding data and security.

4.1.3.4 Trust

Another issue as much in the AI community is the trust. The usage of AI can be intimidating for several reasons, including the fact that it is still comparatively unknown and the fact that its complexity may not be understood by the developer. An obstacle to trust is the fear that AI and robots may overtake humans as the dominating force on earth and take-over crucial infrastructure. Because AI is typically portrayed as having adverse implications, trust issues can be a hindrance. The number of good media articles about AI is rising, but there are still many hurdles to overcome. More exposure to AI and its beneficial applications is therefore necessary. These trust concerns are exacerbated by privacy and security issues, yet more thorough security and privacy regulations in AI foster trust.

4.2 Digital twin and artificial intelligence in smart manufacturing

Modern civilization and the economic growth of the country depend critically on Industry 4.0 and smart manufacturing. To increase the speed and adaptability of traditional production, Industry 4.0 aims to build a global interconnected infrastructure that overcomes the compatibility and interoperability problems within all levels of automation systems and industries. Adoption of DTs in smart factories, which simulate current manufacturing system conditions and update them in real time, results in higher productivity as well as lower costs and energy usage. Shorter product lifecycles are the outcomes of manufacturers switching quickly in response to the considerable increase in changing client expectations.

4.2.1 Current state of art in manufacturing industry

A smart factory's flexible and adaptable processes can address some of the major issues in manufacturing facilities with flexible and rapidly evolving design parameters. DTs can be used in a smart manufacturing environment to effectively stimulate and regulate many parts of complicated industrial systems. The manufacturing sector aims at increasing productivity, adaptability, and profitability, thanks to DTs. DTs increase efficiency while maintaining social interaction through information prediction. Digital simulation is used to improve manufacturing systems in a way that saves time and money. Before production, organizations simulate and check each and every component.

4.2.2 Framework of digital twin and artificial intelligence in smart manufacturing

Organizations can employ DTs for decision-making and management by using a standardized framework, which gives them the means to manage the complicated array of regulations, techniques, and systematic approaches. Effective implementation of the framework within a business can help with model functionalities, interoperability between modules, and illustrations of data collection, simulation models, communications, integrations, and implementations of pertinent standards.

The framework of AI-driven DT in smart manufacturing is depicted in Fig. 4.1. The real-world entity being replicated for smart manufacturing continuously creates data through its IoT sensors and devices. With this data, the AI-driven modeling step can be initiated. Two steps in the data collection process are entity recognition and data access. The following phase is data validation, which is accomplished by standard data preparation, integration, and cleaning. The data inherently includes pertinent factory events. To make these events more explicit and to make the model-building process easier, event labeling is done moderately, that is,

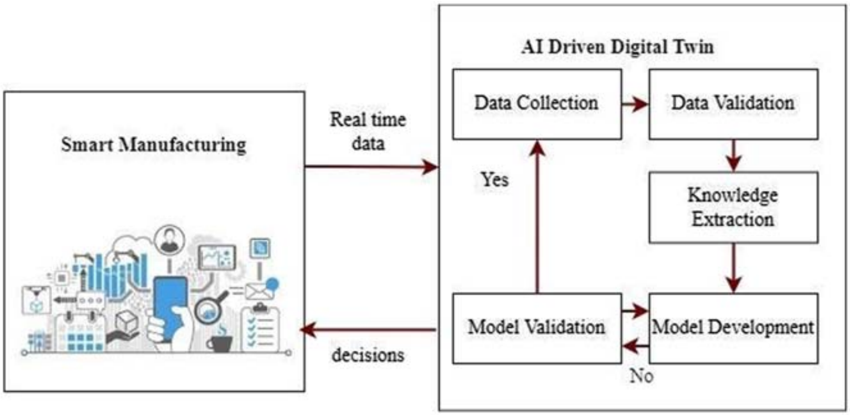


Figure 4.1 Framework of artificial intelligence–driven digital twin in smart manufacturing.

with human involvement. Unsupervised learning of activities (like event clustering) can be used as an additional step to help event detection and classification. In this procedure, all observed events are described and grouped according to their characteristics. In conclusion, an expert would watch the created clusters and their characterizations, intervene as needed, and give the clusters labels.

The persistent verification of the model, which occurs in incremental steps and validates the model as it is extracted, is an essential aspect of the model development stage. The pertinent parameters of the model are kept for further usage after an extracted model has been approved. Then, as an element of a mathematical model, the model can be used to run a number of what-if scenarios, which are then assessed in relation to preset performance measures. The outcomes of these studies can assist decision-makers in determining how to best operate a certain smart factory.

4.2.3 Artificial intelligence—driven digital twins and the future of smart factories

A virtual design of a car, factory, building, aircraft, institution, hospital, government, and almost any other thing or system is provided by a DT, which enables insights into how that entity or process will behave in the actual world under any and all possible circumstances. Users can create a system that offers insightful information about how a variety of real-world environments, physical, or other changes will affect the real-world model. The DT is focused on combining deep learning technologies with real-world experience data to create algorithms that will alter the behavior of the DT. For instance, a car designer can create a DT of an automobile and then use that model to assess how the vehicle would behave in challenging driving situations, such as snow-clad or wet roads. The information from sensing devices, CAD designs, and engineering disciplines, together with real-world data examined by abrasive deep learning models "trained" to model how it would behave under various situations, form the foundation of the DT.

Following the creation of a DT, information about the environment in which it functions is gathered via a time-sensitive sensor, controller, and other systems. These data are used by algorithms strengthened by deep learning technology to assess how variations in size/scale, humidity, chemical processes, or any other aspect of the twin's world will affect the twin. Additionally, the technologies could be used to compose large factories as well as individual things. In one instance, designers create a DT depending on different systems and components in a factory, including the equipment, operator abilities, controls, equipment, and potentially dangerous procedures. The model is created based on input and put through several situations based on AI algorithms to account for all conceivable circumstances pertaining to design, implementation, output, productivity, and automation.

4.2.3.1 Machine learning for predictive maintenance

Imagine a new system that uses ML to evaluate data and foresee potential system breakdown a few years from now. To fully appreciate the extent of the predictive modeling done to foretell when the component or system may fail and, more significantly, why the collapse may occur, it is necessary to first comprehend the ML technique. This, therefore, makes it possible to optimize the system in a way that will increase the asset and system as a whole lifespan. It is crucial to identify the pertinent factors in the ML approach to provide solutions to particular queries. Noise, overfitting, and bandwidth utilization are all decreased in this method. The term "feature subset selection" relates to this method. The procedure with data reduction would be utilized to construct the entire system. The production system's data is captured and given to a ML algorithm, which creates the prediction system using the new information and data, including statistical models. A summary is carried out while the data is moving through this procedure, assisting in moving only the data required to answer the question. This minimizes the response time and reduces the bandwidth utilization.

The monitoring of the tool surface for process irregularities is one example. Be aware that a variety of process variations may occur depending on the type of the operation of the product category and the necessary cycle time. The way servo motors operate is another illustration. In this situation, it is possible to quantify factors like rpm, force, temperature, vibrations, and rotation velocity. Up to 15,000 variables may be present. Only 50 variables and 1 TB/year might be left after the reduction, though, if feature subset selection is used. Unsupervised learning is an initial stage in identifying or discovering new data and is also used to monitor machines. Supervised learning responds to particular queries about the spindle and general machine behavior, resulting in a 20% improvement in asset availability, or an estimated 3 hours of use each day. The intellectual ability of manufacturing facilities can be further advanced by maximizing system performance and lifetime.

4.2.3.2 Factory and shop floor

In particular, manufacturing systems and governance in industrial companies face new issues as a result of the megatrend of the dynamic market environment and specific customer demand, which has a substantial impact on the financial performance. In this context, the data availability on industrial activity serves as a technological enabler to raise the significance of subjects like AI- and data-driven techniques. This also creates new opportunities for optimizing (novel) manufacturing systems, such as line-less portable assembly systems, which make it possible to assemble big components quickly and efficiently by utilizing scheduling and modeling software. Improved DT flexibility to dynamically change boundary circumstances on the factory and shop floor scales is the main goal of using AI at this level.

To achieve better resource scheduling and reallocation, AI is expected to assist industrial planners in developing plans with increased key performance indicators, identifying optimization measures, and autonomously implementing such measures in the future (E-factor). Decision trees could also be used in DT to construct traditional rules for smart systems at the stage of green design and production planning, facilitating decision-making in multifunctional operations and strategy development. To address the dynamic scheduling issues involving common resources, route adaptability, and unpredictable raw material deliveries, [5] presented a Petri-net-based dynamic scheduling strategy through a deep Q-network incorporating graph convolution network. Similar results of metaheuristic techniques, including the genetic algorithm as well as other optimization techniques [6–9], were used to address the scheduling issues in production lines.

4.3 Digital twins in the intelligentization of automotive autonomous driving

The long-term progress of automated vehicles in the near future depends on DTs. In the automotive industry, DTs are utilized to build a virtual representation of a networked car. They can gather the vehicle's functional and behavioral data, analyze its overall performance, and provide clients with a customized service. Simulation is becoming more important than ever in transport systems, development, and technology as interconnected and driverless vehicles quickly enter our daily lives. In a field where there are so many unknowns, simulation is ideal for testing because it offers a risk-free atmosphere that is expandable and versatile enough to handle changing criteria and a wide range of variables while also having the ability to analyze numerous scenarios in a short amount of time.

4.3.1 Advancing data maturity in the automotive industry

The three components of the DT are the actual components in the physical world, its virtual representations, and the model relies on a view that unites the two worlds are depicted in Fig. 4.2. The left half of the image shows the actual road ahead as well as its internet through a browser interface on the satellite navigator (SatNav). In this situation, the driver must make three decisions: which way to go by looking at the SatNav, which way to go by looking at the actual road, and which way to go by mentally superimposing the SatNav direction onto the actual road. Timing, some degree of driving experience, and concentration are required for this.

The car in the right side of the image uses augmented reality (AR) to give the driver a merged perspective of the physical and virtual worlds as they relate to navigating road bends. As a result, the driver may concentrate on the road with less mental strain, distraction, and risk of human error. By utilizing various technological capabilities supported by Industry 4.0, big data analytics, and simulation methodologies, this concept may be expanded all over the manufacturing value chain to conduct activities efficiently. For a very long time, car manufacturers had difficulties in ensuring precise vehicle design, efficient manufacturing, and top-notch sales and servicing.

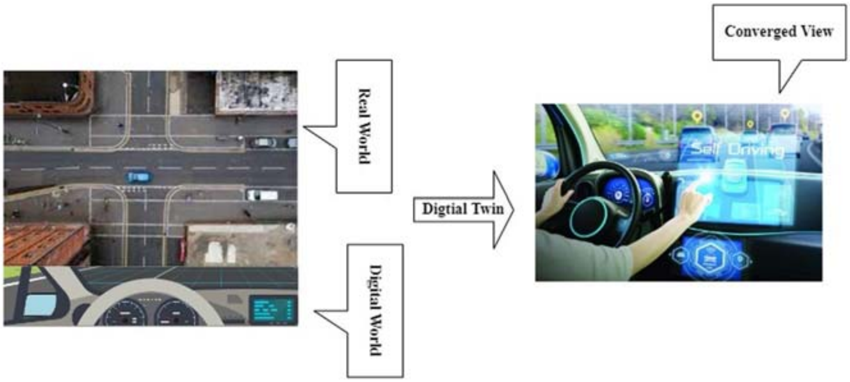


Figure 4.2 Concept of digital twin in autonomous automated driving.

The process of developing an automotive product is lengthy and intricate. From design to introduction, the manufacturing of a new car model generally takes 5–6 years. The profitability and long-term viability of an automotive company are actually dependent on effective design. The corporate reputation and viability of the company might be damaged by even a minor flaw in the industrial design. Consider Mercedes Benz, the business that introduced its A Class, at a cost of USD 1.5 million for product development. After it was introduced, the engine blew a Moose test, leading to the suspension of 2500 brand-new vehicles. Mercedes later fixed the issue by including stability control and redesigning the car's suspension. The change's implementation cost an astounding USD 250 million.

To efficiently manage the end-to-end process, an automobile product lifecycle facilitates data inputs from multiple supply chain contributors. The majority of the data utilized or produced at each phase, meanwhile, is still segregated and hardly connected with the phases that follow in the lifecycle of a product. As a result, there are now larger discrepancies between the traditional and digital versions of things. The DT has the ability to alleviate a number of issues that now occur in the electric vehicle industry by facilitating the continuous integration of analog and digital representations of product concepts, shop floors, and actual automobiles on the road.

4.3.2 Architecture of the automated driving digital twin test

A DT-assisted modeling approach for AV (automated vehicle) is developed in accordance with the properties of DT technology and the results of prior studies. Components of physical entity, virtual entity, data processing and assessment components make up the three elements of the DT-assisted simulation framework, as shown in Fig. 4.3. In the DT scenario, the DT vehicle uses the DT simulation components for simulation verification while the AV of real entity elements uses physical sensors to collect real data. The virtual entity uses the data processing and assessment components to store data. The DT components provide virtual perception information to the physical entity components. The AV executes choice and monitoring in accordance with the virtual information it has received. The following sections contain detailed descriptions of each.

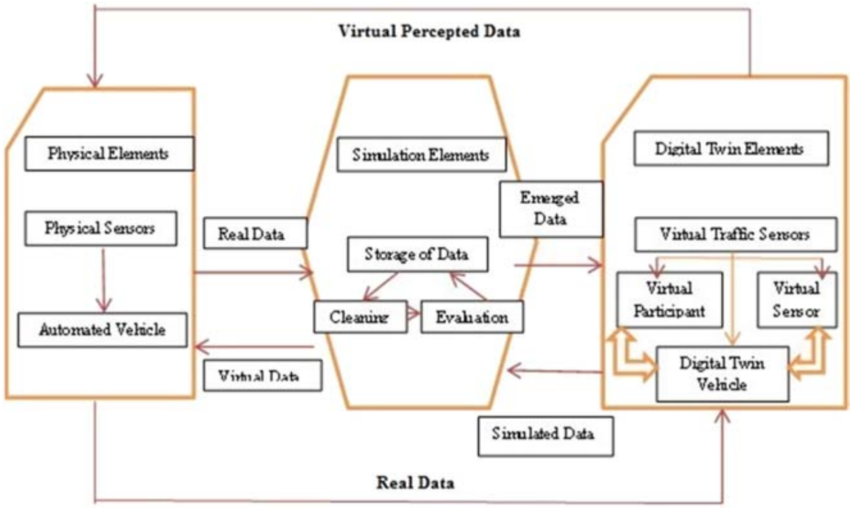


Figure 4.3 Architecture of digital twin in autonomous automated driving.

4.3.2.1 Physical entity

The digitization procedure from the physical context to virtual context is implemented using the physical data obtained by the real sensing devices in the physical entity components. Regarding the simulation test for driverless vehicles, an AV outfitted with a controller performs in the actual test environment while collecting factual data (location, orientation, defect, etc.) via GNSS, on-board IMU and other sensing technologies. To make the link between the DT vehicle and the AV under test, genuine data obtained are simultaneously delivered to the DT modeling modules through a network communication module. However, the actual data collected by the physical entity sections is also sent to the data handling and assessment sections for data processing, which is useful for simulating past data and evaluating it. Information on virtual perception will also be provided to the controller for autonomous driving. To produce more accurate simulation results, the AV decides and controls using the actual test domain and the real-world actuator after obtaining the simulated perception information.

4.3.2.2 Virtual entity

The components of DT simulations are digital representations of certain significant events or new real states in physical phenomena. The DT automobile maintains the mobility status of the DT automobile compatible with AV at the suitable frequency by receiving actual location data from actual detectors in actual component modules. Therefore, the simulated detectors can detect the relevant data from exceptional cases and convey the load consumption simulation results to the data handling and assessment modules for data processing. The DT modeling elements might provide repetitive and intense stimulation test cases. The virtual perception data is given back to the physical entity components of the autonomous driving controller.

4.3.3 Simulations and feasibility studies in autonomous driving

Simulators are frequently used to accelerate the creation of concepts for autonomous vehicle systems. For the automated driving system to observe, decide, organize a journey, and deliver control commands as if it were actually in the physical surroundings, the autonomous car modeling replicates the external conditions by feeding wearable sensors data to the system. A regulated and secure environment is offered by the simulation for the design and testing of autonomous driving systems.

Early automobile electronics were limited to basic components like combustion and charging. All virtual machines now have a wider range of applications, from engine management to suspension management to convenience management, and new electronically controlled technologies are constantly being developed. The trustworthiness of the centralized controller of the recently constructed architectural structure must therefore be secured through verification. Hardware in the loop simulations, often known as HILS [10], is a technique for creating and testing sophisticated real-time systems.

Co-simulation is a technique that distributes the modeling and simulation of many environmental subsystems. By offering a customizable solution, co-simulation shows the viability of multidomain and simulated systems. Due to the large number of elements with various mathematical properties and domains, it is highly helpful in traffic situations [11]. When operating a car, numerous things need to be taken into account, including other vehicles, pedestrians, and the locations of traffic lights. Co-simulation allows us to simulate these components simultaneously.

The accuracy can be increased by using road GIS data and image sequences for modeling simulation. It can take some time to gather visual information about the road at a specific location and combine it with GIS information. The movement of the vehicle in relation to its surroundings is simulated using a variety of mathematical models. Numerical results in motion equations and linear kinematics are the foundations of quick, low-accuracy models.

4.3.4 Challenges in automotive manufacturing value chain

Vehicle to Wireless technology can be used for linked automatic driving tests in addition to supporting vehicle driving safety, efficiency improvement, and other application functions through the DT-based linked self-driving test prototype system. Additionally, testing for autonomous vehicles can be seen as one of the key ways that wireless technology is applied to vehicles. Even though the test method has been shown to be effective, there is still room for development because it is simply a crude prototype system. On the issue of the response latency to automated vehicles, the auto industry is still at odds. In other words, we are unsure if the suggested method can satisfy the standards for response delay for autonomous driving. The suitable communication quality requirements must be set as autonomous vehicle technology advances. The DT-based linked self-driving test will also be regarded as a 4G/5G information network technology. In light of this, testing procedures should be enhanced indefinitely. In this method, the user experience is poor since in-vehicle testers cannot view the virtual scenes created in cyberspace. Consequently, combining virtual reality (VR) and AR could be future study focuses. It is important to make sure that the created virtual scene accurately depicts the actual traffic scene. The traffic database is currently incomplete. That is to say, there is currently no assurance that the test scenario will encompass and accurately reflect the real traffic environment. The test case collection will also be regularly upgraded in tandem with the traffic database

4.4 Digital twins in intelligent urban transportation

Intelligent urban transportation systems (IUTS) are more advanced than traditional transportation systems. These technologies substantially increase the amount of contact between drivers and passengers on the road while using the most current advancements in traffic flow control and transportation modeling to provide end users more information and a greater degree of safety. The IUTS encompasses the whole of municipal services, including but not limited to traffic police, ambulances, fire departments, and any and all other emergency services. One of the key elements of these systems, which use mathematical modeling techniques to analyze the transport network and develop solutions for transport issues like traffic management, traffic light optimization, public transportation, and investment justification for building transportation infrastructure, includes DTs. The most effective use of the capabilities of the present transportation infrastructure is made possible by combining strategic transport planning technologies with IUTS systems, as is the choice of the optimal future development route [12]. Technologies for controlling city transportation systems are currently under development; to accelerate project implementation, reference models of IUTS services are required. This enables specific models of transportation infrastructure to be developed and implemented with proper information systems.

4.4.1 Adaptive traffic signal control using a digital twin approach

Reduce and redistribute waiting times at intersections to enhance the driving experience of a traveler using a DT technique for adaptive traffic signal control (ATSC). While ATSC and linked car ideas may speed up travel in signalized corridors and cut down on junction wait times, it is practically difficult to cut down on traffic delays in crowded traffic situations. We have created a DT-based ATSC, which takes into account both the waiting times of cars at the intersections just upstream and downstream of the relevant junction, to address this flaw in the classic ATCS using connected vehicle (CV) data. Urban transportation systems and the experts in charge of running them face a recurring issue of traffic congestion. According to published research, ATSC systems have the ability to enhance signalized intersectional performance via the reduction of delays, travel times, and queues, which will increase capacity and enhance the overall level of service at intersections. However, the traffic data gathered via inductive loops and other traditional sensor systems put a limit on such performance enhancement. Real-time signal optimization at signalized intersections is expected to change considerably as a result of the availability of trajectory data from CV technology. The term "CV technology" refers to quick and continuous electronic connection between automobiles and infrastructure, also known as vehicle-to-vehicle (V2V) and vehicle-to-infrastructure communication [13]. This communication increases mobility and safety while minimizing the environmental impact of transportation. DT technology has the potential to significantly transform traffic management and operations as the industry gradually moves toward intelligent or smart transportation systems. A DT is a representation of a physical process or item that uses real-time, two-way data interchange between the digital and physical worlds. The idea of developing "twins" is to facilitate better decision-making. The idea of the transportation DT is the real-time collection of traffic data from various physical systems, including sensors, CV, traffic signals, and traffic surveillance cameras, to construct a digital replica of the original systems. Even though the idea of DT is similar to that of CPS, transportation DTs are expected to use the embedded sensor systems of physical transportation systems to provide real-time and time-sensitive transportation services rather than concentrate only on CPS domain applications. The main hindrance is collecting and merging data from many physical system sources to generate a virtual representation of real-world traffic operations for real-time traffic management. Since there is not a single accepted definition of DT technology, it is theoretically under development. For instance, DT comprises multi-physics, multiscale, and probabilistic simulations of a complex product in manufacturing sectors that mimic the behavior and environmental reactions of its corresponding physical twin. The DT module reproduces a precise digital model of the road and enables modeling and experimentation to try out solutions and predict various scenarios.

4.4.2 Data-driven scenarios based on digital twin leveraging artificial intelligence

A data-driven simulation model can be broken down into its component parts as follows:

- Algorithms that define the simulation model [14]
- Connection components, also known as IoT systems
- Model extraction from data using ML and data mining
- The use of their software

Information that the real-world entity has created or is now producing: The success of digital modeling is influenced by this third element, which is a critical aspect of a DT. The following components make up a data-driven simulation model: (1) simulation model defining algorithms; (2) connection components, such as IoT systems; and (3) data created by the real-world entity or that which is currently being created. The success of digital modeling is impacted by this third element, which is a critical aspect of a DT. Modeling simulations with data data-driven simulation models are simulation models that are parametrized and extracted from data. Some of the most pertinent benefits of data-driven simulation modeling include the following:

Resemblance to the actual system: In comparison to conventional approaches, data-driven models have a tendency to more accurately represent the real systems that they model. Real systems may sometimes display behaviors that are difficult to predict and describe in advance, and these behaviors can only be recorded via data.

Possibility of ML and AI for model enhancement: Data open up the possibility of ML and AI techniques for modeling the challenges in traditional simulation to depict a phenomena. In addition, simulation and integration of ML and AI techniques may be used to better understand the behavior of specific systems [15].

The aforementioned principles, coupled with some successful adoptions of data-driven methodologies, have helped promote a change in emphasis from conventional simulation modeling to a more data-driven approach. The development of data creation and storage, algorithms, and the continuously evolving requirements of industrial businesses have all contributed to this change.

The modeling of data-driven simulations has the following problems:

- Absence of model creation that is mostly data-driven
- The majority of methods for creating models that are now accessible cannot be categorized as automated simulation modeling
- These responsibilities are just a portion of the PLC in a typical reconfigurable smart plant, as well
- The PLC is interesting because it emphasizes the relevance of every component of a production system in terms of the lifespan of a product.

4.0 Industry: The underlying technologies of Industry 4.0 have made it feasible to synchronize models and physical entities in real time. The Industry 4.0 environment wherein current factories are created are not expressly supported by previous data-driven modeling studies.

Heterogeneity of data: Smart factories are connected to a large variety of data sources. Additionally, data produced by IoT devices comes in a wide variety of forms, including logs, photos, videos, etc. Deploying integration techniques is necessary to use this diverse range of data. The majority of current efforts concentrate on homogeneous data sources.

Validation of data: The data gathered from smart factories present varied difficulties since it often includes noise and missing numbers. This data is often contaminated by noise, which is brought about by the production environment and human mistakes, both in terms of frequency and volume. As the validity and quality of the data heavily influence the quality of the derived models, having tools to perform automatic checking of the streaming data for accuracy is crucial. The majority of previous efforts were not focused on data validation, which is essential for guaranteeing the accuracy of models.

System reconfigurability: The reconfigurable manufacturing systems has been introduced in response to market needs for mass customization. Ideas for simulation modeling that were outlined in earlier techniques are inapplicable to complex situations that change regularly, such as systems for reconfigurable manufacturing.

Smart manufacturing with digital twins: Flexible and adaptable processes as part of a smart industry may address some of the major issues in production facilities with dynamic and rapidly changing boundary conditions. DTs may be used in a smart industry setting to effectively stimulate and regulate many parts of complicated industrial processes. Adoption of DTs has several advantages, including the ability to monitor machine condition in real time, increased dependability, predictive maintenance potential, and the provision of specialized services to industry key holders.

These advantages are obtained in a smart industry, thanks to the data that are continually gathered and sent through IoT devices. Following this, the information is used in crucial tasks like planning, upkeep, logistics, and decision-making. The ultimate objective of Industry 4.0 is to achieve intelligent and data-driven decision-making inside the smart manufacturing environment to increase revenues and sustainability.

4.4.2.1 Data-driven smart factories with digital twins

The notion of a data-driven DT was inspired by how much data is being produced in smart factories on a daily basis. Data is the fundamental component that may be utilized to ascertain and monitor the states of complex systems in the manufacturing environment. Hence, data is the focus of this paragraph. High-fidelity models for industrial systems may be developed by effectively using this data. The main techniques that may be utilized to extract information from such data are ML and process mining tools. They will be responsible for leveraging the information that was retrieved to improve the model's capabilities in the simulation and, by extension, the DT architecture. This information will be updated online to reflect any changes made in the actual production environment.

This will make it possible for several features to constantly enhance various parts of manufacturing processes even when certain adjustments are made. The novel aspect of the suggested framework is that it makes use of recent developments in ML and process mining to develop data-driven models that are constantly validated and updated while overcoming the limitations of earlier methods for automatic or semi-automatic simulation model development.

4.4.2.2 Important components of data-driven digital twins

The following are key components that allow a data-driven DT for smart manufacturing [16]:

Data collection: The environment within a smart industry is associated with massive amounts of data gathered from several sources. Entity identification must be done initially before data collection can begin. At this stage, the real-world system that is being modeled is located, and information on the entities pertinent to the DT's objective is gathered. Upon completion of this job, a database will be created and filled with the data that is continually produced by the designated entities inside the industry's production systems. Several different types of sensors are affixed to industrial components, and they capture data that are useful for conducting health monitoring and defect detection activities.

User contributions: Customers and other stakeholders in the production system often contribute information about their preferences, limitations, and demands.

Internal network: By allowing equipment and industry components to communicate, the internal network makes it possible to gather detailed information about the industry as a whole. IoT, cloud, and fog computing breakthroughs have made this viable.

The following are some of the several types of data that are being produced:

- **Diagnostic information:** This information is helpful for assessing the condition of the production systems. It is often gathered via machines' built-in sensors.
- **Logs and traces:** The history of how parts or machines have operated logs are used to keep track of everything, which may be quite helpful in understanding the procedures that are in place in a manufacturing setting.
- It is a common practice to modify machine operation to achieve predetermined objectives by taking into account the feedback, limitations, and demands of the end users.

- Data integration is a crucial step in the data collection process. It describes the process of converting multi-modal data in the form of images, logs, audio, etc., into a usable format and is appropriate for the job that we are trying to complete.
- Data validation: Data must first go through a careful examination since it is the primary factor in determining if the model is accurate. This might take the form of cleaning and validity checks.

  The following are only a few data-related issues.
- Noise: Mistakes caused by the measurement equipment, the environment, and human error might taint the results.
- Data may have missing values for a number of reasons, including device malfunctions, networking issues, and other circumstances.
- Multiple modalities: The sensors included in the smart industry architecture may record numerous types of data, including pictures, text, and audio.
- The production environment often generates enormous volumes of data. Model creation could be challenging and inaccurate because of the size and the likely high dimension. Many ML algorithms find it difficult handling the data that has a high degree of dimension.

4.4.2.3 Challenges with digital twins for data-driven smart factories

The following list of connected difficulties pertains to the framework for data-driven DTs in smart factories [14]:

This challenge, which is identifying and completely defining the right amount of human engagement to enhance the data-driven approach, is the use of a predominantly data-driven technique that depends on human contact to enable automation. Accuracy is assured by clearly defined places for human input.

Data-driven simulation modeling combine setup, interpretability, and effectiveness. Interpretability is the feature of a data-driven or intelligent strategy that provides a systematic way for a stakeholder to comprehend the choices made by the DT. Accuracy and timeliness are two components of the data-driven DT that are referred to as efficiency.

- Making decisions in real time: DTs can help stakeholders make wise choices based on various performance metrics. As a result of DTs that are data-driven pertinent information from all acquired data, which might be very useful to the stakeholder, such decision support is made feasible. The requirements for timeliness should be linked to the importance and weight of the related choices in terms of their criticality. The level of detail in the data being gathered should reflect this. Safety-related choices, particularly those in safety-critical systems, must be made more quickly than production-related ones.

- Changing objectives: Smart manufacturing systems seek to provide reliable and affordable production frequencies. This goal is strongly connected to other traits like production system dependability, reduced material waste, reduced energy usage, etc. In addition, environmental objectives, including reducing greenhouse gas emissions, are others that should be taken into account. Building simulation models that reflect, update, and serve such a broad range of changing needs is a very difficult task that must be overcome.
- Creation of high-fidelity DTs: Because the proposed framework is data-driven, models often accurately mirror the related production systems and take into account the most recent behaviors of processes in smart factories. Additionally, this accuracy is continually maintained by continuing validation of both data and models.
- A better knowledge of decision-making and processes: A key component of our suggested strategy is process discovery. This is accomplished via mining the gathered event logs as well as other data-driven components. This contributes to a better understanding of how the system's process runs and will be helpful in making better decisions. The stakeholders may make pertinent choices on the future of the system and the DT by employing the system's process flows.
- Enhanced reliability: Ongoing model and data validation is responsible for the proposed framework's increased dependability. The focus on continuous validation as opposed to validation at set intervals makes it easier to ensure that the system is changing in a way that is suitable for the rate at which new data is entering. The validation mechanism makes sure that the model accurately depicts the data it is modeling and that the data, which is a critical component of our framework, is accurate.
- Agile manufacturing: A solid foundation for embracing the idea of agile manufacturing, which allows manufacturing organizations to adapt quickly to market changes while still maintaining excellent quality and minimizing costs, may be found in the data-driven DT. DTs that are data-driven are essential for the implementation of Industry 4.0. With the many and quick reconfigurations that contemporary production systems go through over their lifespan, manual simulation modeling is not an option. Due to this, we looked at the conditions

that would allow for the data-driven creation of simulation models for smart manufacturing systems, which would serve as the foundation for their DTs. DTs that are driven by real-time data and created automatically from data collected by IoT devices in smart factories may meet several requirements, such as the need for simulation models that are constantly updated and precisely represent changes to plant layouts. Additionally, integrated ongoing model validation will be possible with data-driven DTs and may begin as soon as elements of the model are being retrieved. This will be made feasible by the availability of data from the current system. The potential also provides a variety of requirements and hindrances that must be addressed. Even if every aspect is automated, certain operations will still need human intervention. However, their mainstreaming will benefit from their particular identity and differentiation. For instance, experts will be required to determine the purpose of the simulation and identify key occurrences. The system in place and the objectives of the data-driven DT would have a significant impact on the appropriate ratio of human expert knowledge to data. In an effort to fulfill the requirements of data-driven DT creation, we have created a high-level conceptual framework. We believe that as additional techniques for assuring data quality become accessible, this data-driven simulation modeling will attract increasing attention. To further demonstrate our concept, we also provide a high-level case study and talk about the potential problems that come with it.

4.4.3 Digital twins integrated with artificial intelligence for smart transportation

AI is employed extensively in many different facets of society, and the creation of smart cities is advancing at a rapid rate. The current research status of the intelligent development of transportation infrastructure is defined and anticipated with an eye toward smart cities. This is done largely on the basis of the kind of space, the type of function, and the utilization of the facility. The key categories are people and vehicles, people and other items, and vehicles and transportation systems. Other categories include people and transportation systems. Researchers in this field have concluded that DTs and AI technologies provide important benefits for managing the transportation spatial information network and categorizing transportation infrastructure. To provide guidance for future intelligent development and construction of transportation infrastructure in smart cities, the intelligent development of transportation infrastructure is analyzed and predicted in terms of functional design, intelligent development, and successful integration of new media. To act as a blueprint for future intelligent development and building of transportation infrastructure in smart cities [17].

When designing transportation infrastructure, it is necessary to take into consideration a wide range of data sources, focus on the macrostructure and data analysis of the platform, and conduct an exhaustive investigation of the functional needs. It is possible that the deployment of DT may be able to properly handle the problems that are now plaguing the transportation sector. Intelligent transportation systems are able to effectively manage the traffic on road networks, and they can also execute smart changes in the monitoring of traffic in smart cities. Smart cities are also referred to as "smart cities." A digital transportation infrastructure platform must be built with a large storage capacity, high storage efficiency, simple structure, and stable operating environment. Some of the data sources that must be integrated are building information modeling, geographic information systems, and aerial photography data of traffic conditions. To effectively advance the active two-way information exchange between vehicles and roads and to boost smart traffic effectiveness, it is necessary to develop a real-time transportation management system that is accurate, efficient, and comprehensive. Only then will it be possible to achieve success in this endeavor.

Nowadays, intelligent technologies are being used widely in a variety of facets of modern life, and the creation of intelligent infrastructure for the transportation industry is an extremely important topic. Intelligent vehicle highway systems, also known as IVHS, were the precursors of what would later become known as intelligent urban traffic systems (IUTS). By using cutting-edge information technology, data transmission technology, sensor technology, electronic control technology, and computer technology, IUTS builds a large-scale, all-around operating, real-time, accurate, and efficient integrated transportation management system. This is achieved by effectively and thoroughly implementing these technologies. Intelligent transportation systems have the ability to expand road capacity, decrease energy use, reduce environmental pollution, minimize traffic congestion, and improve the efficiency of transportation. People, cars, and roads can all work together harmoniously to gain these advantages [18].

Information and communication technologies are key enablers for the development of an efficient, secure, and intelligent transportation system because they provide the fundamental assurance for real-time dynamic information interaction of people, vehicles, roads, and the environment in intelligent transportation systems. This is due to the fact that they make it possible to develop an efficient, secure, and intelligent transportation system. To implement the collection of the vehicle's own state information, the perception of the driving environment information, the planning and tracking of vehicle trajectories, as well as the efficient change of the path during congestion, wireless communication technology is applied to intelligent transportation systems. To put all of these things into action, was the main aim. The idea of synchro modal road transport mechanism was implemented so that different transportation infrastructures may be integrated and optimized in real time. Because of this process, transportation shifted from being carried out on highways to being carried out on interior canals and railways. Through the use of DTs, a symbiotic contact between the virtual and physical worlds was established. This interaction facilitated order synchronization, mode selection, reduced costs to an acceptable level, and enabled more dynamic and changeable lead times. Therefore, IUTS is beginning to become the primary driver of the evolution of transportation in the future. It is possible that the infrastructure for transportation will be completely covered by ubiquitous communication system. The intelligent integration of people, automobiles, roads, and the environment will be made possible by this, allowing for transmission of information between vehicles and cars on the road in real time. Additionally, by using DTs in IUTS, the road network and traffic infrastructure in the actual physical location may be painstakingly mapped to VR. The vehicular ad hoc network, also known as VANET, is incorporated into the modern transportation infrastructure to achieve effective communication between vehicles and infrastructure or between vehicles and other vehicles, which helps enhance driving safety, prevent traffic jams, and better coordinate the traffic network. Furthermore, the use of DTs in the construction of transportation infrastructure can enable the system to build an entire network of infrastructure rather than just a single component. Once the system has been fully integrated, it can finally achieve the goal of transparent interconnection of the road network transportation infrastructure. The real-time performance of DTs may increase with the advent of 4G, 5G, and even more potent communication technologies. This improvement is further magnified when end-side-cloud collaborative computing is implemented. It is also possible to simulate uncharted territory in real time without using an HD-Map. Second, by improving the algorithms used for behavior simulation and prediction, it may be possible to obtain more accurate behavior prediction.

4.4.4 Comparative analysis of application of deep learning to intelligent transportation

In addition to taking the development of autonomous vehicles to a new level, deep learning (DL) applications have improved the performance of public transportation and ride-sharing firms; maintenance costs were reduced, safety and security on transit routes were increased, and traffic management and planning were improved [19].

4.4.4.1 Prediction of traffic characteristics

The prediction of traffic characteristics is one of the most popular uses of DL in transportation. Information on traffic characteristics may help drivers make more informed route decisions and traffic control organizations manage traffic more effectively. Traffic flow, traffic speed, and travel time are the major factors of importance. Since these traits do not coexist, techniques for predicting one of them may also be used to estimate the value of the other traits. A forecast value is often categorized as short-term (S) for each traffic feature based on the length of prediction for that characteristic.

Forecasts within a prediction window of less than 30 minutes, between 30 and 60 minutes for medium-term (M) predictions, and more than 60 minutes for long-term (L) predictions. Results from one dataset are challenging to transfer to other datasets because driving behavior and traffic variables might differ across places. Historically, autoregressive integrated moving average modeling and other parametric and statistical techniques have been employed to forecast traffic features. However, these techniques often fail to anticipate irregular traffic patterns. However, nonparametric approaches are currently being employed in traffic characteristic prediction to attain improved accuracy as a result of ML and, furthermore, DL methodologies.

4.4.4.2 Traffic accident implications

The objectives of incident identification based on traffic characteristics and incident risk prediction for a specific site are to assist traffic management agencies in reducing incident risk in hazardous areas and traffic congestion in incident locations. A few crucial characteristics may assist in anticipating traffic mishaps even when certain factors, such as drivers' conduct, are not highly predictable [20]. Human mobility, traffic flow, geographic location, weather, time of day, and weekday are some of the characteristics that may be considered as markers of a traffic incident. However, because accident variables in urban areas, where people and cars are often dense, differ greatly from those in small towns with dispersed populations, a single model cannot typically be used in multiple locations. Since incident data is often diverse, incident prediction and incident detection are more difficult than incident risk prediction. To get around this problem, they modified just one aspect of the data (hour, day, or place) in each step, and then they verified whether the resultant data point was negative or not. It was included in the pool of data to be taken into account when it was observed to be negative.

4.4.4.3 Identification of the vehicle

Applications for re-identification (Re-ID) range from computerized ticketing to time-based trip planning. Recognizing license plates is the first step in Re-ID since they are unique to each vehicle. A visual attention model is used to implement DL models for recognizing license plates. The model first generates a feature map using the most common colors seen on license plates, uses a CNN model to extract data from the plates, and then applies an SVM to the retrieved data. The characters on a license plate might be difficult to see due to bad lighting, blurry images caused by moving cars, poor camera quality, traffic occlusion, and even hidden license plate images. To get around this, they have suggested using a CNN layer to extract glaring elements like the color and type of the car, and they've also utilized a Siamese neural network to tell the difference between identical license plates.

4.4.5 Challenges and research directions on intelligent urban transportation

4.4.5.1 Digital twins in the area of smart city transportation confront the following challenges

The development of a new type of smart city is being pursued using a brand-new technology path called the DT city, under circumstances where the city's accumulated data shifts from quantitative to qualitative change and in light of significant advancements in information technology, such as perception modeling and AI. It is a cutting-edge approach to developing technologies that promote sustainable operation and urban intelligence. However, given the many difficulties facing modern urban administration, it is important to think about how to escape the constraints of conventional smart cities and progressively upgrade to a "digital twin city." The DT city is built on a foundation of models and data, thus building a complete digital model is a crucial first step. There continues to be data fragmentation in many fields from the perspective of the current application of traditional smart city development. The three bases that are typically present in most cities are the housing and urban-rural construction system, the spatiotemporal big data platform led by natural resources and land planning, and the city base map for urban security and comprehensive governance based on the line of public security politics and law. Every base map develops its own system and often only supports the applications of that system. Other departments are not permitted to utilize it whenever they want or on demand. It is challenging to give up and incorporate the number since it has been gathered over a long period of time. Therefore, it is tough and difficult to execute the urban traffic simulation method [21].

4.4.5.2 Topics for digital twin research in smart urban transportation in the future

The development of the DT intelligent transportation system will be further aided by the ongoing advancements in information technology, the gradual improvement of 5G standards, the establishment of commercial networks, and the network performance of large bandwidth, high speed, and low latency. This will be a significant boon to the industry. The performance of 5G ultra-high-speed networks enables V2V collaborative automatic driving, automated driving in vehicle formations, and remote automatic driving, as well as safe and reliable communication in high-speed movement. On the other hand, 5G networks are required for remote automated driving. On the other hand, the fast development of 5G has combined the IoT and AI to enable the transportation system to "connect all things." As a result, the four elements of "human-vehicle-road-environment" transportation may be "migrated" into DTs from the real world. The "digital, networked, and intelligent" components of smart transportation may now be fully used because of the significant advancements made to traffic data in the digital age. Previously, it was believed that this was not feasible. The most cutting-edge trend in smart transportation is called "digital twins," but there is still work to be done before they can completely combine real-world global management, synchronous visualization, and virtual-real interaction. This is despite the fact that

DTs are currently the most cutting-edge trend in smart transportation. DTs, on the other hand, offer novel thoughts, novel approaches, and novel ideas for intelligent transportation, which will continue to develop in the future and will ultimately result in the creation of an entire technical operating system that is powered by technological advancements based on 5G and demand upgrades. It is now possible to model undiscovered areas in real time without the need of having extremely precise maps because of the development of cutting-edge communication technologies, such as 5G, 6G, and other cutting-edge technologies, as well as end-side-cloud collaborative computing. The deduction of predicted behavior may also be made more accurate by improving the behavior simulation and prediction algorithms. Furthermore, with more powerful computation, it is possible to deduce even more parallel worlds at the same time. In addition, when the technology, known as V2X (vehicle to everything), develops further, there will be a larger range of people involved in traffic and the situations will get more difficult. The best way to enhance simulation is yet another topic worthy of investigation. Making choices in real time and exercising remote authority over other individuals are going to be the two of the most important criteria for the whole twin system. For example, the question of whether or not data can be transported rapidly and securely to the cloud and the backend, as well as the question of whether or not situational awareness enables the transmission of control instructions back to the actual world. The process of data transmission has to be safe and dependable, and it also needs to be efficient enough to be finished in a timely manner. Utilizing related technologies such as blockchain may make it possible to make this information-closed-loop system safer and more resilient. Another product of advanced urban information technology development and continuing urban information technology construction is the DT city. The DT city that corresponds to the physical city takes full use of the city-wide big data that is produced in the early phases of the project to offer platforms, tools, and methodologies for complete municipal decision-making, intelligent administration, and worldwide optimization [22].

4.5 Conclusion

Digitalization and AI are significant drivers of sustainable behaviors and thought, which are being discussed and promoted more globally. For businesses to grow and continue operating, a thorough approach of sustainability can be achieved through continually connecting, handling, and interpreting all available information throughout the entire value chain and communicating them to a DT or shadow. AI-driven DTs are anticipated to provide the additional manufacturing transparency and understanding necessary to facilitate a demand-oriented and real-time capable analytical foundation, taking factors into account throughout the product lifecycle, for Industry 4.0, which would have been facing unique demands. We believe that by rearranging and combining a number of extremely important topics both horizontally as well as vertically, a complex formation will develop that could actually enable the research throughout this analysis to make a contribution to more AI-driven methods for research and assist various branches in making new developments in their respective individual sustainable smart fields.

References

[1] G. Zhou, C. Zhang, Z. Li, et al., Knowledge-driven digital twin manufacturing cell towards intelligent manufacturing, Int J Prod Res. 58 (4) (2020) 1034–1051.

[2] L. Li, T. Qu, Y. Liu, et al., Sustainability assessment of intelligent manufacturing supported by digital twin, IEEE Access 8 (2020) 174988–175008.

[3] S. Almeaibed, S. Al-Rubaye, A. Tsourdos, et al., Digital twin analysis to promote safety and security in autonomous vehicles, IEEE Commun. Stand. Mag. 5 (1) (2021) 40–46.

[4] X. Gao, J. Cai, Optimization analysis of urban function regional planning based on big data and GIS technology, Tech. Bull. 55 (11) (2017) 344–351.

[5] L. Hu, Z. Liu, W. Hu, Y. Wang, J. Tan, F. Wu, Petri-net-based dynamic scheduling of flexible manufacturing system via deep reinforcement learning with graph convolutional network, J. Manuf. Syst. 55 (2020) 1–14.

[6] Q. Liu, H. Zhang, J. Leng, X. Chen, Digital twin-driven rapid individualised designing of automated flow-shop manufacturing system, Int. J. Prod. Res. 57 (2019) 3903–3919.

[7] Z. Liu, W. Chen, C. Zhang, C. Yang, Q. Cheng, Intelligent scheduling of a feature-process-machine tool supernetwork based on digital twin workshop, J. Manuf. Syst. 58 (2020) 157–167.

[8] E. Negri, V. Pandhare, L. Cattaneo, J. Singh, M. Macchi, J. Lee, Field-synchronized Digital Twin framework for production scheduling with uncertainty, J. Intell. Manuf. 32 (2020) 1207–1228.

[9] A. Rezaei Aderiani, K. Wärmefjord, R. Söderberg, Evaluating different strategies to achieve the highest geometric quality in self-adjusting smart assembly lines, Robot. Comput.-Integr. Manuf. 71 (2021) 102164.

[10] J. Cho, D. Hwang, K. Lee, J. Jeon, D. Park, Y. Kim, et al., Design and implementation of HILS system for ABS ECU of commercial vehicles. In Proceedings of the ISIE 2001, 2001 IEEE International Symposium on Industrial Electronics Proceedings (Cat. No. 01TH8570), Pusan, Korea, 12–16 June 2001; Volume 2, pp. 1272–1277.

[11] N. Kim, D. Karbowski, A. Rousseau, A modeling framework for connectivity and automation co-simulation, SAE Int. J. Engines 11 (2018) 1–010.

[12] A. Rudskoy, I. Ilin, A. Prokhorov, Digital twins in the intelligent transport systems, Transp. Res. Procedia 54 (2021) 927−935.
[13] S. Dasgupta, M. Rahman, A.D. Lidbe, W. Lu, S. Jones, A transportation digital-twin approach for adaptive traffic control systems, arXiv preprint arXiv 2109 (2021) 10863.
[14] S.Y. Teng, M. Touš, W.D. Leong, B.S. How, H.L. Lam, V. Máša, Recent advances on industrial data-driven energy savings: digital twins and infrastructures, Renew. Sust. Energy Rev. 135 (2021) 110208.
[15] S. Mylvaganam, Applications of AI and possibilities for process control, Industrial Tomography, Woodhead Publishing, 2022, pp. 823−852.
[16] N. Stojanovic, D. Milenovic, Data-driven digital twin approach for process optimization: an industry use case. In 2018 IEEE International Conference on Big Data (Big Data), pp. 4202−4211. IEEE, 2018, December.
[17] G. Bhatti, H. Mohan, R.R. Singh, Towards the future of smart electric vehicles: digital twin technology, Renew. Sust. Energy Rev. 141 (2021) 110801.
[18] J. Wu, X. Wang, Y. Dang, Z. Lv, Digital twins and artificial intelligence in transportation infrastructure: classification, application, and future research directions, Comp. Electr. Eng. 101 (2022) 107983.
[19] A.K. Haghighat, V. Ravichandra-Mouli, P. Chakraborty, Y. Esfandiari, S. Arabi, A. Sharma, Applications of deep learning in intelligent transportation systems, J. Big Data Anal. Transp. 2 (2) (2020) 115−145.
[20] M. Parseh, F. Asplund, New needs to consider during accident analysis: implications of autonomous vehicles with collision reconfiguration systems, Accid. Anal. Prev. 173 (2022) 106704.
[21] M.Z. Serdar, M. Koç, S.G. Al-Ghamdi, Urban transportation networks resilience: indicators, disturbances, and assessment methods, Sust. Cities Soc. 76 (2022) 103452.
[22] S.P. Ramu, P. Boopalan, Q.V. Pham, P.K.R. Maddikunta, T. Huynh-The, M. Alazab, et al., Federated learning enabled digital twins for smart cities: concepts, recent advances, and future directions, Sust. Cities Soc. 79 (2022) 103663.

CHAPTER 5

Industry 4.0: survey of digital twin in smart manufacturing and smart cities

A. Malini, Umamaheswari Rajasekaran, G.K. Sriram and P. Ramyavarshini
Thiagarajar College of Engineering, Madurai, Tamil Nadu, India

5.1 Introduction

"The Industrial Revolution was one of those extraordinary jumps forward in the story of civilization," as mentioned by Stephen Gardiner. Necessity is the mother of invention, for example, the discovery of fire using flint-stones and the invention of wheels facilitating transportation in the ancient ages. The cognition of man correlates the existing knowledge of things to innovate meeting the needs of the lifestyle. Industry 1.0, the first industrial revolution that began in England, mechanized the production using steam and water. Industry 2.0 involved the use of electrical energy to energize machines.

The growth of electronics and information technology, with the invention of transistors, integrated chips, and programmable logic controller, introduced automation and communication. Industry 4.0 took birth in Germany, a country which is one of the leading manufacturing competitors in the world. The advancements in the field of computing and communication integrated with artificial intelligence (AI) and analytics gave birth to a new concept of cyber physical systems (CPS), wherein machines communicate with machines, machines control machines, the control being triggered by the actions of the intelligent systems.

A virtual representation of the physical object is created with the data collected from the system crafted with a huge number of sensors. The concept of digital twin took birth with the introduction of *Mirror World* concept by David Gelerntner in 1991. *Google Earth* is a good example of the mirror world mapping the actual geography of the real world in a software as a use case. The name digital twin was coined by NASA's John

Digital Twin For Smart Manufacturing
DOI: https://doi.org/10.1016/B978-0-323-99205-3.00013-4

Vickers in 2010. Digital twinning for any use case comprises the knowledge of the physical product, the actual object, virtual replica, and data flowing between the physical and the replica. This concept of virtualization of real-time objects, provides an effective tracking and monitoring of the structure, easing the planning, maintenance, and prediction of future actions based on real-time simulations and visualizations. It involves regular updation from real-time data collection sources, thus the integrated response of the objects is virtualized in their present state. Digital twin and Industry 4.0 play a vital role in modern production and management of engineering activities.

Dr. Michael Grieves is credited for introducing the concept of digital twin in the manufacturing industry, so called by him as Mirrored Spaces Model [1]. In production management, product prototyping, cost minimization, autonomous decision support systems, resource utilization and optimization, quality assurance, profit maximization, maintenance are a few of the many problems to be enlisted. With innovations in the field of sensors, advancements in the field of AI, 3D models and data analytics, the concept of digital twin solves the above-listed problems in the manufacturing industry. Digital twin enhances the knowledge reserves by modeling the problem in the product lifecycle that is yet to occur, having the knowledge of the current state and also the previous states of the equipment. It helps eliminate the need for prototypes to understand the final product giving a depiction of the final product in its simulated working environment. It induces the practice of enhanced data-driven decision-making to manufacturing problems, which are quite unique, expensive, and unlike the problems encountered in other domains of data analytics.

Destructive testing performance of the design can be easily analyzed using digital twin, avoiding the cost of re-designing the model. Mercedes-Benz A-Class failed the Moose Test in 1997, costing the company an overhead of around USD 250 million. Virtual reality helps manufacturers observe the performance of the design in a virtual environment. Augmented reality helps add the algorithmic instructions customizable to the current state of performance. Layering digital twin models with AR and VR technology enhances the use cases of digital twins in the manufacturing industry (Fig. 5.1).

Apart from the manufacturing sectors, digital twin technologies are used extensively in diverse areas, such as healthcare, smart cities, vehicular management, disaster management, pollution reduction, etc. This chapter

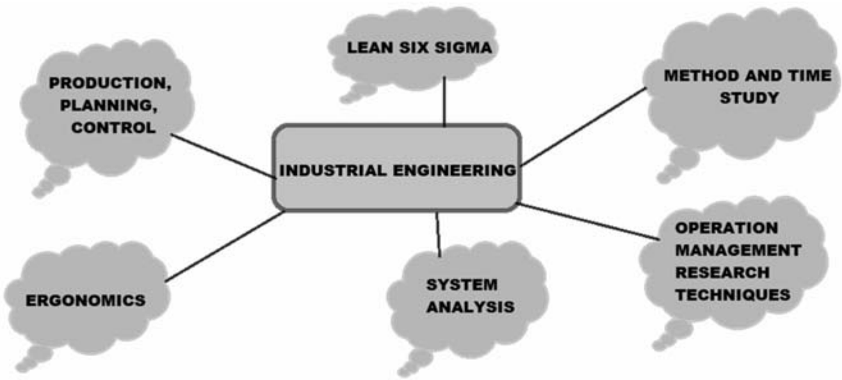


Figure 5.1 Industrial engineering.

discusses digital twin technology, describing its base technologies, its types, its applications in additive manufacturing, automotive manufacturing, and shipbuilding industry, and use cases of digital twin technology in smart manufacturing and smart cities presenting the literature survey made based on a few research papers from reputed journals.

5.2 Digital twin—an introduction

The global marketing competition has increased exponentially in the past decade and has been considered a must for businesses to build a data-oriented model to meet individualization. The Industry 4.0 revolution has promised increased flexibility, productivity, and quality with the help of digital transformation in the areas ranging from manufacturing to services and research operations. Related Industry 4.0 technologies and advanced engineering have greatly altered the way of interaction with physical assets using digital data, which are beneficial for the present engineers.

A digital twin is a digital replica of a physical entity [2]. It can also be defined as a virtual representation of the elements that are manufactured, such as assets, process definitions, and personnel. Many studies have been made in the field of digital twins to achieve goals such as reduction in operational costs in machines, and processes. Till date, most studies in this field involved the manufacturing industry in which the core idea was to validate the design architecture.

Fig. 5.2 represents the Industry 4.0 technologies as a whole, including cloud, Internet of Things (IoT), big data, Machine learning, and extended reality (XR) with an ability for learning and advancement through

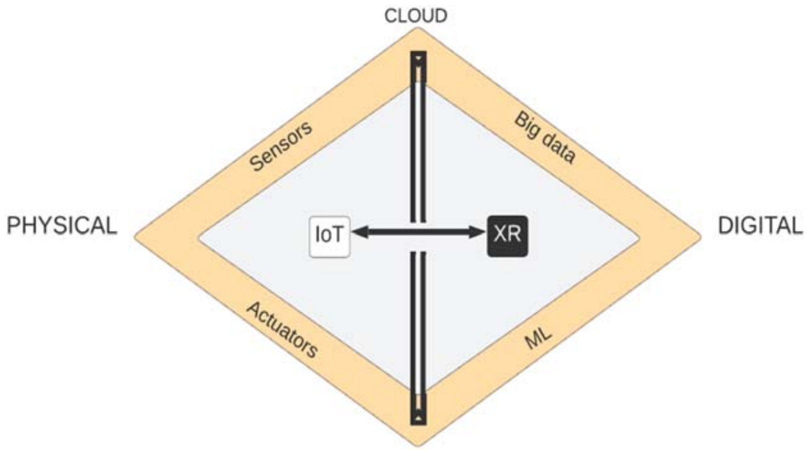


Figure 5.2 Industry 4.0 technologies.

gathering, visualizing, predicting, and analyzing significant features in digital twin. Digital twin grows by the accumulation of big data and learning from it, which makes it efficient as it can predict the patterns and help in on-time decision-making. The use of XR and reinforcement learning is favoring the growth of digital twin in industries. These are the influences of the technologies that have been integrated to provide instant access to digital models that virtually represent their physical complements.

5.3 Types of digital twin

1. Digital twins are classified into various types based on the level of product magnification [3] and area of application.
2. Component twins/parts twins are considered basic units of digital twins (smallest example of functioning component).
3. Asset twins are the types of twins in which two or more components work together. It gives us an insight into how the two components interact and create performance data, which is then processed into actionable insights.
4. System twins enable the users to visualize how all the assets are functioning together to form a system. This in general provides information about the interaction of the assets previously mentioned and hence the information can be used for performance enhancements [4].
5. Process twins deal with the macro-level of magnification, that is, it provides information about how systems interact and create a

production facility. The systems are synchronized to operate at peak efficiency, which ultimately influences the overall effectiveness.

5.4 Digital twin and base technologies

5.4.1 Extended reality and digital twins

It refers to all real-virtual combined environments and mainly the human-machine interaction with the help of wearable technologies [5]. XR encompasses virtual reality, augmented reality, and mixed reality. As mentioned, digital twin is a virtual or a digital representation of real-world assets that take into account machine learning and behavior analysis [6]. The simulation of the product is done with the help of virtual, augmented, and mixed reality and software that digitizes data from the simulated process of the model and lets the user interact virtually.

5.4.2 Cloud and digital twin

Incorporating cloud in digital twin has opened the way to monitor systems in real time and synchronize real-world activities as mentioned in a study [7], wherein the incorporation of a digital twin for advanced driver assistance system for connected vehicles has been proposed.

This helps in uploading the data to the server through network interfaces as shown in Fig. 5.3. In this, a virtual world is created based on the received data and sends the analyzed result to the connected vehicles. Here, the cloud server calculates the advisory speed and is shown on the vehicle onboard driver-vehicle interface (DVI) device so that it can give appropriate information to the driver.

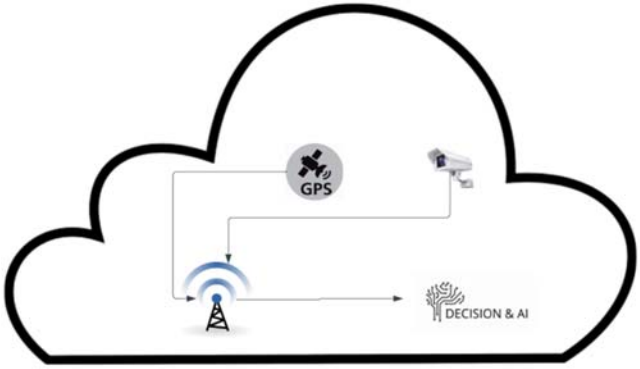


Figure 5.3 Real-time synchronization using cloud.

5.4.3 Machine learning and digital twin

Digital twin produces simulated data. This simulated data is used to train the AI mode, which in turn can be used to teach real-world scenarios to the AI that might otherwise be tedious in the testing phase. The addition of machine learning to any industrial process has proved to make the process more intelligent, as it will be capable of getting more accurate data, understanding visual and unstructured data, and making predictions. Hence, by incorporation of machine learning, we can create a single learning system that can manage complex data.

5.5 Smart cities—an introduction

Smart city is a technological urban area. It involves using different electrical and electronic methods to capture data and then using this data to improve the operational efficiency of the city. Smart cities are smart in the way they harness technology and how they analyze and govern their city [8]. It uses information and communication technologies to increase the operational efficiency and share information with the public to improve government services and citizen welfare.

The mission of smart cities is to optimize city functions, bring in economic growth, and improve the quality of life of its citizens using technology and data analysis. Recent technologies such as automation, machine learning, and IoT are driving smart city projects to a great extent [9].

5.5.1 Working of a smart city

1. Collection of real-time data
2. Analyzing the data
3. Communicating this analyzed data to decision makers
4. Implementing the action decided by the decision makers

Expected automations in smart cities:

1. With the growth in AI, we found many useful applications, such as self driving cars, robots, city brains, etc. Smart city mission uses AI and makes a concept called urban AI [10]
2. A six-step implementation model could be used:
   a. IoT-based smart city platform
   b. Monitoring and analytics
   c. Deep analytics

   d. Smart control
   e. Instant interfacing using user interface
   f. Integrating many solutions [11]
3. In the next few years, we can expect people to adopt to smart home automation [12]

Challenges in implementing smart cities:

1. The IT infrastructure should be flexible enough to adapt to the upcoming changes or else the infrastructure must be fully changed
2. Funds must be sufficient to meet the technical and practical needs of smart city
3. Trained IT professionals are required for proper functioning
4. Inconsistent network connectivity may lead to delay in exchange of information
5. There are cybersecurity risks involved in smart city as it is used by all

5.6 Smart manufacturing—an introduction

Industry 4.0 has been growing through the past few decades. It is being built upon the foundation of a digital evolution, yet with a new level of connectedness by the use of IoT [13]. A new wave of smart manufacturing involves access to real-time information to improve productivity, output, and efficiency [14]. Smart factories are built with the latest and advanced sensors, embedded software, and robotics, which will collect and analyze data and make decisions based on it. Smart factories present opportunities for manufacturing industries to enter into Industry 4.0 (Fig. 5.4).

[16] There is rapid growth and development in communication technology and information technology and more disruptive technologies like big data, cloud computing, IoT, and AI have emerged. The emerging technologies are getting into the manufacturing industries and are enabling the merging of real physical worlds and the virtual worlds with the help of CPS, which marks the arrival of stage four of industrial production (Industry 4.0). CPS increases the smartness of the systems [17]. Due to the advancements in new-generation technologies, such as big data and digital twins, smart manufacturing is evolving as the focus of the global manufacturing transformation. Manufacturing big data using integrated analysis is useful to all the ways of manufacturing. The digital twin helps in cyber-physical integration of manufacturing, which is an important part in the path of achieving smart manufacturing. As digital twin and

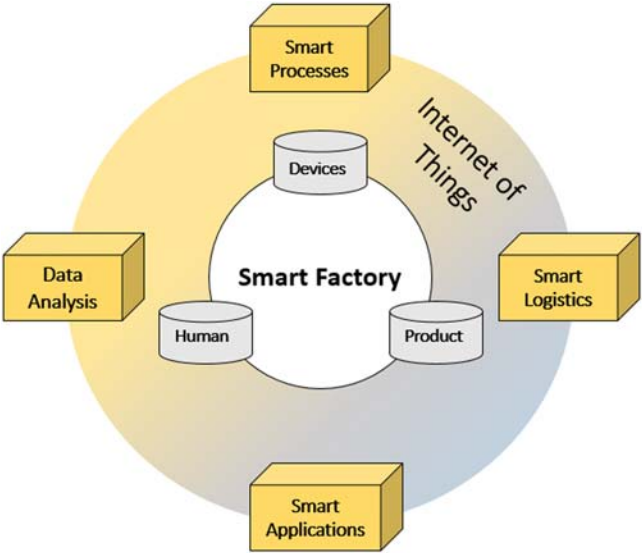


Figure 5.4 Smart factory [15]. *From https://www.researchgate.net/figure/The-main-elements-of-a-Smart-Factory_fig3_332999810.*

big data are contrasting and opposite topics, they can be joined to promote smart manufacturing [18]. Smart manufacturing is an emerging new version of intelligent marketing (IM), which reflects the magnitude and impact of smart technologies.

5.7 Digital twin—use cases in additive manufacturing

With developments in Industry 4.0, additive manufacturing will be widely used to produce customized products for consumers. However, it is time-consuming and expensive to make good products with good mechanical structure with the help of this manufacturing technology. Additive manufacturing is a relatively new way of producing products that are built layer by layer directly, instead of following a series of stages like in substrate manufacturing.

Additive manufacturing is now one of the vital elements of the industrial revolution [19]. It is required to have optimum parameter combinations to obtain a good end product. This is obtained by trial and error method, hence is rather expensive, wastes materials, and is time-consuming because numerous experiments are needed to optimize this process variable within the given environment and machine parameters (Fig. 5.5).

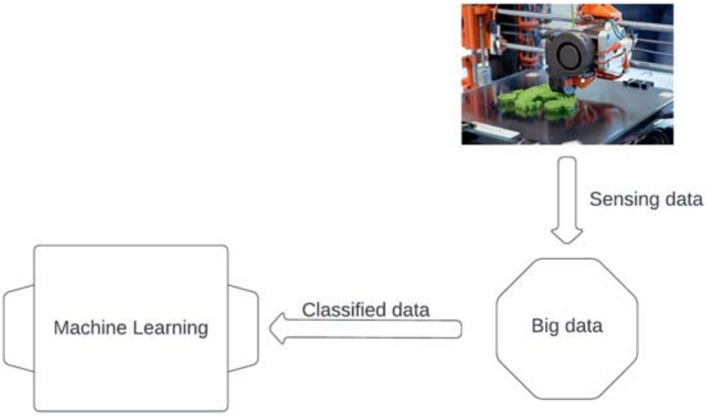


Figure 5.5 Digital twin in additive manufacturing.

To overcome these, digital twin is extensively being used in additive manufacturing for improvising the quality of a part that is produced and shortening the time to test the quality of the product. Digital twin is gradually being used in fields such as repair, overhauls, manufacturing, and others as such. However, it is still in the development state with respect to additive manufacturing technology.

In [20], the profiles of stainless steel 316 L and Alloy 800 H deposits, as well as the secondary dendrite arm spacing and Vickers hardness, were used to validate the proposed digital twin which was used to provide predictive results of the temporal and spatial variations of metallurgical parameters that majorly affect the structure of the component that is being developed. The predicted values of the temperature gradient, cooling rates, solidification rate, etc., matched more accurately than the values obtained from the conduction calculation.

A real-time digital representation of the physical domain in additive manufacturing to accurately predict, monitor, and control the process is needed. To achieve this, there is a lot of computation burden that has been overcome and yet is very much time-consuming based on the availability of the computation capabilities. This data is obtained from experiments, sensors, numerical simulation, etc. For this, we use IoT and cloud computation.

Digital twin is hence blooming in additive manufacturing and is helping it move forward. Significant developments in the fields of machine learning, equipment integration, and algorithms are being incorporated and studied to effectively predict the results.

5.8 Digital twin—use cases in ship-building industry

Ships are one of the complex and most demanding products out in the industry. Their exclusive operational capacity and payload-carrying feature make them one of the most efficient engines out there for import, export, and many others. European shipyards have been the leaders in the market for quite a long time due to their extraordinary evolution in the ship designing process and lifecycle. Engineering is a robust and reliable paradigm, providing the necessary and comprehensive view of the methodological framework of the cruise ship system as a whole; the other advantage being the interaction between all the stakeholders, which is appreciated in this process. In particular, digital twin helps in system engineering or the so-called model-based engineering to integrate, combine, and improve the results and make decisions about the manufacturing and production (Fig. 5.6).

It is important for a ship-building facility to fulfill the expectations of customers and the market. In the constantly evolving and fast-moving market, it is important to characterize the product with high economical standards and technology. To attain this aim, digital twin and digitalization have been the well-known strategies. The most complex machine known as the payload demands high performance and customer satisfaction to attain a fair price. Digital twin is able to guarantee an efficient approach to sharing, integrating, and improving the level of details of a particular design on the payload. The integration of inline and model-based engineering has been seen to obtain huge margin of success, which proposed the digital twin model as a newer evolution.

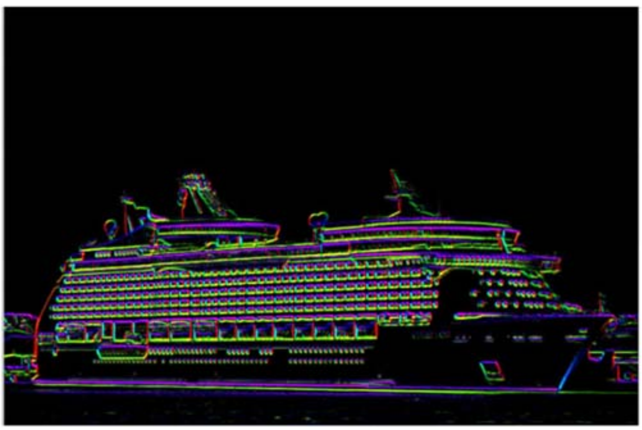


Figure 5.6 Virtual replica of a ship to track its behavior.

The attention toward digital twin and the IoT has been increasing tremendously in recent years among both merchants as well as naval ships [21], some of which are now being deployed as early releases of the upcoming great innovations. This shows that in a decade there will be high competition and efficiency in the shipping industry. The viewing of the lifecycle of the ship with the help of this model can be done by following the basic design phases, a 3D model representing the general arrangement of the model along with its esthetics. This not only helps the business improvement that is existing currently but also helps in the development of value-added services with the help of information collected during the interaction phase.

Since digital twins serve a wide spectrum, it is necessary to have a design pattern, which is structural and behavioral [22]. The former provides engineering insights and the latter provides information and focuses on how the proposed solution can operate efficiently in the simulated real situation or the other operations provided for intercommunication. The possibility of running out of fuel has been taken care by digital twin model with the help of sensors that make possible to achieve the goal of producing models that are more close to reality and real-world location to support the final finished product. This approach helped in risk avoidance and profitability.

The digital twin is implementing "user-centered design" wherein there is need for a domain of discussion. This is necessary to elicit the requirements of the user and propose design solutions from their perspective. The digital twin as mentioned is helping in the process of merging/integrating descriptive and analytical models: all the models proposed have to have an optimum input to predict the scenario or performance of the finished product. Such models have a great impact on the different market segments (Mass Market, Premium, and Luxury) where cruise vessels are meant to operate and be defined in relation to the space ratio (GRT/number of passengers), the ratio between crew members, and a number of passengers.

5.9 Digital twin—use cases in automotive industry

Digital twin in the automotive industry is a virtual replica of all the mechanics, electrical, physical behavior, and even the software architecture of an entire car. Digital twin holds all the real-time performance-measuring sensors and service history for keeping track of replacement, warranty, and configuration setting changes.

The role of the digital twin is as follows:

5.9.1 Product testing

It helps in determining the quality and performance of the proposed model and helps in virtually experimenting with the raw material under various circumstances and situations. This can be a very useful process in terms of testing the new materials that are to be included in the manufacturing line or phase of the product. The results of various tests can also be used to obtain insights into how the new combination can be a better alternative to the existing combination. Crash testing of automobiles is performed to assess the tensile strength and the crash compatibility of the model; generally it is an indispensable destructive testing to test the proposed design of the vehicle. Digital twins help perform crash tests in a nondestructive way by virtually assessing the behavior of the design in the operational environment without the use of prototypes (Fig. 5.7).

5.9.2 Employee training

A digital twin can be used to train the employees remotely with the help of a virtual environment and virtual gear support. This will help the company continue the same production capacity even with the help of a new architecture or new processes lifecycle. The digitalization and insights from real-time data that is captured through several IoT devices also provide information about the maintenance of the manufacturing zone and enhance production.

5.9.3 Sales

This is one futuristic implementation where the facility provides the customer a realistic view of performance and design to receive feedback before the production process for utmost satisfaction.

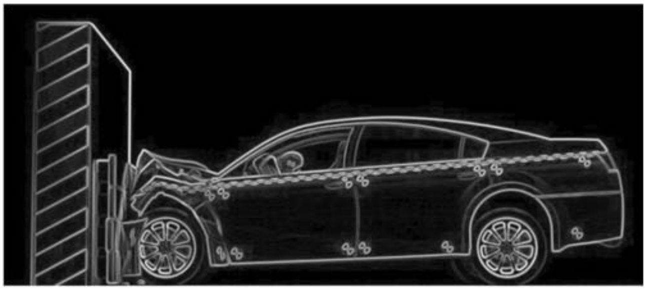


Figure 5.7 Crash test simulation using digital twin.

Digital twins on the whole are being a great advantage for the automotive industry. It resolves the challenges of integrating data from several sources. It helps in verifying new features of the designs and feasibility testing of the product. It can be used to predict the life of a particular part of a machine or as a whole, therefore, helping the industry reduce malfunctions and minimize functional loss. Moreover, it can also be used to predict the customer demand with the help of the results that have been collected in the past.

There is considerable amount of information available at each stage of production and to consider all this data for prediction and analysis there must be a considerable setup. It is very expensive to build a computationally effective computer or mainframe device that can keep track of this data, therefore most companies have considered only 12% of their data for prediction and analysis to neglect these setup costs.

Reinforcement learning is a type of machine learning where there is presence of an agent and when put in an uncertain situation it performs a random activity. These activities are then analyzed and provided with a reward or a punishment. This improves performance of the agent over time and later helps make logical decisions. This has been a current add-on to the digital twin, which aids in decision-making and simulating human creativity in certain conditions and situations.

5.10 Applications of digital twin in smart manufacturing

This chapter reviews the use of big data and digital twin technology and the difference between the mentioned two technologies and their roles in smart manufacturing. The data generated from the manufacturing industry includes structured, semistructured, and unstructured data including the data produced right from the product design stage through all the stages of the product lifecycle. [23]. This chapter also reviews the concept of "Digital Twin Shop Floor," discussing its four components. It addresses the convergence of physical and digital shop floors as one of the challenges discussed, concludes the convergence and physical space shop floor with the virtual space is in the stage of research and development, highlighting the current scenario to be in the third stage where there is interaction between the physical and the virtual space [24].

In this chapter [25], the authors developed a process control called "Digital Engine," designing the virtual space using computer-aided applications, establishing connections between the physical and virtual entities to collect and organize data, applying Q-Learning algorithm—a deep reinforcement learning algorithm enriching the knowledge domain of the machines. In this paper [26], the authors developed a Learning and Analysis Model using big data and digital twin and tested it on the production lane of Power Switchgear equipment.

This chapter [27] reviews the role of digital twin in the various industries. It is concluded through their analysis that 38% of all the digital twin use cases so far reported, thus analyzed using publications, company-specific technologies, patents, etc., is applied on prognostics and health monitoring, 35% on production, and 18% on design in the product lifecycle. This chapter describes the development of Supervised Learning Based Artificial Intelligence-Digital Twin Framework for Manufacturing Industry. Quality of data speaks on the efficiency of the Machine Learning Model. Models trained with the manufacturing data collected by any nonautomated methods are not assured to give the maximum possible accuracy. The authors in this chapter proposed a digital twin-driven data collection for generating training datasets and automatic labeling using simulation methods for training manufacturing-machine learning models, reducing human intervention. They conclude that their approach can be used for controlling the production process [28].

Nowadays, robots are used widely in the manufacturing sector (Fig. 5.8). Controlling a system but from a distant location is called

Figure 5.8 3D model of a digital twin robot arm [31]. *From https://sketchfab.com/3d-models/smily-arm-d58a41fc723e4d8a847754f938f5e5b3*.

teleoperation. In this chapter [29], the authors proposed a digital twin for collaborative operation of multiple robots in manufacturing. Digital twins were created for the industrial robots that can be visualized using AR glasses. They used reinforcement learning algorithms for synchronization between the target and robotic motions. The designed three different modes of operations in the digital twin can be easily switched by the human-in-the-loop. It is concluded in the chapter that the proposed system has high efficiency. This chapter discusses the developments in decision support models using digital twin for production processes using agent-based simulation and discrete event simulation [30].

[32] Digitalization of robotic systems enables improvised automation and remote controlling abilities. A digital twin which is edge-based is proposed, which leverages the cloud-to-things continuum, which offload computation and intelligence from the robots to the network. This was established in an E2E scenario integrating the cloud-to-things continuum, 5G connectivity, and intelligence capabilities. This was checked through a set of experimental evaluations [33]. Digital twin is used to detect accurate sensing control of the machines by combining the virtual replica and sensory data.

Blockchain is a decentralized ledger for secure storage and updation of data. It is also one of the major developing technologies laying foundations to the adoption of Industry 4.0 at a very faster rate. All the data is stored as blocks in blockchain. The first block in the chain is called the genesis block. Nodes form the end-to-end devices involved in data communication in the blockchain network. Special types of nodes called mining nodes are used for recording the data communication in the blockchain. Every node in the network stores a copy of the ledger. Several consensus protocols are used, like PoW, PoS, PoET, to arrive at a mutual agreement between the nodes. The cryptographic and digital signature algorithms used in the blockchain offer a high degree of data security. These decentralized ledgers provide a platform for peer-to-peer exchange of data generated in huge amounts by sensors and other devices in the value chain. Smart contracts stored in the blockchain engine similar to triggers in the database engines get executed when certain conditions are met based on the pre-written and a stored program enhancing the decentralization of the distributed ledger. With the state of the digital twin updated continuously, it is necessary to store the previous states and to ensure the accuracy of the stored data. The immutability offered by the blockchain helps to securely store data ensuring accuracy.

This chapter surveys the use of blockchain technology in smart manufacturing and Industry 4.0. It identifies eight cyber security issues in manufacturing, including interoperability among devices, failure of key nodes (single point of failure in centralized system), and trust issues among the participants in the network. It highlights 10 metrics categorized into four types as the criteria for employing blockchain in manufacturing by highlighting resistance to data tampering, decentralization, and transparency [34]. In this chapter [35], the authors proposed a digital twin structure called "Spiral DT Framework" and proposed a new blockchain variant called "Twinchain," for the management of digital twin data. Their approach is illustrated suggesting a framework for the manufacturing of surgical robots, where it is practically infeasible to monitor the working of the robots with a physical duplicate. This chapter also proposes a data management method for the data generated by the digital twin for product lifecycle management. Actions of the participants in the network and the interactions between the virtual copy and the physical equipment are recorded as a separate transaction, chained along with the existing blocks. It also demonstrates a case study for the application of the proposed method for the product lifecycle management of turbines [36].

The concept in which many physical firms work together to produce a finished product is termed as social manufacturing. This chapter proposes a digital twin collaboration platform for social manufacturing resource management using blockchain technology [37]. Building information modeling (BIM) is the digital 3D representation of the materialistic structural entity. This chapter presents an approach for using blockchain with smart contracts along with BIM for implementing digital twins for construction projects [38].

In this chapter [39], the authors developed blockchain-integrated digital twin model for information sharing among stakeholders in construction projects. The real-time updation of the digital twin states is done using the data collected by various sensors. The blockchain is used for recording the transaction assuring the authenticity of the data updation, and making the process traceable. This chapter demonstrates the use of blockchain network in additive manufacturing by exemplifying its use cases for building aircraft components using digital twin. Production Organization Approval is needed for every single component produced to be used in any aircraft. It conceptualizes digital twin for additive manufacturing supply chains highlighting the use of blockchain technology [40].

5.11 Applications of digital twin technology in smart city projects

Globenewswire, a global press release service, estimated that the market will attain a share of US $4 billion by 2027 [41], thus giving us a demonstration of the level of applicability of the technology by stating financial returns. In the development stage, the digital twin incorporation helps engineers take more informed decisions; this is achieved as the engineers can predict the steady-state of a product long before its first actual build. Common automation software can be used to calculate the right performance resulting in accurately tuned controls acting on a system. In the maintenance phase, a digital twin can help in calculating the optimum load on the component and impact on the lifecycle of the component with respect to different scenarios. Hence, it exponentially reduces the maintenance cost. When talking about sales, a digital twin is used to qualify customers and provide them with accurate information about the performance and operation of the machine given the constraints. AI provides insights into the possible scenarios, budgets, and information about failures in which it works without even an engineer consultation.

Singapore is the first country to develop a complete virtual twin of the entire nation [42]. A market research organization, ABI Research, has suggested that the use of digital twin technology in urban planning can reduce US$ 280 billion by 2030 in a report [43]. Genesys International Corporation, a software company in Mumbai, has initiated a project to develop the digital twin of the entire urbanized country. As listed in [44], many leading technology companies have invested in digital twin technology to simulate different situations. Microsoft has launched Azure Digital Twin models using which users can connect multiple devices to the cloud and perform analytics with the virtual twin of the real world entity. IBMs digital twin innovation aids product management.

Increased urbanization involving upward mobility as a result of better education in rural and underdeveloped areas of the country drives a huge class of civilized population to live in cities. In [45], the author summarizes the Industry 4.0 manufacturing technologies into two categories as front-end base technologies. In [46], the author examines the reason for urbanization as the implied demand raised by the civilized denizens of the cities for a better standard of living than the present. In [47], the authors highlight digital twin as the feasible technology to acquire data without time delay and discuss the guidelines for implementing digital twin in production technology. In [48], the authors discussed the technologies and challenges and uses of developing a digital twin of a real-time manufacturing entity. In [49], the authors have presented the requirements and challenges in developing digital twins for smart cities. In [50], the authors emphasize treating digital twins in smart cities as CPS.

In [51], the authors discussed developing a digital twin of a city in Ireland, where the system uses real-time data collected by IoT sensors in the smart cities. They discuss developing a real-time feedback system using digital twin technology, wherein the citizens can provide feedback on the changes planned by the urban planners. In [52], the authors discuss developing the design of digital twins for fault diagnosis of photovoltaic systems. In [53], the authors developed a digital twin model for managing the drainage systems. They concluded that their model can better help the urban planners and water managers to detect the occurrence of flood and manage water bodies. In [54], the authors proposed a digital twin framework called AgriLoRa, a smart agriculture innovation that helps farmers detect plant diseases, manage weeds, and nutrient deficiencies of plants. In [55], the authors proposed the concept of smart cities where real-time data collected from institutions, such as universities, is used for comfort monitoring. In [56], the role of big data technology in implementing smart city projects and the challenges has been detailed. In [57], the authors demonstrate five different use cases of digital twins in establishing smart cities. Digital twin helps urban planners to optimize the traffic congestion. In [58], the authors developed a reference model of intelligent transport systems using a digital twin. In [59], optimization of cutting parameters of CNC machines to reduce carbon emission is presented. In [60], the authors presented a case study for developing GIS-enabled digital twin for evaluating carbon emissions.

5.12 Summary

Technology is trending everyday, with innovators discovering new means to solve existing problems using a new domain of knowledge. Digital twin is a virtual replica of a real-world entity. The concept of digital twin technology is a child born out of many parent-end technological advancements, such as AI, cloud computing, XR, IoT, and Internet of Services. The digital twin market, which was evaluated to be US$3.1 billion in 2020 is expected to achieve US $48.2 billion by the end of 2026 with a compound annual growth rate of 58%, as published by MarketsandMarkets [61].

Although the Digital Twin Technology can be extended for a specific use case in a domain, it still requires standardization. The ISO 23247 series, 2021 has defined a basic framework for digital twin technology in manufacturing [62]. Keyword search of digital twin and smart manufacturing in Google Scholar gives about 16,000 results for filters applied to result publications since 2018. In digital twins used for product lifecycle management, 38% is applied in prognosis health management [27]. Apart from manufacturing, digital twin solutions are observed commonly in the areas of smart agriculture, smart cities, healthcare, mitigation planning, disaster management, reducing carbon emissions, reducing global warming, etc. Urban planners can use digital twins of the cities to avoid problems of water logging, flood, drainage systems, optimization of traffic flow, managing pollution level in the city. It helps urban planners to better visualize and plan the functioning of the society. Although the use of digital twin technology is emphasized more in city planning, the cities adopting the technology are few, which is increasing along the gradual foundations being laid by Industry 4.0 digital transformation.

References

[1] M.W. Grieves, Product lifecycle management: the new paradigm for enterprises, Int. J. Prod. Dev. 2 (2005) 71−84.

[2] S. Aheleroff, X. Xu, Zhong, Y. Ray, Y. Lu, Digital twin as a service (DTaaS) in Industry 4.0: an architecture reference model, Adv. Eng. Inform. 47 (2021) 101225. Available from: https://doi.org/10.1016/j.aei.2020.101225.

[3] What is a digital twin? | IBM (2022).

[4] M. Liu, S. Fang, H. Dong, C. Xu, Review of digital twin about concepts, technologies, and industrial applications, J. Manuf. Syst. (2020). Available from: https://doi.org/10.1016/j.jmsy.2020.06.017. S0278612520301072.

[5] C. Semeraro, M. Lezoche, H. Panetto, M. Dassisti, Digital twin paradigm: a systematic literature review, Comput. Ind. 130 (2021) 103469. Available from: https://doi.org/10.1016/j.compind.2021.103469.

[6] J. Jiang, M. Tobia, R. Lawther, D. Branchaud, T. Bednarz. Double vision: digital twin applications within extended reality. ACM SIGGRAPH 2020 Appy Hour. 2020. Available from: https://doi.org/10.1145/3388529.3407313.

[7] Z. Wang, X. Liao, X. Zhao, K. Han, P. Tiwari, M.J. Barth, et al., [IEEE 2020 IEEE 91st vehicular technology conference (VTC2020-Spring) - Antwerp, Belgium (2020.5.25-2020.5.28)] 2020 IEEE 91st Vehicular Technology Conference (VTC2020-Spring) - A Digital Twin Paradigm: Vehicle-to-Cloud Based Advanced Driver Assistance Systems, pp. 1−6, 2020. Available from: https://doi.org/10.1109/VTC2020-Spring48590.2020.9128938.

[8] https://en.wikipedia.org/wiki/Smart_city (Accessed 10th June 2022).

[9] https://internetofthingsagenda.techtarget.com/definition/smart-city (2020).

[10] F. Cugurullo, Urban artificial intelligence: from automation to autonomy in the smart city, Front. Sust. Cities 2 (2020) 38.

[11] https://www.scnsoft.com/blog/iot-for-smart-city-use-cases-approaches-outcomes (2018).
[12] https://legrand.co.in/smart-spaces/7-iot-smart-city-trends-on-the-rise-in-2021/ (2021).
[13] What Is Industry 4.0? | Manufacturing Digital (2020).
[14] What is Industry 4.0 and how does it work? | IBM (Accessed on June 12th 2022).
[15] https://www.researchgate.net/figure/The-main-elements-of-a-Smart-Factory_fig3_332999810 (2019).
[16] P. Zheng, Z. Sang, R.Y. Zhong, Y. Liu, C. Liu, K. Mubarok, et al., Smart manufacturing systems for Industry 4.0: conceptual framework, scenarios, and future perspectives, Front. Mech. Eng. 13 (2) (2018) 137–150.
[17] Digital twin and big data towards smart manufacturing and Industry 4.0: 360 degree comparison | IEEE Journals & Magazine | IEEE Xplore.
[18] https://ieeexplore.ieee.org/abstract/document/8119409 (2017).
[19] L. Zhang, X. Chen, W. Zhou, T. Cheng, L. Chen, Z. Guo, et al., Digital twins for additive manufacturing: a state-of-the-art review, Appl. Sci. 10 (23) (2020) 8350. Available from: https://doi.org/10.3390/app10238350.
[20] G.L. Knapp, T. Mukherjee, J.S. Zuback, H.L. Wei, T.A. Palmer, A. De, et al., Building blocks for a digital twin of additive manufacturing, Acta Mater. 135 (2017) 390–399.
[21] V. Arrichiello, P. Gualeni, Systems engineering and digital twin: a vision for the future of cruise ships design, production and operations, Int. J. Interact. Design Manuf. (IJIDeM) (2019). Available from: https://doi.org/10.1007/s12008-019-00621-3.
[22] E. Gamma, R. Helm, R. Johnson, J. Vlissides, Design patterns - elements of reusable object-oriented software code, Addison-Wesòey, 1994.
[23] Q. Qi, F. Tao, Digital twin and big data towards smart manufacturing and industry 4.0: 360 degree comparison, IEEE Access 6 (2018) 3585–3593.
[24] F. Tao, M. Zhang, Digital twin shop-floor: a new shop-floor paradigm towards smart manufacturing, IEEE Access 5 (2017) 20418–20427.
[25] K. Xia, C. Sacco, M. Kirkpatrick, C. Saidy, L. Nguyen, A. Kircaliali, et al., A digital twin to train deep reinforcement learning agent for smart manufacturing plants: environment, interfaces and intelligence, J.Manuf. Syst. 58 (2021) 210–230.
[26] P. Wang, M. Luo, A digital twin-based big data virtual and real fusion learning reference framework supported by industrial internet towards smart manufacturing, J. Manuf. Syst. 58 (2021) 16–32.
[27] F. Tao, H. Zhang, A. Liu, A.Y. Nee, Digital twin in industry: state-of-the-art, IEEE Trans. Indust. Inform. 15 (4) (2018) 2405–2415.
[28] K. Alexopoulos, N. Nikolakis, G. Chryssolouris, Digital twin-driven supervised machine learning for the development of artificial intelligence applications in manufacturing, Int. J. Comp. Integr. Manuf. 33 (5) (2020) 429–439.
[29] C. Li, P. Zheng, S. Li, Y. Pang, C.K. Lee, AR-assisted digital twin-enabled robot collaborative manufacturing system with human-in-the-loop, Robot. Comput.-Integr. Manuf. 76 (2022) 102321.
[30] C.H. dos Santos, J.A.B. Montevechi, J.A. de Queiroz, R. de Carvalho Miranda, F. Leal, Decision support in productive processes through DES and ABS in the Digital Twin era: a systematic literature review, Int. J. Prod. Res. 60 (8) (2022) 2662–2681.
[31] https://sketchfab.com/3d-models/smily-arm-d58a41fc723e4d8a847754f938f5e5b3 (2021).
[32] L. Girletti, M. Groshev, C. Guimarães, C.J. Bernardos, A. de la Oliva, An intelligent edge-based digital twin for robotics, in: 2020 IEEE Globecom Workshops (GC Wkshps), 2020, December, pp. 1–6. IEEE.

[33] W. Xu, J. Cui, L. Li, B. Yao, S. Tian, Z. Zhou, Digital twin-based industrial cloud robotics: framework, control approach and implementation, J. Manuf. Syst. 58 (2021) 196–209.
[34] J. Leng, S. Ye, M. Zhou, J.L. Zhao, Q. Liu, W. Guo, et al., Blockchain-secured smart manufacturing in industry 4.0: a survey, IEEE Trans. Syst. Man Cybern.: Syst 51 (1) (2020) 237–252.
[35] A. Khan, F. Shahid, C. Maple, A. Ahmad, G. Jeon, Toward smart manufacturing using spiral digital twin framework and twinchain, IEEE Trans. Indust. Inform. 18 (2) (2020) 1359–1366.
[36] S. Huang, G. Wang, Y. Yan, X. Fang, Blockchain-based data management for digital twin of product, J. Manuf. Syst. 54 (2020) 361–371.
[37] M. Li, Y. Fu, Q. Chen, T. Qu, Blockchain-enabled digital twin collaboration platform for heterogeneous socialized manufacturing resource management, Int. J. Prod. Res. (2021) 1–21.
[38] Y. Celik, I. Petri, Y. Rezgui, Leveraging BIM and blockchain for digital twins, in: 2021 IEEE International Conference on Engineering, Technology, and Innovation (ICE/ITMC), 2021, June, pp. 1–10. IEEE.
[39] D. Lee, S.H. Lee, N. Masoud, M.S. Krishnan, V.C. Li, Integrated digital twin and blockchain framework to support accountable information sharing in construction projects, Automat. Const. 127 (2021) 103688.
[40] C. Mandolla, A.M. Petruzzelli, G. Percoco, A. Urbinati, Building a digital twin for additive manufacturing through the exploitation of blockchain: a case analysis of the aircraft industry, Comput. Indust. 109 (2019) 134–152.
[41] Top 5 Benefits of Digital Twins - Virtual Commissioning (2019).
[42] https://venturebeat.com/2022/02/23/how-singapore-created-the-first-country-scale-digital-twin/#:~:text=Recently%2C%20Singapore%20completed%20work%20on,transportation%20models%20of%20the%20country.
[43] https://www.abiresearch.com/press/use-digital-twins-urban-planning-yield-us280-billion-cost-savings-2030/.
[44] https://www.emergenresearch.com/blog/top-10-digital-twin-companies-impacting-industry-4-0-innovations-in-2021 (2023).
[45] A.G. Frank, L.S. Dalenogare, N.F. Ayala, Industry 4.0 technologies: implementation patterns in manufacturing companies, Int. J. Prod. Econ. 210 (2019) 15–26.
[46] A. Cocchia, Smart and digital city: a systematic literature review, Smart City (2014) 13–43.
[47] T.H.J. Uhlemann, C. Lehmann, R. Steinhilper, The digital twin: realizing the cyber-physical production system for industry 4.0, Procedia Cirp 61 (2017) 335–340.
[48] A. Rasheed, O. San, T. Kvamsdal, Digital twin: values, challenges and enablers from a modeling perspective, IEEE Access 8 (2020) 21980–22012.
[49] J. Fürst, B. Cheng, B. Hebgen, Realizing the digital twin transition for smart cities, Open J. Internet of Things (OJIOT) 7 (1) (2021) 32–42.
[50] G. Mylonas, A. Kalogeras, G. Kalogeras, C. Anagnostopoulos, C. Alexakos, L. Muñoz, Digital twins from smart manufacturing to smart cities: a survey, IEEE Access 9 (2021) 143222–143249.
[51] G. White, A. Zink, L. Codecá, S. Clarke, A digital twin smart city for citizen feedback, Cities 110 (2021) 103064.
[52] P. Jain, J. Poon, J.P. Singh, C. Spanos, S.R. Sanders, S.K. Panda, A digital twin approach for fault diagnosis in distributed photovoltaic systems, IEEE Trans. Power Electr. 35 (1) (2019) 940–956.
[53] M. Bartos, B. Kerkez, Pipedream: an interactive digital twin model for natural and urban drainage systems, Environ. Model. Softw. 144 (2021) 105120.

[54] P. Angin, M.H. Anisi, F. Göksel, C. Gürsoy, A. Büyükgülcü, AgriLoRa: a digital twin framework for smart agriculture, J. Wirel. Mob. Netw. Ubiquitous Comput. Dependable Appl. 11 (4) (2020) 77–96.
[55] A. Zaballos, A. Briones, A. Massa, P. Centelles, V. Caballero, A smart campus' digital twin for sustainable comfort monitoring, Sustainability 12 (21) (2020) 9196.
[56] E. Al Nuaimi, H. Al Neyadi, N. Mohamed, J. Al-Jaroodi, Applications of big data to smart cities, J. Internet Serv. Appl. 6 (1) (2015) 1–15.
[57] L. Deren, Y. Wenbo, S. Zhenfeng, Smart city based on digital twins, Comput. Urban Sci. 1 (1) (2021) 1–11.
[58] A. Rudskoy, I. Ilin, A. Prokhorov, Digital twins in the intelligent transport systems, Transp. Res. Procedia 54 (2021) 927–935.
[59] L. Zhao, Y. Fang, P. Lou, J. Yan, A. Xiao, Cutting parameter optimization for reducing carbon emissions using digital twin, Int. J. Precis. Eng. Manuf. 22 (5) (2021) 933–949.
[60] J. Park, B. Yang, GIS-enabled digital twin system for sustainable evaluation of carbon emissions: a case study of Jeonju city, south Korea, Sustainability 12 (21) (2020) 9186.
[61] https://www.marketsandmarkets.com/Market-Reports/digital-twin-market-225269522.html (2022).
[62] https://www.iso.org/standard/75066.html (2021).

CHAPTER 6

Digital twins and artificial intelligence: transforming industrial operations

B. Shuriya[1], P. Sivaprakash[2], K. Arun Kumar[2], M. Saravanakumar[2] and A. Rajendran[3]
[1]CSE, PPG Institute of Technology, Coimbatore, Tamil Nadu, India
[2]IT, Rathinam College of Arts and Science, Coimbatore, Tamil Nadu, India
[3]ECE, Karpagam College of Engineering, Coimbatore, Tamil Nadu, India

6.1 Introduction

Transformation in the production process is referred to as the industrial revolution. It began in the 15th century when wealthy businessmen gathered a workforce to produce textiles at home. It lasted until the past several decades until a steam engine was invented, and the efficiency it produced changed the industrial landscape, ushering in what is known as Industry 1.0. When making a vehicle in Industry 1.0 [1], the constituent pieces were transported to the chassis while it was stationary. The entire assembling procedure was labor-intensive and inefficient. With time, the assembly line idea, which shortens the production lead time, was implemented [2]. The subsequent industrial revolution ushered about through the development of computers ultimately gave impetus to the development of software-related production. The emergence of electronic equipment and data analytics in information system, superseded manual workers in the factory environment, noted a beginning of third uprising, which was named as third industrial revolution/uprising. As a consequence, the production system was highly automated, cutting the lead times significantly [3]. The digitization of industry through the fusion of the real and the virtual is perhaps the most recent disruptive innovation, or fourth industrial revolution. Its goal is to create intelligent machines made up of embedded systems parts, where another sensor module gathers data and indeed the activator system manages the physical mechanism in authentic. It also intends to save energy and resources, boost productivity, and integrate technology into engineering. Every product in the

Digital Twin For Smart Manufacturing
DOI: https://doi.org/10.1016/B978-0-323-99205-3.00012-2

production line will be able to be identified, tracked, and controlled, thanks to internet-assisted manufacturing. This chapter [4] offers an overview of the digital system, one of the industrial enablers. In a nutshell, the purpose of a virtual environment is really to build a sizable virtual model of a piece of equipment to imitate behavior and produce intelligent predictions about the actual product. The relevance of digital twin (DT), a thorough analysis of its uses, and its possible integration into certain production processes are all covered in the current chapter [5]. A couple of the suggested [6,7] DTs' self-drawn schematic representations have been thoroughly explained to help comprehend in a better way. There is little proof of a case study validation demonstrating the application of DT, despite the fact that DT has been studied by researchers. As a research report validation [7], special deployment of DT has indeed created for a discrete manufacturing process like frictional stir welding. To assess and forecast the actual friction stir welding machine's health, a virtual model was created. Many the machine's characteristics have been predicted using DT. The created DT is virtualized and interacts continuously with the friction stir welding device [8]. It receives sensory information from the database, interprets and analyzes, and also displays machinery information in a timely manner. The DT sends suggestions to enable the input data in response [9]. An approach for deploying DT in machinery with machines has also been put out, and it defines the collaboration between the DTs connected to machine. The idea of DT and how it is used in various contexts are introduced in the next section.

6.2 Digital twin in industry

Industry 4.0 DT strategy uses the virtualization paradigm for operation. DTs, according to NASA, are "incorporated, diversification, multidimensional, probability simulations of some as vehicle or subsystem that utilize the peak physical simulations currently accessible, sensing upgrades, including collection history to mimic the lifespan of all its floating counterpart" [3]. Here is the explanation of this phrase. The DT involves a number of methods for analysis to provide a full view of the significant advantages of an equipment and anticipate its effectiveness [10]. As an illustration, consider the following: a thermal analysis helps identify the temperature profile of the transmission; a wearing model to calculate the wear it produces; dynamics modeling for fault diagnostics; and others. This is a model with varied aspects of physics in one component. If separate analyses need different solvers, this analysis may be multi-scaled. Probabilistic simulations are crucial because, in addition to predicting performance in real time, DT must also estimate the remaining machines in the network [11]. As previously said, DT is seen as a facilitator for the deployment of Industry 4.0. In the present technological world, persistent steps have been taken to integrate Industry 4.0 principles in the enterprise facility. A corporation spends a substantial amount of money creating prototype of the completed article to evaluate its effectiveness. For instance, whenever any equipment is built, the technicians or controllers must test the prototype [12].Working with prototypes can occasionally be dangerous since there may be workplace dangers. These barriers are removed by the DT idea, which also gives employees a place to study in a virtual setting. Without going backwards or rebuilding prototypes for more testing, the operator's problems may be fixed right away. The DT approach is anticipated to help businesses upskill their workforces while incurring the lowest expenditures possible. It is a financially viable method of promoting the manufacturing industry as Machinery/Industry 4.0 adoption, though facing a conceptual phase in Internet of Things (IoT) and other technologies that is in trend. Similarly, data twinning has many operational defects [13].

A prospective DT structure that connects the real and virtual worlds is shown in Fig. 6.1. One may classify, as tangible elements of the physical cosmos, the parts of a machine. Numerous sensors and data-gathering devices are interconnected with these components. The collected data is transmitted to a cloud infrastructure in which it is evaluated to track the machine's overall health and performance. A range of information computational needs based on machine learning and simulation will be employed [4] to monitor individual machine parts, make pertinent predictions about the process, and transfer this knowledge to the controls that are physically associated with the machines. The digitized reality integrates the experiences of the product's parts with its present state throughout order to predict a package's typical lifespan and protect the integrity of the equipment. An analysis of the magnitude of the input from the virtual environment may be done by forecasting utilizing only some major aspects, knowledge about the condition of a few key pieces of process equipment and how long they will remain functional, suggestions for something from the user about how to operate a device in safe manner, regulation over a few specific requirements that could be used to ensure safe procedure of a device, etc.

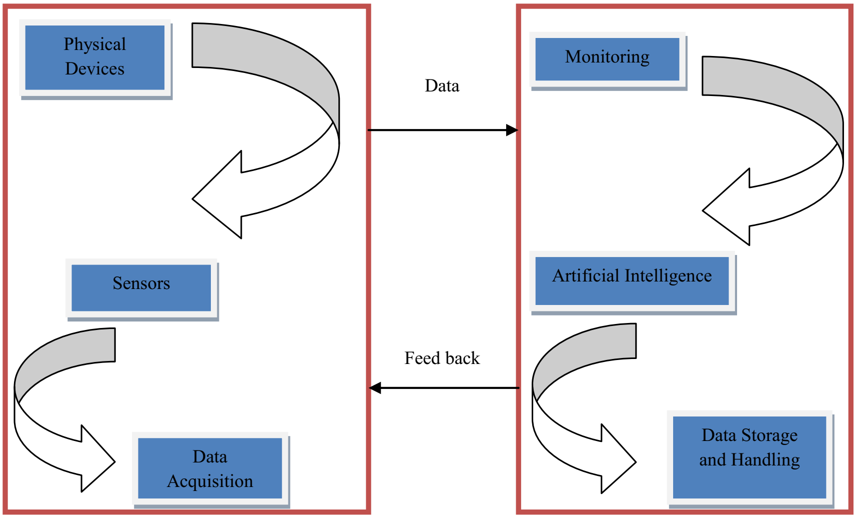


Figure 6.1 Digital twinning framework.

6.3 Data acquisition in digital twin using Internet of Things

One of the first steps in digitizing a company is machine data capture. Machines that are network-connected are used to collect, store, and analyze data. Manufacturing might be more effectively managed and possibilities for process improvement could be discovered by using the data that are readily available. The underlying ideas behind machine data collection in manufacturing and production will be the main topic of this section. Three IoT communication technologies—GSM, Sigfox, and LoRaWAN—that may provide isolated data transfer are available for long-term product monitoring [14]. Various IoT technologies are combined into a single module for the test system, and data collection is done on an open source platform.

6.4 Manufacturing process digital twin model

Although the use of DTs for certain deployed assets may be instructive, the manufacturing process appears to provide a particularly strong and alluring application. Fig. 6.1 depicts a real-world manufacturing process together with a computer representation. The DT serves as an almost real-time computer-generated picture of what is happening on the production floor [8]. Thousands of sensors scattered throughout the physical production process together record a wide range of characteristics, from ambient factors inside the factory to the behaviors of the working machines and ongoing projects. The DT program me continuously analyses streams of incoming data [10]. The investigations may discover unexpected tendencies when comparing the manufacturing process's actual performance in a particular dimension to a targeted range of tolerable performance over time. Such comparison of information may lead to a potential change in some components of the production process in the real world. Fig. 6.1 attempts to represent this interplay between the physical and digital worlds. One such journey exemplifies the enormous benefit of the technological twin: hundreds of sensors are fed a new medium, which performs near-real-time analytics to optimize company processes in an accessible manner [11]. The DT application that is constantly updated, together with five essential enablers—sensors and actuators from the real world, integration, data, and analytics—allow the paradigm of Fig. 6.1 to be realized precisely. The components are discussed in the next section.

6.4.1 Sensors

The production process generates signals that allow DT to gather design and operating data about the physical procedure in the actual world.

6.4.2 Data/information

The actual working and environmental data gathered by the sensors are combined with the bill of materials, 10 business systems, and design criteria. Data may also comprise other items like working drawings, connections to external data sources, and records of consumer complaints.

6.4.3 Integrating

Due to its technological incorporation, detectors may transmit information from the physical environment toward the electronic one and vice versa between the physical and virtual worlds, which includes edge, networking, and security.

6.4.4 Analytics

The DT employs simulation studies and visualization procedures to analyze the data using analytics techniques to generate insights.

6.4.5 Digital twin

A DT's objective is to identify undesirable deviations from ideal conditions along any of the many dimensions. Such a difference gives rise to a justification for business optimization; either the twin has a logical defect (which is preferable), or a chance to reduce costs, improve quality, or raise efficiency has been found. The opportunity that follows could lead to a real-world action.

6.4.6 Actuators (trigger)

When a physical action in the real world is needed, the DT fulfils it utilizing actuators that are able to interface with people and start the physical process. It is obvious that there are many more complexities in the world of a physical process (or object) and its digital equivalent analog than a single model or framework can capture. By using this perspective, one can begin the actual process of creating a DT.

6.5 Industrial machinery maintenance

In the industrial business, maintenance has always been a crucial component that provides vital needs like cost reduction, extended equipment life, and better safety and dependability. Contrarily, preventative maintenance has attracted a lot of attention over the years, with hundreds of articles in the field. Industry 4.0's popularity brought AI techniques into the spotlight, rendering predictive maintenance an even more significant topic of focus. There are three methods of maintenance. The first is reactive maintenance, which involves performing very little to no preservation up until the machine breaks. The other type of management is called preventive maintenance, and it is focused on replacing or repairing equipment according to a set calendar plan, regardless of its state. This method offers advantages over RM, but it runs the risk of replacing parts that may still be in excellent working condition without the need to increase delays and loss. Predictive maintenance is the most current and latest technique that aims to correctly calculate the machinery's remaining useful life based on numerous sensor inputs [15]. Unplanned equipment downtime frequently costs businesses money. Due to the preventive approach, anticipating early machine repair demands can increase financial benefit and decrease needless maintenance operations. Additional benefit of predictive maintenance is reduced costs, which would be directly tied to the other advantages. This means minimizing fatal malfunctions and lowering the need to replace particular component. Predictive maintenance has a wide range of industrial applications. The IoT and new services are continually collecting a significant amount of event data linked to failures and defects. Occurrences, which by definition comes in the form of data streams, document how an asset behaved.

Complex event processing (CEP) is being used for technical, behavioral, predicting data analysis, and event processing is a tool for determining sequences of occurrences to derive meaning. Although selecting an appropriate event has been a framework for information processing for about three decades, there have been significant developments in the previous decade because of cutting-edge uses for the IoT and deep learning. Additional factor contributing to the increased interest in process automation is the availability of substantial streams of sensor information that may be extensively produced. The channels of data are used by predictive modeling to forecast future occurrences. Utilizing predictive analytics and CEP simultaneously improve predictive maintenance performance. The adoption of event processing systems that employ leading technologies for big data and streaming analytics has recently expanded. Using an accessible compute pipeline, consolidated occurrence data, including failures and cautions, is related to machinery unavailability and may be considered predictive indicators [16]. Depending on the SOPHIA structure, an event-based IoT and deep learning architectural style for predictive maintenance for Industry 4.0 is employed. Calabrese et al. accomplished fault prediction utilizing event system logs [17]. Classical mechanics, computational methods, and DT were used to examine predictive maintenance for resources and raw materials [18]. To boost equipment utilization, this project sought to develop a predictive maintenance methodology available as an open event processing system. To evaluate the factors of a processor's health state, data-driven methods are used in conjunction with deep learning framework and the DT concept. Instead of being a predictive analytics system, the infrastructure under consideration might be a project management system, thanks to the DT. The DT created in conjunction with the open-source event-driven platform is provided in [2] and the DT idea utilized with it is described in [6]. Three major types of maintenance methods—statistical, AI-based, and model-based—may be used to categorize systems that can evaluate equipment conditions for predictive and therapeutic reasons [19]. Mechanical and theoretical understanding of the equipment that has to be monitored is required for the model-based approach. Regardless of the difficulties in the data science pipeline, the artificially intelligent technique has been used more and more in predictive maintenance applications since it does not necessitate a mathematical framework as the quantitative technique does. In their evaluation of the use of neural network models and conceptual frameworks in the context of project management, diverse application areas, including troubleshooting, failure can occur, outlier detection, timeframe to failure, and residual usable lifespan prediction [20].

Convolution neural networks are frequently employed for PM objectives, claims [21]. Random forest was the approach most frequently utilized in PM implementations. RF was discovered to become more difficult and to need more computing time than the other machine learning approaches used in PM contexts [22]. The writers also mentioned that while neural networks only used prior data, required little to no professional expertise, and had to deal with the difficulties of an advanced analytics process, they were among the most commonly used algorithm strategies in commercial processes. The results of prediction systems utilizing the techniques *k*-means neighbor, feed-forward Bayesian network, logistic regression, vector machine, as well as naive Bayesian were examined in a subsequent research [23]. Regarding failure prediction, Rivas et al. employed the long short-term memory (LSTM) recurrent neural network (RNN) architecture, another variety of ANN incapable of utilizing memory [24]. The autoregressive integrated moving long-term average is used to anticipate potential failures and qualitative flaws [25]. To diagnose machine downtimes, they essentially utilized this strategy to forecast future failure spots in the data set. Another study [17] showed an architectural network that employed tree-based methods to forecast the likelihood of failure, with the gradient boosting machine-producing models that outperformed the decentralized RF models and extreme multilayer preceptor models for classification. Potential topic in PM is the application of deep learning algorithms. Artificial neural networks were employed in this context [26] to perform the task of extracting features, while deep neural networks were utilized [27] to diminish the disadvantages of dimensionality (Fig. 6.2).

6.6 Case study JSC 120A digital twin in artificial intelligence manufacturing

The study of AI has changed several sectors, as well as how we live (AI). The development of a new sophisticated technology that could also

Figure 6.2 Digital twin in artificial intelligence manufacturing model.

respond in a way that is comparable to human intelligence aims to understand the fundamentals of intelligence. Areas of research in this field include robotics, language recognition, picture acknowledgment, and computational linguistics, including optimization techniques [12]. Machine intelligence is used in computing, robots, political and economic life choice, control mechanisms, and testing the system. Software is used to assist in avoiding traffic while driving; smartwatches can track and predict health issues; robots in our homes can read books to our children in their own voices; and our cleaning robot can clean.

DT with AI will bring changes in our daily life. The degree of manufacturing sector information technology is continuously increasing as a result of the ongoing development of intelligent manufacturing technology in several nations throughout the world. Enterprises must increase the management and control measures of each module in the production workshop to improve the company's capacity to regulate the production process to improve production rates and deal with emergencies in the production process in a timely way [13]. Large amounts of data, data needs, and data structures are encountered by firms during the manufacturing process as a result of consumers' specific product requirements, which makes it challenging for businesses to manage and evaluate data. Therefore a fundamental issue in the contemporary intelligent manufacturing sector is how to efficiently and promptly address feedback for the use patterns of the machinery in the industrial workplace as well as achieve prompt condition monitoring [16]. The evolution of contemporary and advanced information technology, including IoT, software defined, big data, machine intelligence, etc., has aided in the transition from conventional production to intelligent manufacturing [17]. Autonomy and active self-optimization are the most important aspects of intelligent manufacturing [18] in the transformation of DT manufacturing units into intelligent manufacturing that can intelligently perceive, simulate, comprehend, anticipate, optimize, and control. Research on a knowledge-driven system framework [20] can not only improve the quality of products but also lower production expenses.

The potential of industrial automation is greater than the problem it poses to traditional production. Smart factory has more blatant sustainability features. The investigation on how to construct a sustainable development assessment advanced automation driving system for intelligent manufacturing applications has led to the creation of an advanced automation driving system based on the traditional electronic double mapping system [21]. The development of smart manufacturing initiatives in a responsible way is focused on information technology. As sensor technology and digital processing have evolved, the industrial IoT technologies, focused on technological infrastructure, have become the main trend in the growth of the industry [19]. Controlling carbon emissions in industrial workplace provides certain challenges due to the diversity and instability of distinct manufacturing operations [28]. To evaluate and improve the model in the simulated workshop, a research was conducted, which suggested a smart industrial workshop with a smart technology-driven carbon emission prediction management framework [22].

The essential element of intelligent production is DT workshop. It comprises an actual workshop, a virtual workshop, a workshops support system, and workbench twin data, with the virtual workshop being the most significant of all [23]. The creation of a virtual workshop involves three main directions and a number of other components, such as the use of digital complex geometries to depict the workshop's personnel, equipment, and goods. Production components such as the speed trajectory of the workshop equipment and various production instructions, as well as simulations of the operating condition of the workshop equipment, are examples of behavior elements [24]. Rule components evaluate, analyze, forecast, and optimize the production process using the workshop's physical environment to construct a virtual workplace. As depicted in Fig. 6.3, periodic equipment failures during the actual manufacturing process impact the expenses and schedule of a project. It is frequently challenging and expensive to undertake fault screening if repairs are made after the issue has already been occurred.

As a result, it is crucial to implement detection systems for mechanical failures and equipment serviceability [25]. A 3D monitoring approach based on the available information from the workshop was provided in the research, which was focused on the visually pleasing surveillance of DT sessions [26]. It was also examined how legitimate 3D visualization at work interacts with DTs. Workshop geometric modeling, workshop real-time data management, workshop multi-level 3D visualization monitoring, and workshop status board construction methods are proposed and explained in detail, along with a multi-level 3D visualization review count as well as a real-time information virtual workbench mode of operation.

Through real-world case studies, the usefulness of the proposed strategy is demonstrated [26] The workshop production line integrates the usage of essential communications technology on the foundation of intelligent workshop machinery. For the purpose of realizing surrealist virtual legitimate of digital simulation real material objects, it primarily uses simulated data continuous communication and virtual-real method as an approach. The workshop's products may be produced in accordance with real applications, and an internal virtual model of the intelligent workshop can be created. Batch processing scheduling is among the most important factors affecting manufacturing productivity and is always essential to the process of production. In the actual production scheduling process, there are a number of unanticipated events, such as asymmetric information, abnormal disturbances, and other factors that can lead to implementation

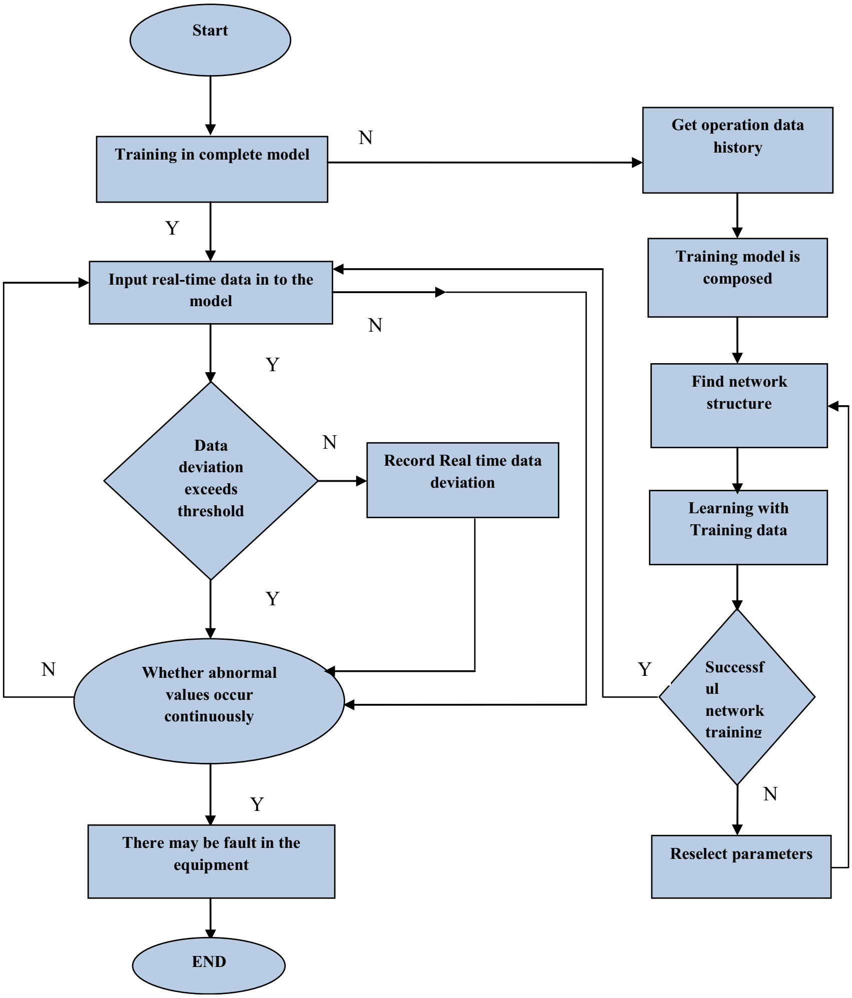


Figure 6.3 Fault screening.

deviations and decrease the efficiency and caliber of scheduling execution. Conventional production techniques fall short of adequately addressing these problems. A new job shop scheduling approach [27] based on DTs is offered to decrease programming deviation due to the emergence of DTs, which would have the properties of virtual reality engagement as well as actual mapping and symbiosis development.

Considering the aforementioned research, it can be seen that smart technologies had already made strides in the area of industrial automation, particularly through the use of virtual workshops, which can actually reduce the likelihood of equipment breakdown and then also help staff make timely adjustments to the overarching schedule changes of the training session and improving the effectiveness of equipment power generation [14].

It can also produce items in a fictitious 3D environment. It is possible to considerably simplify product geometry confirmation, installation of viability validation, and processes deployment by altering the components and products of varied sizes and assembly interactions. The iterative method also significantly reduces the production times, costs, and also the costs of physical prototypes. Electric spindle JSC 120A is an important component that directly affects the accuracy of the tool. As discussed above, data acquisition is processed by sensors and index management is carried out by combining experimental results and its simulation is shown in Fig. 6.4. The AI techniques that have been implemented collaboratively to process DT in multiple dimensions such as time, temperature, vibrations are shown in Fig. 6.5.

6.7 Challenges and future work

There are many challenges in machine learning and deep learning in DT.

6.7.1 IT Infrastructure

6.7.1.1 The overall IT infrastructure is the first significant obstacle

To support the algorithms' execution to keep up with the rapidly expanding field of AI, advanced facilities in the form of contemporary equipment and software are needed. The current issue with the infrastructure is the high cost of building and maintaining modern technologies. The cost of a powerful graphics processing unit (GPU) capable of running machine and deep learning algorithms can range from US $1,000 to US $10,000. To properly run such systems, the infrastructure must also have modernized hardware and software. Using GPUs "as a service" to obtain cost-effective on-demand GPUs through the cloud is one way to overcome this difficulty. Several companies, like Amazon, Google, Microsoft, and NVIDIA, are providing distinctive on-demand services that are comparable to conventional cloud-based apps; therefore, lowering the demand barrier. However, data analytics still faces difficulties due to poor infrastructure and expensive costs. Making sure that the cloud infrastructure provides strong security and remains a difficulty when using it for data analytics and DTs.

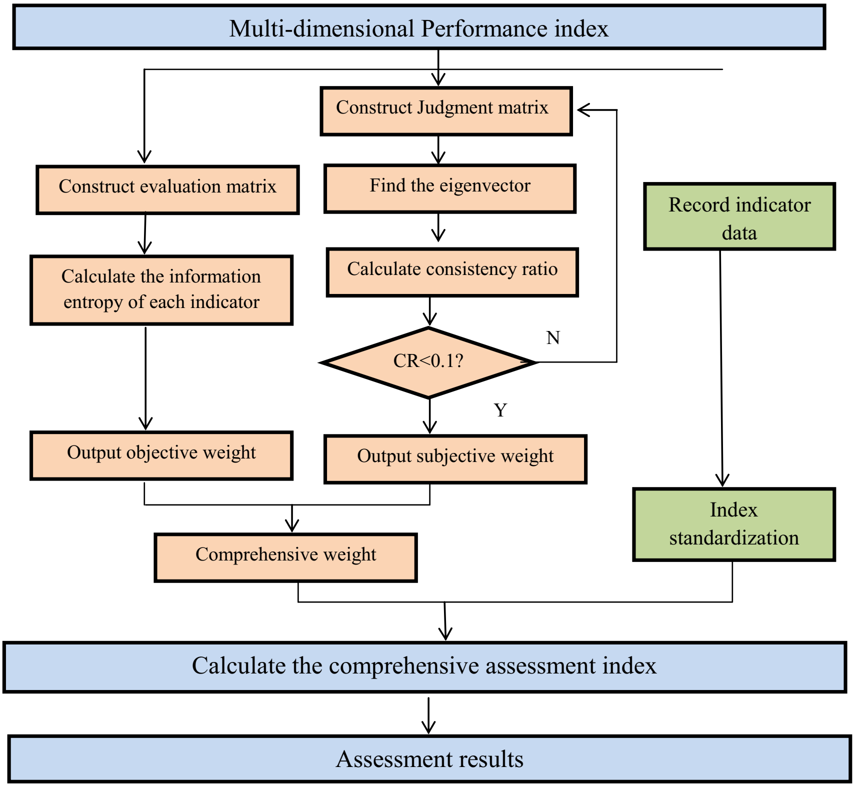


Figure 6.4 Artificial intelligence steps in spindle JSC120 A.

6.7.1.2 Information

It is critical to make sure the data is of high quality from a data perspective. To ensure if AI technologies are fed the highest grade of data, the data has to be sorted and cleaned.

6.7.1.3 Privacy and security

Anyone involved in the computing business should be worried about privacy and security, and executing data analytics is no exception. Because AI is still relatively new, laws and regulations have not yet been properly created. The challenges with oversight, legislation, and controls related to AI will increase as the technology develops. Future legislation will guarantee the creation of algorithms that safeguard user data. A new law known as the Data Protection Act guarantees the confidentiality and security of the information in the UK and across all of Europe. This emphasizes the

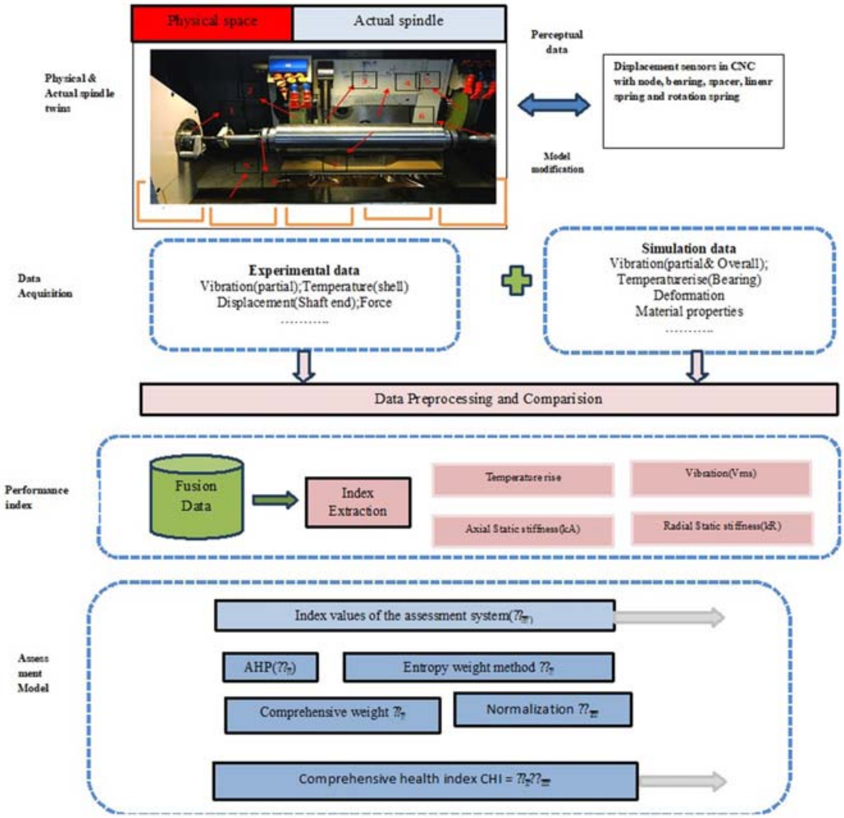


Figure 6.5 Digital twin in artificial intelligence manufacturing.

issues with handling data while constructing AI algorithms, despite having an overarching rule regarding data and security. A distributed model-training system called decentralized intelligence is one technique to ensure the safety of personal information, in addition to legislation. By permitting user information in an instructional method to stay concentrated without even any data sharing, it overcomes security and privacy issues when using predictive analytics within a DT.

6.7.1.4 Trust

Another issue that the majority in the AI community are concerned with is trust. The usage of AI can be intimidating for several reasons, including the fact that it is still relatively new and the fact that the complexity may not be understood by the developer. A barrier to trust is the fear that robots and AI may overtake humans as the dominating force on earth and takeover crucial infrastructure. Because AI is typically portrayed as having negative consequences, trust issues might be a hindrance. The number of good media articles about AI is increasing, but there are still many hurdles to overcome. More exposure to AI and its beneficial applications is thus necessary.

6.7.1.5 Expectations

The belief that data analytics can be utilized to address all of our issues is the final hurdle to overcome. AI usage requires careful study, and taking the effort to identify the right application makes sure that regular models could not achieve the same outcomes. Like other emerging technologies, it has the potential to boost things like manufacturing and the creation of smart cities. The high expectations are due to the fact that potential customers just consider the advantages and think they would immediately save time and money. Applying data analytics requires keeping in mind that the field is still in its infancy. It is clear from the sheer number of scenarios that employ "AI" in places where it is unnecessary, as opposed to other circumstances where it is appropriate. Continually to and understanding of AI are needed to allow people to get the necessary baseline knowledge of the area and learn how it may be employed.

6.7.2 Internet of Things/IIoT challenges

The following is a list of the challenges that the digitalization and IIoT face:

6.7.2.1 Information, confidentiality, protection, and loyalty

Due to massive growth of connected systems, both in the household and businesses, the challenge of collecting substantial amounts of data has worsened. Controlling the flow of data while assuring its organization and efficient utilization is a difficult task. With the introduction of big data, the dilemma becomes more significant. The adoption of IoT contributes to a rise in the amount of unstructured data. IoT must sort and organize data to handle the quantity of data, as doing so increases its usefulness and value. If otherwise, the information will be destroyed otherwise it will cost too much to get value out of the vast amounts acquired. This might because the information might be sensitive. Cybersecurity assaults pose substantial challenges since thieves infect computers and can bring them down to harm an organization's infrastructure. There is a chance that cybercriminals would target certain organizations with thousands of linked IoT devices to seize control of them and use them for their own purposes. An example of this is the Mirai botnet debate, in which around millions of IoT devices have been taken over and used to launch a disseminated denial-of-service attack (DDoS). The fast expansion of IoT raises the risk of DDoS assaults. In addition, the lack of focus on privacy and security issues increases the chance of an attack. The most recent security features and protection must be used when installing the devices; otherwise, there is a vulnerability that provides a doorway for thieves to access a larger, connected IoT environment.

6.7.2.2 Machinery facilities

Due to IoT technology's quick advancement when compared to the already-used systems, the IT infrastructure is lagging. IoT growth is facilitated by modernizing outdated infrastructure and integrating new technology. A modernized IoT infrastructure offers the chance to make use of cutting-edge technology and use cloud-based apps and services without having to spend a lot of money upgrading current systems and equipment. Adding outdated equipment to the IoT ecosystem presents another problem for IoT systems. Retrofitting IoT sensors to legacy devices is one approach to address this, ensuring that data is not lost and enabling analytics on aging computers.

6.7.2.3 Connectivity

Considering this expansion of IoT usage, connection issues continue to be of concern. When real-time monitoring is the objective, they are very common. The simultaneous connection of a large number of sensors in a manufacturing process is a considerable problem. This general aim of connectedness is being impacted by difficulties with factors like power interruptions, software faults, or persistent deployment failures. One sensor's incomplete connection might have a significant impact on the process's overall objective. Connected devices, for example, are one source of data used by computer algorithms; this creates a big challenge when all the data is required for it to operate efficiently, and the platform's ability to function may be negatively impacted by the absence of IoT data. Retrofitting technology and recording the information the machine has already produced is one technique to ensure that all the information is recorded. Imputation technique used to find substitute values for missing internet sensor information, ensuring complete connectivity and making it simpler for AI technologies to run without high precision with little to no missing data.

6.7.2.4 Presumption

Comparable to machine learning, it is challenging to achieve internet aspirations since businesses and end users are confused about what to expect from the use of technology devices. The fact why IoT is expanding rapidly is promising because that demonstrates that corporations and end users are aware of its potential and the advantages of an interconnected, intelligent environment for everybody. The idea that IoT apps could be used for an extended period of time and without permission can be damaging since it has a domino effect that puts a lot of pressure on security and privacy issues and exasperates confidence problems. IoT is similar to AI in that it can only be fully utilized with the right foundational knowledge.

6.7.3 Challenges in digital twinning

This subsection mostly highlights the challenges associated with employing intelligent automation. But as the investigation continues, it has become clear that the challenges associated with information analytics and IoT are similar to those associated with intelligent automation, some of which have been discussed below:

6.7.3.1 Infrastructure of IT

IoT and predictive analysis problems are related to the current IT infrastructure, which makes them comparable. The DT needs equipment for IoT and database management success; they will help with the effective functioning of a Virtual Environment. Without a connected and carefully thought-out IT infrastructure, the cyberphysical system would not be successful in accomplishing its stated goals.

6.7.3.2 Useful data

The next challenge is gathering the data necessary for a digital model. It has to have increased; speckle data that is streamed continuously. There is indeed a chance that perhaps the simulation model will underperform if the information is incomplete and conflicting because it will be using inaccuracies and missing data. The total amount and strength of IoT signals are essential for DT data. Planning and monitoring of smartphone ownership are needed to verify that proper data is obtained and used for a DT's best utilization.

6.7.3.3 Privacy and security

It is obvious that the security and privacy concerns with DTs present a barrier in an industrial context. They are problematic for sensitive system data both because of the enormous volume of data they utilize and because of the risk they offer. The main enabling technologies for DTs, IoT, and data analytics must adhere to the most recent security and privacy rules to overcome this difficulty. Trust issues with DTs can be addressed in part by taking security and privacy into account.

6.7.3.4 Trust

From both an organizational and user perspective, trust-related challenges are difficult to overcome. More details on the technology are required, as well as a basic explanation, to ensure that terminal and businesses comprehend the benefits of a digital workplace, particularly helping in eliminating the credibility barriers. A different strategy for addressing the trust issues is model validation. For user trust to be maintained, it is crucial to confirm that DTs are operating as anticipated. With greater knowledge, DTs are more widely trusted. The enabling technology will provide a deeper understanding of the procedures to be followed to secure privacy and security practices throughout development, thus addressing the issues with trust.

6.7.3.5 Expectations

Industry giants Siemens and GE are accelerating the use of DTs, but caution is still advised to emphasize the difficulties in setting realistic expectations for DTs and the need for greater knowledge. The organizations' adoption of DT technology will be ensured by the requirement for strong IoT infrastructure foundations and a deeper grasp of data needed for analytics. It might be difficult to refute the notion, which only current advancements should indeed be taken into account while using the digital model. To guarantee that proper steps are taken while establishing DT systems, the advantages and disadvantages of the expectation of DTs must be explored. It is obvious that the deployment of a DT has issues related to both IIoT/IoT and data analytics. There are particular obstacles pertaining to the modeling and construction of the challenges that IoT as well as data analytics share together; IoT throughout user experience, confidentiality, as well as architecture among the digital workplace.

6.7.3.6 Standardized modeling

Due to the lack of a standardized modeling methodology, the next problem in the creation of DTs in all its forms is the modeling of such systems. Regardless of where it is predicated on thermodynamics or technology, there ought to be a standard process from the initial concept through a simulation of a DT. When developing and implementing a DT, standardized procedures guarantee that the user and domain are understood and that information flows smoothly between each step.

6.7.3.7 Domain modeling

Another problem resulting from the necessity for consistent use is making sure if the information about the domain usage is sent to all of the developmental and operational phases of the modeling of such a digital workplace. The DT will thus be useful in the future when used in disciplines like IoT and data analytics. These are vital in the future since they ensure that they be considered when developing DTs, rather than when utilizing the IoT with data processing. Table 6.1 below summarizes the hurdles for data analytics and IIoT/IoT, as well as the overall combined problems for something like a virtual environment, including challenges, particularly for IIoT deployment.

Table 6.1 Challenges of data analytics and Internet of Things in the integrated digital twin.

Virtual twin/state machine/DT	
Evaluation of data	Evaluation of data
Framework of IT	Framework of IT
Information	Information
Confidentiality	Confidentiality
Assurance/guarantee	Assurance/guarantee
Certainty	Certainty
Presumption	Presumption
	Availability

6.8 Future work

The use of DTs might have a significant impact on the way that personnel is trained, how complex technological plans are created without wasting physical resources, and also how infrastructure is improved and climate change is mitigated. According to Richard Kerris, vice president of Omniverse development at Nvidia, "it's hard to conceive where DTs won't have an influence on health care, music, education, bringing city kids on safari." In manufacturing, the future work includes:

1. product development
2. design customization
3. shop floor performance maintenance
4. predictive maintenance

DTs are machine-specific virtual duplicates, and creating and maintaining them costs money. As a result, employing them for predictive maintenance duties is not scalable.

6.9 Conclusion

The advantages of DT in AI manufacturing industries are well documented in numerous prototype development to shop floor activity optimization to production management and real-time equipment condition prediction. Although there have not been many investigations on the usage of digital twinning in the healthcare sector, there is a lot of scope for improvement. This report also included a case study that covered a DT paradigm. Therefore, it transforms into a traditional optimization method for the entire factory by modeling the ecosystem and a group of independent DTs that could share states and make distributed decisions.

Because each state machine is controlled by a sophisticated DT at the manufacturing level, this pattern may be represented by a deterministic phase diagram in Fig. 6.6. By employing AI in the manufacturing DT model, the extensibility, scalability, reliability, and security are the characteristics that improve the production. This is in a cloud that exchanges data with the machine, analyzes the multiple data streams, and shows the results in a timely manner on a monitor. The twin controls the machinery in real time by feeding suggestions directly through DT, which lets the user enter data based on those suggestions. It has the capacity to archive analyses performed for various processing settings over the duration and provide that as summary statistics.

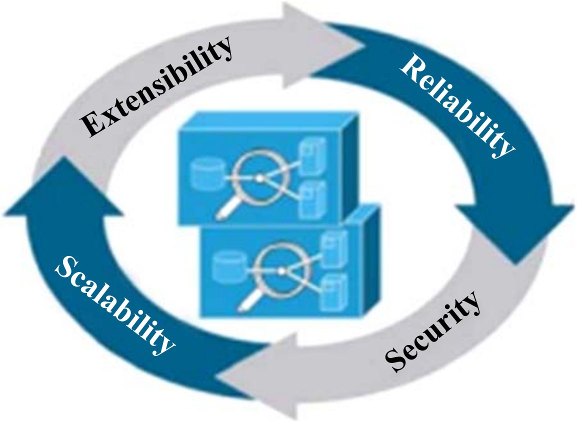


Figure 6.6 Improved feature.

References

[1] N. Carvalho, O. Chaim, E. Cazarini, M. Gerolamo, Manufacturing in the fourth industrial revolution: a positive prospect in sustainable manufacturing, Proc. Manuf. 21 (2018) 671−678.
[2] P. Nowotarski, J. Paslawski, Industry 4.0 concept introduction into construction SMEs. In IOP conference series: materials science and engineering (Vol. 245, No. 5, p. 052043), 2017, October. IOP Publishing.
[3] E. Glaessgen, D. Stargel, The digital twin paradigm for future NASA and US Air Force vehicles, in: 53rd AIAA/ASME/ASCE/AHS/ASC structures, structural dynamics and materials conference 20th AIAA/ASME/AHS adaptive structures conference 14th AIAA, p. 1818, 2012, April.
[4] Z. Liu, N. Meyendorf, N. Mrad, The role of data fusion in predictive maintenance using digital twin, in: AIP conference proceedings (Vol. 1949, No. 1, p. 020023), 2018, April. AIP Publishing LLC.
[5] L. Varona, A. Legarra, M.A. Toro, Z.G. Vitezica, Non-additive effects in genomic selection, Front. Genet. 9 (2018) 78.
[6] I. Graessler, A. Pöhler, Integration of a digital twin as human representation in a scheduling procedure of a cyber-physical production system, in: 2017 IEEE international conference on industrial engineering and engineering management (IEEM), pp. 289−293, 2017, December. IEEE.
[7] F. Tao, J. Cheng, Q. Qi, M. Zhang, H. Zhang, F. Sui, Digital twin-driven product design, manufacturing and service with big data, Int. J. Adv. Manuf. Technol. 94 (9) (2018) 3563−3576.
[8] H. Cao, P. Folan, Product life cycle: the evolution of a paradigm and literature review from 1950−2009, Prod. Plan. Control. 23 (8) (2012) 641−662.
[9] F. Tao, F. Sui, A. Liu, Q. Qi, M. Zhang, B. Song, et al., Digital twin-driven product design framework, Int. J. Prod. Res. 57 (12) (2019) 3935−3953.
[10] Q. Qi, F. Tao, Digital twin and big data towards smart manufacturing and industry 4.0: 360 degree comparison, IEEE Access. 6 (2018) 3585−3593.
[11] F. Xiang, Z. Zhi, G. Jiang, Digital twinstechnology and its data fusion in iron and steel product life cycle, in: 2018 IEEE 15th international conference on networking, sensing and control (ICNSC), pp. 1−5, 2018, March. IEEE.

[12] H. Zhang, G. Zhang, Q. Yan, Dynamic resource allocation optimization for digital twin-driven smart shopfloor, in: 2018 IEEE 15th International Conference on Networking, Sensing and Control (ICNSC), pp. 1–5, 2018, March. IEEE.
[13] F. Tao, M. Zhang, J. Cheng, Q. Qi, Digital twin workshop: a new paradigm for future workshop, Comp. Integr. Manuf. Syst. 23 (1) (2017) 1–9.
[14] M.Z. Alom, T.M. Taha, C. Yakopcic, S. Westberg, P. Sidike, M.S. Nasrin, et al., A state-of-the-art survey on deep learning theory and architectures, Electronics 8 (3) (2019) 292.
[15] M. ETSI, Mobile edge computing (mec); framework and reference architecture. ETSI, DGS MEC. 3 (2016) 1–18.
[16] F. Ameri, R. Sabbagh, Digital factories for capability modeling and visualization, IFIP International Conference on Advances in Production Management Systems, Springer, Cham, 2016, pp. 69–78. September.
[17] J. Vachálek, L. Bartalský, O. Rovný, D. Šišmišová, M. Morháč, M. Lokšík, The digital twin of an industrial production line within the industry 4.0 concept, in: 2017 21st international conference on process control (PC), pp. 258–262, 2017, June. IEEE.
[18] M. Zhang, Y. Zuo, F. Tao, Equipment energy consumption management in digital twin shop-floor: a framework and potential applications, in: 2018 IEEE 15th international conference on networking, sensing and control (ICNSC), pp. 1–5, 2018, March. IEEE.
[19] C. Zhuang, J. Liu, H. Xiong, Digital twin-based smart production management and control framework for the complex product assembly shop-floor, Int. J. Adv. Manuf. Technol. 96 (1) (2018) 1149–1163.
[20] A. Rasheed, O. San, T. Kvamsdal, Digital twin: values, challenges and enablers from a modeling perspective, IEEE Access. 8 (2020) 21980–22012.
[21] F. Tao, H. Zhang, A. Liu, A.Y. Nee, Digital twin in industry: state-of-the-art, IEEE Trans. Ind. Inform. 15 (4) (2018) 2405–2415.
[22] W. Shi, J. Cao, Q. Zhang, Y. Li, L. Xu, Edge computing: vision and challenges, IEEE Internet Things J. 3 (5) (2016) 637–646.
[23] C. Mouradian, D. Naboulsi, S. Yangui, R.H. Glitho, M.J. Morrow, P.A. Polakos, A comprehensive survey on fog computing: state-of-the-art and research challenges, IEEE Commun. Surv. Tutor. 20 (1) (2017) 416–464.
[24] K. Xia, C. Sacco, M. Kirkpatrick, C. Saidy, L. Nguyen, A. Kircaliali, et al., A digital twin to train deep reinforcement learning agent for smart manufacturing plants: environment, interfaces and intelligence, J. Manuf. Syst. 58 (2021) 210–230.
[25] K. Borodulin, G. Radchenko, A. Shestakov, L. Sokolinsky, A. Tchernykh, R. Prodan, Towards digital twins cloud platform: microservices and computational workflows to rule a smart factory, in: Proceedings of the10th international conference on utility and cloud computing, pp. 209–210, 2017, December.
[26] M. De Donno, A. Giaretta, N. Dragoni, A. Bucchiarone, M. Mazzara, Cyber-storms come from clouds: security of cloud computing in the IoT era, Fut. Internet 11 (6) (2019) 127.
[27] L. Girletti, M. Groshev, C. Guimarães, C.J. Bernardos, A. de la Oliva, An intelligent edge-based digital twin for robotics, in: 2020 IEEE globecom workshops (GC Wkshps), pp. 1–6, 2020, December. IEEE.
[28] K. Wärmefjord, R. Söderberg, L. Lindkvist, Shaping the digital twin for design and production engineering. Volume 2: advanced manufacturing, 2017.

This page intentionally left blank

CHAPTER 7

The convergence of digital twin, Internet of Things, and artificial intelligence: digital smart farming

Shipra Yadav[1], Amir Ahmad Dar[2], Pankaj Dhumane[3] and D. Kalaskar Keshao[4]
[1]IICC, RTM Nagpur University, Nagpur, Maharashtra, India
[2]Department of Mathematics, Lovely Professional University, Punjab, India
[3]Sardar Patel College, Chandrapur, Maharashtra, India
[4]Dr. Ambedkar College, Chandrapur, Maharashtra, India

7.1 Introduction

Development of many countries depends heavily on agriculture, which is also essential to achieving Sustainable Development Goal 2 of "Zero Hunger" [1]. To fulfill the demands of a projected population of 10 billion people by 2050, the Food and Agriculture Organization estimates that agricultural output must increase by 40% between 2012 and 2050 [2]. The creative application of technologies like drones, applications, and machines coupled with social, organizational, and institutional shifts is one strategy for enhancing the production.

Around 70% of the freshwater consumed globally is used for agriculture [3]. This makes a strong case for the development of technologies like the Internet of Things (IoT) to increase the amount of food produced on farms while reducing the amount of water required in agriculture.

Irrigation systems utilize the majority of the freshwater that is present, and 40% of the freshwater used in developing nations is wasted due to leakages and over irrigation [4]. The availability of freshwater has become a global concern due to factors including climate change and population growth, specifically due to rainfall.

The regions facing scarcity [5] call for a different viewpoint on irrigation systems and their optimization to guarantee food security for the expanding population [6]. In agriculture, appropriate irrigation that is

Digital Twin For Smart Manufacturing
DOI: https://doi.org/10.1016/B978-0-323-99205-3.00007-9

managed by field sensors is crucial, as inadequate or excessive watering reduces crop output [7]. AI can improve the farming process in this context by collecting data on plant conditions and computing it with high performance and low cost [8], maintaining crop yield at normal standards, reducing water waste, and ultimately increasing the availability of potable water [6].

A digital twin model based on the IoT can be applied in farms to effectively recognize their current environment to capitalize on this worldwide concern. This means that a virtual representation of a farm should be able to behave depending on the systems' analyses and judgments as well as gather information from the farm. The fundamental creation of a digital twin for smart farming using the IoT to regulate an irrigation system based on a farmer's and/or AI choice is presented in this chapter. Section 2 of this chapter provides examples of IoT applications in agriculture, Section 3 introduces the idea of a digital twin in the context of agriculture, Section 4 details the creation of the digital twin, Section 5 describes the initial findings and analysis, and Section 6 concludes the chapter.

7.2 Internet of Things in agriculture

The majority of the literature on the development of IoT technologies in agriculture consists of exploratory research that demonstrate systems in small pilot projects [9]. The development of equipment and devices used on farms to gather information about the soil, crop quality, weather conditions, and other factors can be divided into two categories when it comes to the use of IoT in agriculture [10,11]. The second category includes the development of platforms that are used to store, organize, analyze, and visualize data to help in the decision-making [12,13].

The term "smart farming" appears while reading the literature on the application of information and communication technologies (ICT) in agriculture. Although the term "smart farming" has been in use for some time, there is still a need for a comprehensive definition of the term that encompasses the technology now employed in the agriculture industry. To integrate information and communication technologies in the cyber-physical farm management cycle, smart farming entails integrating them into machinery, equipment, and sensors [14,15].

Several technologies, including IoT, big data, AI, process management, etc., are perceived as being included in this notion. According to the literature, ICT usage in agriculture is a developing field that currently faces some challenges, but there are also many advantages associated with its use.

7.3 Digital twin smart farming

According to the research by [16], a digital twin model is one in which allows data transfer between a physical and digital entity automatically, as seen in Fig. 7.1. By utilizing technologies like big data, IoT, AI, etc., a digital twin is able to link information about the farm and business and is able to act depending on a choice made automatically by the system.

By extending the idea of smart farming, a digital twin for a smart farm or a digital smart farm is suggested. Building discrete services to understand the data of a specific system, such as an irrigation system, a seeding system, etc., and bringing them together in a cyberphysical system is how a digital smart farm is executed. This makes it possible to combine various systems and gives farmers a thorough understanding of how their crops are doing. It is possible to adjust the farm to changes in the environment, weather, markets, water limitations, etc., by employing a digital smart farm.

7.4 Digital smart farming system

This section, which is separated as follows, describes a digital smart farm based on two initiatives (The Sensing Change and SWAMP projects): The previous two projects are summarized in Section A, the system design

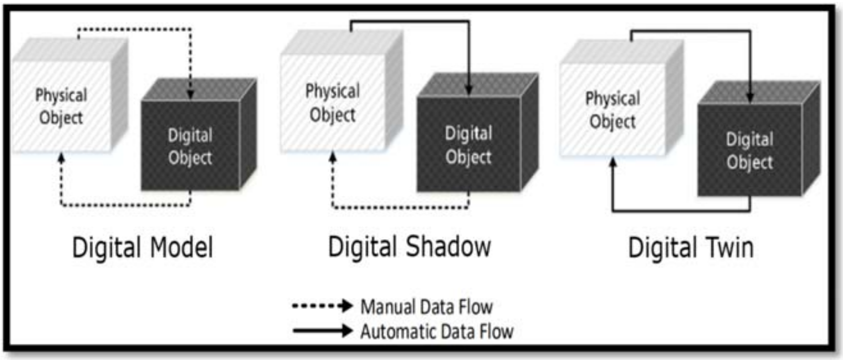


Figure 7.1 Digital twin concept [16].

is described in Section B together with its hardware and devices, and the system architecture is shown in Section C along with cloud services and other components.

7.4.1 Sensing change and smart water management platform programmers are related works

The Sensing Change project's approach was based on the idea that it could be applied to any type of agricultural activity and that it could make use of low-cost commercial tools and supplies [17]. Three key parts make up the system: the monitoring station, the smartphone app, and the cloud system (Fig. 7.2). This project created an information-gathering and information-analysis monitoring system for a farm. However, it was the farmers who made the decisions and took the necessary steps.

The SWAMP project, on the other hand, is creating a hands-on, IoT-based smart water management platform for precision irrigation in four locations across Brazil, Italy, and Spain [18]. The SWAMP platform can be designed and implemented in various ways, resulting in several SWAMP systems that are tailored to meet the needs and limitations of various settings, countries, climates, soils, and crops. This indicates that the decision-making process can be entirely handled by the farmer, by a machine, or by a combination of the two. According to Fig. 7.3, the SWAMP design is separated into five layers.

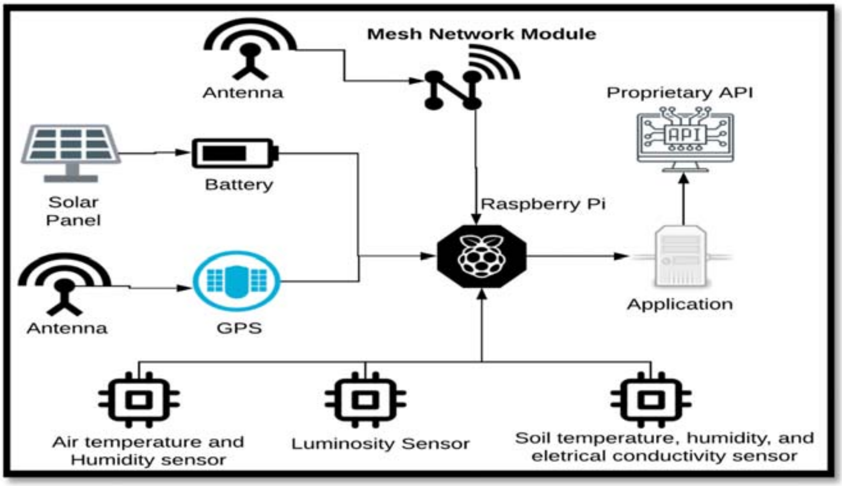


Figure 7.2 Sensing change system diagram [17].

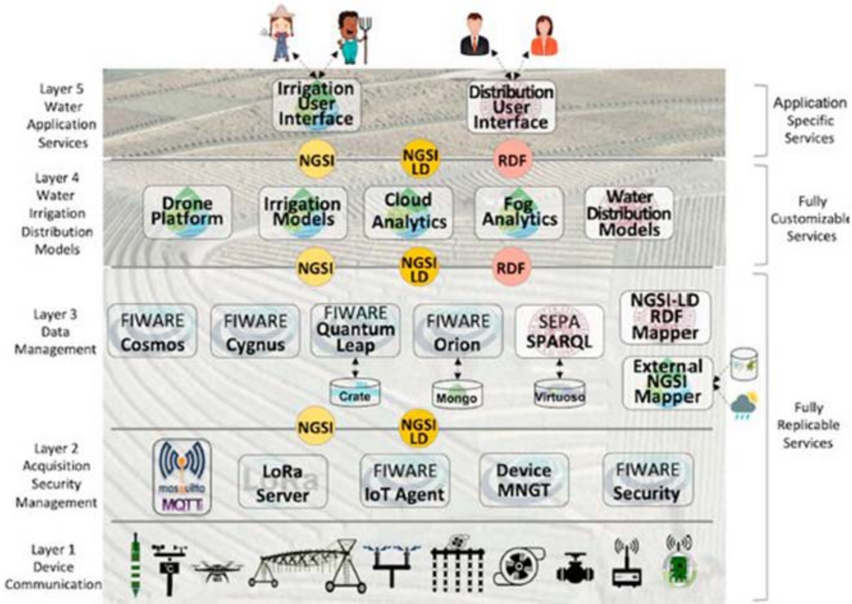


Figure 7.3 Smart water management platform project architecture layers.

7.4.2 A system design

The system comprises a field-installed probe that measures ground temperature at 7 cm depth (DS18B20), soil moisture at depths of 7, 28, 50, and 72 cm, ambient light, and geographical position (CSMv1.2). The Raspberry Pi-3 module receives probe signals via the I2C bus (CSM v1.2 and BH1750), GPIO (DHT22), serial bus (Venus GPS), and One-Wire bus (DS18B20). a module for ADS1115 is also employed for the conversion of the CSMv1.2A/D signal. This data is read by the Raspberry module using a Python script, which displays numbers as percentages of soil moisture. The script then generates a payload including all probe data and delivers it to the Orion broker for subscription via the IoT agent. A prototype of the system utilized for laboratory testing is shown in Fig. 7.4. The final model of the probe that can be seen in the figure will be used in the field.

7.4.3 System architecture

Numerous equipment and systems, such as soil probes, weather stations, irrigation systems, seeders, harvesters, etc., are used on the farm. These tools and equipment are linked to the cloud through a gateway, which

Figure 7.4 System design.

communicates data to an IoT agent. The suggested system architecture is shown in Fig. 7.5, along with the services employed.

1. A service called Fiware IoT Agent converts many communication protocols to the cloud-based standard.
2. The term "fiware" Orion is a context broker that enables you to control every stage of the context information lifecycle, including updates, queries, registrations, and subscriptions.
3. A document-based database called Mongo DB is used to store the most recent data in a complex structure.
4. Draco is a generic enabler that is a different data persistence method for controlling context history.
5. Time-series data are kept in MySQL, an open-source relational database management system.
6. MySQL Grafana is an open-source analytics and monitoring tool for building data dashboards.

This digital environment is intended to visually enlighten the data gathered by IoT and to deliver data to the systems based on the decision-making

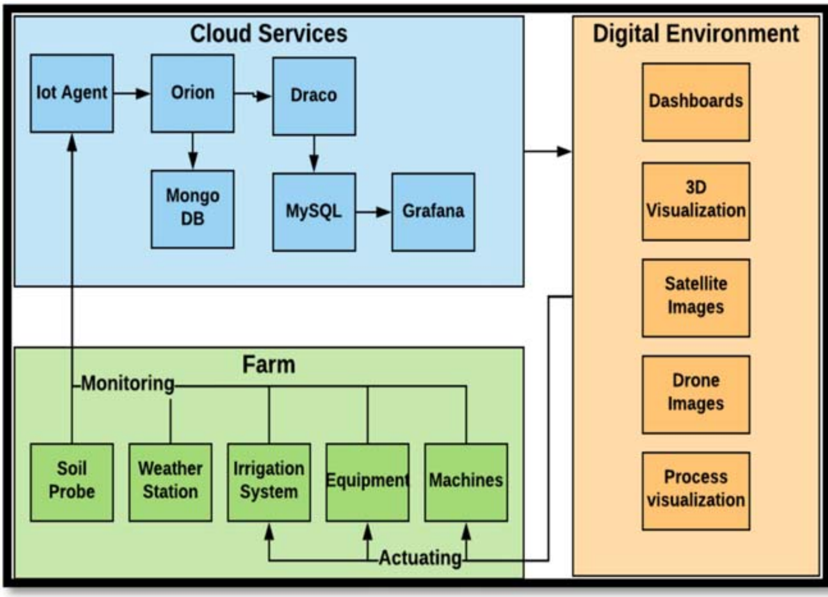


Figure 7.5 System architecture.

process carried out inside of it. Information can only currently be displayed visually on dashboards.

However, all of the other settings must be built in an integrated manner to properly construct the digital smart farm. The information gathered and analyzed in the cloud and represented digitally should be entered into the physical system via the cloud or by integrating programmable logic controllers into the machinery, equipment, and irrigation system.

7.5 First result and analysis

The system's initial testbed findings are shown in Fig. 7.6 in our laboratory. On the basis of the thermogavimetric data, the soil moisture sensor was calibrated [19]. This initial test shows that the probe can send data to the cloud and that it is possible to display that data in a dashboard that updates in real time. It is obvious that the air temperature and humidity have dropped abnormally, which suggests a hardware or communication issue that has to be further investigated.

Fig. 7.7 displays field data that was gathered using a nearby weather station. The Penman-Monteith equation can be used to extract the

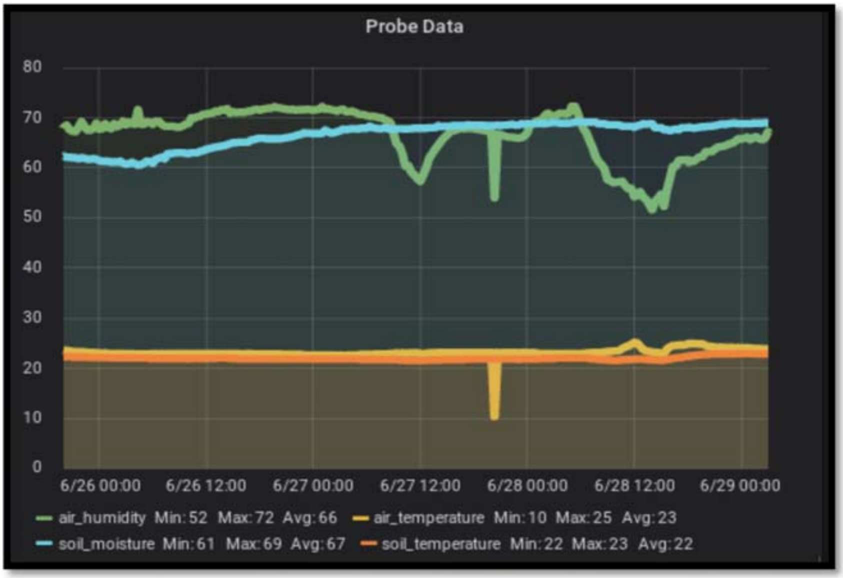


Figure 7.6 Dashboard with probe data.

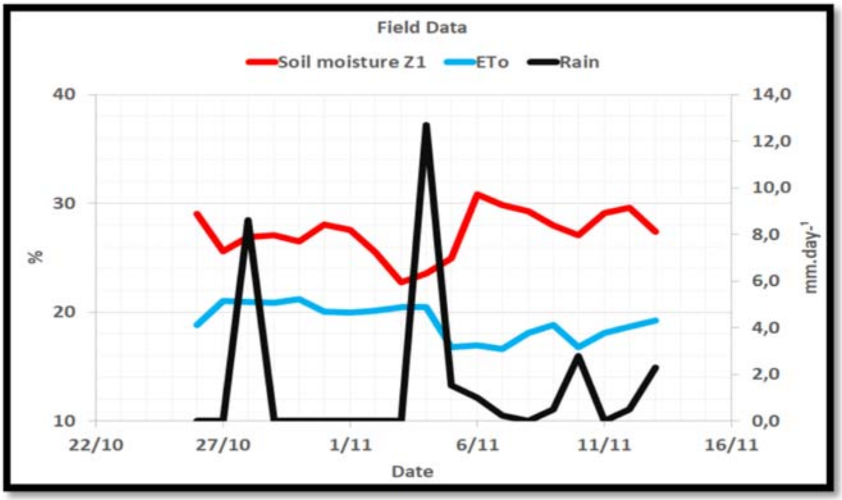


Figure 7.7 Field data collected.

reference evapotranspiration (ETo) using data from this meteorological station, including air temperature and humidity, wind velocity and direction, rainfall solar radiation, dew point, rain forecast, and rain chance [20].

The crop evapotranspiration is calculated by multiplying the ETo by the crop factor (Kc) for the specified crop. The ETo stands for the amount of water, in millimeter, that the reference crop uses [21].

The initial findings show that the technology is functional and capable of uploading data to the cloud for usage in spreadsheets and dashboards. Additionally, it is possible to display the water patterns in the soil and extract ETo using the nearby weather station. It is clear from Fig. 7.7 that during periods of drought, the soil moisture reduces and increases after each rainfall.

7.6 Conclusion

Farmers can connect various assets and systems utilizing the digital twin concept and IoT technology to have a better understanding of the various factors and elements that affect the farm's behavior, final yield production, and resource use. This essential component helps farmers make wiser decisions and minimize their influence on the environment's water, land, and soil resources. This chapter outlines the preliminary steps in creating a digital smart farm. However, numerous systems must work together to represent all of the farm's functions before a digital smart farm can be fully implemented.

According to this study, system architecture and cloud implementation are effective and may be utilized in the deployment of the subsequent steps, which include the creation of AI algorithms and other digital contexts. Once the complete system is operational, it will be feasible to comprehend how farms use resources and how that affects agricultural productivity. This promotes sustainable development and enhances food security for everyone on the planet.

References

[1] Goal 2: Zero Hunger, United Nations. http://www.un.org/sustainabledevelopment/hunger/ [Online] (2020).
[2] The State of Food and Agriculture: Leveraging Food Systems for Inclusive Rural Transformation. Food and Agriculture Organization of the United Nations. [Online]. Easily accessed at: http://www.fao.org/3/a-I7658e.pdf percent 0A percent 5Cn http://www.ncbi.nlm.nih.gov/pubmed/24897208, 2017, vol. 2, no. 7929.
[3] AQUASTAT, 2016 http://www.fao.org/nr/water/aquastat/waterusage.
[4] J. Panchard, S. Rao, T.V. Prabhakar, J. Hubaux, H. Jamadagni, Common sense net: a wireless sensor network for resource-poor agriculture in the semi-arid areas of developing countries, Inf. Technol. Int. Dev. 4 (2007) 51–67.

[5] R. Gonzalez Perea, E. Camacho Poyato, P. Montesinos, J.A. Rodriguez D'az, Optimization of water demand forecasting by artificial intelligence with short data sets, Biosyst. Eng. 177 (2019) 59–66.
[6] M. Pulido-Velazquez, F.A. Ward, Water conservation in irrigation can improve water use, Proc. Natl Acad. Sci. U S Am. 105 (47) (2008) 18.
[7] A.C. Charles, A.A. Namen, P.P.G.W. Rodrigues, Comparison of data mining methods applied to a surface meteorological station, RBRH 22 (0) (2017).
[8] Proceedings of the International Conference on IoT in Social, Mobile, Analytics and Cloud, I-SMAC 2017, by S. Athani and C. H. Tejeshwar.
[9] Internet of Things in agriculture, C. Verdouw, 9, volume 11, issue 035 of CAB reviews: perspectives in agriculture, veterinary science, nutrition, and natural resources [Online]. 2016. Available: http://www.cabi.org/cabreviews/review/20163379897.
[10] R.R. Agale, Automated irrigation and crop security system in agriculture using Internet of Things, in: International Conference on Computing, Communication, Control and Automation (ICCUBEA), pp. 1–5, 2017.
[11] K.L. Krishna, O. Silver, W.F. Malende, K. Anuradha, Internet of Things application for implementation of smart agriculture system, in: Proceedings of the International Conference on IoT in Social, Mobile, Analytics and Cloud, I-SMAC 2017, pp. 54–59, 2017.
[12] S. Suakanto, V.J. Engel, M. Hutagalung, D. Angela, Sensor networks data gathering and job management for decision support of smart farming, International Conference on Information Technology, 2016 http://linkinghub.elsevier.com/retrieve/pii/S2214317316301184.
[13] P.P. Jayaraman, A. Yavari, D. Georgakopoulos, A. Morshed, A. Zaslavsky, Internet of Things platform for smart farming: experiences and lessons learned, Sensors 16 (11) (2016) 1–17.
[14] D. Pivoto, P.D. Waquil, E. Talamini, C.P.S. Finocchio, V.F.D. Corte, Gd.V. Mores, Scientific development of smart agricultural technologies and their implementation in Brazil, Inf. Process. Agric. 5 (1) (2018) 21–32 [Online]. Available. Available from: https://linkinghub.elsevier.com/retrieve/pii/S2214317316301184.
[15] S. Wolfert, L. Ge, C. Verdouw, M.J. Bogaardt, Big data in smart farming - a review, Agric. Syst. 153 (2017) 69–80.
[16] W. Kritzinger, M. Karner, G. Traar, J. Henjes, W. Sihn, Digital twin in manufacturing: a categorical literature review and classification, in: IFAC-PapersOnLine, vol. 51, no. 11, pp. 1016–1022, 2018. [Online]. You can get it at: https://doi.org/10.1016/j.ifacol.2018.08.474.
[17] R.F. Maia, A.L.H. Tran, Precision agriculture employing remote monitoring systems in Brazil, in: 2017 GHTC 2017 - IEEE Global Humanitarian Technology Conference, Proceedings, vol. 2017-Janua, pp. 1–6.
[18] C. Kamienski, J. Soininen, M. Taumberger, S. Fernandes, A. Toscano, T.S. Cinotti, et al. Swamp: an iot-based smart water management platform for precision irrigation in agriculture, in: Global Internet of Things Summit (GIoTS), June 2018, pp. 1–6.
[19] D.A. Robinson, C.S. Campbell, J.W. Hopmans, B.K. Hornbuckle, S.B. Jones, R. Knight, et al., Soil moisture measurement for ecological and hydrological watershed-scale observatories: a review, Vadose Zone J. 7 (1) (2008) 358–389.
[20] R.G. Allen, L.S. Pereira, D. Raes, M. Smith, W. Ab.Guidelines for computing crop water requirements-FAO Irrigation and drainage document 56, Crop. Evapotransp., pp. 1–15, 1998.
[21] J. Doorenbos, W. Pruitt, Guidelines for forecasting crop water requirements, FAO Irrig. Drain. Pap. 24 (1977) 144.

CHAPTER 8

Digital twin meets artificial intelligence: AI-augmented industrial automation systems using intelligent digital twins

G.K. Kamalam[1] and Vani Rajasekar[2]
[1]Department of Information Technology, Kongu Engineering College, Perundurai, Tamil Nadu, India
[2]Department of CSE, Kongu Engineering College, Tamil Nadu, India

8.1 Introduction

High competitiveness [1] and mass customization [2] in the industry require automation to boost efficiency and also adaptability [3,4]. Cyber-physical systems (CPS) employment in accordance with artificial intelligence (AI) provides the solution for the problem of automation of sector in the industry. CPS is stated as "physical process integration with computer through infrastructures established for communication" [5], and it allows for adaptive monitoring and control of physical assets [6−8]. Future industrial automation systems (IAS) can efficiently control the real systems and automatically are well suited to the requirements of new customers by combining existing networking and AI capabilities, eliminating system engineers' knowledge and experience, and solely depending on analysis of environmental parameters. The architecture involving AI and digital twin (DT), which covered the entire essential components of DT fulfills multiple use cases in AI-enhanced IAS [9].

8.1.1 Objectives

AI was examined in general and also in relation to the automation in industrial processes in this survey, establishing framework for AI-enhanced IAS (Section 8.2). Thereafter, intelligent architecture for DT was derived, allowing this framework to be realized (Section 8.3). The roles of AI agents in application level and infrastructure level are discussed (Section 8.4). DT application and digital shadow in manufacturing are presented (Section 8.5). Section 8.6 concludes the chapter.

Digital Twin For Smart Manufacturing
DOI: https://doi.org/10.1016/B978-0-323-99205-3.00003-1

8.2 Artificial intelligence in industrial automation (IA)

8.2.1 Artificial intelligence

Intelligence is defined as the ability of human to act intellectually and logically bringing out a practical action for an unforeseen problem [10]. The process of human intelligence is represented in four steps. The first step represents the observing the information and perception of information. The second step involves analyzing and storing the information. Based upon second step, reasoning is the third step. Execution of reasoning is performed in the fourth step. Using subsequent history of already analyzed or otherwise information that is preprocessed helps in better decision-making during unforeseen problems, often termed as "Learning," which is a supplementary characteristic that enhances the performance without considering basic intelligence. Consequently, AI is the capability of an artificial system to perform accordingly to the unforeseen situations [11,12]. The technical transition of characteristics of intelligence, including watching or recognizing, analyzing, efficient decision-making, and indulging action, in software aiming to build a problem-solvable machine is known as AI. Modeling and simulation, recognition of patterns, system comprising knowledge, robotics, and machine learning are few well-known subfields within AI. General AI framework design for IAS is possible because of the robust parallels amid the features of AI systems and its subfields.

8.2.2 Industrial automation systems—an artificial intelligence framework

Fig. 8.1 shows the framework for IAS. The concept of framework based on the components of AI enhance traditional IAS through innovative interfaces. It is a software component that resides in CPS cyber part, internally or remotely over global area network. It uses data acquisition and information API to collect data from the IAS. Networking API provides more information by allowing access to entities, such as computers, representations of environment, people, through conventional interfaces among network. The process of intelligence is done within the AI component using the information supplied. The outcomes are sent to IAS through Feedback API, where they are processed. The Feedback API sends updated control code generated by the components of AI to the CU, for example. Eventually, the AI2AI API allows direct communication among components of AI, whether in the same domain or across domains. This facilitates knowledge-sharing and improves systems performance. The

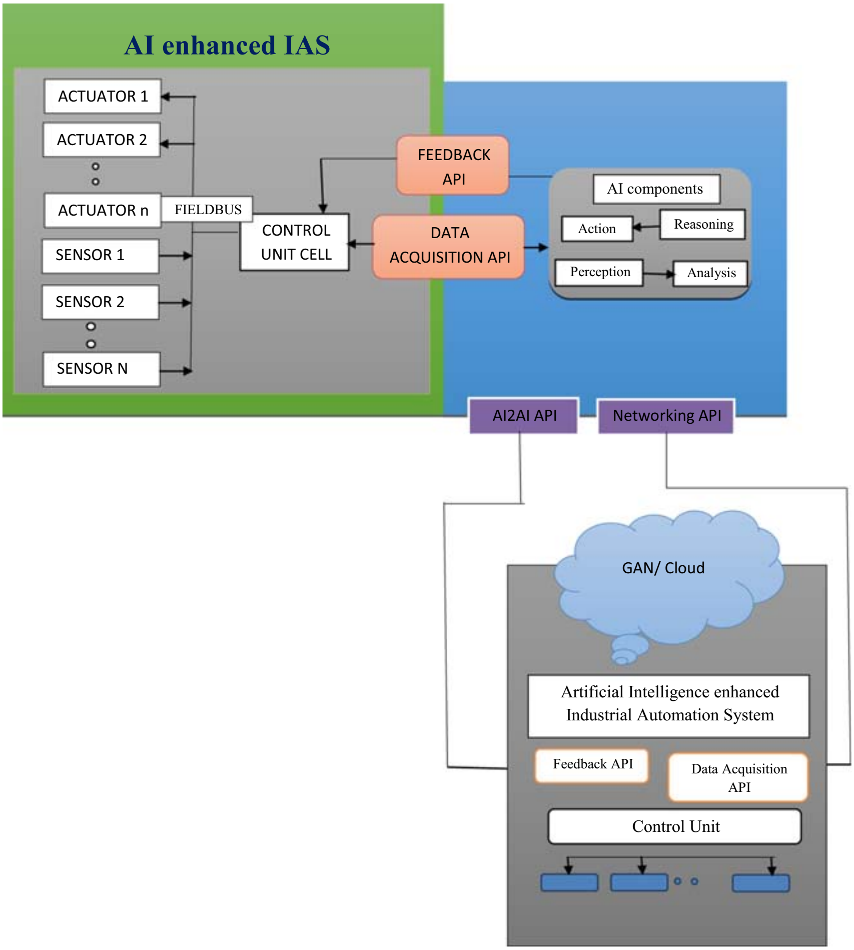


Figure 8.1 Artificial intelligence-augmented industrial automation system and its components and interfaces.

intelligent DT (IDT), which provides an existing notion and interface of framework for the deployment of AI features, can be used to achieve an AI-augmented IAS.

8.3 Digital twin with intelligence

DT is a "physical asset is represented virtually in a CPS performs matching its static and dynamic properties," according to the definition [13]. DT stores and maps numerous physical asset models, some of which are executable, known as simulation models. In this case, an asset represents future entity to be produced or an entity existing in real world [14]. IDT is an expansion of DT, comprising static and dynamic properties as well as the potential to watch, analyze, and learn from its physical environment, allowing existing models to change or enable the interaction of real assets and environment. As such, the architecture proposed [15] and represented in Fig. 8.2 is interpreted as a certain manifestation of AI-enhanced IAS framework specified in Section 8.2.2. IDT depends on representation of real asset model, just as the conventional DT. It also includes a model-management feature that allows users to access prior versions of the model developed during different stages of its lifecycle. A synchronization interface stays synchronized with potentially changing interdisciplinary models. The information about other DTs and their relationship to itself is subsequently added by a DT-2-DT relations component. An IDT, like a traditional DT, has a unique ID that allows the DT to be identified and addressed throughout its lifecycle, as well as organizational or technical specification component includes meta-data in real asset and a data acquisition interface that collects and stores real assets' operational data. IDT, on the other hand, includes numerous additional components

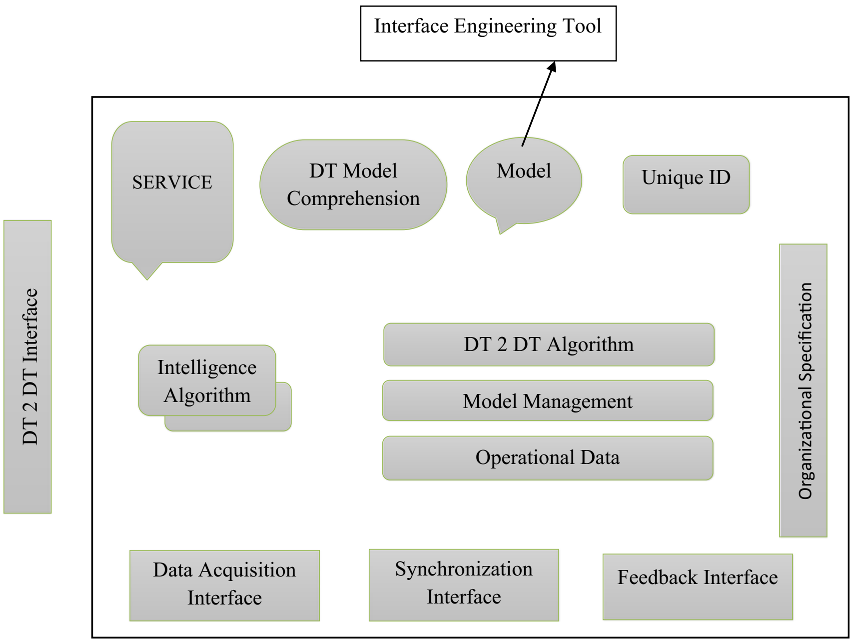


Figure 8.2 Architecture of intelligent digital twin.

that go behind traditional DT functions. A DT component addressing comprehension model enhances the capacity to comprehend and organizes data and models based on their semantic details. In addition, services supported by real asset are saved. Eventually, the information given by components discussed employs intelligent algorithms to bring out the functionality of AI, indicated in Section 8.2.1. Feedback interface transfers the results back to real asset using semantic technology. DT-2-DT-Interface finishes architecture by bringing out semantic interchange of data, models, or relations through communication with other IDT. The AI2AI API and Networking API of AI-enhanced IAS framework are combined in this interface.

8.3.1 Digital twin' intelligent integration with computing and networks

A brief outline on DT, its integration with underlying computing and network infrastructure, specifying challenges overcome by AI are discussed.

8.3.1.1 Digital twin

In Industry 4.0, a DT combines any industrial process using mechanisms for feedback involving closed loop. It generates physical items as digital reproductions usable in cyberspace, mimicking their actual counterparts' behaviors, and providing control feedback systems. The controlling of loop begins when physical object provides sensor data along with present state to digital duplicate, and loop ends delivering real-time directives back to the physical thing. Machines in industry are augmented with software capability objects with self-management skills with the ability to adhere to changes at a fast pace as a result. Cyber-physical integration carried in this way, resulting in a new set of tools for monitoring, controlling, and predicting actions, as well as correctly optimizing the factory floor. Domain specifying design, production, and health checks of system, DT for industrial applications outperform traditional systems. These enable stronger concert among the aspects of design together with manufacturing by simulating real-world industrial environment and making remote control operations and machine fault detection easier.

8.3.1.1.1 Challenge 1

Identifying the way of employing streams of data obtained in real time from sensors in DT to improvize maintenance and control of operations remotely.

8.3.1.2 Computing

Physical objects in Industry 4.0 are low in performance, restricted hardware, or hardware satisfying a particular activity. Software components of physical objects are now becoming functions of virtualization, which is modular in nature, its execution outsourcing to computing capable rich cloud resources, thanks to the development of virtualization. Cloud-based solutions were first used to execute such concepts [16], as they provided the elasticity and computational power required for supporting DT. Cloud service providers, on other hand, are unable to guarantee network performance between the actual object and its digital duplicate, which deteriorates as distance in network and number of cloud service providers within the network increase. This results in time-varying delay in network, unexpected jitter, limited capacity, and loss in data plague cloud-based DT. These flaws prohibit the cloud computing platform from fully supporting tasks that are sensitive to time, that is, tasks that act based on the time of completion, such as remote control performed in real time. Computing like edge computing and fog evolved as an enhanced capability of cloud computing to address its drawbacks. While edge computing uses static substrates to give computer capabilities near physical objects, fog computing incorporates volatile, limited resources that are mobile (which includes physical objects). DT offloads work that are time-sensitive in nature from physical device by utilizing edge and fog computing, which adds to further hardware cost reductions. Furthermore, new algorithms for effective data filtering can be employed with the goal of enhancing privacy and security [17], and data access is possible only in a trusted infrastructure of private nature. Near proximity, edge-based DT might exploit information of radio network to alter physical object operations or optimize resource allocation to improve the experience of users quality of experience (QoE).

8.3.1.2.1 Challenge 2

Assigning cloud computing resources for DT in the most efficient way to meet key performance indicators (KPIs) like network latency and security.

8.3.1.3 Networks

DTs' underlying network infrastructure is made up of a variety of dynamic and heterogeneous topologies. As illustrated in Fig. 8.3, it can be separated into three sections:

- Access ring
- Aggregation ring
- (Radio) access network ([R]AN)

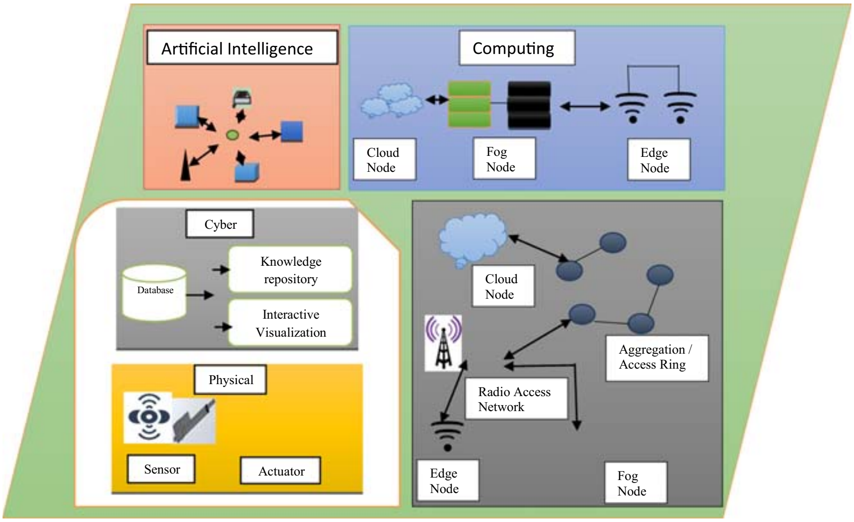


Figure 8.3 General concept for digital twin (DT).

Aggregation ring located away from physical objects uses connectivity that is wired to connect cloud-based DTs, which is ideal for bringing out human-scale services that are responsive in nature and delay-tolerant tasks. Access rings combine many (R)ANs and are closer to the physical items. The access rings locally exist, providing radio network information to edge-based DTs, which is helpful in performing time-critical operations (e.g., remote manipulation).

(R)AN is located near factory outlet and provides wired and wireless access to the actual objects. A variety of Radio Access Technologies (RATs) are present (e.g., WiFi, LTE, 5G), each with its own set of characteristics in terms of latency, range, data rate, power output, and scalability. Wired technologies is the technology that well-suits to meet DTs' communication needs. Wireless technologies are becoming more interesting in the (R)AN because of limitations in flexibility, mobility, and connections of high-density nature. The vital operations in industrial contexts, on the other hand, are vulnerable to radiofrequency interference. Therefore, RATs must be interference-free, operate on licensed bands, and provide a carefully controlled environment. 5G, according to Industry 4.0, is a crucial enabler for meeting the requirements needed for communication set forth by the DT [18], wherein using radio augmentation and slicing of the network as well as virtualization becomes the core feature. Simultaneously, WiFi 6E appears to be another possibility for Industry 4.0, with early studies demonstrating its capacity to withstand interference and noise while meeting the critical need for most use cases.

8.3.1.3.1 Challenge 3

Creating DT in such a way that it makes the best utilization of varied RAT resource while avoiding radio interference issues. To meet the problems mentioned above, DT must provide real-time and well-secured performance. Additionally, DT integration with network and computational infrastructure challenges should be addressed. AI agents are good candidates for dealing with such problems because they can use machine learning methods to utilize current data sources together, including information about the context at the application and infrastructure level.

8.4 Artificial intelligence agents—digital twin

When creating the in-network or on-device deployment methodologies, the pervasiveness of the cloud-to-things continuum was taken into account (i.e., fog, edge, and cloud). Additionally, AI agents with expertise in cloud area include computationally demanding learning using massive real-time data privately created by processes performed in the industry [19].

8.4.1 Enhancements in application

Agents of AI listed below specify various additions built on top of DT that improvise the robust and reliable nature of existing process while paving a path to new feature and capability that depends on automated-rich processes.

8.4.1.1 Movement prediction

Operating a physical object in remote via its digital counterpart over a wireless link can be subject to unpredictably significant jitter and packet loss due to radiofrequency interference. As a result, the remote operator suffers lagging behavior, which disrupts the physical object's real-time control and leads to a dangerous situation. It is going to take a system that can recover from such unpredictable behaviors while maintaining the remote control operational. In the event that movement commands are lost, AI stands out as a viable contender for forecasting future moves. In this context, movement prediction makes use of ML algorithm of time-series nature to predict future orders. To avoid packet loss and significant latency, movement prediction is implemented in fog, running when occurrence of failure happens, or at the edge, piggybacking predictions with each actual order.

8.4.1.2 Task learning

A few extremely complex and dynamic occupations in industrial environments that call for human presence and expertise persist. Traditional finite state machine-based agents cannot respond to unforeseen occurrences, such as the existence of unpredictable obstacles, making them unsuitable for automating such activities. Task learning AI agents based on IL and RL algorithms provide workable solutions, which help overcome such challenges because they are created to learn from and then interact with a dynamic environment. Initially, task learning is taught by trial and error observation of human-based procedures in a virtual environment facilitated by DT. The system's performance is next examined in simulated setting with unforeseen and random events. Finally, it is intended for its runtime deployment to support safe, dependable, and low-latency task execution (i.e., fog or edge) on the factory floor. Task learning, for instance, might introduce generalization and adaptation when driving a lift truck to carry packages. As a result, the DT can learn to react quickly when obstructions in the path are introduced, as well as changes in the shape or location of parcels. Risk reduction: Safety becomes more crucial in a DT design as remote control techniques become more widespread and physical devices become more autonomous. In situations where humans and machines work together, either of their failures could be dangerous. To identify and reduce unsafe situations, surveillance cameras on factory floors could be modified to do pattern recognition and image segmentation. In recent years, it has become clear that AI programs created utilizing CNN algorithms perform exceptionally well on computer vision tasks. CNN algorithms, which are used for risk reduction to analyze a video feed and find potentially hazardous scenarios. This gives DT the ability to stop or alter the real object's operation as a preventative measure. Deployment performed in runtime well-suits to the edge or, in situations with a higher degree of autonomy, the fog since fast countermeasures are required. A broadcast of live video, for example, can be used in risk mitigation to see a human operator who is dangerously close to an operating industrial machine and then utilize that knowledge to shut down the machinery.

8.4.1.3 Predictive maintenance

Compared to general-purpose systems, industrial physical objects are often held to higher standards of dependability and predictability. Emergency repairs and unplanned downtime because of some technical problems are key challenges for industrial companies. It is necessary to predict and categorize a component's future state to decide whether maintenance is necessary to prevent future failures. Both prediction and classification issues can be solved with great accuracy using ML-based methods. Consequently, a predictive maintenance AI agent that combines ARIMA, LSTM, LR, and SVM algorithms is a strong option for anticipating defects or repair needs. To schedule physical item maintenance, predictive maintenance first determines if the given sensor data could result in failure scenarios. This AI agent can be installed anywhere, from the edge to the cloud, because it is not doing time-sensitive activities. Predictive maintenance, such as LSTM, can estimate future vibrations and evaluate whether repair is necessary, for instance, if historical data demonstrates that strong vibrations occur when a screw breaks (e.g., SVM).

8.4.2 Infrastructure-related enhancements

The advancements in the computing and network domains that can affect and enhance the functioning of a DT are highlighted by the AI agents listed below.

8.4.2.1 Dynamic scaling

DT coexisting in smart factories under the same cloud-to-thing continuity is advantageous, thanks to recent advancements in virtualization technology. Appropriate resource scaling is necessary throughout the lifecycle of a given application to ensure if certain KPIs relating to DTs are met without degrading the performance of others. Such a topic is categorized as an NP-hard problem in the existing literature, which implies that under realistic runtimes, optimal scaling rules cannot be created. As a result, by applying algorithms based on RL, RT, RF, MLP, and BN, Markov decision process-based AI solutions can be used to create almost optimal scaling techniques in a reasonable amount of time. Dynamic scaling is achievable based on scaling policies developed with the aid of the aforementioned algorithms, which includes information about the use of resources, the time and date, the job, and the number of instances and sessions. Scaling decisions made through dynamic scaling can subsequently be used to satisfy KPIs and service level agreements. The ideal place for the runtime deployment of this AI agent is on the network side, depending on inference time and network latency to the orchestrator (i.e., edge or cloud). Dynamic scaling, for example, increases the virtual CPU (vCPU) allocation to the virtual object responsible for controlling a new robotic arm so that its processing time remains below a threshold when it is introduced to the production floor.

8.4.2.2 Privacy, security, and intrusion detection

The construction of a digital factory needs DTs in an industrial setting to distribute massive amounts of network traffic along the cloud-to-things continuum. For infrastructure operators and their tenants, this makes detecting and security breach and intrusion diagnosis exceedingly challenging and complex. An exhaustive study of all network data would take an inordinate amount of time, making early detection of attacks or security breaches impossible. K-means, autoencoders, and PCA are examples of machine learning algorithms that are great for reducing traffic volume and accelerating traffic inspection. In privacy, security, and intrusion detection, these algorithms are used to spot fraudulent communication to prevent remote control of actual objects through their digital counterparts. Additionally, federated learning and transfer learning seem to be machine learning strategies, which provide group training to many industry players while protecting the location and privacy of private data due to the training data not being centralized. Depending on whether or not there is a need for on-site security measures, both the edge and the cloud are suitable deployment places for AI agents.

8.4.2.3 Heterogeneous network selection

The challenge of having the best connection arises in an industrial setting with multiple RATs, which directly affects the structure and operation of DTs. In the past, network infrastructure-generated rules were used with specialized subject knowledge and experience to accomplish RAT selection. On the other hand, it can be challenging to apply this kind of RAT selection to DTs in dynamic and heterogeneous industrial settings. It indicates that a heterogeneous network (HetNet) selection AI agent that uses machine learning techniques (such RL, ANN, and fuzzy logic) can help with the aforementioned problems. It selects the appropriate RAT and, if applicable, the optimal handover candidate for each physical object on the manufacturing floor using relevant information for local radio context. The European Telecommunications Standards Institute (ETSI) has defined multi-access edge computing, and a number of radio information services, including WLAN access information service and radio network information service, that provide radio context information [20]. With the aid of this data, HetNet selection may anticipate when an AGV, for instance, will lose protection and its connection to the attachment point. The DT can make use of this data to instruct the AGV to adjust its RAT for smoother movement throughout the factory floor and both its connection to the attachment point and protection will be lost. This AI agent should be installed at the edge or in the fog because it depends on locally accessible data.

8.5 Digital twin for smart manufacturing

It is crucial to remember that DTs are more than simply data; they also contain models and algorithms that guarantee the highest level of agreement between the real and virtual worlds and allow decisions (feedback) to be made on the actual system after the fact. Additionally, prognostics, diagnostics, monitoring, and control can be performed on a DT [21]. An example model for the DT was put forth by Lu et al. [22]. It is made up of three parts: (1) actual (physical), (2) virtual (digital), and (3) two-way communication, which are used to represent their dynamic mapping, i.e., information flow from virtual space to real space and data flow from virtual space to virtual space.

According to ISO/DIS 23247-1 [14] a dynamic depiction of manufacturing components, such as persons, goods, resources, and process definitions, known as a "digital twin" changes and progresses in step with its real-world counterpart [23]. The three main types of DTs are thus highlighted [24]: twins for goods, twins for equipment, and twins for production techniques. To connect the product design and production processes, a DT of the process is required [24,25]. The DT of a manufacturing process, also known as the DT for factories, is required to operate as a complex system with multiple synchronized subsystems.

It might include every DT involved in that procedure, including those of the product, the physical resources, and the labor force of the manufacturing line under discussion [26]. The physical space receives real-time controlling instructions to improve process administration, support decision-making for system design and solution evaluation [27], etc. The digital shadow, which duplicates and models real processes to nearly reflect reality as possible is a prerequisite for DT [28].

8.5.1 Digital shadow for smart manufacturing

It may incorporate all DTs involved with the specific process, including those of the discussed production line's physical resources, labor force, and product. The physical space receives real-time controlling instructions to improve process administration, support decision-making for system design and solution evaluation, etc. The digital shadow, which duplicates and models real processes to as nearly reflect reality as possible, is a prerequisite for the DT.

When the condition of the real thing changes, the digital object also does. One may use DT, where digital objects create feedback for the control of the physical object, as an example of how the data flows are fully integrated for both directions [29]. A DT, then, is made up of all data obtained through engineering modeling activities (digital model) and operational information collected during actual activities (digital shadow).

Every manufactured item or component creates a data profile with a digital shadow. This data profile consists of process data, operation and condition data, etc. Thanks to an extensive database, the production system may be accurately and in real time represented digitally. The digital shadow creates a database for the optimization and communicates in real-time with the manufacturing system [30]. Algorithms for data collecting, analysis, evaluation, and consolidation were used to develop this database. The digital shadow created a common platform that combines data from various sources and stores it, allowing data to be linked to the proper context [31].

The digital shadow's main goal is to deliver the required information at the appropriate time and location. A gap will form between the digital factory and a complete digital image of the production without a digital shadow [32]. Since the digital shadow "is needed in application of techniques and data analysis model and assessment in industrial context" [33], it is accepted that it is necessary. The significance of the digital shadow becomes crucial because a strong digital shadow lays the groundwork for extensively investigating industrial processes, especially for complicated or enormous data.

8.6 Conclusion

This study presents a futuristic vision for industrial automation systems incorporating AI algorithms. As a result, the framework for intelligent IAS fulfills four characteristics. Features include information observation and perception, analysis and information storage, reasoning carried out on outcome analysis, and execution of logic results. As a result, the architecture for IDT presented was capable of realizing AI components' personalities in the framework. The significant functionality of AI in overcoming the issues and challenges in Industry 4.0, particularly dealing with DT, is presented. AI agents for DT for application level and infrastructure level are presented. The authors in future work should consider the integration of the architecture of IDT together with the cloud technology, which is important in realizing a DT-2-DT interface.

References

[1] G. (Jason) Liu, R. Shah, R.G. Schroeder, The relationships among functional integration, mass customisation, and firm performance, Int. J. Prod. Res. 50 (3) (2012) 677−690.
[2] C.W.L.L. Hart, Mass customization: conceptual underpinnings, opportunities and limits, Int. J. Serv. Ind. Manag. 6 (2) (1995) 36−45.
[3] P. Marks, Q. Yu, M. Weyrich, Survey on flexibility and changeability indicators of automated manufacturing systems. In: Proc. of the IEEE 23rd International Conference on Emerging Technologies and Factory Automation (ETFA), 2018 pp. 516−523.
[4] M. Moghaddam, M.N. Cadavid, C.R. Kenley, A.V. Deshmukh, Reference architectures for smart manufacturing: a critical reviewOct J. Manuf. Syst. 49 (2018) 215−225.
[5] E.A. Lee, Cyber physical systems: design challenges. In: Proc. of the 11th IEEE International Symposium on Object and Component-Oriented Real-Time Distributed Computing (ISORC), 2008, pp. 363−369.
[6] P. Hehenberger, B. Vogel-Heuser, D. Bradley, B. Eynard, T. Tomiyama, S. Achiche, Design, modelling, simulation and integration of cyber physical systems: methods and applications, Comput. Ind. 82 (Oct. 2016) 273−289.
[7] N. Jazdi, Cyber physical systems in the context of industry 4.0. In: Proc. of the IEEE International Conference on Automation, IEEE, 2014, pp. 1−4.
[8] M. Weyrich et al., "Evaluation model for assessment of cyber-physical production systems," 2017, 169−199.
[9] B. Ashtari Talkhestani, et al., An architecture of an intelligent digital twin in a cyber-physical production system, Automatisierungstechnik 67 (9) (2019) 762−782.
[10] S. Legg, M. Hutter, A collection of definitions of intelligence − frontiers in artificial intelligence and applications, Advances in Artificial General Intelligence: Concepts, Architectures and Algorithms, IOS Press, 2007.
[11] G. Robinson, Artificial intelligence and natural man by Margaret A. Boden, Philosophy 54 (207) (1979) 130−132.
[12] E. Rich, K. Knight, Artificial Intelligence, 1, McGraw-Hill, 1994.
[13] B. Ashtari Talkhestani, W. Schlögl, M. Weyrich, Synchronisierung von digitalen Modellen, atp magazin 59 (2017) 62−69.
[14] B. Ashtari Talkhestani, N. Jazdi, W. Schlögl, M. Weyrich, A concept in synchronization of virtual production system with real factory based on anchorpoint method, Proc. CIRP 67 (2018) 13−17.

[15] B. Ashtari Talkhestani, N. Jazdi, W. Schloegl, M. Weyrich, Consistency check to synchronize the digital twin of manufacturing automation based on anchor points, Proc. CIRP 72 (2018) 159–164.
[16] K. Borodulin, et al., Towards digital twins cloud platform: microservices and computational workflows to rule a smart factory, Proc. 10th Int'l. Conf. Utility Cloud Comput. (2017). New York, NY.
[17] M. De Donno, et al., Cyber-storms come from clouds: security of cloud computing in the IoT Era, Future Internet 11 (6) (2019).
[18] L. Girletti, et al., An intelligent edge-based digital twin for robotics, IEEE GLOBECOM Wksp. Adv. Tech. 5G Plus (2020). Taipei, Taiwan, Dec.
[19] M.Z. Alom, et al., A state-of-the-art survey on deep learningtheory and architectures, Electronics 8 (3) (2019).
[20] ETSI, Multi-access Mobile edge computing (MEC); framework and reference architecture, Group Spec. 003 v2.2.1, December (2020).
[21] B. Schleich, N. Anwer, L. Mathieu, S. Wartzack, Shaping the digital twin for design and production engineering, CIRP Ann. 66 (1) (2017) 141–144.
[22] Y. Lu, C. Liu, I. Kevin, K. Wang, H. Huang, X. Xu, Digital twin-driven smart manufacturing: connotation, reference model, applications and research issues, Robot. Comput. Integr. Manuf. 61 (2020) 101837.
[23] ISO DIS23247-1, Automation systems and integration – Digital Twin framework for manufacturing – Part 1: overview and general principles (under development), 2019.
[24] J. Bao, D. Guo, J. Li, J. Zhang, The modelling and operations for the digital twin in the context of manufacturing, Enterp. Inf. Syst. 13 (4) (2019) 534–556.
[25] C. Zhuang, J. Gong, J. Liu, Digital twin-based assembly data management and process traceability for complex products, J. Manuf. Syst. (2020). In press.
[26] K. Schützer, J. de Andrade Bertazzi, C. Sallati, R. Anderl, E. Zancul, Contribution to the development of a Digital Twin based on product lifecycle to support the manufacturing process, Procedia CIRP 84 (2019) 82–87.
[27] H. Zhang, Q. Liu, X. Chen, D. Zhang, J. Leng, A digital twin-based approach for designing and multi-objective optimization of hollow glass production line, IEEE Access. 5 (2017) 26901–26911.
[28] T. Bauernhansl, Krüger, G. Schuh, WGP-standpunkt industrie 4.0. German Academic Society for Production Engineering (2016). Available from: https://wgp.de/wp-content/uploads/FINAL_WGP_Standpunkt_2025.pdf.
[29] W. Kritzinger, M. Karner, G. Traar, J. Henjes, W. Sihn, Digital Twin in manufacturing: a categorical literature review and classification, IFAC-PapersOnLine 51 (11) (2018) 1016–1022.
[30] T.H.J. Uhlemann, C. Lehmann, R. Steinhilper, The digital twin: realizing the cyber-physical production system for industry 4.0, Procedia CIRP 61 (2017) 335–340.
[31] G. Schuh, P. Jussen, T. Harland, The digital shadow of services: a reference model for comprehensive data collection in MRO services of machine manufacturers, Procedia CIRP 73 (2018) 271–277.
[32] M. Landherr, U. Schneider, T. Bauernhansl, The application center industrie 4.0-industry-driven manufacturing, research and development, Procedia CIRP 57 (2016) 26–31.
[33] G. Schuh, C. Kelzenberg, J. Wiese, T. Ochel, Data structure of the digital shadow for systematic knowledge management systems in single and small batch production, Procedia CIRP 84 (10) (2019) 94–100.

This page intentionally left blank

CHAPTER 9

Digital twin technologies for automated vehicles in smart healthcare systems

R. Indrakumari[1], T. Poongodi[1], Shrddha Sagar[1] and Vijayalakshmi[2]
[1]School of Computing Science and Engineering, Galgotias University, Greater Noida, Uttar Pradesh, India
[2]Department of Data Science CHRIST (deemed to be University), Lavasa, Maharashtra, India

9.1 Introduction

IR 4.0, which refers to the 4th industrial revolution, is to track and control machinery and equipment in real-time by locating sensors during the production process and seek control over the whole value chain of the product lifecycle, hence improving quality. It helps in reducing and even eliminating downtime, since the data obtained from the equipment informs when the machine requires maintenance or when the machine is going to breakdown and, therefore, improves quality the quality of the product. The manufacturing industries are rapidly changing to make the manufacturing process more agile, flexible, and noticeable to customers.

Industry 4.0 is an initial stage in the industrial revolution that concentrates on machine learning, interlinkage, real-time data, and robotization. Industry 4.0 or smart manufacturing is a new technique that connects physical objects to digital information to generate a smart ecosystem for organizations that have a focus on production. In every company, the operating procedure is different and requires a real-time connection with people, partners, and processes. Hence, industry 4.0 plays a significant role in this situation. It is not a technology to improve manufacture, but it has the potential to revolutionize the entire manufacturing business. Industry 4.0 gives importance to the use of digital technology and the Internet of Things (IoT) to access real-time data. It offers a holistic and comprehensive approach to the production business [1]. It interlinked physical objects to digital technology for better collaboration and also has access to partners, products, and vendors.

Digital Twin For Smart Manufacturing
DOI: https://doi.org/10.1016/B978-0-323-99205-3.00008-0

Connected and automated vehicles (CAVs) will become a critical aspect of future urban transportation as vehicle automation and artificial intelligence (AI) increase. Several companies, as well as government organizations, colleges, and others, have begun investigating the technologies' possible applications and benefits [2]. One of the businesses that could profit from CAV is healthcare. The human aspect in the automated vehicle (AV) system, to be precise—whether as a passenger in fully self-driving cars or as a driver in the early stages of the technology. The healthcare industry now has a big opportunity to contribute to the CAV debate.

While some people are concerned that autonomous vehicles would harm human health, others are optimistic. While others have expressed optimism by pushing more automobile journeys rather than more active modes of transportation like walking and biking. By tracking our health metrics on the road via passive health monitoring equipment, AVs have the potential to improve human health. This could assist diagnose both acute and long-term illnesses by providing a frequent, likely daily, update on important health markers, like early warning of a heart attack or asthma attack while driving, for example. As biosensors grow more common, the act of measuring health indicators and vital signs will become more convenient, mobile, and cost-effective, remote diagnosis and AI are becoming increasingly advanced. In this chapter, we narrate the convergence of Industry 4.0 with AVs in healthcare applications.

9.2 Autonomous vehicles

Fully autonomous vehicles are unlikely to be commercially available before 2020, according to a McKinsey & Company's analysis. Because these technologies are ready, researchers may assist the industry in increasing production and generating greater advantages.

The adoption of AVs in the industrial sector has the potential to address the majority of technical difficulties in the following areas [3]:

Economical: Energy such as electricity, rather than conventional fuels, can lower production costs and improve efficiency. Unmanned approaches can also help firms save money on their payments.

Digital conversion: Using cloud computing to handle massive data recorded by AV sensors allows manufacturers to keep track of all information and stay on top of current events.

Vulnerability: The vehicle's safety is ensured by a real-time tracking and monitoring system. Human interaction is avoided, resulting in improved technological acceptance and a long-term client connection.

Scalable: More partners in this ecosystem increase resilience and reduce the danger of reliance on a single component, allowing for continual investment at various levels and making the market more competitive.

Eco-friendly: The decrease in waste/pollution emission preserves the living environment and increases residents' contentment. Clean energy also helps complete the supply chain by contributing to the whole manufacturing lifecycle

9.2.1 How automated vehicles can make the healthcare industry safer

According to research conducted by the Centre for Automotive Research, automated driving technology can benefit the healthcare business in a variety of ways [4].

9.2.1.1 Increased passenger and vehicle safety

Human error is responsible for nearly 94% of all motor vehicle collisions, as per the National Highway Traffic Safety Administration (NHTSA). AVs have the potential to increase driving safety and by eliminating the human error component that causes crashes and deploying superior divining technologies, we can reduce the number and severity of crashes. Given the rising concern over distracted driving and DUI-related fatalities, as well as the increasing number of elderly drivers, automated driving systems have the capability to make the future a lot safer for everyone on the road

9.2.1.2 Monitoring the health

While some people are concerned that AVs would harm human health, others are optimistic. While few have expressed optimism by pushing more automobile journeys rather than more active modes of transportation like walking and biking. By tracking our health metrics on the road via passive health monitoring equipment, AVs have the potential to improve human health. This could assist diagnose both acute and long-term illnesses by providing a frequent, likely daily, update on important health markers, like early warning of a heart attack or asthma attack while driving, for example. As biosensors grow more common, the act of measuring health indicators and vital signs will become more convenient, mobile, and cost-effective, and remote diagnosis and AI are becoming increasingly advanced.

9.2.1.3 Improved emergency response times

The passenger monitoring system can send a notification to the person to seek help if there is evidence of an emergency (through means of biosensors or other methods). If the occupant of the vehicle is not alert or responsive to the warnings, the vehicle can quickly transmit the information to emergency response centers and pull over to the side of the road to await an ambulance. In an emergency, precise location data from the vehicle's GPS will aid first responders in locating the vehicle more quickly and conveniently.

9.2.1.4 Senior and persons with impairments can move about with ease

With the world's population aging rapidly, AVs will be able to give older citizens and people with disabilities with 24-hour mobility services, allowing them to maintain their independence while attending appointments. Previously, it was established that preventative treatment had therapeutic as well as economic benefits in lowering the need for emergency medical care.

9.2.1.5 Mobility

Finally, AV technology innovators promise to offer a new mode of transportation for people and products that will revolutionize how people travel. For healthcare providers, this mobility change can take numerous forms, including an on-demand automated shuttle to hospitals (employees and patients), a mobile office offering on-demand health services, such as vital monitoring, blood testing, and nurse consultations. The developments mentioned above have a lot of potential in terms of bridging the gap between increasing vehicle technology and healthcare demands. Coordination between advanced driving technology businesses and healthcare providers could increase the use of sensors and AI data-mining approaches. It could also help professionals get regular access to patient health data, allowing them to treat patients with chronic diseases, including high blood pressure, diabetes, and cardiovascular issues, required to be monitored more closely. Medical sensor applications in autos are a rapidly increasing research and development issue with a variety of study and application options.

9.2.2 Self-driving vehicles in the healthcare sector

Presently available mobility technologies also have some challenging issues. Analysts predict that plug-in electric vehicles will account for 10%

of light-duty vehicle sales in the United States by 2025, with even faster adoption due to lower battery cost, global regulatory reforms, and the interactions among electric drivetrains and autonomous driving systems [5]. A combination of with fully integrated mobility networks that permit multimodal trips and encourage active modes of transit results in the reduction of several chronic health issues like asthma, obesity, and hypertension. The potential of converging patient illnesses and care demands resulted in decreased illness. Moreover, due to pollution, health systems should plan in different perspectives from the respiratory specialists required for oncology investments. However, the health system carrying financial risk for the entire cost of care would profit financially from decreased illness incidence, as there would be less need for trauma care due to fewer projected accidents.

Patient no-shows, with missed appointment rates ranging from 18% to more than 30% in several large clinics, pose a financial burden thereby reducing efficiency. Transportation is sometimes a major impediment to accessing care, particularly for chronic diseases that necessitate regular appointments. Collectively, these studies suggest that lack of transportation may be related to lack of regular medical attention, less healthcare resource utilization, and missed medical appointments, especially for persons below poverty line. Healthcare systems or emerging players could use the power of AVs and connected vehicle infrastructure to develop mobile care units that maximize health professional activities, transporting nurses, physicians, and others to patient homes or remote care sites.

Vehicle interiors may now use emerging technologies like additive manufacturing, virtual reality, and augmented reality to produce highly optimized autonomous mobile care units to accomplish tasks that were previously performed in hospitals. For example, 3D printing a personalized cast for a fractured bone on the spot, performing vital checks, or consulting with medical experts. Few design companies have indeed introduced autonomous ambulance prototypes that "virtually locate an emergency physician with paramedics and Emergency Medical Technicians (EMTs)." And, using analytics the location of the complete self-driving fleet could be optimized throughout the day. Healthcare systems in the upcoming years will be promoting greater mobility access, better coordinating treatment, and providing essential services. Patient satisfaction would almost certainly improve, perhaps leading to greater experience scores and, as a result, not only higher performance payments but also a potentially improved brand in the marketplace.

9.3 Industry 4.0 in the healthcare industry

Industry 4.0 is an extensively used paradigm that satisfies various requirements in the healthcare domain using highly customized innovative techniques. It facilitates the complete remote monitoring system and satisfies the requirement of an individual by optimizing cost and time [6]. Industry 4.0 accomplishes different functionalities and it would be beneficial for individuals since it resolves numerous medical issues. Moreover, it provides a highly flexible intelligent system that can be customized according to the requirement of individual patients. It completely satisfies the demands such as glucose level detection, bioelectronic medicines, next-generation inhaler, and electronic-based testing [7]. It affords more flexibility in designing and manufacturing, wherein the system can be digitally controlled. Industry 4.0 is capable of performing the below-mentioned functionalities in the medical domain:

- Improves productivity and accuracy
- Enhances quality
- Provides digital storage of medical data to create awareness about the next stage of diseases
- Offers efficient medical data analysis with various medical technologies
- Minimizes inventory by saving patient details in the digital format (computer-aided design file)
- Improves tool and material management
- Manufactures customized implantable devices using smart components
- Tracks new diseases by exploiting digital technologies and sensor systems
- Determines relevant information according to the patient data which are identified
- Facilitates centralized system in the hospital premises
- Harnesses right control strategies for intricate surgeries
- Minimizes cost and time

9.4 Significant technologies related to Industry 4.0 in the healthcare sector

Industry 4.0 promotes digitization using various technologies that provide timely data, satisfaction, and safety to patients. Some of the significant technologies used in the healthcare sector are described further.

9.4.1 Internet of Things in Healthcare 4.0

Recently, the IoT has created several possibilities in the medical domain by connecting a number medical devices via the Internet and gathering valuable information by providing control of the patient treatment process. Moreover, it assists in remote monitoring of the treatment and testing, which provides patient satisfaction. Wireless Body Area Network (WBAN) is built by attaching or implanting the sensors and actuators in the human body [8]. Healthcare has been viewed as an attractive domain for IoT applications and the paradigm reshaped the healthcare domain from both social and economic perspectives using promising technologies. It significantly decreases the healthcare costs with better outcomes, although it requires behavioral changes in different stakeholders involved in the healthcare system. The performance upgradation with wireless technologies promotes remote real-time monitoring of different physiological parameters, permits early diagnosis of diseases, manages medical emergencies, and simplifies the care-taking process of various chronic diseases. Moreover, sensors, diagnostics, and medical devices play a significant role in leveraging IoT in the healthcare sector. In IoT-enabled scenarios, smart objects are interconnected to acquire knowledge about the environment and users to make an efficient decisions [9]. Mass flow and pressure sensors are utilized in the medical domain based on the requirement during surgery. Sensors give information about the blood pressure, temperature, etc., of the patient. The different IoT paradigms in the healthcare sector are described below:

1. The Wearable IoT follows the telehealth ecosystem to deal with automated interventions. WIoT facilitates consistent monitoring data, such as wellness, behaviors, and habits by associating patients with medical centers for enriching individual everyday life [10].
2. The Internet of Health Things system is built by interconnecting wearables, mobile applications, and other smart objects, and leverages professionally graded active sensor devices [11].
3. The Internet of Medical Things comprises applications that contain wearable and implantable devices that can be fixed to a smartwatch or a smartphone and it acts like a personal hub [12].
4. The Internet of Mobile-Health Things (m-IoT) evolves 4G networks. It affords a connectivity model among Low power Wireless Personal Area Networks, which emphasizes intrinsic features for the participating entities worldwide [13].

5. The Internet of Nano Things applications implement diagnostic processes, personalized monitoring, proactive monitoring, chronic disease management, etc., in the nanoscience domain [14].

It is interesting to evaluate IoT as an inevitable and global network that supports and supports the functionality of physical world integration. This is achieved by gathering, analyzing, and evaluating IoT sensor-generated data that will be present in all things and incorporated into the public communication network. Many estimates expect a sudden rise in the number of connected devices to 50 billion in 2020 [15]. All across history, the globe has seen numerous technological revolutions. The first version of the industrial revolution was the mechanization of manufacturing by utilizing water and steam power; the second industrial revolution, using electric power, announced mass production; and the third industrial revolution, using electronics and IT to automate the production process in future [16].

Technological advancements in ITCs in recent years have produced a range of resources that have changed lives, such as the Internet, robots, drones, IoT, and so on. In addition, things connect on a worldwide network: the Internet. Indeed, this pattern will also make its way throughout industrial manufacturing, which will gradually benefit from developments in ICT and computer science [17]. The introduction into the manufacturing environment of IoT and services is ushering in a fourth revolution in the industry: Industry 4.0. This new kind of sector is based on the smart enterprise model, that is, factory smart [18].

IoT is a modern idea in the current world of wireless telecommunications that is rapidly gaining ground. The definition is the pervasive existence of diversified objects or things around. For example, products such as tags for radio frequency (RFID), sensors, actuators, handsets, etc. They can connect and work with their neighbors to achieve mutual goals through specific management systems. The key strength of the IoT definition is its strong effect on different aspects of daily life and the actions of future users [19]. Moreover, cloud computing can support the virtual infrastructure for utility computing that integrates control and storage devices, analytics software, visualization systems, and customer distribution. The framework consists of services that are commodities and distributed in this manner. A cost-based framework was proposed by researchers for cloud computing that would allow businesses and consumers to access apps from anywhere by offering end-to-end services [20].

The IoT, an evolving global technological infrastructure based on the Internet that enables the exchange of goods and services within global supply chain networks, influences the protection and privacy of the stakeholders involved. Measures that guarantee the resilience of the architecture to attacks and data are essential to be established for authentication, access control, and customer privacy.

Various fields of the applications that are affected by the Internet are divided based on the capacity, coverage, size, heterogeneity of the network, and more. The four areas of applications are personal and home, enterprise, public service, and mobile (Fig. 9.1).

To attack and maintain the consistency of the data, the resilience of the architecture to attacks and data it is significant to create authentication, access control, and consumer privacy. The new concepts and technologies are known to be blockchain and the IoT. These innovations are rapidly being embraced by companies for groundbreaking business results. Building trust without the intervention of third-party entities in distributed environments is a technical development that is likely to promote many sectors, including IoT [21].

At present, not only traditional computers are connected to the Internet but also a large heterogeneity of devices, such as TVs, computers, equipment, vehicles, people, electrical appliances, smartphones, etc. Moreover, more than 50 billion devices will be connected to the Internet

Figure 9.1 Internet of Things application-based classifications.

by 2021, according to estimates. Although IoT can provide us with useful advantages, the possibility of experiencing different security and privacy threats is also increased; in such cases, few threats are newly identified.

Before the advent of IoT, the most reported security threats were information leakage and Denial of Service, but with the IoT, security threats went far beyond these. In general, huge amount of personal information is exchanged and transmitted among connected devices in an IoT network, which poses privacy concerns as well as issues. Security solutions that could afford high standards of protection for different kinds of devices are in demand and require a mechanism that can perform auditing in such an environment.

9.4.2 Big data analytics in Healthcare 4.0

Extensive analysis using big data techniques provides more life-protecting outcomes. Moreover, doctors have to understand historical information of the patient to afford better treatment, hence this technology provides useful information to identify the sign of sickness. Big data techniques play a significant role in Healthcare 4.0 applications, for instance, social media reshapes the interaction strategies for obtaining health-related information, sharing medical data, and reviewing medical records. Hence, accessing social networking websites, online forums, and social media sources resulted in providing valuable information and it dramatically changes the medicine practice [22]. Stream data processing systems monitor patients in real time and generate a massive amount of structured and unstructured data rapidly promoting substantial market penetration of sensors, personal devices, and wireless communication technologies [23].

The records used to maintain clinical information obtained from images, medical tests, and descriptions are Personal Health Records (PHR), Electronic Medical Records (EMR), and Electronic Health Records (EHR). PHR helps in managing chronic diseases, promotes health maintenance, and manages health-related information. EMR maintains real-time data and supports clinicians in making efficient decisions. EHR takes care of health records retrieved from multiple organizations. A huge amount of biological data, which includes proteomics, metabolomics, microbiomics, genomics, transcriptomics, and epigenomics are gathered on an unprecedented scale. Furthermore, the data can be categorized into patient-level, tissue-level, molecular-level, and population data.

Some of the significant roles of Industry 4.0 in the healthcare sector are depicted in Fig. 9.2, (Table 9.1).

9.4.3 Various applications of Healthcare 4.0

The significant applications of Healthcare 4.0 are depicted in Fig. 9.2.

9.4.3.1 Monitoring physiological data

The remote monitoring system consists of three major components: (1) sense and gather data according to the movement, (2) relay data using communication technologies to a datacenter, and (3) analyze data to acquire relevant clinical information. Advanced medical sensors, such as gyroscopes, accelerometers, humidity, temperature, blood pressure, glucose, ECG, and gas facilitate persistent remote monitoring of a patient's physiological conditions [24]. Data is transmitted from IoT devices to remote data centers and leverages reliable services, scalable processing, and infinite storage with cloud computing. Moreover, reliable network connectivity is required to store, process, and retrieve medical records.

9.4.3.2 Smart pharmaceuticals and tracking medications

Medication noncompliance is one of the common issues among chronically ill people, elderly, and cognitively disabled persons. Tracking systems

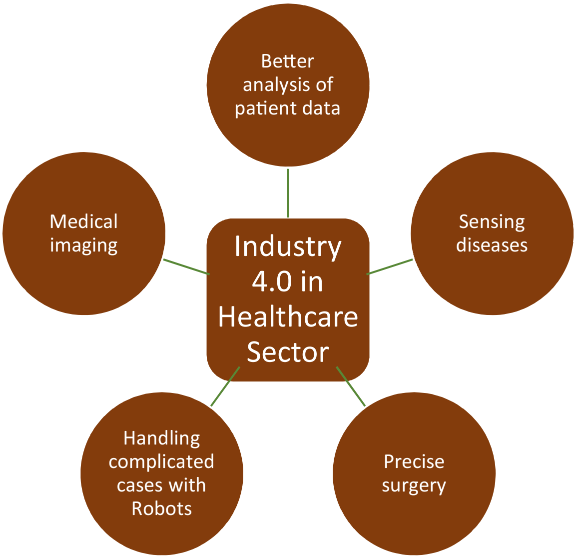


Figure 9.2 Influence of Industry 4.0 in the healthcare sector.

Table 9.1 Industry 4.0 technologies and its applications in healthcare.

Technology	Potential applications in healthcare
IoT	Integrates health issues and medicine supplies through traceability, drug distribution
Big Data	Cross-referencing of data for disease diagnosis, specific treatment according to disease characteristics
Cloud Computing	Integrates database, which holds patient data and healthcare services by creating applications
Artificial Intelligence, Machine Learning, and Deep Learning	Disease detection, treatment identification, behavioral analysis, decision-making, prediction, and equipment maintenance
Blockchain	Maximizes security and reliability and minimizes bureaucracy
3D Printing	Printing of tissues, organs, implants, medications, etc.
Augmented Reality	Provides better training to healthcare professionals. Agile in new technological implementation.
Autonomous Vehicles	Informing local traffic regarding ambulance priority
Autonomous and Collaborative Robots	Elderly care, robotic surgery, rehabilitation assistance, treatment, surgery, telemedicine, etc.

are effective tools for clinicians to assess the treatment efficacy with the quantitative data for managing diseases. Nowadays, healthcare applications are available to remind about the prescription, scheduling, and tracking intake of medicines. Hence, it promotes timely drug delivery in the treatment process by reducing adverse effects and optimizing effectiveness. Early prototypes supported elderly people by integrating RFID and sensor networks. The advanced techniques with ingestible or wearable sensors along with IoT techniques in the smart pharmaceuticals permit communication via wireless connection for compiling, storing, and analyzing the data.

9.4.3.3 Self-management and prevention of chronic diseases

Big data technologies significantly provide solutions by shifting from the curing stage to the prevention of diseases. Currently, the research is focused on designing intelligent systems by providing effective feedback to patients. Algorithms are devised for preventing diseases by designing interventions to handle behavioral changes and by recognizing mutable risk factors [25]. Empowering and educating fitness exercises and good nutritional habits assist in preventing obesity and diabetes [26].

9.4.3.4 Personalized healthcare

It is completely dependent on the patient to make specific decisions, hence it is meant to be user-centric. Collecting data from different heterogeneous sources is extremely difficult, thus data analysis enables efficient healthcare decision-making. The sources can be implantable (both micro and nano)sensors, wearable sensors, therapy delivery equipment, such as defibrillator vests, insulin pumps, fall detectors, etc. In Healthcare 4.0, the biology of an individual permits achieving high impact on screening, prognosis, screening, surveillance, and pharmacogenomics [27].

9.4.3.5 Rehabilitation

It is anticipated to improve people's quality of life and enable substantial cost savings for healthcare services. WBAN technologies facilitate continuous tracking of the physical movement of a patient with the rehabilitation practices. Moreover, rehabilitation is commonly characterized by various constraints and solutions and involves real-time feedback, virtual reality integration, and data fusion. With immediate responses, the patients can control and change their physiological activities to improve their performance and health.

9.4.3.6 Assisted living

Elderly persons and individuals suffering from chronic diseases can avoid visiting hospitals; they can have treatment by staying at home, known as enhanced living environments (Fig. 9.3).

9.5 Cloud computing

The term "cloud computing" refers to a computing paradigm that allows performing cloud computing activities. "Utility Computing" refers to on-demand hiring of computing resources (processing power, storage, and associated networking components) with little or no interaction with the supplier. The cloud simplifies operations since it eliminates the need for rigorous resource dimensioning and planning, allowing for short-term

Figure 9.3 Significant applications in Healthcare 4.0.

pay-per-use pricing without the user's immediate commitment [28]. Furthermore, cloud customers benefit from seemingly limitless on-demand infrastructure, which they can either exploit or sell as a service: the most well-known platforms are infrastructure, portal, and software as a service application (IaaS, PaaS, and SaaS, respectively).

In particular, cloud is important to fulfilling several IoT requirements, to the degree according to some views, it is planned as one of the higher levels of the IoT. A trend that began in the last decade is driving the present move to cloud services: that is, the addition of new capabilities to field equipment, giving them additional intelligence and flexibility, allowing some functions to be moved to the cloud, improving scalability and responsiveness (and, in the end, cost savings).

Although there are certain problems in the cloud computing paradigm, communication among the end system and the datacenter, hosting the data center has grown apparent over time, especially concerning cloud services that include expense, bandwidth, latency, and availability, which all contribute to limiting a variety of cloud computing applications. This has increased the growth of universal mobile devices, which calls into question the cloud model. Indeed, the cloud does not fulfill all the requirements of several applications in many contexts, especially for healthcare, resulting in the need for a different architecture.

Fog computing increases the delivery of on-time services and dramatically mitigates a variety of cloud-related problems when sending data to the cloud, which includes delay, jitter, and cost overheads. To satisfy the requirements of low latency distributed applications, it also provisions user mobility, variability of tools and interfaces, and distributed data analytics [29]. It also makes controlling and programming compute storage, and networking capabilities among data centers and end devices much easier. Moreover, fog computing is thus an authoritative tool for enabling the decentralized and intelligent processing of unprecedented IoT sensor-generated data volumes that are deployed to combine physical and cyber environments, assisting IoT in realizing its full potential.

The cloud-based IT platform serves as a technological backbone for connecting and collaborating the many components of the Industry 4.0 application [9]. Organizations need improved data exchange with Industry 4.0. Reaction times are reached in milliseconds or even faster across sites and businesses [10]. Digital manufacturing is the idea of connecting many devices to the same cloud for sharing information. It can be used for a shop floor set of machines as well as full plant [11].

9.6 Importance of artificial intelligence in industry 4.0

Artificial intelligence (AI) is a computer knowledge corporation through extensive development work in the fields of image processing, natural language processing, machine learning, robotics, etc. AI approaches are conventionally considered black-box approaches due to the lack of reliable suggestions for reassuring the industry as these approaches will operate frequently and effectively for them. The efficiency of machine learning approaches is extremely vulnerable to the experience of the developer and their preferences. Therefore, implementation of AI in industrial applications is limited.

On the other hand, industrial AI is a systematic technique that focuses on the creation, analysis, and effectiveness of relevant efficient machine learning algorithms for applications of Industry 4.0. It serves as a formal methodology and discipline to afford solutions for industrial applications and functions as a bridge linking AI academic research results to industry professionals. AI approaches are not having a more quantitative influence on the growth of productivity of the product [30].

In today's sectors, in terms of consumer demand and competitiveness, new challenges are emerging. They need an incremental upgradation known as Industry 4.0, which involves the integration of AI techniques with new digital techniques, such as the IIoT. As a backdrop for its deployment in industry, it is vital to explicitly identify its structure, methodology, and challenges, because industrial AI is in its preliminary stages [31].

The core of AI is analytics, which can only offer value if other elements are present. Big data technology and cloud are both important components of the source of information (information) and the industrial AI architecture.

9.7 Additive manufacturing

Industry 4.0 supports a production system with smart technology. Here, additive manufacturing has the potential to satisfy the essential requirements of Industry 4.0. In this IoT generation, creation and production have become adaptable, productive, and mechanized more than ever. This industry makes us intelligent as we can develop a more complex algorithm to combine information structure systems and machines. Machine and information systems can image tasks like talking to each other, information sharing, making a decision, and production evaluation. All these can be possible without human interference. Industry 4.0 gives rise to additive manufacturing and smart manufacturing plants, which have transformed the manufacturing with fast prototyping and anaglyph 3D. Additive manufacturing is related to industrial production that produces a 3D object by putting material in layers and controlled by a computer system.

In general terms, "additive manufacturing" is a process of producing physical objects by digital file. It is not only reducing the gap between the physical world and digital world but also creating a product that is not possible using the traditional manufacturing process. It can transform virtual objects into physical ones through a procedure of putting material layer by layer.

9.7.1 Process flow of additive manufacturing

Additive manufacturing has some interesting features like product design freedom, customization, topology optimization, and consolidation, making it a

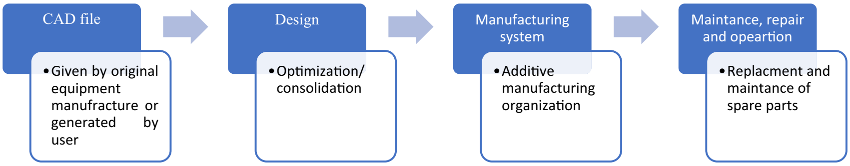


Figure 9.4 A simple process of additive manufacturing.

disruptive technology in the supply chain. It can save market time and manufacturing costs. The additive manufacturing process is simple so that the end-user can create a complex product by themselves without having to depend on others like manufacturers or suppliers [32]. A simple process is given in the below figure (Fig. 9.4).

9.8 Benefits of additive manufacturing (AM) in Industry 4.0

9.8.1 Produces less waste

Additive manufacturing is the opposite of traditional manufacturing, it adds only the required product at the exact amount to generate a product so as to avoid material wastage [33].

9.8.2 Promote digitization

In additive manufacturing, the continuous connection between machines, objects, robots, and devices is necessary. And this connection is possible only with the digitization of production activity. So manufacturing organizations must invest in IoT and digital technologies.

9.8.3 Simplification

The production process of additive manufacturing is very simple, especially in product assembly. The traditional manufacturing process is very complex and involves multiple manufacturing steps, so labor costs are increased and also take more time to assemble multiple parts. However, additive manufacturing allows printing multiple groups into a single piece.

9.8.4 Reduce time and cost

In additive manufacturing, the prototyping process of objects is easy, fast, and cheap. Milling manufacturing techniques include material cost and configuration. If the product prototyping time and cost are low, an organization can make changes according to requirements without any trouble.

9.8.5 Increased productivity

The additive manufacturing process is based on a highly automated fabricated step that can be run for a whole day to increase productivity. It also offers built-in flexibility.

9.8.6 Challenges of additive manufacturing

9.8.6.1 High cost

In additive manufacturing, machine and material cost can be high. Parts that require high strength have to be made of steel, which makes metal parts more expensive. The cost of some machines can be millions of dollars. In addition, the items themselves may require special repairs before use. For example, metals should be in the form of powder and of high quality. This can make object materials more expensive. The good thing is that additive manufacturing does not use material in large volumes [34].

9.8.6.2 Still a new technology

Till now, additive manufacturing is in the infancy stage. As such, there is shortage of qualified professionals, with limited knowledge and understanding of a company that wants to start using this technology. Standard guidelines and protocols also do not exist. There is also a shortage of infrastructure and the required spare parts are also not easily accessible.

9.8.6.3 Range of material

The material used in additive manufacturing has grown but not as a very vast comparison to traditional manufacturing.

9.8.6.4 Software options

The software used in additive manufacturing is very limited. The software working process is also not easy so a professional is needed to operate the software. However, recently, many software companies entered this field like Dassault Systems, Adobe, and Autodesk.

9.8.6.5 Reproducibility

In additive manufacturing, repetition and reproduction are not very high. Some differences exist between the products which are made from the same digital file on the same machine or a different machine.

9.9 Advanced robotics

Robotics is everywhere, in industry, infrastructure, education, security, agriculture, healthcare, and tourism but Industry 4.0 has given new life to robotics technology. This advanced technology can perform difficult tasks with ease. These are operated by sensors and software to perform tasks like recognition, analysis, and acting according to the information received from the environment. "Cobots" are robots that interact and are specially designed for working around people and also avoiding repetitive tasks by workers. Cobots are compatible with Industry 4.0 and promote collaboration between machines and humans [35].

The most advanced level of industrial automation is the integration of humans and robots. This collaboration represents cutting-edge manufacturing technology. Additionally, cobots assist humans by helping them work faster and better and this is the main objective of Industry 4.0. Some cobot qualities make them ideal for automation as they are safe, smart, and simple.

9.9.1 Safe

The Techman Robot is exceptionally safe for use. They are based on physical force limitation, which means they are immediately prevented from harming people and machines if they make contact with an object.

9.9.2 Smart

In comparison to program-based robots, the cognitive features enabled by cobots help in avoiding accidents. The payloads for the TM Series feature sensors that enable image capture, recognition, and barcode reading. Machine learning can be used to train robots to perform specific tasks.

9.9.3 Simple

Cobots can be easily programmed, they are not like the robots used in automation. Difficult and comprehensive programming is not required, non-IT professionals can also operate it very easily. Additionally, cobots assist humans in working faster and better.

9.9.4 Various design principles followed in Industry 4.0

Decentralized decisions, interconnection, transparency, and technical support were identified as the four design principles of Industry 4.0 by performing quantitative text analysis and qualitative literature assessment. The design principles are explained in the following subchapters.

9.9.4.1 Interconnection

The internet of everything (IoE) is formed by connecting machines, sensors, devices, and people via the IoT and IoP. Wireless communication technologies enable ubiquitous Internet access and play a key role in growing engagement. Interconnected devices and people can share information via the IoT, which creates the basis of a cooperative effort to achieve common goals. Human−Human (H-H), Human-Machine (H−M), and Machine−Machine (M−M) collaboration are the three types of collaborations in IoE [36]. Common communication protocols are critical in interconnecting machines, sensors, devices, and people. These standards make it possible to mix and match modular devices from various vendors. This modularization allows Industry 4.0 smart factories to respond quickly to the changing market demands or customized orders [37].

9.9.4.2 Information transparency

Participants in the IoT require context-aware information to make informed decisions [38]. Context-aware systems use information from both the virtual and actual worlds to complete tasks. E-documents, e-drawings, and simulation models are the best examples of virtual world information. In addition, the position or circumstances of a tool are prominent examples of physical world information. However, the raw sensor data must be collected to construct the higher-value contextual information and analyzed to evaluate the physical environment. The outcomes of data analytics must be included in help systems that should be available to all IoE participants for maintaining transparencies [39] of information that is crucial to the process

9.9.4.3 Technical assistance

Humans' primary function in Industry 4.0 smart factories evolves from the lower-end machine operator to the higher-end strategic decision-maker and a flexible problem-solver. Humans require aid systems due to the emerging difficulties in the production process, as cyber-physical system develops complicated networks and makes decentralized judgments. For assuring that humans can make educated decisions and resolve technical problems on short notice where these systems must aggregate and represent information in a comprehensible manner [40]. In terms of linking individuals with IoT, smartphones and tablets currently play a key role. Wearables are expected to become more popular in the future as present technology improves [41].

9.9.4.4 Decentralized decisions

The combination of interconnected and decentralized decision-makers provides for better decision-making and increased overall productivity by combining local and global information at the same time [42]. The participants in the IoE perform their assignments as independently as feasible. Tasks are only delegated to a higher level in the event of exceptions, interferences, or conflicting aims.

9.10 Conclusions

Today, the industry can no longer rely on 3G/4G wireless networks to meet the experience goals, such as reliability, short delay, energy efficiency, etc. required for the four industrial visions. 5G is essential for the deployment of IoT and M2M, which form the basis of Industry 4.0, thus serving as the catalyst for Industry 4.0 vision. 5G will link billions of devices to machines, manufacturing systems, and transportation systems via wireless networks. As a result, 5G will boost the "Internet of Things," allowing Industry 4.0 to flourish. As a result of the flexible, automated manufacturing process over time, 5G will deliver flexibility to industrial operations with faster, more reliable communications between machines, sensors, and computer systems. This will increase the overall productivity. Finally, AV technology innovators promise to offer a new mode of transportation for people and products that will revolutionize how people get about. For healthcare providers, this mobility change can take numerous forms, including an on-demand automated shuttle to hospitals (employees and patients) and a mobile office offering on-demand health services, such as vital monitoring, blood testing, and nurse consultations. The developments mentioned above have a lot of potential in terms of bridging the gap between increasing vehicle technology and healthcare demands. Coordination between advanced driving technology businesses and healthcare providers could increase the use of sensors and AI data-mining approaches. It could also help professionals get regular access to patient health data, allowing them to treat patients with chronic diseases, such as high blood pressure, diabetes, and cardiovascular issues. Medical Sensor applications in auto is becoming a novel research and development area and to ne continued in near future.

References

[1] M. Hermann, T. Pentek, B. Otto, Design principles for Industrie 4.0 scenarios, in: 2016 49th Hawaii international conference on system sciences (HICSS), IEEE, 2016 (pp. 3928−3937).

[2] A. Sharma, Z. Zheng, Connected and automated vehicles: opportunities and challenges for transportation systems, smart cities, and societies, in: T.W. Brydon, C. M. Wang (Eds), Automating cities: design, construction, operation and future impact, Singapore: Springer, 2021, pp. 273−296.

[3] S.A. Bagloee, M. Tavana, M. Asadi, T. Oliver, Autonomous vehicles: challenges, opportunities, and future implications for transportation policies, J. Mod. Transp 24 (4) (2016) 284−303.

[4] NHTSA, Automated vehicles for safety, NHTSA. [online] Nhtsa.gov. <https://www.nhtsa.gov/technology-innovation/automated-vehicles-safety>, 2021.

[5] T.J. Crayton, B.M. Meier, Autonomous vehicles: developing a public health research agenda to frame the future of transportation policy, J. Transp. Health 6 (2017) 245−252. Sep 1.

[6] S.S. Thonte, O.G. Bhusnure, V.G. Makanikar, O. Pravin, D. Sagar, Smart bioelectronics: the future of medicine is electric, Imagine (2016). Mar.

[7] T. Poongodi, A. Rathee, R. Indrakumari, P. Suresh, IoT sensing capabilities: sensor deployment and node discovery, wearable sensors, wireless body area network (WBAN), data acquisition, in: Principles of Internet of Things (IoT) Ecosystem: Insight Paradigm, Springer, Cham, 2020, pp. 127−151.

[8] T. Poongodi, T. LuciaAgnesbeena, S. Janarthanan, B. Balamurugan, An industrial IoT approach for pharmaceutical industry growth, in: Accelerating Data Acquisition Process in the Pharmaceutical Industry Using Internet of Things, Elsevier, 2020, pp. 117−252.

[9] S. Hiremath, G. Yang, K. Mankodiya, Wearable Internet of Things: concept, architectural components and promises for person-centered healthcare, in: 2014 4th International Conference on Wireless Mobile Communication and Healthcare-Transforming Healthcare Through Innovations in Mobile and Wireless Technologies (MOBIHEALTH), IEEE, 2014 Nov 3 (pp. 304−307).

[10] N.P. Terry, Will the internet of things transform healthcare, Vand. J. Ent. Tech. L. 19 (2016) 327.

[11] N.K. Jha, Internet-of-medical-things, in: Proceedings of the on Great Lakes Symposium on VLSI 2017, GLSVLSI '17, ACM, New York, USA, 2017.

[12] R.S. Istepanian, S. Hu, N.Y. Philip, A. Sungoor The potential of Internet of m-health Things "m-IoT" for non-invasive glucose level sensing, in: 2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, IEEE, 2011 Aug 30 (pp. 5264−5266).

[13] E. Omanović-Mikličanin, M. Maksimović, V. Vujović, The future of healthcare: nanomedicine and internet of nano things, Folia Medica FacultatisMedicinae Universitatis Saraev. 50 (1) (2015). Jun 30.

[14] N. Waxer, D. Ninan, M.D. Alfred Ma, N. Dominguez, How cloud computing and social media are changing the face of health care, Phys. Execut. 39 (2) (2013) 58.

[15] S. Ullah, H. Higgins, B. Braem, B. Latre, C. Blondia, I. Moerman, et al., A comprehensive survey of wireless body area networks, J. Med. Syst. 36 (3) (2012) 1065−1094.

[16] T. Poongodi, R. Krishnamurthi, R. Indrakumari, P. Suresh, B. Balusamy, Wearable devices and IoT, A handbook of Internet of Things in Biomedical and Cyber Physical System, 2020, , pp. 245−273. Springer, Cham.

[17] M.M. Hansen, T. Miron-Shatz, A.Y. Lau, C. Paton, Big data in science and healthcare: a review of recent literature and perspectives: contribution of the IMIA Social Media Working Group, Yearb. Med. Inform. 9 (1) (2014) 21.

[18] S. Vicini, S. Bellini, A. Rosi, A. Sanna, An internet of things enabled interactive totem for children in a living lab setting, in: 2012 18th International ICE Conference on Engineering, Technology and Innovation, IEEE, 2012 Jun 18 (pp. 1−10).

[19] R. Chen, M. Snyder, Promise of personalized omics to precision medicine, Wiley Interdiscip. Rev. Syst. Biol. Med. 5 (1) (2013) 73−82.

[20] A.L. Albertin, de Moura, R.M. Albertin, The internet things will go far beyond things, Comput. Net. (2017) 12−17.

[21] M. Haddara, A. Elragal, The readiness of ERP systems for the factory of the future, Procedia Comp. Sci. 64 (2015) 721−728. Jan 1.

[22] S. Weyer, M. Schmitt, M. Ohmer, D. Gorecky, Towards Industry 4.0-standardization as the crucial challenge for highly modular, multi-vendor production systems, Ifac-Papersonline 48 (3) (2015) 579−584.

[23] I. Veza, M. Mladineo, N. Gjeldum, Managing innovative production network of smart factories, IFAC-PapersOnLine 48 (3) (2015) 555−560.

[24] J. Gubbi, R. Buyya, S. Marusic, M. Palaniswami, Internet of Things (IoT): a vision, architectural elements, and future directions, Fut. Gener. Comp. Syst. 29 (7) (2013) 1645−1660.

[25] H. Lasi, P. Fettke, H.G. Kemper, T. Feld, M. Hoffmann, Industry 4.0, Bus. Inf. Syst. Eng. 6 (4) (2014) 239−242.

[26] T.N. Gia, M. Jiang, A.M. Rahmani, T. Westerlund, P. Liljeberg, H. Tenhunen, Fog computing in healthcare internet of things: a case study on ECG feature extraction, in: 2015 IEEE International Conference on Computer and Information Technology; Ubiquitous Computing and Communications; Dependable, Autonomic and Secure Computing; Pervasive Intelligence and Computing, IEEE, 2015 October 26 (pp. 356−363).

[27] M. Landherr, U. Schneider, T. Bauernhansl, The application center Industrie 4.0-industry-driven manufacturing, research and development, Procedia CIRP 57 (2016) 26−31. Jan 1.

[28] P. Srivastava, R. Khan, A review paper on cloud computing, Int. J. Adv. Res. Comp. Sci. Softw. Eng. 8 (6) (2018) 17−20.

[29] D. Bermbach, F. Pallas, D.G. Pérez, P. Plebani, M. Anderson, R. Kat, et al., A research perspective on fog computing, in: International Conference on Service-Oriented Computing, Springer, Cham, 2017 November 13, pp. 198−210.

[30] J. Lee, H. Davari, J. Singh, V. Pandhare, Industrial artificial intelligence for Industry 4.0-based manufacturing systems, Manuf. Lett. (2018) 18. Available from: https://doi.org/10.1016/j.mfglet.2018.09.002.

[31] V. Alcácer, V. Cruz-Machado, Scanning the industry 4.0: a literature review on technologies for manufacturing systems, Eng. Sci. Technol. Int. J. 22 (3) (2019) 899−919.

[32] W.W. Wits, J.R. García, J.M. Becker, How additive manufacturing enables more sustainable end-user maintenance, repair and overhaul (MRO) strategies, Procedia CIRP 40 (2016) 693−698. Jan 1.

[33] L.E. Murr, W.L. Johnson, 3D metal droplet printing development and advanced materials additive manufacturing, J. Mater. Res. Technol. 6 (1) (2017) 77−89.

[34] Esa Automation, Additive manufacturing in Industry 4.0. [online]. Available from: <https://www.esa-automation.com/en/additive-manufacturing-in-industry-4-0/>, 2021.

[35] D. Howlader, J. Giordano, Advanced robotics: changing the nature of war and thresholds and tolerance for conflict-implications for research and policy, J. Philos. Sci. Law 13 (2) (2013) 1−9.

[36] G. Schuh, T. Potente, C. Wesch-Potente, A. Hauptvogel, Sustainable increase of overhead productivity due to cyber-physical-systems, in: 11th Conference on Sustainable Manufacotring, 2013, pp. 332−335.
[37] D. Zuehlke, SmartFactory—towards a factory-of-things, Annu. Rev. Control. 34 (1) (2010) 129−138.
[38] H. Kagermann, Change through digitization—value creation in the age of Industry 4.0, in: Management of Permanent Change, Springer Gabler, Wiesbaden, 2015, pp. 23−45.
[39] D. Lucke, C. Constantinescu, E. Westkämper, Smart factory-a step towards the next generation of manufacturing, in: Manufacturing Systems and Technologies for the New Frontier, Springer, London, 2008, pp. 115−118.
[40] D. Gorecky, M. Schmitt, M. Loskyll, D. Zühlke, Human-machine-interaction in the industry 4.0 era, in: 2014 12th IEEE International Conference on Industrial Informatics (INDIN), IEEE, 2014 July 27, pp. 289−294.
[41] M. Awais, D. Henrich Human-robot interaction in an unknown human intention scenario, in: 2013 11th International Conference on Frontiers of Information Technology, IEEE, 2013 December 16 (pp. 89−94).
[42] T.W. Malone, Is' empowerment'just a fad? Control, decision-making, and information technology, BT Technol. J. 17 (4) (1999) 141−144.

CHAPTER 10

Impact of internet of things and digital twin on manufacturing era

M. Nalini, M.R. Bharathkumar, R. Keerthivasan, N. Nithyashree and V. Dhanashree
EIE, Sri Sairam Engineering College, Chennai, Tamil Nadu, India

10.1 Internet of Things

An Internet of Things (IoT) network consists of physical stuffs known as "THINGS" that are implanted with input and output sensor, processing software, and other technologies that permit them to share data with other devices and systems over the internet.

Analysts predict that more than 10 billion IoT devices will be in use by 2020, with 20 billion or more by 2025, ranging from simple household items to complicated industries.

The IoT has developed as among the supreme important late-20th-century technologies in recent years. Now that we can connect ordinary goods like kitchen appliances, auto rickshaws, thermostats, and baby monitors to the internet via embedded systems, we can have continuous forms of communication, processes, and things.

The IoT is a network of networked computing devices, mechanical, electronics, and digital equipment, products, and people with unique identities and the process of data transfer without the requirement for a human-to-human or human-to-computer interface.

IoT is promptly being utilized by businesses through a wide range of different sectors to enhance the efficiency and productivity, better understanding of consumer needs to provide better customer satisfaction and service, make smarter decisions, and raise the significance of their organization.

10.2 Importance of Internet of Things

Customers rely on this expertise to operate more intelligently and gain complete self control. The IoT is critical to businesses to supply the

Digital Twin For Smart Manufacturing
DOI: https://doi.org/10.1016/B978-0-323-99205-3.00010-9

necessary smart devices to help them automate homes. With the support of IoT, organizations may have a comprehensive understanding of how their system runs, which includes data on everything from performance and dependability to availability and logistical processes [1].

Organizations may use the IoT to automate processes and save money on labor. It also reduces waste and helps enhance quality by lowering supply chain management systems costs and enhancing transparency in product buying and selling.

Physical entities may exchange and gather data with minimum help by utilizing low-cost systems and computers, cloud, big data, different algorithms, and communication devices. Digital computers can record, monitor, and modify every interaction between linked parts in this hyper-connected world. Traditional and online worlds collide and cooperate.

10.2.1 Working

IoT system consists of various smart devices that collect, transmit, and respond to information from their surroundings using embedded systems, such as CPUs, sensors, and communication hardware. It is a connection to an Access Point that exchanges sensor data, which is then either sent to the cloud for analysis or analyzed locally [2]. These gadgets periodically communicate with one another and perform actions based on the information they receive. People can interact with the devices to set them up, give them instructions, or retrieve data, but the majority of the tasks can be completed without human intervention.

The installed IoT apps control the devices' connectivity, network, and communication networks. The IoT may also use artificial intelligence (AI) and machine learning to make data collecting activities simple and engaging.

10.3 Norms and framework for the Internet of Things

A number of additional IoT standards will be on the future, which include:

1. The Internet Engineering Task Force have designated IPv6—which is over Low-Power Wireless Personal Area Networks (6LoWPAN) as an open type standard (IETF). The 6LoWPAN protocol allows any low-power radio, such as 804.15.4, Bluetooth Low Energy, and Z-Wave, to connect to the internet.

2. ZigBee—ZigBee is a low-power consuming, low-data-rate type network technology that is commonly seen in industrial environments. The Institute of Electrical and Electronics Engineers created the 802.15.4 standard, which ZigBee is built on. Dot is a universal language for IoT developed by the ZigBee Coalition that allows smart devices to communicate and function securely across any network.
3. LiteOS—LiteOS is a Unix-like operating system designed for wireless communications (OS). LiteOS (IoV) is compatible with mobile phones, wearables, smart manufacturing applications, home automation, and smart automobiles, and it also acts as an application framework for smart devices.
4. AMQP (Advanced Message Queuing Protocol)—AMQP is an open source protocol for internet-based asynchronous messaging. AMQP enables organizations and applications able to communicate in a safe and dependable manner. The protocol is utilized in two applications: client-server communications and the management of IoT devices.
5. Long Range Wide Area Network (LoRaWAN)—This is a WAN protocol used to connect millions and millions of low-power devices, like smart cities.
6. OneM2M—OneM2M is a machine-to-machine application interface that may be embedded in both software and hardware to allow it to connect with other devices. OneM2M was created to provide scalability standard that would enable IoT applications from various industries to connect with one another.

10.4 The following are the Internet of Things frameworks

1. Amazon Web Services (AWS) IoT is an IoT cloud computing service created by Amazon. This technology is intended to make it simple and reliable to connect smart devices to the AWS cloud and other connected devices.
2. Arm MbedIoT is an IoT app development platform that uses Arm microcontrollers. By combining Mbed tools and services, the Arm MbedIoT platform aims to build a sustainable, networked, and secure ecosystem for IoT devices.
3. Microsoft's Azure IoT Suite is a platform comprising a collection of services that enable people to interact with and receive information from their connected systems, as well as perform various operations on

data, such as multidimensional analysis, transformation, and aggregation, and visualize those operations in a business-friendly manner.
4. Calvin is an open source IoT platform created by Ericsson for designing and managing distributed applications that allow devices to connect with one another. Calvin includes an app development framework as well as a runtime environment for managing running apps.
5. Brillo/Weave, created by Google, is a platform for swiftly creating IoT applications. Brillo, an Android-based operating system allows for the construction of embedded low-power devices, and Weave, an IoT-oriented communication protocol, serves as the communication language between the device and the cloud. Both these are the platform's two essential backbones.

10.5 Benefits of Internet of Things

Enhanced communication between connected electronic devices; access to retrieve information from anywhere, at any time, on any device; time and money savings by transferring data packets via a linked network; and task automation helps improve a company's service quality while reducing the requirement for human involvement.

10.5.1 Internet of Things's drawbacks

1. The risk of a hacker collecting personal data increases as the number of linked devices increases and more amount of information is shared between them.
2. Enterprises may have to deal with a significant number of IoT devices, maybe millions, and collecting and managing data from all of those devices will be tough.
3. If the system contains a defect, every associated device will almost certainly become corrupted.
4. Because there is no global standard for IoT interoperability, connecting devices from various manufacturers is problematic.

10.6 What is the Internet of Things in the workplace?

The implementation of IoT technology in the industrial settings, especially in terms of sensor and device instrumentation and control using cloud technologies was known as industrial IoT (IIoT). Machine-to-machine communication (M2M) has lately been used in a variety of sectors to provide wireless automation and control [3]. However, with the growth of cloud computing and other related technologies (such as analytics and machine learning), businesses may achieve a new degree of automation, as well as new revenue and business models. The Industry 4.0, that is, the fourth industrial revolution, is also known as the IIoT [4]. The IIoT is often utilized in the following ways:

Production that is smart

1. Preventive maintenance and predictive maintenance and connected assets
2. Grids of the upcoming future
3. Cities that are smart are those which are technologically advanced
4. Logistics with a smart network
5. Supply chains with smart digital technology

10.7 Internet of Things device management

Security, interoperability, power/processing capabilities, scalability, and availability are just a few of the concerns that might thwart the successful implementation of an IoT system and its associated devices. Many of these concerns may be addressed by IoT device management, which can be accomplished through the use of standard protocols or vendor-provided services.

Device management part enables enterprises to integrate, organize, monitor, and remotely manage internet-enabled devices on a broad scale, including features critical to assuring IoT device health, connection, and security throughout their lifecycles [5]. Among these qualities are:

1. Registration and activation of the device
2. Authentication and authorization of device
3. Configuration of the device
4. Provisioning of device
5. Diagnostics and monitoring of device
6. Troubleshooting a device
7. Updates to device firmware

Two of the available standardized device management type protocols are the Open Mobile Alliance's Device Management and Lightweight Machine-to-Machine protocols.

Amazon, Microsoft, Google, IBM, GE, and many more companies provide IoT device management services and software.

10.8 Internet of Things connectivity and networking

The communication, networking, and connection protocols used with internet-connected devices are heavily influenced by the IoT application. There are several connectivity options and communication options available, as well as numerous IoT applications.

Communication protocols include CoAP, DTLS, MQTT, DDS, and AMQP. Wireless protocols include IPv6, LPWAN, Zigbee, Bluetooth Low Energy, Z-Wave, RFID, and NFC. There are cellular, satellite, Wi-Fi, and Ethernet connections available.

Each option will have its own set of tradeoffs in terms of power consumption, range, and bandwidth, all must be considered when selecting connected devices and protocols for a particular IoT application.

Most IoT devices communicate with an IoT gateway or other type of edge device, where data may be analyzed and sent locally or sent to the cloud. Some devices provide built-in data processing capabilities, which reduces the amount of data that must be sent to the cloud. This type of processing typically makes use of the device's built-in machine learning capabilities, and it is becoming more prevalent as IoT devices generate more data.

10.9 Application of Internet of Things

From consumer IoT and commercial IoT to manufacturing IoT and industrial IoT, the IoT offers a wide range of real-world applications called IIoT. IoT applications may be found in a different range of industries, including automotive, communications, and energy (Fig. 10.1).

In the consumer market, smart houses with smart thermostats, smart appliances, and linked heating, lighting, and electrical devices may be handled remotely via computers and smartphones.

Wearable gadgets equipped with sensors and software may collect and analyze user data, as well as convey signals about the users to other technologies, to make their lives easier and more comfortable. Wearable devices are also used in public safety, for example, to improve first responder response times during emergencies by providing efficient routes to a location or to track construction workers' or firefighters' vital signs in potentially life-threatening conditions.

IoT provides various advantages in healthcare, including the ability to more closely monitor patients through data analysis. In hospitals, IoT

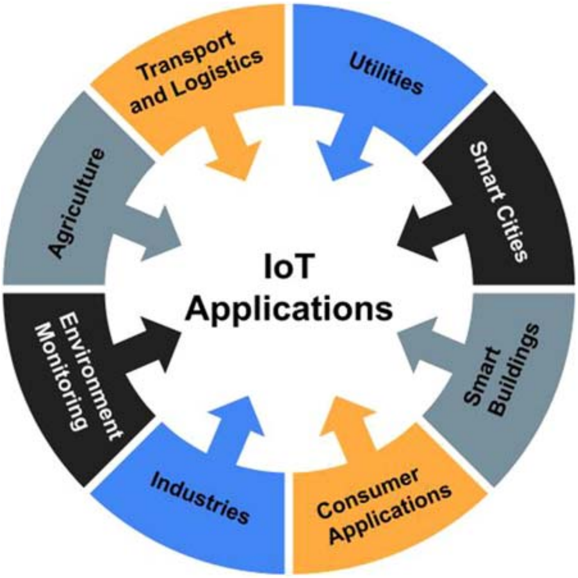


Figure 10.1 Internet of Things applications.

technologies are widely employed to carry out activities such as pharmaceutical and medical equipment inventory management.

Sensors that detect the number of people in a room, for example, can assist smart buildings in saving money on power. The temperature can be automatically controlled, such as putting on the air conditioner if sensors detect that a conference room is full or turning down the heat if everyone has left the office.

Smart farming systems based on IoT may employ networked sensors to monitor things like light, temperature, humidity, and soil moisture in agricultural areas. The IoT may also be used to automate irrigation systems.

In a smart city, IoT sensors and installations such as smart lighting and smart meters may help with traffic relief, energy saving, environmental monitoring and mitigation, and cleanliness.

10.10 Qualities of Internet of Things

The IoT has the following important characteristics.

10.10.1 The ability to connect

The infrastructure of the IoT is primarily dependent on connection. The infrastructure for the IoT is to be linked to other IoT devices. Anyone, anywhere, wherever, and at any time should be able to connect at all times. Nothing makes sense until there is a connection.

10.10.2 Identity and intelligence

Pulling out information from shaped data is crucial. For example, a sensor generates data, but that data is only meaningful if it is correctly comprehended. Every IoT device has its own unique identifier. This identification can be used to trace the equipment and, on occasion, query about its status.

10.10.3 Scalability

The number of things linked to the IoT zone expands by the day. As a result, an IoT setup should be able to withstand rapid expansion. The amount of data created as a consequence is massive, and it must be managed effectively.

10.10.4 Complexity is dynamic and self-adapting

Internet of Things devices should be capable of adapting to changing the settings and conditions while in use. Assume you have a security type of camera. It should be able to function in a range of environments and lighting circumstances (morning, afternoon, night).

10.10.5 Architectural design

Internet of Things architecture cannot be uniform in nature. It should be hybrid, allowing devices from many manufacturers to collaborate in an IoT network. No engineering branch owns the IoT. IoT becomes a reality when many areas come together.

10.10.6 Safety

When a user connects all of his or her devices to the internet, there is a chance that complex personal information will be conceded. As a result, the user may incur a loss. As a result, data safekeeping is a top priority. Additionally, the necessary equipment is vast. IoT networks may also be at danger. As a result, the safety of the equipment is critical (Fig. 10.2).

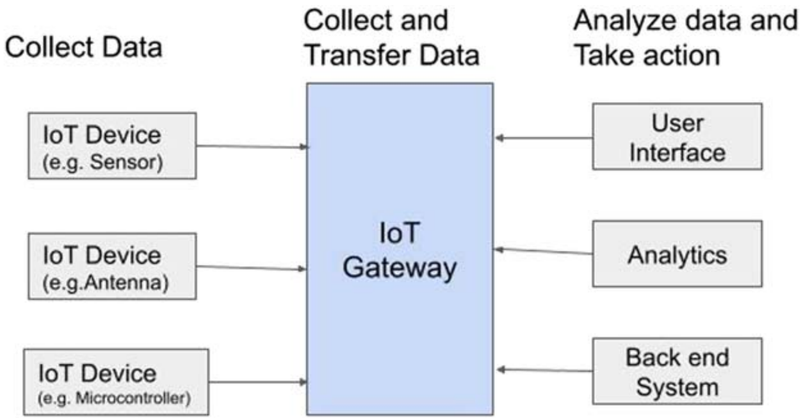


Figure 10.2 Internet of Things system example.

10.10.7 Digital twin

A digital twin is a type of virtual object or system that extends its lifespan, is modernized from real-time data, and aids decision-making through simulation, machine learning, and reasoning.

In addition to physical assets, digital twin technologies may be used to duplicate processes to collect data and predict how they will perform.

A digital twin is a piece of computer software that generates simulations established on real-world data to predict how a product or process will perform. These applications can employ the IoT (Industry 4.0), AI, and software analytics to optimize their output [6].

Because of the numerous developments in machine learning and aspects such as big data, these virtual models have become a commonplace in modern engineering to drive innovation and improving performance. In summary, having one may aid in the improvement of key technical trends, the prevention of expensive failures in physical items, and the testing of different processes and services via enhanced analytical, monitoring, and predictive skills.

The concept of digital twin originated at NASA, where full-scale replicas of early space capsules were used on the ground to reflect and diagnose flaws in orbit, ultimately giving way to completely digital simulations.

However, the term acquired currency after Gartner named digital twins one of the top ten critical technology trends for 2017, forecasting that “billions of objects would be represented by digital twins, a dynamic

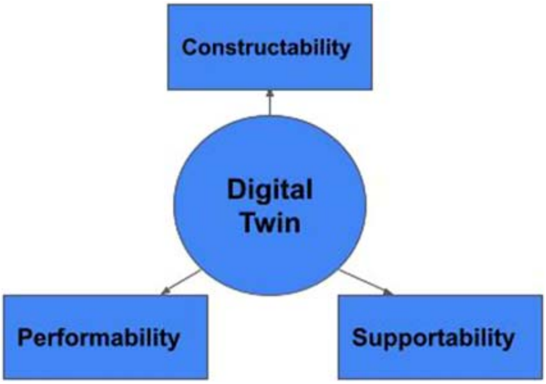


Figure 10.3 Digital twin.

software representation of a real object or system, within three to five years." Gartner identified digital twins as a top fashion a year later, forecasting that "by 2020, digital twins would exist for billions of objects," citing an estimate of 21 billion amount of linked sensors and endpoints.

An advanced twin might be a computer program that uses real-world information about a physical question or framework as inputs and predictions. How those inputs will impact the digital twin's framework is shown in Fig. 10.3.

10.10.8 Benefits of digital twin

The following are some of the advantages of digital twins:

1. Product monitoring.
2. A digital twin monitors the product during the whole manufacturing process.
3. IoT sensors continue to deliver updates on the product's production on a regular basis.
4. Digital twin analyzes all of the data and constantly enhances the output.
5. Digital twin enables forecasting future status of related business assets using various modeling techniques, as well as evaluating the consequences of any key concerns that must be addressed.
6. Coordination of teamwork is improved.
7. Access to information systems and system automation with 24-hour shifts, technicians may focus more on cooperation, resulting in increased productivity and operational effectiveness.

10.10.9 Disadvantage of digital twin

1. Internet connectivity is critical to the success of technology.
2. It is a matter of security.
3. Instead of 2D drawings, the digital twin concept is built on 3D CAD models.
4. Throughout the full supply chain, digital twins will be required.
5. Globalization and new industrial techniques are among the problems to be addressed. As the physical product ages, managing all of these design data for the digital twin among partners and suppliers will be difficult.

10.10.10 Key elements

A digital twin is made up of three important components:

1. Data from the past: Individual device output records, aggregate techniques, and output records for specified structures.
2. Currently available data: Tangible data from equipment sensors, producing fields and equipment sources, and distribution chain system outputs. Outputs from other business areas, such as customer service and buying, can also be used.
3. In the future, machine learning and engineering contributions will be employed.

10.10.11 Use cases of digital twin

10.10.11.1 Smart cities

One of the applications for digital twins is smart cities.

The potential of cities to progress ecologically and economically may be significantly strengthened by adopting digital twin, which allows users to construct frameworks that guide their future goals and aid in tackling the complex problems that cities face [7]. In the case of a disaster, such as an earthquake, the digital twin gives critical real-time information, such as which regions have been destroyed and which hospitals may be affected, allowing city planners to respond quickly.

10.10.12 Management of natural disaster

Climate change has lately had an impact on the world, but digital twins will continue to address it by intelligently building smarter infrastructure and services, devising incident response plans, and tracking climate disasters.

10.10.12.1 Application of digital twin

Digital twins are widely used nowadays. According to an estimate by Deloitte, the global marketplace value for digital twins is expected to extend the range of US $ 16 billion by 2023, with a compound annual growth rate of 38%, with IoT technology driving this increase. A virtual/digital version of a real-world entity is referred to as a digital twin. A device, person, method, or system assists a company in making model-driven choices. Digital twins are changing how people work in a variety of sectors and commercial uses. Important applications of digital twin are shown in Fig. 10.4.

10.10.12.2 Automotive industry

Digital twins are used in the automobile sector to produce digital photographs of linked cars. This technology is used by automakers to create the ideal automobile before the development process begins [8]. They model and assess the manufacturing process as well as possible difficulties after the vehicle is on the road.

10.10.12.3 Future prospects

According to NEC, "digital twins will be one of the most essential IT tools in many industries, particularly manufacturing." "We also switch up product production and testing in other sectors." If we produce data that can be gathered and analyzed in any way in the future, we will have a unique digital twin for every gadget manufactured. It will be able to put

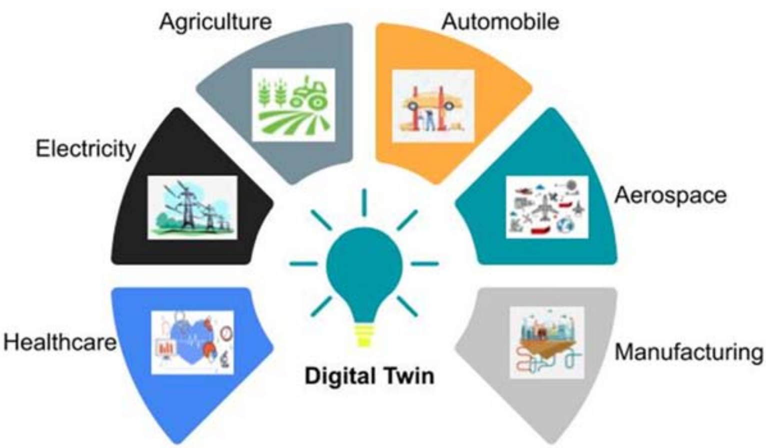


Figure 10.4 Digital twin applications.

it in place. The notion of a "digital triplet" symbolizes the next phase in the advancement of the digital twin. Instead of employing a single digital twin for each aircraft development, Boeing creates a unique digital model for each aircraft it produces [9]. Individual models may be given real-time data from connected sensors, and AI analysis can be used to provide real-time product lifecycles, predictive maintenance, and other projections. Humans will soon be able to collect real-time data from wearables and create their own digital triplet, which will include your genetic code. With this data, anybody in the world might conceivably receive highly tailored, but cost-effective treatment.

10.10.12.3.1 For better service

People that use apps such as remote troubleshooting are typically accessible for digital twins. Instead of depending on established methods, employees may perform diagnostic tests from anywhere and utilize virtual models to direct customers to the right repair process. The information gathered during these sessions will be extremely beneficial for future product planning and development [10].

10.10.12.3.2 Digital twin is simulation or not...

No, not at all. A digital twin begins as a simulation; however, the capacity to update in real time distinguishes a digital simulation from a digital twin.

Engineers can utilize simulation to perform tests and evaluations on a virtual representation of a physical asset. The simulation, on the other hand, is static. In other words, the simulation will not keep up with the actual asset until the engineer adds new parameters to it.

Twins receive real-time updates from actual assets, processes, or systems when they disagree. As a consequence, engineers base their testing, evaluation, and analytic work on real-world circumstances. As the digital twin's state grows dynamically, it matures as it gets fresh inputs from the actual world and gives increasingly accurate results.

10.10.12.3.3 Simulations versus digital twins

Both are digital models that can simulate many system characteristics, but because digital twins are virtual worlds, they are far more intriguing to research. Primary peculiarity between a digital twin and a simulation is one of scale [11]. Digital twins can conduct an unlimited number of

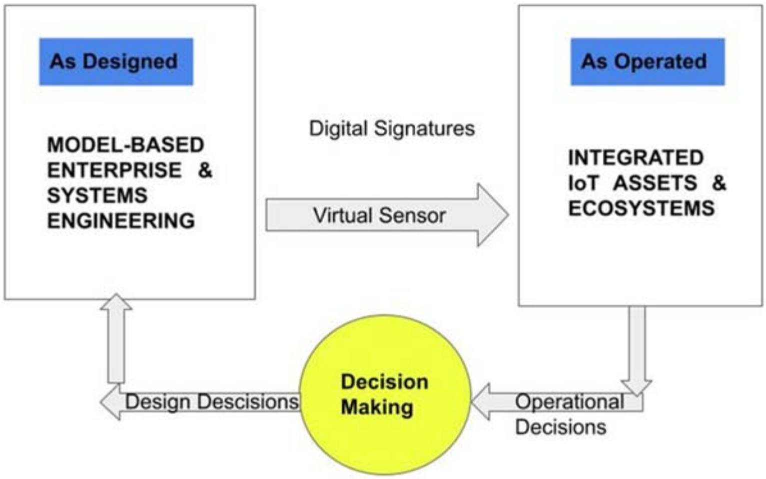


Figure 10.5 Simulations versus digital twin.

relevant simulations to examine many processes, although simulations generally focus on a single process.

This is not the end of the distinction. Real-time data, for example, is rarely relevant for simulation. The digital twin, on the other hand, is based on a two-way information flow that begins when the object sensor sends pertinent data to the system processor and continues until the processor insight is presented to the user together with the original source item.

Digital twins can evaluate problems from many more perspectives than traditional simulations, and when combined with the added computer power that comes with virtual environments, they are continually updated better in various areas. The data provides us with the greatest opportunity to improve our goods and operations, which is shown in Fig. 10.5.

10.10.12.3.4 Working of digital twin technology

A digital twin consists of three primary components:

1. Past data—Information on specific machines, processes, and systems' previous performance.
2. Modern data examples include current data from device sensors, output from manufacturing platforms and systems, and output from systems across the supply chain. You may also incorporate data from other business divisions' systems, such as customer service and purchasing.
3. Data from the future, including machine learning and engineer input.

Digital twin types Digital twins originate in many shapes and sizes. Depending upon the size of the product, many sorts of digital twins are classified. These twins are the most dissimilar in terms of applicability. Different sorts of digital twins frequently exist in a system or process. Let's look at the many types of digital twins and their applications [12].

Component twins The component twin is the smallest example of a digital twin's working component. Parts twins are identical to the same twin save for minor differences.

Twins with asset A resource is created when two or more components work together to activate an asset. Asset twin allows to investigate how these aspects interact and create rich performance of data that can be studied and transformed into actionable insights.

Unit twin Unit twin is the next degree of amplification, permitting to look how diverse components interact to produce a fully functional system. System twins give insights into asset relationships and can promote better performance.

10.10.12.3.5 Process involved in digital twins

A macrolevel extension, process twins, demonstrates how systems interact to generate a full manufacturing complex. Do all of these systems synchronize and function at peak efficiency, or does one system's delay effect the others? Process twins aid in determining the precise timing scheme that influences the overall ability.

10.10.12.3.6 Things to consider before implementing digital twins

Revise your data security protocols According to Gartner, by 2023, 75% of digital twins for IoT-connected OEM devices would employ at least five distinct types of connection endpoints. The quantity of data gathered from all of these endpoints is massive, and each one poses a security risk. As a result, before deploying digital twin technology, firms should assess and improve their security procedures. In terms of security, the following areas are of the highest importance:

1. Encrypting data
2. User responsibilities and access privileges are clearly defined
3. Principles of least privilege
4. Defending against known device flaws
5. Security audits are performed on a regular basis

10.10.12.4 Verify the authenticity of the data

Thousands of distant sensors linked via erratic networks input data into digital twin simulations. Companies that want to adopt digital twin technology should be able to sort out bad data and deal with gaps in the data.

10.10.12.4.1 Educate the group

Users of digital twin technology must adjust to new modes of working, which might impede the development of new technological abilities [13]. Organizations must guarantee that their staff have the necessary skills and resources to deal with this digital twin concept.

10.10.12.4.2 Difference between Internet of Things and digital twin

1. A virtual and digitalized clone of a product, item, service, or system is referred to as a digital twin, whereas the IoT is a network of linked and controllable things.
2. The digital twin includes the ability to create and build a simulated environment, whereas the IoT encompasses hundreds of millions of linked things.
3. IoT is based on the union of physical items and the virtual world, whereas digital twins are based on the union of physical objects and the virtual world.
4. The three forms of digital twins are the physical product, the digital product, and the network that connects the two, whereas IoT networks are split into four categories: cellular, local and personal area networks (LAN/PAN), low power wide area networks (LPWAN), and mesh networks.

   Digital twin versus Internet of Things**:**

Parameters of Comparison	Digital Twin	IoT
Definition	It is a logical structure that holds actual data and information from other apps	It is a network of physical items or entities that act on data and are sensors and processors
Origin	NASA employed it for the first time in 2010 after David Gelernter mentioned it in 1991	In 1982, Peter T. Lewis said in a lecture that the IoT had its initial use in a drink vending machine at Carnegie Mellon University

(*Continued*)

Parameters of Comparison	Digital Twin	IoT
Types	The physical product, the digital product, and the connection that is made between the two products are the three different digital twins	There are four types of IOTs networks. They are cellular; local, personal area networks (LAN/PAN); low power wide area networks (LPWAN); and mesh networks
Characteristics	Enhanced connection, data homogeneity, re-programmability, digital trails that aid in issue diagnosis, modularity, and customization of goods and modules	Intelligent elements include networked architecture, decentralization, complexity, and size and space considerations
Applications	Manufacturing, urban planning and construction, healthcare industry, and even in the automotive industry	In industries such as medical and healthcare, logistics, communication, manufacturing, agriculture, food, and maritime operations, smart home devices, and consumer applications are becoming increasingly popular

References

[1] A. Fuller, Z. Fan, C. Day, C. Barlow, Digital twin: enabling technologies, challenges and open research, IEEE Access. 8 (2020) 108952–108971.
[2] H. Elayan, M. Aloqaily, M. Guizani, Digital twin for intelligent context-aware iot healthcare systems, IEEE Internet Things J. 8 (23) (2021) 16749–16757.
[3] A. Saad, S. Faddel, O. Mohammed, IoT-based digital twin for energy cyber-physical systems: design and implementation, Energies 13 (18) (2020) 4762.
[4] V. Kharchenko, O. Illiashenko, O. Morozova, S. Sokolov, Combination of digital twin and artificial intelligence in manufacturing using industrial IoT. In Proceedings of the IEEE Eleventh international conference on dependable systems, services and technologies (DESSERT), 2020, May, pp. 196–201. IEEE.
[5] M. Jacoby, T. Usländer, Digital twin and internet of things—current standards landscape, Appl. Sci. 10 (18) (2020) 6519.
[6] K.E. Harper, C. Ganz, S. Malakuti, Digital twin architecture and standards, IIC J. Innov. 12 (2019) 72–83.

[7] S. Mathupriya, S.S. Banu, S. Sridhar, B. Arthi, Digital twin technology on IoT, industries & other smart environments: a survey, Mater. Today: Proc (2020).
[8] V. Kamath, J. Morgan, M.I. Ali, Industrial IoT and digital twins for a smart factory: an open source toolkit for application design and benchmarking. In 2020 Global Internet of Things Summit (GIoTS), 2020, June, pp. 1−6. IEEE.
[9] A.N. Nasaruddin, T. Ito, T.B. Tuan, Digital twin approach to building information management. In Proceedings of the Manufacturing Systems Division Conference, 2018, p. 304. The Japan Society of Mechanical Engineers.
[10] S. RokkaChhetri, M.A. Al Faruque, IoT-enabled living digital twin modeling, Data-Driven Modeling of Cyber-Physical Systems using Side-Channel Analysis, Springer, Cham, 2020, pp. 155−182.
[11] C.K. Lo, C.H. Chen, R.Y. Zhong, A review of digital twin in product design and development, Adv. Eng. Inform. 48 (2021) 101297.
[12] A. Canedo, Industrial IoT lifecycle via digital twins. In Proceedings of the Eleventh IEEE/ACM/IFIP International Conference on Hardware/Software Codesign and System Synthesis, 2016, October, pp. 1−1.
[13] S. Muralidharan, B. Yoo, H. Ko, Designing a semantic digital twin model for IoT. In 2020 IEEE International Conference on Consumer Electronics (ICCE), 2020, January, pp. 1−2. IEEE.

CHAPTER 11

Fault diagnosis in digital twin manufacturing

Vani Rajasekar[1], K. Sathya[2] and Rajesh Kumar Dhanaraj[3]
[1]Department of CSE, Kongu Engineering College, Tamil Nadu, India
[2]Department of CT/UG, Kongu Engineering College, Erode, Tamil Nadu, India
[3]Symbiosis International (Deemed University), Pune, Maharashtra, India

11.1 Introduction

The manufacturing industry is quickly transitioning through to the next industrial automation with improved modularity, flexibility, and dependability because of the growing information and communications technology. In the cut-throat market, having access to a manufacturing system is important to ensuring high productivity. Machinery fault prediction and treatment play a vital role in reducing system maintenance and unanticipated failure of increasingly sophisticated industrial equipment and devices. Intelligent fault diagnosis (IFD) appears to apply machine learning (ML) approaches for machine defect detection, which automates the procedure of fault identification and tracking [1]. This is in compared to conventional fault diagnosis, where the connection between the measurement parameters and the health states of machineries comes from the plenteous professional knowledge of engineers. The three steps of the conventional IFD approaches are feature extraction, sensor data collection, and fault classification. Through several domain analysis processes, including those in the time domain, frequency domain, and time-frequency domain, features have been extracted from the gathered data. The collected features are utilized in the final fault classification stage to train ML algorithms, such artificial neural networks, support vector machines, and random forests to anticipate faults. The task-intensive manual feature extraction, with its many fault categorization jobs and variable machine operating conditions, has considerable disadvantages, nevertheless. In recent decades, deep learning (DL) has made a substantial contribution to the science of artificial intelligence (AI). DL significantly improves upon the inadequacies of the conventional IFD techniques. Popular DL methodologies like deep belief network, stacked autoencoder, and convolutional neural network

Digital Twin For Smart Manufacturing
DOI: https://doi.org/10.1016/B978-0-323-99205-3.00009-2

(CNN) have immediately drawn increasing amount of attention becoming the very popular devices for IFD due to their ability to automatically extract representative features from the data and appropriately establish non-linear mapping of various health problems. Smart manufacturing has expanded quickly and is becoming more autonomous, digital, and sophisticated as a result of the new generation needs, rapid growth, and increased application of information and communications technology [2,3]. Digital twins (DT) are dynamic representations of physical beings with their activities, behaviors, and regulations rather than only describing three-dimensional objects. A paradigm shift for advancing the growth of intelligent manufacturing is called the "digital twin" today. Through extremely accurate and dynamically optimized simulation models, it simulates and analyzes the whole product lifecycle, lowering design and maintenance costs while boosting manufacturing standard and effectiveness. Hyper realism, tractability, controllability, and unpredictability are the characteristics of a DT.

11.2 Fault diagnosis in digital twin

The dependability and security of the production process are given more consideration as it grows more sophisticated and intelligent. A minor mishap that occurs during production could result in losses that are beyond repair. Therefore a key component of smart manufacturing has been defect diagnostics [4]. Many cutting-edge tools and techniques are utilized in the big data age to diagnose faults, including deep learning, support vector machines, Bayesian networks, and SVM. The training set must include all relevant diagnosis information, and the training and validation data must have the same characteristic distribution for the majority of these intelligent diagnosis approaches to function properly. However, in the real world of production, only a large amount of data is simple to gather under regular circumstances. It is challenging to get thorough and extensive problem information necessary for completely training a diagnosis model. The production environment is also continually shifting, thus the trained model from the previous stage might not be similar to the current stage. Furthermore, rebuilding the generative model is a waste of time and expertise because it consumes a lot of effort and other computational capabilities [5–7]. Transfer learning (TL), a method that was developed to address the problem of sparse training data, has proven to be an effective way to fine-tune a deep structure that has already been pre-trained for other tasks. Though TL is built on pre-trained algorithms from entirely diverse applications, they might not have discovered the most relevant attributes. Thus, in real-world situations when the working conditions and system features are not fixed, the reliability of the diagnosis effectiveness can be greatly damaged. As a result, the two-phase DT-aided fault detection presented in this research uses deep transfer learning (DFDD) to increase the applicability of fault diagnosis for manufacturing that is becoming more autonomous and complicated.

11.2.1 Simulations of digital twin

A virtual representation created to faithfully represent a physical object is called a DT. These sensors transmit information about a variety of performance characteristics of the physical device, including electricity production, temperature, environmental conditions, and more. The processing system then applies this information to the digital version. A DT is essentially a virtual environment, whereas simulations and DTs both use digital models to recreate a system's different processes [8]. The main distinction between a digital model and a simulation is scale: A DT can run as many meaningful simulations as necessary to explore multiple processes, whereas simulation normally only studies one specific process. When utilizing a small number of samples in the particular domain to perfect a pretrained model that was learned on data acquired from the initial condition, the parameter transfer learning technique produces more reliable fault diagnostic accuracy. However, a significant barrier to applying parameter transfer learning is still the absence of measurable data for all fault states in the target domain. There are yet more variances. For instance, real-time data is typically not advantageous for simulations. However, DTs are built around a two-way information flow that begins when object sensors give the system processor pertinent data, and continues when the processor shares insights with the original source object. DTs are able to study more problems from far more vantage points than standard simulations can, with a greater potential to ultimately improve products and processes. This is because they have better and constantly updated data related to a wide range of areas, combined with the added computing power that comes with a virtual environment. The organization of DT is shown in the Fig. 11.1.

11.2.2 Fault diagnosis digital twin

Dr. Michael Grieves first introduced the idea of a DT in a 2003 Comprehensive and Innovative course at the University of Michigan. DTs

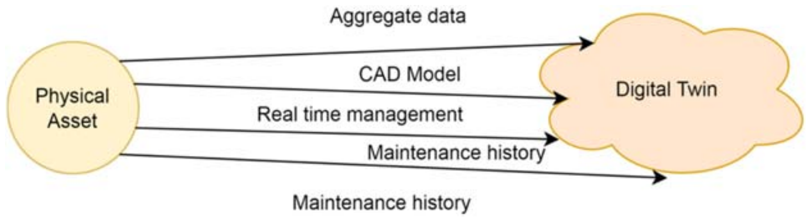


Figure 11.1 Organization of digital twin.

replicate, document, and enhance the entire production process from conception to retirement, including contents of virtual and real spaces as well as their interactions [9]. By modeling in virtual space, the undesired behaviors might be better understood and then altered out. The issue of the data island in the product lifecycle was resolved, and the dynamic update and synchronization between the virtual product and production execution were made possible by a new DT-driven method for product development processes. DT-based manufacturing has become more and more popular among academics as sensor, communication, and computing technologies have advanced. It is a virtual model with extremely high quality that replicates, mirrors, forecasts, and extends the life of its physical counterpart [10]. However, the focus of the most recent studies is mainly on conceptual models and critical technologies associated with DTs. The DT-based fault diagnostics has long been seen as a minor aspect of manufacture. Few of them have conducted more in-depth research on the framework, methodology, and algorithm of defect diagnosis.

11.3 Assistive technologies in digital twin

The reduced-order model (ROM) helps organizations convert data to models, extend their scope and compute faster. ROM can run your DT on embedded devices, cloud, and on-site. The basic idea is that ROM serves as catalyst for DT, enabling more applications that were not possible in the past. Depending on your applicability, data, and the model's system, there are various ways to construct a ROM. The approach can range from being informative with ML and deep learning to being hybrid with statistical models and physics to being entirely dependent on physics.

11.3.1 Types of digital twin

DTs come in a variety of forms depending on how magnified the product is. The field of application is where these twin diverge the most. Different kinds of DTs frequently coexist in a system or process. The different types of DT are:

1. Component twins or part twins
2. Asset twins
3. System twins or unit twins
4. Process twins

11.3.1.1 Component twins or part twins

The fundamental building block of a DT and the simplest illustration of a working component are component twins. Parts twins are essentially the same thing, although they relate to significantly less significant parts.

11.3.1.2 Asset twins

An asset is created when two or more elements operate well together. With asset twins, users can examine how these elements interact, producing a wealth of performances data that can be analyzed and transformed into useful insights [11].

11.3.1.3 System twins or unit twins

System or unit twins, which let you see how various assets combine to create a whole, functional system, are the next degree of magnification. System twins offer visibility into how assets interact and may give performance suggestions.

11.3.1.4 Process twins

The macro level of granularity, called process twins, reveals how systems interact to build a whole manufacturing plant. The precise timing schemes that ultimately affect the overall effectiveness can be found with the aid of process twins.

11.3.2 Digital twin in industries

Despite the benefits that DTs provide, not every company or every product made needs to employ them. Not all objects are intricate enough to require the continuous and intensive influx of sensor data that DTs demand [12]. Additionally, it is not always advantageous financially to devote a considerable amount of resources to the development of a DT.

However, using digital models for a variety of applications does have certain distinct advantages:

1. Physically substantial projects buildings, bridges, and other intricate structures subject to stringent engineering regulations.
2. Projects using complicated machinery vehicles, jet turbines, and aircraft. DTs can contribute to increased productivity in massive engines and intricate machinery.
3. Power apparatus covers both the electricity generation and transmission systems.
4. Manufacturing initiatives similar to industrial settings with cooperative machine systems, DTs are excellent at enhancing process efficiency.

Therefore those sectors that work on large-scale items or projects find most success with DTs:

1. Engineering systems
2. Automobile production
3. Aircraft manufacturing
4. Construction of buildings and manufacturing of railroad cars
5. Electric utilities

11.3.3 Digital twin and Internet of Things

It is obvious that the proliferation of Internet of Things (IoT) sensors contributes to the development of DTs. Additionally, as IoT devices become more advanced, DT situations may involve less complicated and smaller things, providing businesses with more advantages. Based on varying data, DTs can be utilized to anticipate various outcomes [13–15]. This is comparable to the run-the-simulation scenario, which is frequently featured in science fiction movies and in which a potential situation is validated in a virtual setting. DTs may frequently help developers determine where objects should go or how they ought to function before they are actually deployed, as well as optimize an IoT implementation for maximum effectiveness, with the help of additional software and business intelligence. Efficiency gains and other advantages are more likely to be realized the more closely a DT can replicate the original product. DTs might model how the equipment have operated over time, for example, in manufacturing when extensively instrumented equipment are deployed, which might help forecast future performance and potential failure. It is difficult to create a DT, and there isn't a common platform for doing so currently. The idea of a DT framework has been provided by Ian Skerrett, a specialist in the sector with extensive experience in open source. However, this is only the first stage because the technology is still in its infancy. Commercial DT services come from some of the biggest corporations in the industry, in contrast to much technology advancement that are driven by startups. For instance, GE and Siemens, two industrial behemoths with significant manufacturing involvement, are now making their expertise available to clients. GE developed internal digital technologies to create its jet engine manufacturing process. IBM is promoting DTs as part of its IoT drive, and Microsoft is providing its own DT technology under the Azure umbrella in an effort to keep up with these factory floor vendors.

11.3.4 Digital twin and predictive twin

A recent article by Network World contributor Deepak Puri described an Oracle DT solution that gives consumers the choice between a DT and a predictive twin. A narrative of the equipment, a 3D rendering, and information on every sensor in the device are all possible inclusions in the DT. It contributes to make sensor data that mimic choices in real life [16]. According to Puri, the prediction twin "predicts the future condition and behavior of the device." This is based on past information from other devices that can imitate device failures and other urgent scenarios. Microsoft is using the idea to apply to processes in addition to physical objects as part of its DT project. The growth of Industry 4.0 relies on the DT to enable automation, data interchange, and joined-up production processes as well as to reduce risk in product launch. Employees in the industry may keep an eye on processes in real time, offering early warnings of potential breakdowns and enabling real-time performance optimization and assessment with no loss of productivity. A DT is a modeling tool that is created by combining data with technologies like AI, ML, and software analytics [17]. This model can be updated simultaneously with or without its physical counterpart. Because of this, businesses are able to evaluate a fully automated development cycle, from development to implementation to decommissioning. A DT enables the industry to plan for downtime, respond to changing conditions, test design advancements, and much more by simulating actual assets, frameworks, and processes to create continuous data.

11.4 Cyber physical system and digital twin

Digital twins and cyber-physical systems are two components that are crucial for the implementation of manufacturing technologies. To make monitoring, data collecting, interpretation, analysis, and real-time control of resources and raw materials easier, CPS improves communication between smart manufacturing entities like sensors, actuators, control, etc., and cyber computing resources [18]. DT creates digital equivalents with high integrity, knowledge, and flexibility to offer digital predictive services for manufacturing organizations using legitimate and historical information from sensor systems, physics-based models, and advanced analytics. It improves the functions of the CPS's transparency and viability and makes it easier to monitor, simulate, optimize, and control cyber-physical aspects in real-time. To deliver on-demand prediction services to various customers in both physical and virtual locations, a DT-based CPS (DT-CPS) should continuously collect, combine, evaluate, simulate, and synchronize across numerous phases of the product lifecycle. Below is a summary of the main traits and prerequisites for DT integration in CPS.

1. Smart objects and communication infrastructure: Manufacturing equipment should be fitted with intelligent sensors that allow for real-time monitoring and network-wide data sharing. A safe, dependable, and fast platform is necessary for these ongoing data transfers.
2. Enhanced analytics: Without the need for a lot of human intervention or manual feature development, it is crucial to automate the entire process of data pretreatment, perception, evaluation, learning, and execution. The manufacturing systems now have the ability to self-configure, self-adapt, and self-learn, which boosts output and improves speed, flexibility, and effectiveness.
3. Cooperative judgment: To arrive at a globally effective outcome, real-time constraints and data from different sources must be taken into account. This procedure involves assessing the viability, effectiveness, and execution strategies of various orders.
4. Independent and quick model construction and updates: Advanced model mapping among virtual and physical systems and information synchronized ensure the least possible difference between virtual and physical components, which is necessary for real-time control, optimization, forecasting, etc.

11.4.1 Deep learning in digital twin

In an extended group of ML techniques, deep learning (DL) is able to ingest raw data and automatically produce the abstractions needed for a variety of tasks, including classification, regression, clustering, and pattern recognition. DL has several uses in the manufacturing industry since it is particularly effective at identifying complicated structures in high-dimensional data. It enables higher degrees of abstractions without relying on manual feature engineering, and its excellent performance has been demonstrated in a variety of fields, including inventory management, computer vision, fault detection, and voice recognition. It was suggested to use a CPS structure called the 5C-CPS, which offers plug-and-play embedded sensors connectivity that is layered, networked, and allows for smart cyber-physical exchanges [19–21]. To facilitate and implement smart manufacturing, an integrative model based on DT and DL is suggested (DTDL-CPS) in this research. This architecture improves transparency, robustness, and manufacturing efficiency while bringing autonomous, collaborative, self-adaptive, self-learning, and self-maintain features to 5C-CPS design. Emerging technologies like 5G, industrial AI, blockchain, and learning techniques may make it much easier to implement DT in production systems. Briefly, 5G improves network capacity, dependability, and throughput while reducing communication delay. Industrial AI facilitates the application of DTs by bringing self-aware, self-adapt, and self-configure features to the system. Blockchain technology has the potential to improve peer-to-peer connections and do away with middlemen in the networking process. Organizations may begin with the deployment of vital technologies and gradually add other technologies into their manufacturing systems depending on their needs and objectives.

11.4.2 Deep learning in digital twin

To give a step-by-step roadmap for the implementation of these five functionalities, a DTDL-CPS architecture is provided. A step-by-step approach that outlines how to build DTDL-CPS from data collecting to DL for automatic analysis and virtual data modeling as well as to offer on-demand services is presented (Fig. 11.2).

1. Intelligent correlation: The foundational component of DT-based CPS applications is data. Smart sensors, actuators, controllers, etc. on the production shop floor or production enterprise systems like Enterprise Resource Planning, Supply Chain Management, Collaborative Manufacturing Management, and Customer Relationship Management are used to obtain it [22]. However, taking into account the following elements is crucial: Synchronization between various resources, low-latency data transfer to the cloud,

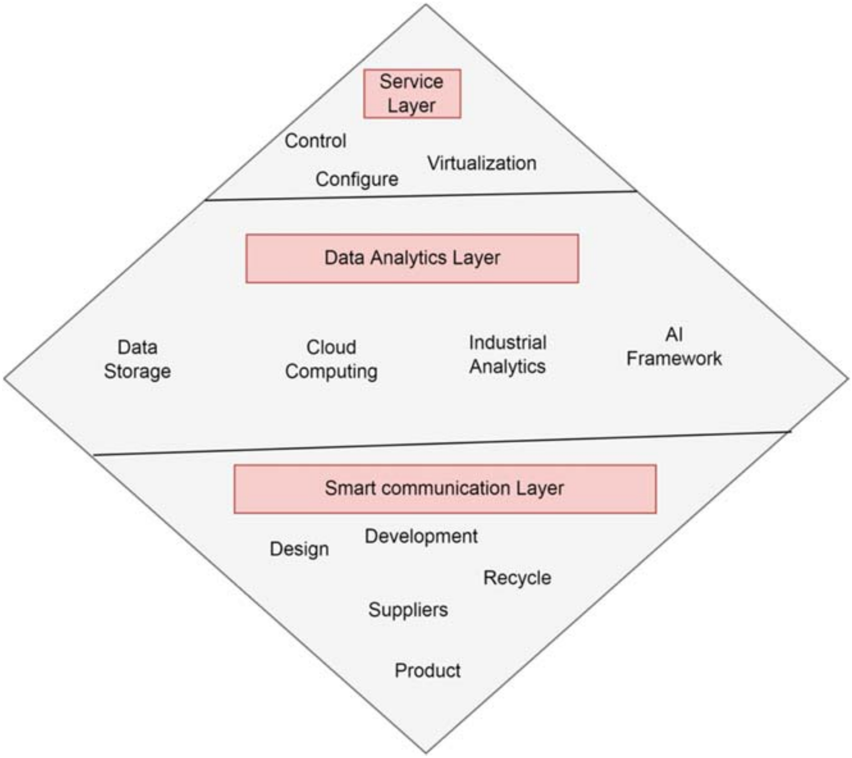


Figure 11.2 Architecture of digital twin with cyber-physical system.

privacy and security, dependability in data transfer, low energy consumption in data transfer, and interconnectedness across various smart things are the first six criteria. Emerging communications systems, including 5G, are anticipated to meet many of these needs in the manufacturing sector. With its ultra-high speed, high dependability, low energy consumption, and increased security, 5G technology enables communications and data transfer. Additionally, the addition of micro-clouds and blockchain technology would improve the capabilities of smart connections.

2. Transformation of data into information: In this layer, a computation resource like Edge or Fog computing may be used to: (a) decrease the transmission delay between smart objects and the cloud; (b) feature extraction data and extract necessary data before sending data to the cloud; (c) maintain interaction among smart objects in the connection layer; and (d) immediately execute control orders to improve

manufacturing resilience and disturbance rejection. For data to distribute learning at this level, ML algorithms with a medium degree of computation complexity and time complexity are suitable.

3. Big data analytics: This layer serves as a hub for advanced AI and data storage. Big data is produced in three main categories: structured, unorganized, and semi-structured. Unstructured data accounts for 95% of big data. Knowledge discovery from unstructured data can be greatly improved by DL approaches for text/image mining and signal processing [23]. And DL does this without the need for manual feature engineering, extracting useful data. So it can greatly enhance autonomous features including real-time control, optimization, and prognosis and health management. If the training model's efficiency is subpar, it is kept in use until the evaluation yields results that meet the performance requirements. The real-time data is then tested using the trained model. Finally, the previous model is revised following each iteration and real-time evaluation. The suggested DL framework aids in the independent updating of learned DL models and the identification of possible data/model divergence. The analytics and data required by the virtual system layer are also provided by this layer.
4. Virtual systems: The most crucial element in this layer for simulating the lives of their physical counterparts are digital models [24]. They are continuously developed, watched over, assessed, and updated to deliver services at a pace that is nearly real time. The suggested framework for creating and maintaining a digital model is shown in Fig. 11.3. It is divided into two main sections. Model building and selection comes first, followed by model performance assessment and updating. The most comparable model from a library of existing models could be chosen using various AI technologies, such as a genetic algorithm. If there was no existing model that was similar, a model is

Figure 11.3 Anomaly detection in digital twin.

created with the aid of more sophisticated DL models, including transfer learning. Using information/data from a base model to construct new models more quickly and efficiently is known as transfer learning. A supervised learning algorithm continuously monitors the performance of both real world and digital models for models that are currently in use to ensure that there is little to no difference among them. The learning agent will adjust the parameters of the digital model in response to any alterations in the physical model.

5. Service layer: When DTDL-CPS is implemented at this level, a highly synchronized and intelligent CPS is produced where services like intelligence, control, visualization, optimization; PHM, etc., are made available for use in the physical system. These services span a wide range of applications, including optimizing production layout, regulating production task order, ordering products from inventories, and boosting peer-to-peer connections. Users' decision-making is facilitated by representation as a service.

11.4.3 Convolutional neural network based digital twin

Convolutional neural network machine tool realization of the suggested concept is employed in a shop floor where DT and DL are used to accomplish self-maintenance, self-configuration, and predictive services. DL has been embraced to deliver autonomous capabilities with repeatable and consistent successes, reducing reliance on humans for decision-making. The functional network as a whole is made more transparent with the usage of DT. Forecasts regarding the remaining useful lives of various components are transmitted to the virtual system layer in this design, where real time and contextual data from machines, inventory, distributors, customers, and maintenance workers are incorporated into DT modeling and optimize preventative maintenance techniques. For implementation, the physical system receives the optimized plan and any additional visual information. All models operate independently and cooperatively to build a closed-loop preventative maintenance framework as this procedure is performed in semi-real time. It offers a useful road map for the creation and implementation of smart manufacturing with improved openness, collaboration, networking, resilience, and effectiveness. New technologies, including 5G, are anticipated to considerably aid in the incorporation of DL and DT in the CPS.

11.5 Digital twin in fault diagnosis

The use of DT technology offers enormous promise across a range of industries, including infrastructure, aircraft, and the car industry. The lack of implementation information has, however, slowed down the practical use of this technology. Here, we concentrate on a DT paradigm for structural model dynamic systems with a single degree of freedom that are changing over two operational time scales in addition to their intrinsic dynamic time scale. Our method divides itself into two parts with purpose: (1) a quantum theory nominal framework for data processing and reaction predictions; and (2) a data-driven ML model for the temporal evolution of the system parameters. It is critical to immediately identify problems when tracking telemetry from a large number of IoT devices. For instance, a fleet manager who oversees hundreds of trucks on the road must adhere to strict schedules and cannot afford unforeseen breakdowns for a fleet of long-haul trucks. These trucks may now send their engine and cargo status to cloud-hosted telemetry applications every few seconds thanks to the IoT technology. For detecting and analyzing IoT telemetry from numerous sources of data, real-time DTs provide a potent software system. A real-time DT is a piece of software that runs on a quick, scalable in-memory computing device. It contains the analytics code and state data useful for tracking a single data source, such as a truck inside a fleet, as well as other data. To keep track of all the sources of data and enable extremely detailed real-time analysis of incoming telemetry, thousands of real-time DTs work together. Real-time DTs improve real-time streaming analytics while also streamlining application design by expanding on the popular DT concept [25]. Real-time DTs get more strength and simplicity by integrating ML approaches. Nevertheless, code for analytics can be written in well-known programming languages.

11.5.1 Anomaly detection in digital twin

ScaleOut Software incorporated Microsoft's well-known ML framework known as ML.NET into its Azure-based ScaleOut Digital Twin Streaming Service to allow ML algorithms to run within real-time DTs. Following deployment, the ML system operates independently for each data source, inspecting incoming telemetry milliseconds after it comes and reporting anomalous occurrences. Additionally, the real-time DT can be set up to create alerts and send them to well-known alerting services. The diagram below shows how a real-time DT that houses an ML algorithm for each truck in a fleet can be used to track engine and load parameters. The real-time DT captures the occurrence and notifies the alerting provider when the ML algorithm detects aberrant parameters. Providing a training set of historical data that has been divided into normal and abnormal categories is all that is needed to train an ML system to recognize abnormal telemetry. The ScaleOut Model Development Tool uses supervised learning to enable users to train and test up to 10 binary classification algorithms provided by ML.NET utilizing this training data. Based on metrics collected for each algorithm during training and validation, the user can then choose the best trained algorithms to deploy.

Along with supervised learning, ML.NET also offers a spike detection method that recognizes sudden changes in telemetry for a particular parameter. Users of the ScaleOut Model Development Tool can use this approach to add spike detection for particular parameters. Additionally, it is frequently helpful to spot odd yet slight changes in the telemetry of a parameter over time. For instance, it might be helpful to notice a modest rise in temperature that could otherwise go unnoticed if the temperature for an electric motor is predicted to remain constant. The solution provides access to a ScaleOut-created linear regression algorithm that identifies and presents inflection points in the telemetry for a particular parameter to meet this demand. Important real-time insights from ML help improve situational awareness and enable quick, efficient responses. For complex datasets that cannot be evaluated with hand-coded algorithms, they frequently can offer useful analyses. Their applicability and acceptance rate are both rising quickly. Real-time DTs can now be quickly improved to automatically evaluate incoming telemetry messages using ML methods that fully utilize Microsoft's ML.NET framework using the ScaleOut Model Development Tool. It is now possible to autonomously and independently analyze thousands of data streams in real time with rapid, scalable performance thanks to the combination of ML and real-time DTs. The best part is that no code is necessary, making model development quick and simple. The ScaleOut Digital Twin Streaming Service boosts the Azure IoT ecosystem by fusing ML with real-time DTs to add significant new capabilities for real-time streaming analytics.

11.5.2 Digital twin in virtual management

The DT can be utilized to create things, test them in actual use cases, specify how customers or end users will use them, and determine how the design will work with the product's surroundings. The digital model is updated with data from the actual machine to allow simulation and idea testing before actual production even gets underway. To plan and restructure the product in reaction to external change, employ DT. A DT for hydraulic support was created to imitate the real thing and to aid in investigation of degradation and diagnosis. The DT is used in CNC machine tools as well. The DT may analyze performance data gathered over time and under various circumstances, decreasing costly production quality errors, lowering unplanned machine downtime, and increasing the quantity of "scrap" produced in each production line. The production process can be enhanced and optimized to achieve greater effectiveness and flexibility. Between physical objects and virtual spaces, there are connections and interactions at the network layer. All components are linked via this layer, allowing them to exchange data and knowledge with other connected components. Middleware, communication protocol analysis, communication protocol/interface conversion, wireless communication, and application programming interfaces are the main technologies covered in the literature review. The applications for DTs that are already available deal with specific and established fields, including healthcare, maritime and shipping, manufacturing, city management, and aerospace. Particularly in manufacturing situations, people are critical to use DT applications. The development and application of DT in the manufacturing industry face one major challenge: human interaction. Many decision-making tasks are still supported by many manual processes based on human interactions, even though some low-level operations can be autonomously completed without human participation. The scientific challenge is to create cognitive DTs that can seamlessly interact with people and other DTs no matter what happens during their encounters. Additionally, the DTs might theoretically support a shift away from the dominant industrial model of extraction, production, consumption, and disposal. The DT can assist businesses transition from a linear to a "circular economy" system, which takes into account nearly zero waste creation and pollution, extends the life of products and materials via recycling, and aids in the regeneration of natural systems.

11.5.3 Digital twin lifecycle and functions

Real-time simulation for the three phases of the product lifecycle design, manufacture, and services presented by DT is an interesting opportunity.

Every stage of the lifecycle allows for the development of the DT, which may perform various tasks. The DT may be able to aid in supply chain integration throughout the whole product lifecycle, if not even the entire supply chain. The use of DTs to assist the network firms and the entire supply chain is still relatively new. Applications called "DTs" are mostly created for forecasting and supporting decision-making. Within the virtual world, the DT could link entities such as goods, people, machines, and businesses. However, given the current situation, this component poses its own difficulties. Interoperability problems may arise from the capacity to gather, aggregate, and communicate data and information among various suppliers, manufacturers, and clients. Since DT has the potential to integrate data seamlessly across a product's lifetime, defining standards and communication protocols to enable interoperability between various DTs is one of the major research issues. The advancement of standards-based interoperability is critical and difficult at the same time for the lifecycle of DT applications. The DT consists of a collection of models with intricately detailed structures and behavior that accurately capture the functioning of the physical system in real time. A lot of data is required when modeling a digital replica of a physical system for real-time validation and optimization. A model of a component, a system of components, or a system of systems can be a DT. The creation and use of precise replicas of reality are necessary for the DT. It is difficult to accurately represent reality in a DT, since it requires sensors, multifunctional models, data from several sources, services, etc. Due to the complexity of actual systems, it is currently difficult to create an appropriate model for a DT using conventional methods. Due to the absence of a clear reference design, solutions for DTs are developed using various technologies, interfaces, and communication protocols, as well as models and data that have been evaluated. To give design requirements and design restrictions where reference architectural aspects, reference information models, and modulation schemes are explicitly established, standard DT technologies are required to be established. To increase modeling efficiency, the modularization design philosophy needs to be investigated. This would make it possible to increase the adaptability and reuse of conventional DT solutions in various applications. Exploring modular methods will help create adaptable DT systems and enable new DT applications.

References

[1] D. Vargo, L. Zhu, B. Benwell, Z. Yan, Digital technology use during COVID-19 pandemic: a rapid review, Hum. Behav. Emerg. Technol. 3 (1) (2021) 13–24.

[2] R.K. Dhanaraj, S.H. Islam, V. Rajasekar, A cryptographic paradigm to detect and mitigate blackhole attack in VANET environments, Wirel. Netw. (2022). Available from: https://doi.org/10.1007/s11276-022-03017-6.
[3] V. Rajasekar, S. Krishnamoorthi, M. Saračević, D. Pepic, M. Zajmovic, H. Zogic, Ensemble machine learning methods to predict the balancing of ayurvedic constituents in the human body: ensemble machine learning methods to predict, Comp. Sci. 23 (1) (2022).
[4] M. Sailer, J. Murböck, F. Fischer, Digital learning in schools: what does it take beyond digital technology? Teach. Teach. Educ. 103 (2021) 103346.
[5] M. Skare, D.R. Soriano, How globalization is changing digital technology adoption: an international perspective, J. Innov. Knowl. 6 (4) (2021) 222−233.
[6] V. Rajasekar, B. Predić, M. Saracevic, M. Elhoseny, D. Karabasevic, D. Stanujkic, et al., Enhanced multimodal biometric recognition approach for smart cities based on an optimized fuzzy genetic algorithm, Sci. Rep. 12 (1) (2022) 1−11.
[7] S. Krishnamoorthi, P. Jayapaul, V. Rajasekar, R.K. Dhanaraj, C. Iwendi, A futuristic approach to generate random bit sequence using dynamic perturbedchaotic system, Turkish J. Electr. Eng. Comp. Sci. 30 (1) (2022) 35−49.
[8] S. Nikou, M. Aavakare, An assessment of the interplay between literacy and digital technology in higher education, Educ. Inf. Technol. 26 (4) (2021) 3893−3915.
[9] H.M. Alakrash, N. Abdul Razak, Technology-based language learning: investigation of digital technology and digital literacy, Sustainability 13 (21) (2021) 12304.
[10] S. Velliangiri, R. Manoharn, S. Ramachandran, V. Krishnasamy, V.R. Rajasekar, P. Karthikeyan, et al., An efficient lightweight privacy preserving mechanism for industry 4.0 based on elliptic curve cryptography, IEEE Trans. Ind. Inform. 18 (2021).
[11] S. Krishnamoorthi, P. Jayapaul, V. Rajasekar, A modernistic approach for chaotic based pseudo random number generator secured with gene dominance, Sādhanā 46 (1) (2021) 1−12.
[12] M. Hilbert, Digital technology and social change: the digital transformation of society from a historical perspective, Dialogues Clin. Neurosci. 22 (2022).
[13] S. Velliangiri, R. Manoharan, S. Ramachandran, V. Rajasekar, Blockchain based privacy preserving framework for emerging 6G Wireless Communications, IEEE Trans. Ind. Inform. 18 (7) (2021) 4868−4874.
[14] V. Rajasekar, P. Jayapaul, S. Krishnamoorthi, M. Saracevic, M. Elhoseny, M. Al-Akaidi, Enhanced WSN routing protocol for Internet of Things to process multimedia big data, Wirel. Personal. Commun. 126 (2021) 1−20.
[15] I. Mustapha, N.T. Van, M. Shahverdi, M.I. Qureshi, N. Khan, Effectiveness of digital technology in education during COVID-19 Pandemic, A Bibliometr. Anal. 15 (2021).
[16] S. Krishnamoorthi, P. Jayapaul, R.K. Dhanaraj, V. Rajasekar, B. Balusamy, S.K. Islam, Design of pseudo-random number generator from turbulence padded chaotic map, Nonlinear Dyn. 104 (2) (2021) 1627−1643.
[17] F. Iodice, M. Romoli, B. Giometto, M. Clerico, G. Tedeschi, S. Bonavita, et al., Stroke and digital technology: a wake-up call from COVID-19 pandemic, Neurol. Sci. 42 (3) (2021) 805−809.
[18] V. Rajasekar, J. Premalatha, K. Sathya, Enhanced biometric recognition for secure authentication using iris preprocessing and hyperelliptic curve cryptography, Wirel. Commun. Mob. Comput. 2020 (2020).
[19] V. Rajasekar, K. Sathya, J. Premalatha, Energy efficient cluster formation in wireless sensor networks based on multi objective bat algorithm. In: Proceedings of the International Conference on Intelligent Computing and Communication for Smart World (I2C2SW), 2018, December, pp. 116−120. IEEE.

[20] B.N. Limketkai, K. Mauldin, N. Manitius, L. Jalilian, B.R. Salonen, The age of artificial intelligence: use of digital technology in clinical nutrition, Curr. Surg. Rep. 9 (7) (2021) 1–13.
[21] V. Rajasekar, J. Premalatha, K. Sathya, Multi-factor signcryption scheme for secure authentication using hyper elliptic curve cryptography and bio-hash function, Bull. Pol. Sci. Tech. Sci. 68 (4) (2020).

CHAPTER 12

Potential applications of digital twin technology in virtual factory

Anamika Singh[1], Md. Akkas Ali[1], Balamurugan Balusamy[2] and Vandana Sharma[1]
[1]School of Computing Science and Engineering, Galgotias University, Greater Noida, Uttar Pradesh, India
[2]Shiv Nadar Institution of Eminence, Delhi, India

12.1 Introduction

Digital twin technology forms the core of the fourth industrial revolution or Industry 4.0, particularly in the manufacturing of products or services. Today, every emerging industry focuses on artificial intelligence (AI), machine learning (ML), and every domain has seen a paradigm shift toward the Internet of Things (IoT), and with all of these digital twins enhances the cost-effectiveness and accessibility to the system. Digital twin technique actually draws a fusion of reality with virtuality that can be better understood as, by making use of digital twin technology in cyber-physical systems, a rough image of actual system to be designed is drawn which acts as a prototype of the working of the proposed system, its drawbacks are noted and recorded, its implementation, and more. Thus, the issues in the system can be efficiently eliminated at each stage of the lifecycle starting from designing to implementation, which makes the system more convenient and cost-effective for the manufacturing industries. Digital twin technology enables a mirror image of the actual product or the system being designed. It facilitates the industry to design a mirror or virtual model of the corresponding physical model that virtually provides a realistic feel to the physical or the real environment of model. The virtual model generated using digital twin explains the past, present, and also the future of the physical model and also records and reports the changes that dynamically take place in the model. Traditionally, the blueprint of system to be designed is made as a whole for the complete system explaining the working, implementation, resources, etc. and applied to generate a final system. If any issues are found with the system, they could only be monitored when the actual

Digital Twin For Smart Manufacturing
DOI: https://doi.org/10.1016/B978-0-323-99205-3.00011-0

and the final system goes under execution and then tracking and modifications that render the system as good for the industries using the system. Many researchers have contributed their work in the field of this technology and noted the part of the digital twin technology being used and how it is implemented is also one of the important aspects to be considered.

12.1.1 Definitions of digital twins

In 2003, Grieves in his presentation was the first to coin the terminology. Later, in 2012, NASA presented a paper titled "The Digital Twin Paradigm for Future NASA and U.S. Air Force Vehicles," which placed a breakthrough in explaining digital twin.

a. NASA 2012: "A Digital Twin is an integrated Multiphysics, multiscale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history etc., to mirror the life of its corresponding flying twin."

b. Chen 2017: "A Digital Twin is a computerized model of a physical device or system that represents all functional features and links with the working elements."

c. Zheng et al. 2018: "A Digital Twin is a set of virtual information that fully describes a potential or actual physical production from the micro atomic level to the macro geometrical level."

d. Madni 2019: "A Digital Twin is a virtual instance of a physical system (twin) that is continually updated with the latter's performance, maintenance, and health status data throughout the physical system's life cycle."

The idea of digital twinning is actually not new. Its foundation was led by NASA in 1960s during its space exploration mission. The history of the digital twin technology is summarized in Table 12.1.

Table 12.1 History of Digital Twin technology.

Year	Description
1960s	NASA introduced initially during its space exploration mission
1991	David Gelernter first proposed with the publication of "Mirror Worlds"
2002	Dr. Michael Grieves first applied the concept of digital twin to manufacturing
2010	NASA's John Vickers introduced the word "Digital Twin"

By 2017, the concept of digital twin became the top among the strategic industries. As discussed, the concept was formally given by Dr. Michael Grieves; the digital twin works with the following three constituents:

1. The physical space which involves physical models
2. The cyber space that includes cyber models
3. A link that establishes the communication between the real world and the cyber entity.

12.2 Digital model

To power up the performance of digital twin, a variety of digital models work with the technology. Traditionally, CAD was implemented to design the digital models. With the help of these models, a detailed design of the physical model being developed could be achieved digitally, the concepts and implementation could be studied prior to obtaining the actual product physically. The modifications on the design, implementation, etc. can be done on the digital model efficiently and the approach has also been proven cost-effective. Some of the models are elaborated here:

- Numerical model: This model implements AI and ML algorithm to predict the future of the model.
- 1D Simulation: The particular model comprises graphs, equations, or formulas that integrate with the embedded system to imitate the performance of the system.
- 3D Simulation: These are the models that note and report the deep insights to the execution and operations of the device. The imitation depicts the functioning of the system under consideration.

12.3 Digital shadow

It can be understood as the shadow of the physical object that is designed digitally, thus named digital shadow. This concept plays a very vital role in digital twin technology. This makes use of sensors that capture the information from vivid environment to the digital or virtual implementation. The shadow of the physical model generated digitally simplifies the immense amount of information held by the physical world object.

12.4 Digital twin

To initiate with digital twin, it uses both the abovementioned approaches; the digital models and the digital shadow. It facilities with designing of the mirror model from the physical object and thus based on various conditions, decisions are made as to whether the project has to be rejected or taken forward for implementation and execution. Digital twin works bi-directionally, the flow of information moves from physical environment to the virtual world and vice versa.

12.5 Foundational concept

Digital twin technology embraces the use of virtual reality as its core concept. Virtual reality is an approach of making a virtual system, which reflects the replica of the real system and allows user interaction as in real environment. It is a computer-generated environment that actually does not exist but is the clear image of what the actual system is all about and hence named "virtual reality." The invention of virtual reality was noted far back in the mid-1950s and it was considered that the first virtual reality machine was Sensorama, which was featured with in-built seats and 3D movies were played with the feel of vivid colors and vibrations to make the audience experience the real environment. Its future has the highest growth potential. According to IDC Research (2018), investing in virtual reality and augmented reality will reach EUR 15.5 billion by the year 2022 and worth around US $184.66 billion by 2026, as it is the fastest emerging and interesting technology all over the world. AI, ML, big data, and IoT are the key technologies that enable digital twin technology.

12.5.1 Applications of virtual reality

Some of the sectors have already experienced the benefits provided by virtual reality (VR) technology, such as medicine, culture, education, and architecture.

1. *VR in military:* Virtual reality has expanded its application in the military sector, such as in the US and the UK, virtual reality plays a beneficial role in training navy, army, air forces, marines, and the coast guards. It allows to simulate weapons, aircrafts, to formulate a boot camp, and more.
2. *VR in education*: By using virtual reality approach, students and teachers can employee themselves to create a teaching and learning environment virtually.

3. *VR in sports*: It can be deployed in sports industry enhancing the coaches and the players to provide and get training on various sports with the feel of vivid environment and to experience the scenario specifically to get better and enhanced performance.

12.6 Crucial technical components of VR

The VR systems are providing the best realistic view to the user, but still the technology has to reach the capabilities of human vision. The complete working of the VR implements some components and the basics that work behind this technology are listed as:

1. *Field of view*: Technically, the capability of human vision is much broad field of view (FOV) than the one provided by the virtual reality headsets. Talking about an average human, one can have the vision of the environment around him of about 200−220 degree arc around their head and to the left and right vision, it is roughly 114 degree arc, what is facilitated in 3D and the handsets today's provide that 114 degree rather than focusing on the overall FOV of humans.
2. *Frame rate*: It is noted in the study that a human can only absorbs the frame rating to 150 FPS, and if the limit exceeds, the information being transmitted is lost on the way to brain. Theaters use 24 FPS while showing movies but it is found that the rate below 60 FPS results in causing headache, disorientation, and nausea in the viewer. So VRs today are now moving to extend the rate to 120 FPS.
3. *Sound effects*: The VR depends on the technique called "spatial audio" to generate the audio that matches the environment created by VR.
4. *Tracking of head and position*: This enables the viewer to move their head positions within the virtual environment. It is right now done by using degrees of freedom, 3DoF and 6DoF.

12.7 Types of digital twin

Digital twin technology is divided into various categories, which can be explained as:

1. *Product*: This category of digital twin facilitates in examining how a particular product performs under various situations and accordingly make modifications in the virtual environment so that the final physical product will work the way it intends to do.

2. *Production*: This helps in validating the product under development before deploying the product into actual production. By this, the companies can design the methodology of production such that the product executes efficiently under various circumstances.
3. *Performance*: The products and smart systems produce numerous amounts of information highlighting their uses and effectiveness, and this category of digital twin gathers all these data to generate actionable decision-making.
4. *Component twins*: These are the foundation unit of the digital twin.
5. *Asset twins*: Combination of two or more components results in asset twins; they integrate components that generate an actionable visual.
6. *System or unit twins*: This involves integrating different assets and report the performance of the entire system.

12.8 Working of digital twin

The implementation of digital twin technology follows the following steps to convert a physical model into a virtual model, which is considered as the mirror model of the specific physical model, the steps goes in the following sequence and modeled in Fig. 12.4.

1. The first step is data collection, wherein the data is assembled from the physical environment and includes physical, manufacturing, and operational data.
2. The data gathered is passed through AI algorithms and software that analyze and synthesize the data.
3. Finally, the mirror virtual model is generated using the physical model data by making use of virtual reality that facilitates the vivid feel to the real environment.

Fig. 12.1 above explains through the example of modeling a car from physical data to the virtual model. This involves gathering data from a real object through sensors, then the data is passed to different AI and ML algorithms. The object being modeled is diagnosed by establishing communication with IoT and with the help of algorithms and analytics software, a virtual mirror model is thus designed to provide the realistic feel of the actual product.

12.9 Components of digital twin

Digital twin technology works basically with its four key components:

1. *Physical object model*: It comprises the virtual model designed by the physical model or the collection of physical objects.

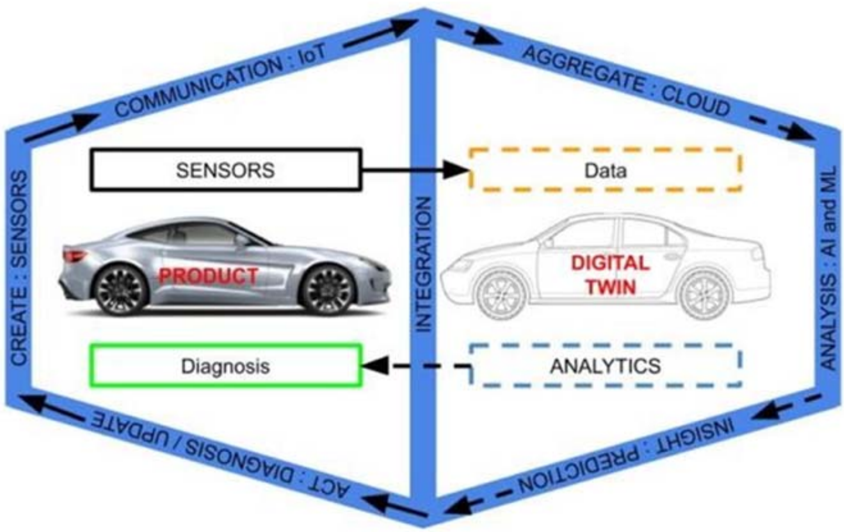


Figure 12.1 Illustration of digital twin implementation.

2. *Time series data*: Using sensors, it collects the series of time from the objects or from other related sources.
3. *Unique identifier*: It is a unique number, such as the asset ID or the equipment number, etc., which associates digital twin from the physical object.
4. *Monitoring capability*: It examines how well the digital twin could monitor the abilities of the object usually making use of sensors, cameras, and likewise.

12.10 Simulation

The concept of simulation is better understood as the process or technique that imitates the functionality of the real world object with the help of different models. Simulation is generally a computer-based application that uses models generated by the software to enable and facilitate decision-making. The model generated is a replica of the actual real world object that has the features, characteristics and the behavior of the physical model. The main focus of simulated objects is to mimic the functions and the operations of the real world object. In simple, simulation is the virtual representation of the actual thing in existence. With the evolution of fourth revolution of industries or Industry 4.0, there have been rapid

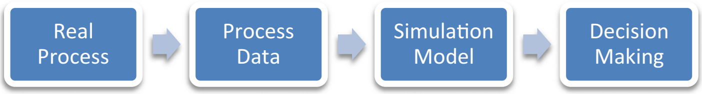


Figure 12.2 Proposal for using simulation.

increase in the automation, integration, and digitization. It is the realistic mirroring of something that exists in the real environment and provide a virtual but vivid view of the same. The technology is not limited to only few sectors but has extended its presence and importance in military, logistics, and hospitals.

Simulation facilitates in decision making on the basis of outcomes of the model deploying it in the actual environment and then ending the cycle of decision. Fig. 12.2 below demonstrates the approach:

The decision-making cycle is as follows:

1. Target the real process from the physical environment.
2. After selecting the physical model, mass up the information from the respective physical object.
3. Design a simulation model based on the data collected from the real-world object.
4. Examine the overall aspects of the model and conclude the process announcing the decision.

12.11 Simulation versus digital twin

The two are alike in some aspects but also differ in some way or the other. The comparison chart between the two is illustrated as:

Comparison parameter	Simulation	Digital twin
Matter of scale	It considers only a specific object or process	Whereas, this technology enables execution of various simulations resulting in the examination of more than one process
Usage	Basically supports designing and sometimes offline optimization in some cases	It facilitates overall designing, execution, and decommission of the lifecycle

(*Continued*)

Comparison parameter	Simulation	Digital twin
Depiction	Only focuses "what may" occur in the physical world	Contrarily, it explains both "what may happen" as well as "what is happening"
Basis	Parameters as input	Responses from the real world related to specific product/process
Interaction	Static	Active

12.12 Literature review

Santos (2020) in the proposed study explained how the transmission of data and information linking the actual world and the simulation system takes place. First, it should be noted that it is not necessary for the physical system and the simulation model to be there in the same enterprise resource planning (ERP), as the communication between the two could be established with the help of cloud technology. The information from the real process moves to the ERP, the data is processed and then a simulation is designed for the real object, which enables decision-making. To compare the data of the actual system and the simulation model, he made use of variance ANOVA test. In such case, the designed simulation model is projected to execute 17 replicas in one cycle, to achieve the accuracy of 1 minutes and confidence interval of 95%. He concluded that the process of gathering data and the reaction generated by digital twin are the procedures that are independent of each other that may occur at different times.

AJH Redelinghuys (2019) with his work elaborated the six-layer architecture (Fig. 12.3) of the digital twin technology in the manufacturing sector, mentioning how data flows between each layer in the architecture starting from physical world to the cloud.

1. *Layer 1 and 2 (Physical twins)*: The two topmost layers comprise the physical twin layer, where in layer 1 all the physical devices are present such as sensors and the layer 2 that is the local controller, provide some functions to the digital twin. Both the layers are considered different but work in integration.
2. *Layer 3 (Local data repositories)*: It consists of the data of the physical model and is present near the physical twin. The data present in the

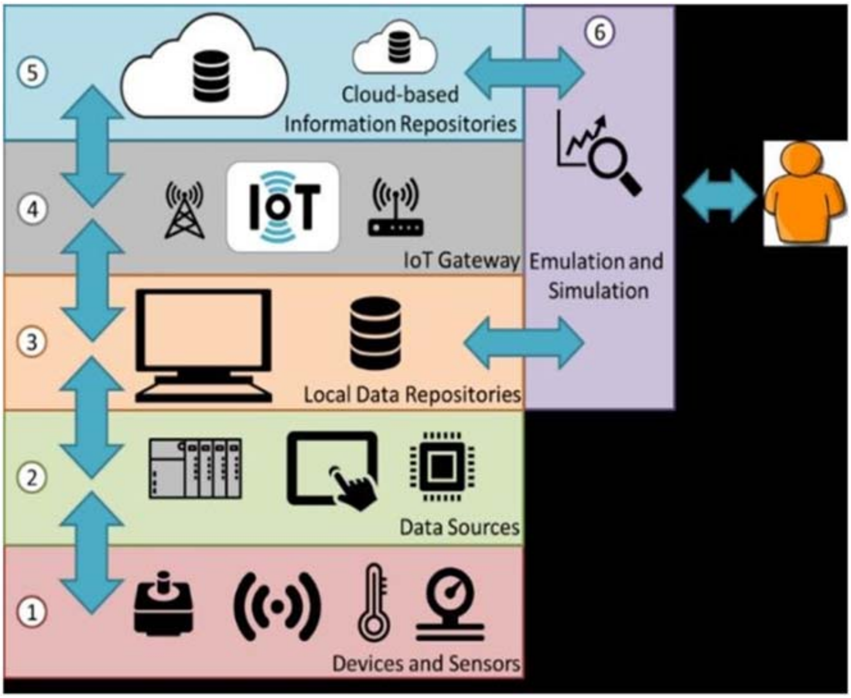


Figure 12.3 Architecture supporting digital twin.

repository hold the details of the layer 1 and in addition to that it adds processing to layer 2 to make data available for the digital twin.

3. *Layer 4 (IoT gateway)*: This layer enables the physical twin to establish communication with the real world. It develops synchronization between the layer 3 and the layer 5. Some of the roles managed by this layer are as listed below:
   a. Gathers information from layer 3 to opt the most suitable and accurate data to enhance future decision-making.
   b. To eliminate the immense data in repository, it selects the data that only need to passed on to data repository.
   c. By putting limit to the data that network gateway process, it avoids bottleneck caused due to bandwidth.
4. *Layer 5 (Cloud-based information repositories)*: For the data held by physical twin and the digital twin, this layer contains database servers enabled by cloud that are the repository of the information. To enhance the accessibility and availability these repositories are deployed to the cloud.

5. *Layer 6 (Emulation and simulation)*: This layer completely depends on the actual application and the infrastructure is provided by layer 1 to layer 5 but the digital twin intelligence is headed by this layer. It is responsible to allocate and allot different roles to the digital twin.

12.13 Potential applications of digital twin

With rapid enhancements in digitization and evolution of the fourth revolution of industries, most of the sectors have already experienced and applied digital twin as their working concepts. Today, almost every industry is shifting its paradigm to virtual scenario and these applications can be characterized by but not limited to the following and illustrated in the below Fig. 12.4.

1. Smart cities
2. Manufacturing
3. Healthcare
4. In industries

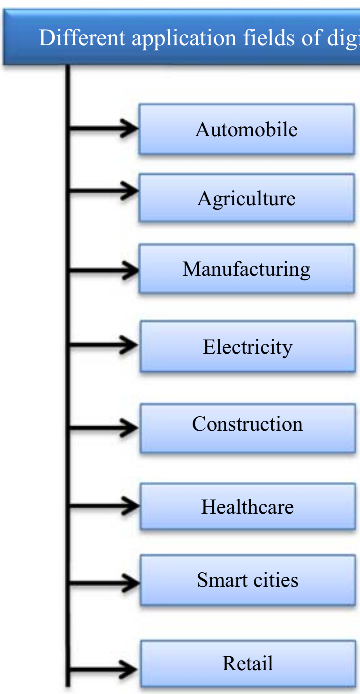


Figure 12.4 Applications of digital twin.

5. Automobile
6. Retail
1. *Smart cities*: Planning and implementation of smart cities by making use of digital twin enhances the development of economy, management of resources efficiently and to uplift the lives of citizen. This works effectively as the cities today are focusing to integrate and rapidly developing their connectivity via IoT. The three things: smart cities, connected community, and the digital twins are directly proportional to each other making a sense that, with the increase in development of more smart cities the connected communities will also gradually increase and thus result in increased use of digital twin technology. In smart cities, the services and infrastructure make use of sensors and activities that are reported and recorded with the application of IoT, with which the future of digital twin technology seems to be of great value. By the application of digital twin, it offers and facilitates two things: one is to design a virtual but real testing environment, and the second, it enables to examine from the environment by performing analyses of the modifications on the data gathered.
2. *Manufacturing*: Digital twin helps the most in the manufacturing sector. Manufacturers were always looking forward for a technology that could monitor the functionality of the system that is under development, resulting in a more efficient and cost-effective system. Thus, the digital technology has widely impacted this sector. With the growth of the industry's leading to the fourth revolution or Industry 4.0, digital twins enhance the connectivity and also provide the mirror visual image of the actual product or process under manufacturing. It makes the manufacturer capable of tracking the performance of the system as well as the responses from the visual model that supports decision-making. Incorporating AI and ML, digital twins hold the power to offer next-level accuracy by making the machines capable of storing immense data that further is needed for analyzing the staging and forecasting. By using digital twins in manufacturing industries, it provides the industry with the potential to test the functionality of the system, analyze the working under different conditions, and decision-making to the virtual model that reflects the image of the real system, thus saving time, cost, and efforts.
3. *Healthcare*: The healthcare sector is another sector that experienced and applied the digital twin technology. The results shown by digital twin in healthcare systems is the matter of innovation and is unpredictable

as it has made impossible things possible. Every sector, including healthcare, primarily achieved better connectivity with the implementation of IoT as the resources turns cheaper and implementation becomes easier. With digital twins, a virtual mirror of body, its functionality, and more could be designed, which further helps researchers, medicos, and trainers to provide training and learning. In addition, it could be implemented in planning and executing various processes involved in surgeries, to analyze and examine the impact of drugs on one's body. Likely, as in manufacturing and smart cities, the digital twin in healthcare also facilitates decision-making. It is also witnessed as an effective approach in modifications and analyses of existing medical equipment and designing the new as per the needs. When digital twin technique and AI work together, they make use of both the real time information and existing data results in life-saving decisions.

4. *In industries*: In the year 2006, General Electric, in a patent application initially cataloged the use of digital twin, where it was noted that they designed an application named "Predix," which acts as a platform for the creation of digital twin. However, the concept was taken back to focus on expanding their patrimony to multinational industries just not limited to software industry. Later, Siemens proposed a concept of "MindSphere," which incorporates both the concepts of Industry 4.0 along with cloud systems that establishe the link or communication between the physical systems and the digital twin. A substitute platform for the development of digital twin and AI is "ThingWorx," designed by power to create (PTC) and is an Industrial Innovation Platform that mainly focuses on the implementation of data from IoT/IIoT and representing it in a visual and actionable model that facilitates the viewer or the user to have deep insights to the system being modeled. IBM has also launched a platform known as "Watson IoT Platform" that handles millions of data gathered from various IoT systems. The benefits provided by this platform are not limited to just one, it offers some additional characteristics which together makes it a feasible tool for digital twin.

   The supplementary features are as listed:
   a. Services based on cloud
   b. Data analytics
   c. Services of blockchain technology

5. *Retail*: When applied in retail sector, the implementation of digital twin offers the opportunity in increasing customer's participation by

designing the virtual models of fashion for the customers. On addition, it makes the retail sector capable of planning, and implementing the security of the stores in a better and more advanced manner.

6. *Automobile*: The automotive sector is also left untouched with the application and usage of digital twin technology, specially indicated by Tesla. By enabling the use of digital twin, a visual modeling of engines of automobiles or the other parts as well could be found profitable when utilizing the twins for simulating purposes and also analyses of data. The working of digital twin and AI together enhances the efficiency and appropriateness of the automobiles as both the technology improve the performance and depicts the present as well as the time ahead staging of the vehicles.

All together can be noted that the digital twin and AI have expanded their use and importance in almost each sectors making the implementation more easier, the systems more cheaper, enhancing the availability and the accessibility of the data, and leading the accuracy to the next level.

12.14 Incorporating technologies

The digital twin technology does not work solely. It integrates with the three basic foundation technologies:

1. Internet of Things
2. Artificial Intelligence
3. Machine learning

12.14.1 Internet of Things

The internet-connected devices are usually quoted as the IoT. It was initially used by Kevin Ashton in the year 1990s in his publication highlighting the concepts of IoT. The technology enables the system to monitor and examine the devices that are connected through internet, thus resulting in advanced world. IoT finds applications in smart cities, smart homes, smarter industries, and smarter transportation, but is not limited to these. Through this, it establishes the transmission between the devices and the sensors with the support of internet.

Fig. 12.5 explains that IoT is adopted widely with every passing year and by 2018, it was reported to be about 17 billion. The prediction was made that by the year 2025, around 75 billion devices will shift to IoT.

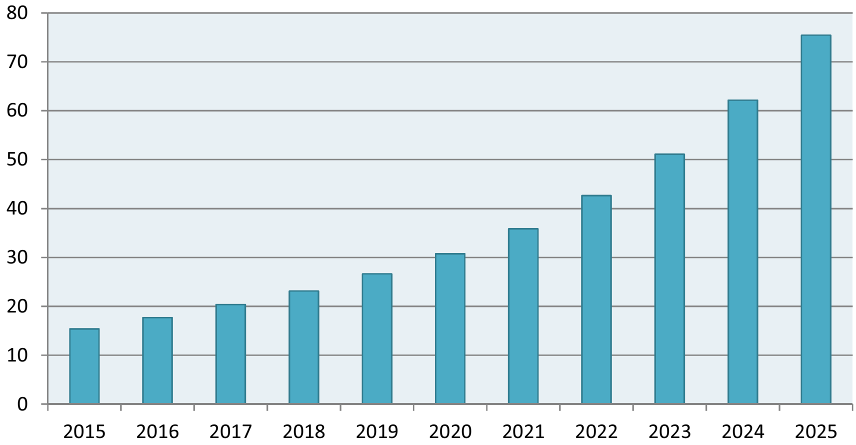


Figure 12.5 Growth of Internet of Things from 2015 to 2025.

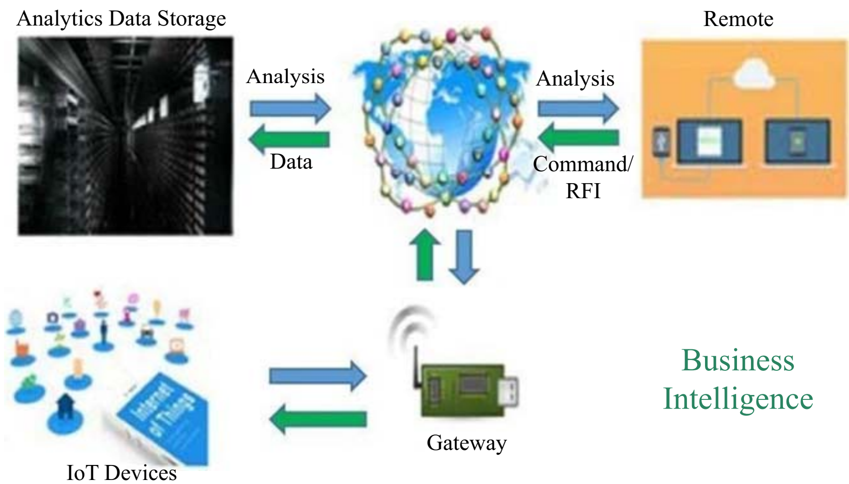


Figure 12.6 The architecture involves analytical data storage, remote devices, the devices supporting the internet of things, and the gateway.

12.15 The general architecture of Internet of Things

The IoT constitutes of the number of smart systems, approaches, devices that work intelligently as well as the sensors. Fig. 12.6 summarizes the architecture as:

12.15.1 Artificial intelligence

The term AI was legally adopted in the year 1956 in a conference at Dartmouth College but the advanced renewal was proposed in 1950 by

Alan Turing. The term AI could be better understood by the definition echoed by various researchers. Some of them are listed in the table below.

Author	Definition
(McCarthy, 1955)	AI is the science and engineering of making intelligent machines
(Minsky, 1968)	AI is the science of making machines, do things that would require intelligence if done by men
(Merriam-Webster)	A branch of computer science dealing with simulation of intelligent behavior in computers

The working of AI could be understood by elaborating on the steps and is the ongoing process resulting in a number of iterations until the expected outcome is attained. The steps are as discussed below:

Step 1. The foremost step is to receive the data, which could be anything like voice, text, graphics, etc.

Step 2. Various algorithms are applied to the data for its processing to make predictions, interpretations, and actions on the received data.

Step 3. The conclusion is drawn from the system on the data received that whether the data processing is successful or failed.

Step 4. The next step is the examination and response performed on the outcome through assessment.

Step 5. These evaluations are then utilized by the system to alter the received data, the algorithms applied, and the output generated.

12.15.2 Machine learning

Machine learning can be determined as a fundamental part of AI. It is the ability of the system to perform and analyze the operations of the particular system without executing the functions actually on the specific system. Different authors coined different definitions and meanings for the term ML.

The first author to explain ML was Arthur Samuel long ago in 1959. He explained the term as:

"Machine learning is the field of study that gives the computers the ability to learn without being explicitly programmed."

The other to explain the meaning of the term was Tom M. Mitchell in the year 1997. He proposed the definition of ML as:

"A computer program is to learn from experience E with respect to some class of tasks T and a performance measure P if its performance in tasks T, as measured by P, improves with experience E."

The definition of ML as per Google is:

"Machine learning is a way to use the standard algorithms to derive predictive insights from the data and make repetitive decisions."

Machine learning and data mining facilitate the system to draw relevant information from the immense amount of data present through various algorithms. Thus, technology incorporates with digital twin technology for more accurate and efficient system performance. For ML, the frequently used algorithms are: decision tree algorithms, Random Forest algorithm, artificial neutral network, SVM, boosting and bagging algorithms. With the shift of today's lifestyle toward digitalization, the things or data need to be recorded and analyzed digitally.

12.15.2.1 Types of machine learning:

The Fig. 12.7 illustrates the different categories of ML algorithm:

1. *Supervised learning*: This category of ML works on two basis, "classification" and "regression." Classification is used to detach the data and the work of regression is to fix the data.
2. *Unsupervised learning:* It is used for withdrawing the data that is productive in nature, grouping of results, etc. The basic task performed by this algorithm is clustering, density estimation, feature learning, etc.
3. *Semi-supervised*: It results with the combination of above two mentioned algorithms and is performed with and without supervision.
4. *Reinforcement learning*: To enhance the performance of the system, this classification of ML is applied to the system or the machines to accordingly find the optimal feature.

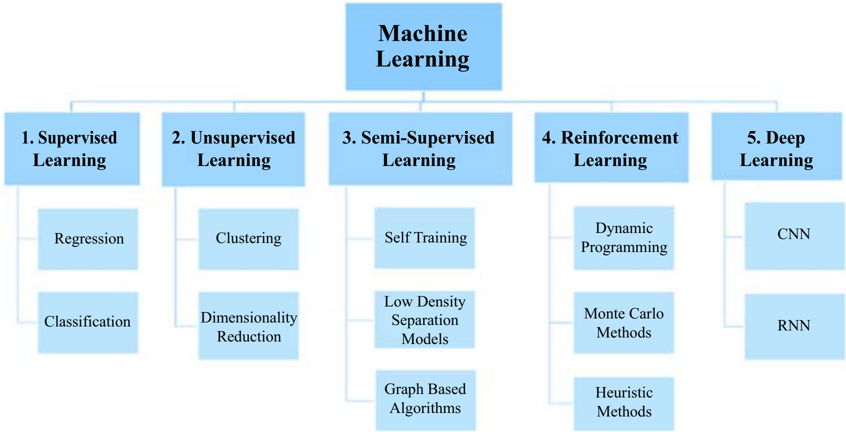


Figure 12.7 Types of machine learning.

12.15.2.2 Growth of machine learning

The ML trend is touching the peak year by year with moving parallel to the digitization of today's scenario.

The market estimate of ML globally was recorded as USD 15.44 billion the previous year and by the following year 2022 it was expected to reach USD 21.17 billion. By 2029, the expected growth of ML is predicted to be USD 209.91 billion.

12.15.2.3 Applications of machine learning

The ML has expanded its application to not just one or two but almost every sector with the shift toward digitalization. The use of ML enhances the availability, accessibility, and the accuracy of data with additional feature of cost-effective system and the break-free performance providing more convenient systems to the physical world. ML facilitates the world by supporting self driven cars, recommendation of products, prediction of traffic, speech recognition, online detection of frauds, medical diagnosis, automatic language translation, and more.

12.16 Pros and cons of digital twin technology

The technology helps Industry 4.0 revolution with its immense advantages, however, has some limitations that should also be reported and recorded at the same time. The pros and cons of the digital twin technology are summarized in the table below:

Pros	**Cons**
Consistent streaming on the staging and uses of the physical model	Internet is the only responsible factor for the success of the technology
Helps in advancements in healthcare systems enabling with designing of new equipments, managing of wards, etc.	The threat of inappropriately deploying the replicates of the physical world
Remotely monitoring the physical space	Underlying lifecycle of designing the digital twin takes too long, which effects the soundness of the software heading the designing, analyses, and performing simulation

(*Continued*)

Pros	Cons
Accelerates decision-making and predictions	As this technology employs IoT, ML, and AI, the challenges faced by these technologies are also shared by the digital twin
Limiting the failures and drawbacks of the system before things occur	Absence of any framework or systematized way to model the physical world into the digital twin
Integrates AI, ML, and IoT for providing real visualization of the real world	It can't be implemented uniquely without using AI, ML, and IoT as its foundation techniques
Facilitates deep insights into the actual system or model by mirroring its virtual image.	Security is one of the major drawbacks of the digital twin technology as it holds immense amount of data
Enhanced accessibility, availability, and accuracy of the data and the system	The data needs to be distinguished as the relevant or the noisy one, as the complete lifecycle of digital twin depends on the data gathered, and noisy data may lead to misrepresentation and misleading performance of the model

12.17 Future scope of digital twin

As discussed previously, the underlying technologies that work with digital twin technology are ML, AI, IoT, big data, and simulation and cloud technologies. With the continuous advancements in industries using these technologies and their applications, the digital twin technology will also witness rapid evolution and acceptance in parallel to these technology. So, it could be fair enough to state that the actual prospective of digital twin is still concealed at the rear of the mist of its time ahead. It is noted that the digital twin's global market is assumed to achieve the rate of 58% and to reach USD 48.2 billion by the year 2026. The Institute of Electrical and Electronics Engineers has a faith that the future of digital twin technology is a crucial aspect in developing machines and also in the human-machine symbiotic relationship.

12.18 Conclusion

Although the technology was proposed long back, it influenced the real world in recent years the most. Digitization is growing year by year and thus making the use of underlying digital twin technology to enhance availability, accuracy, and accessibility of the physical environment data and minimizing the cost and efforts and also provides a secure workspace. Many opportunities could also be noted and adopted when the digital twins work with additional approaches including virtual reality, augmented reality, 3D printing, and more. The technology is still surviving to attain full potential.

Further reading

I.H. Sarker, Machine learning: algorithms, real-world applications and research directions, SN Comput. Sci. 2 (2021) 160.

A.B. Nassif, et al., Speech recognition using deep neural networks: a systematic review, IEEE access. 7 (2019) 19143−19165.

C. Collins, et al., Artificial intelligence in information systems research: a systematic literature review and research agenda, Int. J. Inf. Manag. 60 (2021) 102383.

R.d.S. Mendonca, et al., Digital twin applications: a survey of recent advances and challenges, Processes 10 (4) (2022) 744.

C.H. dos Santos, J.A. Barra Montevechi, J.A. de Queiroz, R.d.C. Miranda, F. Leal, Decision support in productive processes through DES and ABS in the Digital Twin era: a systematic literature review, Int. J. Prod. Res. 60 (8) (2021) 2662−2681.

https://digitalwellbeing.org/artificial-intelligence-defined-useful-list-of-popular-definitions-from-businessand-science/.

https://images.app.goo.gl/aLpYCDrgLGXuPyX86.

https://images.app.goo.gl/WJRp9Me1javNytfk8.

https://learn.g2.com/how-does-vr-work.

https://medium.com/mlearning-ai/different-definitions-of-machine-learning-b46cedff9716.

https://www.cadmatic.com/en/resources/blog/digital-model-digital-shadow-or-digital-twin/.

https://www.challenge.org/insights/digital-twin-risks/.

https://www.designtechproducts-ptc-iiot.com/articles/digital-twin.

https://www.forbes.com/sites/bernardmarr/2018/02/14/the-key-definitions-of-artificial-intelligence-ai-that, https://www.forbes.com/sites/bernardmarr/2018/02/14/the-key-definitions-of-artificial-intelligence-ai-that-explain-its-importance/explain-its-importance/.

https://www.fortunebusinessinsights.com/machine-learning-market-102226.

https://www.ibm.com/in-en/topics/what-is-a-digital-twin.

https://www.ingenium-magazine.it/en/digital-twin-6-sfide-per-7-benefici/.

https://www.lifecycleinsights.com/tech-guide/digital-twins/.

https://www.plm.automation.siemens.com/global/en/our-story/glossary/digital-twin/24465.

https://www.rfwireless-world.com/Terminology/Advantages-and-Disadvantages-of-Digital-Twin, https://www.rfwireless-world.com/Terminology/Advantages-and-Disadvantages-of-Digital-Twin-Technology.htmlTechnology.html

https://www.softwareadvice.com/resources/what-is-digital-twin-technology/.

https://www.twi-global.com/technical-knowledge/faqs/faq-what-is-simulation.

https://www.xrtoday.com/virtual-reality/how-does-virtual-reality-work/.

W. Jin, Research on machine learning and its algorithms and development, in: Journal of Physics: Conference Series, Vol. 1544, No. 1, IOP Publishing, 2020.
S. Kumar, P. Tiwari, M. Zymbler, Internet of Things is a revolutionary approach for future technology enhancement: a review, J. Big Data 6 (2019) 111.
V. Raghunathan, Digital twins vs simulation: three key differences, May 13, 2019. Available from: https://www.entrepreneur.com/article/333645.

This page intentionally left blank

CHAPTER 13

Digital twins in precision agriculture monitoring using artificial intelligence

D. Shamia[1], S. Suganyadevi[2], V. Satheeswaran[3] and K. Balasamy[4]
[1]V.S.B. College of Engineering Technical Campus, Coimbatore, Tamil Nadu, India
[2]KPR Institute of Engineering and Technology, Coimbatore, Tamil Nadu, India
[3]Nehru Institute of Technology, Coimbatore, Tamil Nadu, India
[4]Bannari Amman Institute of Technology, Erode, Tamil Nadu, India

13.1 Introduction

Digital twin holds great potential in advancing smart farming's sustainability and production. It is at present the most talked about innovation. Making AI a part of our regular routine is a overwhelming though, yet generally in corporate and homegrown areas, AI is as of now a common phenomenon. AI delivers relevant data to aid decision-making and warn individuals of potential problems. Based on their aim to incorporate Internet of Things (IoT) devices and connected machines into their equipment, industries employ AI to process the data fed to them.

AI systems have the potential to change the world, but has not yet realized its maximum capabilities. Maintaining this successful balance in enhancing manufacturing processes and improving productivity is vital for the success of digital twin. AI in digital twins has the power to enhance the manufacturing industry in ways which have not yet been envisaged. AI will increase the production by 40% or more by 2035.

Agribusiness incorporates an assortment of cycles, wherein various merchandize are created by normal assets. The rural business comprises various tasks, including gathering crops, plants, taking care of animals, brushing, and more. It includes soil groundwork for most extreme returns, crop upgrade, green administrations, finishing administrations, veterinary administrations, work or cultivating the board, and more. By 2050, the overall people engaged in agriculture is projected to reach around 9 billion and cultivating creation needs to doublefold (70%) to fulfill the needs. Due to different

Digital Twin For Smart Manufacturing
DOI: https://doi.org/10.1016/B978-0-323-99205-3.00004-3

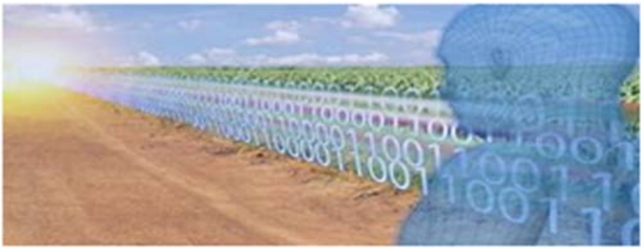


Figure 13.1 Digital twin with artificial intelligence applications in agriculture.

monetary, ecological, and sociological powers, there is shortage of land, water, and other vital resources at this point.

The agriculture industry is now able to maximize yields by analyzing, improving, and planning numerous crop growths throughout the year, thanks to the digital twin technology. It is a well-known fact that farming is characterized by enormous processes shown in Fig. 13.1. Modern technology assists in classifying important and useful activities in essential sectors and achieving the highest position in the value chain. This enables businesses to considerably enhance their performance while also cutting expenses and raising the standard of their commodities in the market.

In agriculture, AI is a developing innovation. Tools and machines dependent on AI have carried the present cultivating framework to another level. This innovation has expanded the usefulness of crops and improved reaping, handling, and showcasing progressively. It helps with monitoring weed and spraying pecticides using PC vision. Computerized reasoning furthermore allows ranchers to find additional viable strategies for protecting their harvests from weeds. People involved in agriculture are right now using AI techniques, for instance, for accuracy, monitoring moisture, soil creation, and temperature in creating districts, allowing them to construct their yields by focusing on the most effective way to manage their harvests and picking the best proportion of water or fertilizer to be used. Without doubt, robots and AI are helping with progressing new, more capable agrarian procedures that take agriculture inside and higher than any time in recent memory to save energy, decrease pesticides, and shorten the market time. These robots foster food without ranchers, more like a lean plant.

Rural innovation has gained a significant headstart, from improvement of grain lifts and counterfeit composts to using satellites. It is early, in any case, to talk about a fully automated workflow in this industry. The value of manufacturing industry will be unimaginably improved by AI. The requirement for best AI arrangements in agribusiness would unavoidably, just advance. However, as far as legitimate venture and testing, we want to ensure there is a coordinated effort between states, science, and organizations. In this way, AI is helping the cultivating business progress. We hope to consider the additional interesting answers as AI in agribusiness will boost developments in different enterprises as AI is expected to grow at a rapid rate to determine our future issues.

As stated by the UN Food and Agricultural Society, food cultivation might be improved to 75% by 2050. To meet this demand, AI is used for larger production capabilities. The major challenge in quality farming is unpredictable weather and environmental conditions. Agriculture is a unique, significant sector worldwide. It plays a significant role in rural development. Today, farmers are facing many challenges in increasing their productivity. Hence, we are introducing smart agriculture using AI. The environmental monitoring and control framework for horticulture is a newly rising idea, as sensors are equipped for providing data on rural fields. AI then helps in the various decision-makingdepending on the sensor data. Farmers are presently using AI methods for accuracy in cultivation, following harvest moistness, soil arrangement, and temperature in developing regions, permitting them to increase their yields by concentrating on the best way to deal with their harvests and choosing the ideal measure of water or compost to be utilized. Currently, food necessities as far as supply and quality are turning out to be increasingly requesting. As the populace increases, there is a growing need for food. Farmers have been communicating the requirement for a revolutionary mechanical method that will help build efficiency, guarantee which food excellence is viable with consistently extending food guidelines and further minimizing expenses. Specific expert agriculturalists as of now utilize innovative methods, which require an exceptionally high capital or above all being unequipped for playing out the necessary undertakings to diminish the burden of manual labor. Decreasing functional expenses in farming must be accomplished by improved utilization of regular assets and disposal of the requirement for manual labor. This must be acquired by cutting-edge innovations, which would screen and manage food creation, food excellence, reduce waste of valuable assets or minimize pernicious effect on the climate.

Precision farming is dependent on monitoring and taking corrective actions in case of intra-field changeability in plants and soil, that promising to be an answer for the issue up to now, there are two primary hindrances to be addressed for more extensive execution of precision agriculture. Right off the bat, planning of a few soils, yields, plants, and natural impacts inside a field or a nursery, creates "information over-burden" for farmers. First, advancements in information reconciliation apparatuses, and robotized dynamic frameworks are needed. Second, information for securing soil, yield, plant, and ecological variables is accessible yet exorbitant since the greater part of it requires soil examining and investigations by research centers. Continuous detecting frameworks are required for precision farming to be broadly executed. Semi and completely computerized gadgets are industrially accessible for most parts of horticultural capacities, from joining to cultivating and planting, from gathering to arranging, bundling and boxing, and getting animals on board.

Nevertheless, current frameworks actually have huge disadvantages as far as adaptability, productivity, vigor, no ongoing observing of soil and plants, high administrator expenses and capital venture. As far as carrying out a few endeavors have been made to screen rural boundaries in a mechanized way, however exceptional, they lack the capacity to work in soil. Most recognized instances of supplement observing by and large concern tank-farming, wherein no dirt is utilized or they simply screen natural boundaries like temperature. The main boundary which could be presently checked by sensors in soil progressively is water content and the need for pre-alignment in that particular soil type. Subsequently, the vitally remaining impediment for executing precision agriculture is the advancement of the detecting frameworks alongside their tools to screen soil quality progressively inside the framework particulars of the application. Fig. 13.2 shows the scenario of AI in healthcare.

Figure 13.2 Artificial intelligence in healthcare.

13.1.1 Digital twin in agriculture

A digital twin is an imitation of a physical object that exhibits the same behavior and states over time in a virtual environment. Physical flows may be separated from planning and control by using digital twins as primary tools in farm management. The pattern is expanding on a variety of advanced innovations: AI, IoT, big data, and digital practices, such as collaborations, versatility, and open development.

They infer a change in production frameworks: associated ranches, new creation gear, associated farm vehicles and machines. They will empower both expanded efficiency and quality and natural assurance. However, they moreover create adjustments in the value chain, plans of action with additional accentuation on information gathering, investigation, and trade. The work vehicle and the execute are vital instruments for advancements in the farming industry. Network and localization advances are enhancing the utilization of these farming instruments. This incorporates driver's help to enhance courses and abbreviate gathering what's more, crop treatment, while diminishing fuel utilization. Be that as it may, it likewise depends on usage of sensors that carry out to data detection to allow precision farming. The sensors stringent checking and command over crop medications allow significant additions in effectiveness and usefulness. Moreover, its availability is encouraging plans of action for advancements with more exact use of tools and consequently more precise charging of equipment use by contractors. One more significant change in the agricultural production process is the rising preference for computerization that increases usefulness by decreasing the need for human labor. This occurs in various stages, from automation of vehicles to improvements in assignment-explicit robots that robotize parts of the creation process (Fig. 13.3).

Though the possibilities of coordinating digital twin advancements, practices and mentality in the horticultural space are great, however its adoption would take time. The area faces huge challenges, from normalization of advances to the capacity to contribute to modernize the tools and associate frameworks. The improvement of digital twin requires innovative guidelines to guarantee the similarity of hardware. For sure, given the life expectancy of farming gear, norms are needed to guarantee that any innovative decision stays interoperable with new tools and is upheld over the long haul by the producers and other industrialists. Normalization in the field is primarily accomplished by the Agricultural Industry Electronics Foundation (AEF) and the AgGateway, each zeroing in on various parts of interoperability (at the machine level or at the ranch organization level).

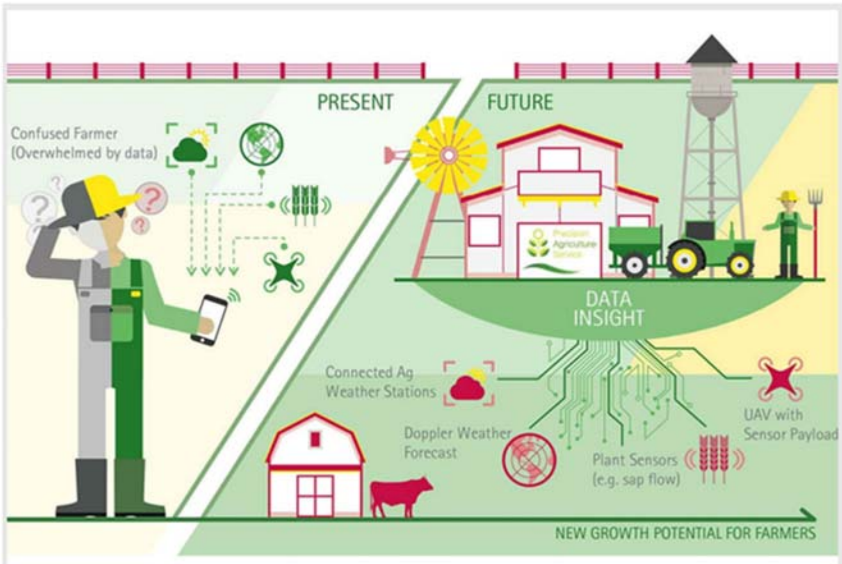


Figure 13.3 Centrality of data insight in future farming solutions.

The new test of Agriculture 4.0 is the need to have information trade and correspondence guidelines that connect the various frameworks together in a brought together framework covering all parts of the farming structure. Another significant test in the reception of the IoT in agribusiness is the advancement of correspondence foundations in provincial regions. Current remote correspondence networks have been sent with a B2C center, having a solid accentuation on metropolitan regions. As observed, the capacity to trade, dissect information (frequently at the stage level) is critical for the outcome of Agriculture 4.0. Subsequently, correspondence organizations must be created in provincial regions.

13.2 Background

IoT-Based Smart Irrigation Monitoring and Controlling System.

Interconnection of large number of gadgets finished web depicts the IoT. Each article is associated with another through special identifier so information can be relayed without human-to-human communication. It permits setting up answers for better administration of regular assets. The brilliant projects installed with sensors empower connection with the physical and legitimate universes as per the idea of IoT. This suggested framework relies on IoT that utilizes constant information. Zigbee is used for correspondence among sensor hubs and base station.

Continuous distinguished data trade and show on the server is developed employing electronic java graphical UI. Remote viewing of field water framework structure reduces human involvement and licenses isolated checking and monitoring on Android handset. Circulated figuring is an attractive clarification of massive proportion of data generated by remote sensors. This work suggests and estimates a cloud-based remote correspondence structure to screen and monitor data from sensors and actuators to study the demand of water by crops.

Remarks:

This method is designed to monitor the irrigation on farm land an does not meet most of the requirements.

Literature survey 2:

Detection of Leaf Diseases and Classification Using Digital Image Processing.

Image monitoring approaches are employed to recognize plant leaf diseases in this chapter. The objective of this work is to use image examination and characterization methodologies to identify and group leaf infections. (1) The suggested system is divided into four parts. They are image preprocessing, (2) leaf segmentation using K-implies bunching to determine diseased zones, and (3) disease detection and classification. Surface elements are removed with the help of quantifiable Gray-Level Co-Occurrence Matrix (GLCM) highlights, and characterization would be completed with the help of a Support Vector Machine (SVM). Surface elements from GLCM are extracted, and the order is completed employing SVM. The system is being verified for the finding of infections in citrus plants. Effort on categorizing disorders in different plant species and developing future research will be performed in the future.

Remarks:

The combination of image handling and IoT in agribusiness is being used to accomplish more excellent produce and reduce crop failure.

Literature survey 3:

Architecture design approach for IoT-based farm management information systems.

Smart farming embraces cutting-edge innovations and associated standards to enhance creation and monetary returns, additionally with the objective to decrease the effect on the climate. One of the critical components of brilliant cultivating is the Farm Management Information Systems

(FMISs) that adopt robotization for information securing and handling, observing, arranging, navigating, recording, and dealing with the homestead tasks. An expanded number of FMISs presently take on IoT innovation to additionally enhance the designated business objectives. Clearly, IoT frameworks in farming normally have diverse utilitarian and quality prerequisites, for example, decision of correspondence conventions, the information handling limit, the safety level, wellbeing level, and interval accomplishment. For increasing an IoT-associated FMIS, it is critical to planning legitimate engineering that encounters associated prerequisites.

Remarks:

A few models for FMISs had been planned in the writing, yet these are typically conceptual and it is not trifling to infer the application of FMIS engineering for the associated setting up of the farm framework.

Literature survey 4:

Precision agriculture farm management information systems require a domain-specific linguistic structure.

FMIS is an imperative part of precision farming, as it facilitates dynamic interactions in the agrarian industry. Designing FMIS is not trivial; it necessitates authentic plan and execution models for enhancing understandability, improving correspondence and assessment of plan options, and coordinating with partners. To address these issues, a Domain-explicit language (DSL) structure is developed and evaluated for the planning and enhancement of horticulture FMIS accuracy. The DSL structure is based on an area-driven planning technique, in which an element outline is provided that addresses the precision farming space's normal and variational highlights. These modules can be developed using widely applicable dialects, although these are more flexible in terms of application of space and less expressive in terms of agribusiness accuracy concerns. To decrease the calculated breach between the application area and the execution, space explicit dialects (DSLs) might be used.

Remarks:

The treatment groups have a smaller dispersion than the regulator groups, and interval required per component is less.

Literature survey 5:

Carrot Yield Mapping: A Precision Agriculture Approach Based on Machine Learning.

Carrot yield maps are critical tools in assisting leaders in enlightening their farmed techniques, as they were elusive and difficult to obtain. The determination was to cultivate a carrot yield map using irregular woods

(RF) relapse computation using an information base comprising satellite imagery data and carrot ground-truth crop analysis. During crop advancement, geo-referenced carrot yield inspection was performed, and satellite information was gathered. The whole imageset was separated into two sections. Preparation and testing. The technique centered on RF relapse and functional to a data base made up of phantom groups showed to be correct and reasonable in predicting carrot harvest.

Remarks:

Coefficient of assurance esteems higher than 0.78 are not generally found.

Literature survey 6:

Detecting and Classifying Pests in Crops Using Proximal Images and Machine Learning.

Pest control is one of the most important tasks on a farm. Observing numerous species from the outside might not be appealing, particularly in large belongings. Appropriately, much investigation work would be devoted to the expansion of persuasive methods for slightly screening latent in gestations. An increasing number of arrangements combine proximal digital images with AI processes; however, because the species and situations studied vary so much, it is difficult to create a reasonable picture of the true cutting edge on the subject. In this unique situation, the objectives of this article are to momentarily depict probably the most applicable examinations regarding the matter of programmed bug recognition utilizing proximal computerized pictures and machine learning; to provide a brought together outline of the exploration up until this point, with extraordinary accentuation to investigate holes that actually wait; to propose some potential focuses for future examination.

Remarks:

Traps may not be the best apparatus for settling on choices connected with treatment need or timing.

13.2.1 Effect of artificial intelligence on agriculture

AI-based advancements aid in enhancing effectiveness in all sectors and managing issues encountered by numerous ventures recalling various fields for the cultivating regions, such as harvest yield, water framework, soil contented distinguishing, yield-noticing, weeding, and yield establishing [1]. Rustic robots have natural desire to pass on highly rated AI applications in the aforementioned space. The agricultural division is facing a problem concerning to population loss, and AI may be able to pass on critical information. Man-made knowledge-based automated courses of action have enlisted ranchers to produce more results with less information, dramatically chipping away at the concept of result, and ensuring quicker go-to-grandstand for produced yields. Farmers will utilize 80 million connected strategies by 2022. In 2050, the usual property is predictable to produce 4.2 million data facts every day on average. The following is a list of the many aspects to which AI has contributed in the province region.

13.2.2 Picture acknowledgment and insight

There has been a huge interest in free unmanned aeriel vehicles (UAVs) and their adoption, which are used for obtaining confirmation and insights, geolocalization, search and salvage, and timberland fire detection (Bhaskaranand and Gibson, 2012, Doherty and Rudol, 2008, Tomic et al., 2013, Merino et al., 2007). Robots or UAVs are turning out to be progressively notable for their flexibility, just as dumbfounding imaging headway that covers everything from development to photography, the capacity to be directed with remote regulator, and the gadgets' capacity to fly, which permits us to perform a ton with these gadgets.

13.2.3 Abilities and labor force

Groeneveld et al. [2] stated that man-made brainpower made it useful for agriculturalists to accumulate huge proportion of data from government similarly as open locales, take apart every single cycle of it and outfit farmers with deals with some unsure issues similarly as it outfits us with a more splendid technique for water framework, which achieves better revisitation of the ranchers. Developing will be considered to be a mix of mechanical similarly as innate capacities soon which won't simply fill in as an unrivaled outcome in regards to quality for all of the ranchers yet furthermore limit their incidents and obligations. The UN communicates that, by 2050, two-third of all people will be alive in metropolitan districts that increases the need for decreasing the burden on ranchers. AI in agribusiness could be crucial as it would help robotize a couple of procedures, reduce possibilities of failures, and give farmers a comparatively straightforward and powerful tool.

13.2.4 Amplify the result

Variety assurance and seed quality, according to Suganyadevi et al. [3], set the most outrageous show level for all plants. Developing techniques had aided in the best assurance of harvests and have even aided in the selection of creamer seed varieties that are appropriate for farmers' needs. It has come to a conclusion by observing how seeds react to various environmental circumstances and soil kinds. Plant infections are less likely as a result of this information being shared in a social setting. As of now, we can fulfill market designs, annual outcomes, and purchaser demands, so ranchers are well equipped to increase crop profit.

13.2.5 Chatbots for farmers

Chatbots are colloquial humble associates that robotize cooperative activities with end clients. Chatbots fueled by computerized reasoning (AI) have empowered us to comprehend normal language and team up with clients in another method. They are essentially ready for marketing, portable, broadcasting, and agribusiness has used this office by associate farmers in getting responses to their unrequited requests, just as giving guidance and changed thoughts.

13.3 Existing methodology

In the existing system a person has to monitor the physical parameters and take further steps. Large number of laborers are needed to sowing seeds, weedingm and cultivating crops. Many of the persons will be affected while spraying pesticides or fertilizers. As DDT and MALATHION are potent pesticides, these are used majorly used by farmers in India.

The disadvantage of this method are human intervention was high, it is not possible to monitor and control the parameters all the time, and depending upon the climate the farmer takes more time for monitoring the parameters.

13.3.1 Agricultural robots

Robotic technologies are being implemented in large-scale industries with little efficiency. Concerning UK Agri-Food chain and UK-RAS (2019), basic development to retail, produces around £108 billion per year, with 3.7 million agents working in a £20 billion business in 2017. A large role in agricultural creation and the board is projected to be played by advanced mechanics.

Experts have lately begun focusing on breakthroughs in the construction of autonomous agrarian instruments as the needed capacity for standard developing equipment Köksal and Tekinerdogan [4]. The guiding principle behind this development is to override human labor and generate actual welfares on both large- and small-scale manifestations Balasamy and Suganyadevi [5]. Here, the space for mechanical headways has escalated convenience enormously Wei et al. [6]. Robots are carrying out diverse agrarian errands freely, for instance, weeding, water framework, observing the estates for approving convincing reports, ensuring that the hostile natural conditions do not impact the creation, increase accuracy, and direct distinct plants in numerous ways.

The invention of a machine known as Eli Whitney's cotton gin was considered a significant advancement. Eli Whitney (1765−1825), a U.S.-regarded trendsetter, envisioned a device in 1794 that enhanced cotton production by essentially speeding up the process of separating seeds from cotton fiber. In one day, it produced 50 pounds of cotton. As a result, the autonomous cultivating robots were provided. A vital electronic model was well-versed in selecting the ideal seeding location [7]. The seed's position was also established with extreme precision. Instruments ensure that seedlings are not impacted by ground movement [8,9]. To ensure that the seed will remain faithful to its original condition, this is critical information. The factory's development was monitored using mechanical devices. Unique biosensors are used to monitor the plant's development as well as its health issues [10,11]. The development of laser weeding, in that a varied concentrated infrared light, surprises the cells of the weeds, has replaced hand weeding. This shaft was propelled by PCs [12]. Automated water framework systems were also established for efficient use of water.

13.3.2 Irrigation system

The agricultural area accounts for 87% of the world's accessible freshwater possessions. Furthermore, this rate is rapidly increasing in tandem with population growth and rising food demand. This forces us to consider more productive tools to guarantee the appropriate usage of water in water system. The physical water system that relied on soil water assessment was interchanged with water system planning operations that were computerized. Plant evapotranspiration, which was affected by a variety of environmental factors such as humidity, wind speed, UV radiations, and, surprisingly, crop issues such as phase of development, plant thickness, soil possessions, and insect infestation, was considered though operating independent water system machines.

Balasamy et al. [13] investigates several water system techniques with the overarching goal of promoting a framework with lower asset use and higher productivity. On the field, devices such as a productivity meter and a pH meter are set up to determine the soil's readiness by measuring the levels of the fundamental components of the soil, such as potassium, phosphorus, and nitrogen. For stream water systems, modified plant irrigators are planted on the field by long-distance development. This technique ensures that the soil is productive and that water is used efficiently.

By sensing the level of water, temperature of the soil, supplement contented, environmental gauging, advancement of fast water framework is built to manufacture the creation without the consideration of a huge number of work. The microprocessor activates the irrigator syphon by turning it ON or OFF. The M2M, or Machine-to-Machine, development has been designed to work with communication and records dividing among everyone and to server or cloud via key connection among all of the cultivating field's center points (Shekhar et al., 2018). An automated electromechanical model for Arduino and Raspberry Pi's soddenness content and temperature was developed in 2018. The data is recognized at standard ranges and provided via Arduino's microcontroller (which is linked to an edge level gear), making it easier to adhere to cutting edge. The signal is sent from the Raspberry Pi 3 (which was introduced with KNN computation) to Arduino, that starts the water focal point for the water framework. The resource will provide water as indicated by the essential, and it would revive and save the sensor data. Sheikh et al. [14] and Suganyadevi et al. [15] also developed a robotized water system framework using Arduino tools to reduce labor and time usage during the time spent with the water system.

Devi et al. [16] and Abdullahi et al. [17] also promoted the prospect of a proficient and mechanized water system framework by improving remote sensors employing arduino tools, which could improve assembly by up to 45%. Ahir et al. [18] and Ahirwar et al. [19] proposed another structure for an autonomous water framework. Different sensors were used in this procedure for different purposes, such as the soil soddenness sensor, which was used to distinguish the sogginess contented in soil; temperature sensor, which was used to perceive temperature; strain regulator sensor, which was used to preserve tension; and nuclear sensor, which was used to advance the harvest. The building blocks were cutting-edge cameras. The outcome of such a huge number of devices is converted to advanced transmission and sent from the multiplexer via remote organizations, such as Zigbee and the area of interest.

The principal method was the subsurface trickle water system, which reduced the quantity of water lost owing to dissipation, overflow because it was unswervingly concealed underneath the yield. Soil soddenness and storm drop sensors were used by professionals to determine the need for water supply to the fields, and these sensors were transmitted over a long-distance internet connection and restricted by daylight-powered charges. A farmer's mobile phone receives text messages from the rain drop sensor and the soil clamminess sensor, informing them of the moisture content in the ground. Similarly, the farmer can use SMS (Chort Message Service) to turn on and off the water supply. As a result, we may assume that this structure will detect areas of the fields that demand more water and will prevent the farmer from watering when it is raining.

Few other innovations are used to detect the soddenness of earth, like soil clamminess sensors. It covers the root zones of the crops (Dukes et al., 2010). To accurately determine the amount of clamminess in the water system, sensors are used. Soil clamminess sensors, in similar ways, help in fundamental water conservation [20,21]. The water on demand water framework is one method for clamminess sensors in which we construct a border based on the soil's field limit, and these sensors enable your controller to water exactly when needed. Sogginess content or level is measured at the appointed time, and watering is allowed in that zone if the content falls below the cutoff. A water framework term is required for the suspended cycle water framework, unlike the water on demand water framework. For each zone, a start and end time and range are required [22,23].

13.3.2.1 Dielectric strategy

Soil mass permittivity is used by sensors to monitor the soil's soddenness content, which is dependent on dielectric reliable (soil mass permittivity). The dielectric constant, in any instance, determines the necessary quantity of water framework [23,24]. Using dielectric soil soddenness sensors, another researcher [25] propose a robotized structure for constant water framework management. The most practical way of evaluation is based on dielectric properties [26]. Soil types and dielectric moisture sensor accuracy were discussed by [27,28]. Only the soil's capacity to transfer power or power is limited by the dielectric constant. The assessment of dirt's dielectric characteristics is determined by the general liability of its many components, such as minerals, air, and water. Because water has a higher dielectric value (Kaw = 82) than any of the other solids in the soil, clamminess in the soil has the greatest impact on the permittivity value measured.

As an alternative method for determining the dielectric's reliability, domain reflectometry may be used. There it is. We're still waiting for an electromagnetic pulse to go through a dirt-covered transmission wire. Dielectric constant (Kab) and transmission time (*t* in a split second) are well-known to have a significant impact on how fast a signal travels down a transmission line.

13.3.2.2 Neutron balance

For mechanical water framework innovation, the foundations of sensors are projected to play a key role. Single sensors are capable of managing the watering of many zones of a field at once. Additional advantages include the ability to water specific zones using numerous sensors at the same time. It is necessary to install a sensor in the driest zone to offer a tolerable water framework for the whole field when a single sensor is used to submerge numerous zones at once. Water-absorbing sensors should be installed in the root zone of harvesting (without any air gaps around the sensor). This will guarantee that crops have enough water to grow. Later, we'll have to connect the SMS controller to the sensor. The controller will regulate operation after the sensor responds. The soil water breaking point for this connection should then be selected. After that, water is sprayed on the sensor and let to sit for a day without any more action. The organized water framework's sensor now has an edge due to the water content, as previously shown in the diagram.

Once the sensors have collected data, the microcontrollers can function. Automated water framework is a vital aspect of the whole process. The circuit is raised to 5 volts with the help of a transformer, platform rectifier circuit (an electronic power supply component that converts AC commitment to DC outcome), and a voltage regulator. After that, a new microcontroller is installed. The microcontroller processes the data from the sensors. Most likely, the OP-AMP is being utilized to transport soil conditions sensed by sensors to the microcontroller through the connection between the sensors and the microcontroller. Irrigation systems use syphons to collect information about soil quality during run time (Fig. 13.1). Wetness sensors and microcontrollers make it possible to automate the water framework communication [29,30].

13.3.3 Weeding

Thomas K. Pavlychenko, a pioneering weed experimenter, was mentioned in Zimdahl's paper "A History of Weed Science in the United

States" (2011). *Brassica pinnatifida*, the wild mustard plant, needs more water than an all-purpose oat plant to improve, whereas *Ambrosia artemisiifolia* needs more water than a corn plant to improve. By multiplying the plant's dry matter content in pounds per acre by its water need, one may calculate the amount of water needed per acre. In addition, light has a substantial impact on plant growth. Tall weeds, in general, block sunlight from reaching the plants. In contrast, other weeds, such as redroot pigweed, green foxtail, and standard milkweed spotted spurge, are more forgiving of concealment. More than $12 billion in agricultural production is lost each year in India because of weeds, according to a research led by experts at the ICAR, which is more money than the center has been reimbursed for producing in 2018–2019. Weeds not only take up space but also have an influence on the growth of other plants, thus eradicating them is essential [31].

In standard lighting, Blasco et al. [32] developed a fantasy-based weed recognition development. For outside field weed recognition, it was formed using hereditary assessment detecting a region in Hue-Saturation-Intensity (HSI) hiding space. It makes use of unusual lighting situations such as bright and dark, and these speedy circumstances were mosaicked to see if Gaultheria semi-infera GAHSI could be used to detect the location in the arena while hiding space once those two cutoff points are visible at all times. GAHSI was responsible for ensuring the existence and is either of such an area. By separating the GAHSI-allocated and a distinguishing hand separated reference picture, the GAHSI execution was examined. The GAHSI performed similarly in this regard.

We need to distinguish between the harvest seedlings and the weeds before supporting a weed control motorized structure [33,34]. To differentiate carrot plants from grass seeds, a method was utilized. This approach was developed by Chang and Lin [35] using the key morphological brand name assessment of leaf shape. This system's appropriateness varies between 53% and 76% for distinguishing between plants and weeds, depending on the leaf size assortment. Another weeding procedure that was used was advanced imaging. This concept included a self-organizing neuronal connection. However, because this approach did not produce satisfactory results for business needs, it was discovered that a NN-based invention recently appeared that allows one to detect species differences with a precision of 77%.

In today's world, numerous automated systems are created, but in the past, distinct genuine approaches that relied on the real relationship with the weeds were used. Weeding, according to Chang and Lin [35] and Choudhary et al. [36], is in need of the position and also amount of weeds. Intra segment weeding is performed with old type spring or duck foot prongs, which broke the ground and refined the root attachment point, allowing the weeds to advance their witling. However, as refined can destroy the connection point between the produce and the dirt, this is not a wise strategy. As an outcome, no-contact treatments like laser medicines [37] and small-scale sprinkling, that could not disturb root-dirt connection, were implemented. Nakai and Yamada (2013) described the system for using plant robots to hide weeds and developing ways for controlling robot locations if an event of unequal fields occurs in rice production. For smothering the weeds and controlling the robot's position, it used the Laser Range Fielder technology. A mechanical weed management device was described by Cillis et al. [38]. Numerous graphical schemes were combined in the robot. One is dim level vision that is utilized in growing a section design to coordinate the robot along lines and other is concealing-based vision that is crucial and it is utilized to isolate a single crop amid the weeds. The line affirmation method was created using a one-of-a-kind estimation with a 3 cm precision. The basic primer for this construction was created in a nursery for weed control within a yield line. Costa et al. [39] pointed to a comparative development in their assessment (2015). The visualization-based innovations are employed to organize the robots beside the section plan to eliminate weeds and select a sole crop among all weed plants. Fig. 13.4 shows the component and flowchart of proposed model.

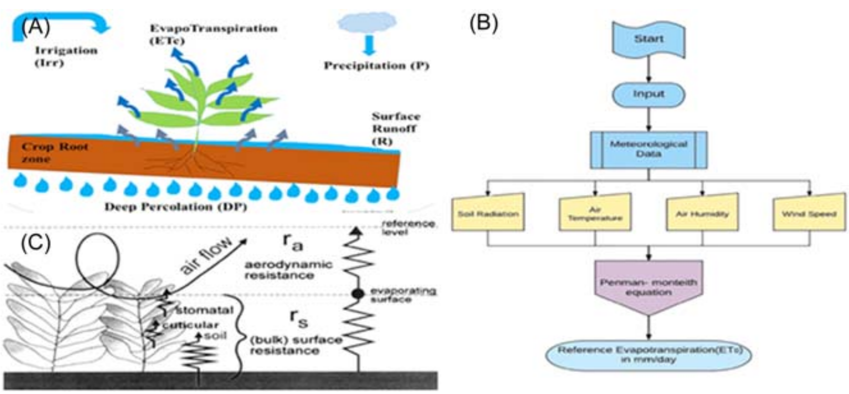


Figure 13.4 (A) Components of the soil water balance for the evapotranspiration model source: University of Minnesota (B) flowchart for evapotranspiration reference [40] (C) FAO Penman-Monteith method.

13.4 Proposed methodology

In this proposed system, we develop a precision agriculture system by using hanging robot with virtual assistance, in that various sensors, microcontroller are used. In this proposed system, we used AI, which acts as a virtual assistant. AI is used to take a decision and action instead of human being. Real-time monitoring of plant growth could be done with the assistance of artificial intelligence programming. For this, we use MATLAB software. In case if any disease is detected in the leaf or fruits of the plant or if the plant growth is affected due to climate changes then the MATLAB will process it with the help of AI. And that image will be send to the microcontroller unit with the help of serial communication device called Zigbee.

In case if any disease is detected then that information will be send to the microcontroller, so the microcontroller will take the required action, that is, a pesticide motor connected with the robot will automatically turned ON. And if the growth of the plant is reduced then the fertilizer will automatically turned ON. Our proposed system consists of a gas sensor, which helps monitor greenhouse gases in the atmosphere. In this chapter, gas sensor is used to monitoring the greenhouse gases in the environment. Because the increase in greenhouse gases will highly affect the plants growth. Light sensor is used for automatic Lights ON and OFF in farm land based on light intensity. Various sensors like temperature and humidity are used to monitoring environmental condition of the agricultural land. Thus, our proposed system for precision agriculture using AI and wireless sensor network can be implemented. Advantages are AI in Precision Agriculture provides better efficiency and accurate results, simplified farming processes, higher yields and more profitability, hanging robot reduces resource consumption & human intervention, improves plant growth, and fertilizing and pesticides can be automatically applied to the plant without human help.

The first module consists of sensing module, consisting of Arduino Uno controller board, jumper wires, DHT11 sensor, LDR sensor, humidity sensor. These sensors are working on 5 V, supplied from Arduino Uno board. Fig. 13.5 presents the block representation of proposed model. The ground data pins of sensors are connected to Arduino Uno circuit board. Where the Uno board needs an external power supply of up to 12 V. The second module is nothing but a storage module. Here we have connected a step down transformer. The input voltage for this transformer is 230 V AC supply. This will be applied to that transformer. The transformer will step

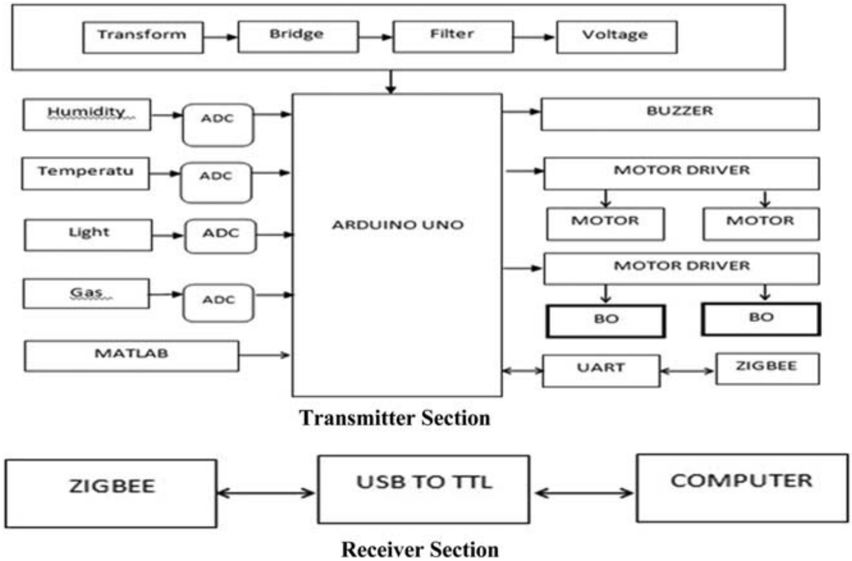


Figure 13.5 Block diagram of proposed model.

down it to 12 V AC, generating AC supply. The result starting from the step transformer will be given to the extension rectifier. Among the rectifiers, the extension rectifier is the most productive rectifier circuit. We can characterize span rectifiers as a kind of full-wave rectifier that involves at least four diodes in an extension circuit design to productively change over exchanging (AC) current to an immediate (DC) current.

The Bridge rectifier unit converts AC supply into DC supply. Here, a 1000 μf capacitor is connected, which filters the DC supply. A capacitor input channel could be a divert circuit in which the essential part is a capacitor related in comparing with the consequence of the rectifier in an immediate power supply. The capacitor extends the DC voltage and lessens the wave voltage parts of the outcome. Sifted yield is given to voltage controller 7805 and 7812. A voltage controller produces a proper result voltage of a pre-set greatness that stays consistent paying little mind to changes to its feedback voltage or burden conditions. It is having 14 electronic material/produce pins (of which 7 could be used as PWM yields), 7 straightforward wellsprings of data, a 15 MHz stoneware resonator (CSTCE16M0V53-R0), an ICSP header, USB affiliation, power jack, and reset button. The data from MATLAB will be send through serial communication. MATLAB helps in image processing. When a diseased image or fruit is uploading in MATLAB the image processing technique will process it and the send the right information to the microcontroller. The microcontroller which will take further steps for that. In case if diseased has been detected in the controller then a fertilizer motor will be turned ON. The microcontrollers controller other parameters such as light intensity hazardous greenhouse gases, which is a major problem for plant growth. In case if any greenhouse gases are detected more than the threshold level then the robot will intimate it to the concerned person.

13.5 Conclusion

The innovative Industry 4.0 presents an opportunity to enhance precision agriculture and a valuable chance to conquer the primary shortcomings of our present farming framework and the restrictions of concentrated agribusiness. AI is pervasive throughout the digital twin technology, not just on the factory floor. AI algorithms to optimize industrial operations supply chains and enable them respond better and predict market changes. The farming area is of indispensable significance for the locale. It is going through a course of progress to a market economy, with generous changes in the social, lawful, underlying, useful, and supply setups, similar to the case with any remaining areas of the economy. AI can be fitting and useful in agribusiness area as it streamlines the assets use and productivity. It tackles the shortage of assets and work generally. Reception of AI is very helpful in horticulture. Man-made brainpower can help achieve innovative transformation and drive agribusinesses to take care of the expanding human populace of world. Man-made brainpower will supplement and challenge as well as provide best choices to farmers.

Before very long, agricultural bots became a vital piece of brilliant cultivating, they assist ranchers with managing a wide scope of difficulties and receive an extraordinary number of rewards. Man-made intelligence innovations are a remarkable chance for the EU economy to create extra development and thriving. Hanging robots will be of massive assistance in the field of agribusiness with the increment in populace as they are fundamental at the absolute starting point of a yield cycle. It won't just decrease time yet additionally yield better development dependent on examined information. Hanging bots are not simply utilized in the examination of soil and fields yet additionally in sowing seeds and shooting plant supplements in the soil.

With the advancements in research and development that innovative work upholds the combination between heterogeneous advancements and heterogeneous businesses and the farming modern biological system permits imaginative abilities to unreservedly practice their capacities, Industry 4.0 can happen. Thus, agrarian innovation will develop higher than ever and jump to new open doors.

References

[1] R. Liu, Y. Zhang, Y. Ge, W. Hu, B. Sha, Precision regulation model of water and fertilizer for alfalfa based on agriculture cyber-physical system, IEEE Access 8 (2020) 38501–38516.

[2] D. Groeneveld, B. Tekinerdogan, V. Garousi, C. Catal, A domain-specific language framework for farm management information systems in precision agriculture, Precis. Agric. 22 (2020) 1067–1106.

[3] S. Suganyadevi, D. Shamia, K. Balasamy, An IoT-based diet monitoring healthcare system for women, Smart Healthc Syst Des Secur Priv Asp (2021). Available from: https://doi.org/10.1002/9781119792253.ch8.

[4] Ö. Köksal, B. Tekinerdogan, Architecture design approach for IoT-based farm management information systems, Precis. Agric. 20 (2018) 926–958.

[5] K. Balasamy, S. Suganyadevi, A fuzzy based ROI selection for encryption and watermarking in medical image using DWT and SVD, Multimedia Tools and Applications, Springer, 2020. Available from: http://doi.org/10.1007/s11042-020-09981-5.

[6] M.C.F. Wei, L.F. Maldaner, P.M.N. Ottoni, J.P. Molin, Carrot yield mapping: a precision agriculture approach based on machine learning, AI 1 (2) (2020) 229–241. Available from: https://doi.org/10.3390/ai1020015.

[7] J.G.A. Barbedo, Detecting and classifying pests in crops using proximal images and machine learning: a review, AI 1 (2) (2020) 312–328. Available from: https://doi.org/10.3390/ai1020021.

[8] S. Suganyadevi, V. Seethalakshmi, CVD-HNet: classifying pneumonia and COVID-19 in chest X-ray images using deep network, Wireless Pers. Commun. (2022). Available from: https://doi.org/10.1007/s11277-022-09864-y.

[9] V. Palazzi, F. Gelati, U. Vaglioni, F. Alimenti, P. Mezzanotte, L. Roselli, Leaf-compatible autonomous RFID-based wireless temperature sensors for precision agriculture, in: 2019 IEEE Topical Conference on Wireless Sensors and Sensor Networks (WiSNet), 2019, pp. 1–4.

[10] S. Suganyadevi, V. Seethalakshmi, K. Balasamy, A review on deep learning in medical image analysis, Int. J. Multimed. Info Retr (2021). Available from: https://doi.org/10.1007/s13735-021-00218-1.

[11] G. Gyarmati, T. Mizik, The present and future of the precision agriculture, in: 2020 IEEE 15th International Conference of System of Systems Engineering (SoSE), 2020, pp. 593–596.

[12] K. Balasamy, D. Shamia, Feature extraction-based medical image watermarking using fuzzy-based median filter, IETE J. Res (2021) 1–9. Available from: https://doi.org/10.1080/03772063.2021.1893231.

[13] K. Balasamy, N. Krishnaraj, K. Vijayalakshmi, An adaptive neuro-fuzzy based region selection and authenticating medical image through watermarking for secure communication, Wireless Pers. Commun (2021). Available from: https://doi.org/10.1007/s11277-021-09031-9.

[14] J.A. Sheikh, S.M. Cheema, M. Ali, Z. Amjad, J.Z. Tariq, A. Naz, IoT and AI in precision agriculture: designing smart system to support illiterate farmers, in: International Conference on Applied Human Factors and Ergonomics (2020).

[15] S. Suganyadevi, K. Renukadevi, K. Balasamy, P. Jeevitha, Diabetic retinopathy detection using deep learning methods, in: 2022 First International Conference on Electrical, Electronics, Information and Communication Technologies (ICEEICT), 2022, pp. 1−6, Available from: https://doi.org/10.1109/ICEEICT53079.2022.9768544.
[16] K.R. Devi, S. Suganyadevi, S. Karthik, N. Ilayaraja, Securing medical big data through blockchain technology, in: 2022 8th International Conference on Advanced Computing and Communication Systems (ICACCS), 2022, pp. 1602−1607, Available from: https://doi.org/10.1109/ICACCS54159.2022.9785125.
[17] H.S. Abdullahi, F. Mahieddine, R.E. Sheriff, Technology impact on agricultural productivity: a review of precision agriculture using unmanned aerial vehicles lecture notes of the institute for computer sciences, in: Social Informatics and Telecommunications Engineering (2015) 388−400.
[18] K. Ahir, K. Govani, R. Gajera, M. Shah, Application on virtual reality for enhanced education learning, military training and sports, Augment. Hum. Res 5 (7) (2020). Available from: https://doi.org/10.1007/s41133-019-0025-2.
[19] S. Ahirwar, R. Swarnkar, S. Bhukya, G. Namwade, Application of drone in agriculture, Int. J. Curr. Microbiol. App. Sci. 8 (1) (2019) 2500−2505.
[20] M.J. Aitkenhead, A.J.S. McDonald, J.J. Dawson, G. Couper, R.P. Smart, M. Billett, et al., A novel method for training neural networks for time-series prediction in environmental systems, Ecol. Model 162 (1−2) (2003) 87−95.
[21] A.R. Al-Ali, M. Qasaimeh, M. Al-Mardini, S. Radder, I.A. Zualkernan, ZigBee-based irrigation system for home gardens, in: 2015 International Conference on Communications, Signal Processing, and their Applications (ICCSPA'15) (2015), Available from: https://doi.org/10.1109/iccspa.2015.7081305.
[22] M. Albaji, A. Shahnazari, M. Behzad, A. Naseri, S. BoroomandNasab, M. Golabi, Comparison of different irrigation methods based on the parametric evaluation approach in Dosalegh plain: Iran, Agric. Water Manag 97 (7) (2010) 1093−1098.
[23] K. Anand, C. Jayakumar, M. Muthu, S. Amirneni, Automatic drip irrigation system using fuzzy logic and mobile technology, in: 2015 IEEE Technological Innovation in ICT for Agriculture and Rural Development (TIAR), 2015, Available from: https://doi.org/10.1109/tiar.2015.7358531.
[24] D. Anthony, S. Elbaum, A. Lorenz, C. Detweiler, On crop height estimation with UAVs, in: 2014 IEEE/RSJ International Conference on Intelligent Robots and Systems, 2014, Available from: https://doi.org/10.1109/iros.2014.6943245.
[25] G. Arvind, V.G. Athira, H. Haripriya, R.A. Rani, S. Aravind, Automated irrigation with advanced seed germination and pest control, in: 2017 IEEE Technological Innovations in ICT for Agriculture and Rural Development (TIAR), 2017, Available from: https://doi.org/10.1109/tiar.2017.8273687.
[26] T. Bak, H. Jakobsen, Agricultural robotic platform with four wheel steering for weed detection, Biosyst. Eng 87 (2003) 2125−2136.
[27] T. Bakker, K. van Asselt, J. Bontsema, J. Müller, G. van Straten, An autonomous weeding robot for organic farming, Field and Service Robotics (2006) 579−590.
[28] J. Bendig, A. Bolten, G. Bareth, Introducing a low-cost mini-uav for thermal- and multispectral-imaging, in: XXII ISPRS Congress, 2012, pp. 345−349.
[29] K. Bhagyalaxmi, K.K. Jagtap, N.S. Nikam, K.K. Nikam, S.S. Sutar, "Agricultural robot" (Irrigation system, weeding, monitoring of field, disease detection), Int. J. Innov. Res. Comput. Commun. Eng. 4 (3) (2016) 4403−4409.
[30] M. Bhaskaranand, J.D. Gibson, Low-complexity video encoding for UAV reconnaissance and surveillance, in Proceedings - IEEE Military Communications Conference (MILCOM), 2011, pp. 1633−1638.
[31] S.J. Birrell, K.A. Sudduth, S.C. Borgelt, Comparison of sensors and techniques for crop yield mapping, Comput. Electron. Agric. 14 (2−3) (1996) 215−233.

[32] J. Blasco, N. Aleixos, J.M. Roger, G. Rabatel, E. Molto, Robotic weed control using machine vision, Biosyst. Eng. 83 (2) (2002) 149−157.
[33] W. Bond, A.C. Grundy, Non-chemical weed management in organic farming systems, Weed Res. 41 (5) (2001) 383−405.
[34] R.A. Buchanan, Bush Regeneration: Recovering Australian Landscapes, The Open Training and Education Network, Redfern (1989) 242−246.
[35] C.-L. Chang, K.-M. Lin, Smart agricultural machine with a computer vision-based weeding and variable-rate irrigation scheme, Robot 7 (2018) 38. Available from: https://doi.org/10.3390/robotics7030038.
[36] S. Choudhary, V. Gaurav, A. Singh, S. Agarwal, Autonomous crop irrigation system using artificial intelligence, Int. J. Eng. Adv. Technol 8 (5S) (2019) 46−51.
[37] S. Chung, M. Choi, K. Lee, Y. Kim, S. Hong, M. Li, Sensing technologies for grain crop yield monitoring systems: a review, J. Biosyst. Eng 41 (4) (2016) 408−417.
[38] D. Cillis, A. Pezzuolo, F. Marinello, L. Sartori, Field-scale electrical resistivity profiling mapping for delineating soil condition in a nitrate vulnerable zone, Appl. Soil Ecol. 123 (2018) 780−786.
[39] F.G. Costa, J. Ueyama, T. Braun, G. Pessin, F.S. Osorio, P.A. Vargas, The use of unmanned aerial vehicles and wireless sensor network in agricultural applications, in: 2012 IEEE International Geoscience and Remote Sensing Symposium, 2012, Available from: https://doi.org/10.1109/igarss.2012.6352477.
[40] A.M. De Oca, L. Arreola, A. Flores, J. Sanchez, G. Flores, Low-cost multispectral imaging system for crop monitoring, in: 2018 International Conference on Unmanned Aircraft Systems (ICUAS), 2018, Available from: https://doi.org/10.1109/icuas.2018.8453426.

This page intentionally left blank

CHAPTER 14

Digital twins and cyber-physical system architecture for smart factory

A. Kodieswari[1], K.R. Sabarmathi[2], A. Kavitha[3] and N.R. Gayathiri[4]
[1]Department of Information Technology, Bannari Amman Institute of Technology, Erode, Tamil Nadu, India
[2]Bannari Amman Institute of Technology, Erode, Tamil Nadu, India
[3]Dr. N.G.P. Institute of Technology, Coimbatore, Tamil Nadu, India
[4]Department of Artificial Intelligence and Data Science, Bannari Amman Institute of Technology, Erode, Tamil Nadu, India

14.1 Introduction to digital twins and cyber-physical system

14.1.1 Digital twin

Digital twins (DTs) are virtual lookalikes of physical systems or objects that data scientists and developers can use to run simulations before actual systems or objects are constructed and deployed in the real world. These physical systems may include airplanes, wind farms, buildings, bridges, jet engines, and so on. It is actually a computer program that uses real-world data to create simulations that can foresee how a process or product will perform once developed. These programs can also take real-time IoT data and apply AI and data analytics to optimize performance. These virtual models help improve the performance of the system and also drive innovation in developing the product. It also prevents costly failures in the physical objects.

14.1.2 Working of digital twin technology

The existence of a DT starts with specialists in applied math or information science exploring the physical science and functional information of an actual item or framework to create a numerical model that restores the original.

The designers ensure that DTs guarantee that the virtual model can get input from sensors that assemble information from this present reality variant. This allows it to mirror and mimic what's going on with the original variant continuously, setting out open doors to accumulate experiences into execution and any likely issues (Fig. 14.1).

Digital Twin For Smart Manufacturing
DOI: https://doi.org/10.1016/B978-0-323-99205-3.00001-8

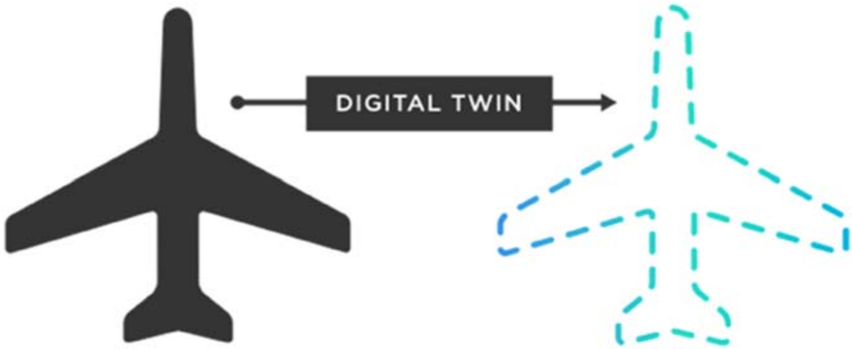


Figure 14.1 Digital twin of a space plane.

A DT can be as amazing or as straightforward as you expect, with contrasting measures of data deciding how definitively the model recreates this present original version.

It is mainly utilized as a model to offer criticism on the item as it is evolved or might go about as a model by its own doing to demonstrate what could happen with an actual variant when fabricated.

14.1.3 Challenges solved by digital twin technology

As it tends to be utilized across great businesses, from auto, electrical, to medical services, it has proactively been utilized to tackle countless difficulties. These difficulties incorporate exhaustion testing, improvements in vehicles, corrosion resistance for ships in coastlines. Different applications have incorporated the modeling of company buildings to decide work processes and staffing to track down strategy upgrades. In such cases, DT helps devise a solution and test it virtually via programs rather than real world. For instance, DT can be created for smart cities to greatly reduce the cost incurred for recreation in times of design failure (Fig. 14.2).

14.1.4 Invention of digital twin

The idea of DT was first put forth by David Gelernter's 1991 book "Mirror Worlds," with Michael Grieves of the Florida Institute of Technology.

In the Society of Manufacturing Engineers gathering in Troy, Michigan, Grieves officially presented the idea of the DT in the year 2002 at the University of Michigan.

Figure 14.2 Digital twin for smart city.

Later, NASA originally grabbed the idea of the DT and, in a 2010 Roadmap Report, John Vickers of NASA gave the idea the name. The thought was utilized to make advanced space capsules or containers and test them at zero cost expenditure.

The DT idea spread further still in 2017, when Gartner named it as one of the best 10 key innovation patterns. From that point forward, the idea has been utilized in an always developing exhibit of modern applications and cycles.

The innovation behind DTs has extended to incorporate structures, production lines, and even urban communities, and some have contended that even individuals and processes can possess DTs, growing the idea considerably further.

14.1.5 Digital twin usage

Digital twins can be broken down into three broad types, which reveal the individual instances when the process can be used. The types are listed below:-

1. The digital twin prototype (DTP),
2. The digital twin instance (DTI), and
3. The digital twin aggregate (DTA).

14.1.5.1 Digital twin prototype
The DTP consists of designs, analyses, and processes to realize a physical product. The DTP exists before there is a physical product.

14.1.5.2 Digital twin instance
The DTI is the DT of each individual instance of the product once it is manufactured.

14.1.5.3 Digital twin aggregate
The DTA is the aggregation of DTIs whose data and information can be used for interrogation about the physical product, prognostics, and learning.

There are different sorts of computerized twins relying upon the degree of product enhancement. The greatest contrast between these twins is the area of use. It is normal to have various sorts of DTs coincide inside a framework or cycle. We should go through the kinds of DTs to gain proficiency with the distinctions and how they are applied. They include the following types:
- Component twins or part twins
- Asset twins
- System twins or unit twins
- Process twins

Let us go through the types of DTs and understand their differences when applied on developing a virtual representation of a product or process.

14.1.5.3.1 Component twins/part twins
Component twins are the fundamental part of the DT. This is the twin of a single unique component in a whole system. These components have a great impact directly on the systems' performance and functionality. Component twins are more concerned with the stability and durability of individual parts. Part twins are related to components of a little less importance.

14.1.5.3.2 Asset twins
Asset twins describe how individual components work together as an entire asset. It involves the user to visualize the interaction among the components. It can be the combination of component twins. This helps

the developer check the entire system without building the system in the real world.

14.1.5.3.3 System twins

The system twins, also known as unit twins, work on a higher level. They combine individual asset twins and give the opportunity to check how individual assets work together. Whereas, asset twins combine individual component twins. For instance, system twin brings all the units necessary for the production of the system under one roof.

14.1.5.3.4 Process twins

Process twin represents an entire production facility and provides insight into combining all the modeled units. The process twin influences the overall effectiveness of the product or system being designed.

14.1.6 Design of digital twins

DTs can be made for a variety of applications, for instance, to test a model or configuration, conduct a survey on how an item or interaction will function under various circumstances, and decide and observe their lifecycles.

A digital twin plan is made by collecting information and making computational models to test it. This can incorporate a connection point between the virtual model and a genuine real-world item to send and get criticism and information progressively.

14.1.6.1 Data

A DT requires information about an item or cycle for a virtual model to be made that can address the ways of behaving or conditions of this original item or technique. This information might connect with the lifecycle of an item and incorporate design descriptions, development cycles, or designing data. It can likewise incorporate development data, including hardware, materials, parts, techniques, and quality verification. Information can likewise be connected with activity, for example, continuous input, and verifiable examination and preserve records. Different information utilized in DT design can incorporate business information or end-of-life techniques.

14.1.6.2 Modeling

When the information has been accumulated it tends to be utilized to make computational scientific models to show working impacts, forecast states like exhaustion, and decide ways of behaving. These models can endorse activities in view of designing powerful solutions via simulation, material science, chemical science, measurements, AI, business rationale, or goals. These models can be shown by means of 3D portrayals and magnify reality demonstrating to help human understanding of the discoveries.

14.1.7 Linking digital twin to real-world systems

The discoveries from DTs can be connected to make an outline, for example, by taking the discoveries of items and placing them into a production line twin, which can then illuminate an industrial level twin of the item. By involving connected twins in this manner, empowering brilliant modern applications for true functional applications of events and improvements is conceivable.

14.1.8 Benefits of digital twin

The advantages of a DT varies depending when and where it is utilized. For instance, utilizing DTs to screen existing items, like an air cooler, oil pipeline, or smart car can decrease support cost and save a large number in related costs. Advanced twins can likewise be utilized for prototyping in front of assembling, minimizing item imperfections, and shortening time to showcase. Different occasions of DT use can incorporate cycle upgrades of the product against yield or product or the outcome.

Few familiar advantages are increased availability and reliability through checking and reproduction to further develop execution. They can likewise decrease the chance of mishaps and spontaneous downtime through disaster, lower support costs through foreseeing disaster before it happens, and guarantee production objectives are not influenced by planning service, fix, and the requesting of new parts. DT can likewise offer upgrades by dissecting customization models and guarantee item quality through execution testing continuously.

However, DTs are not suitable in all occurrences as it can levitate complexity. Some business problems simply do not need a DT and can be solved without the associated investment in time and cost. However, in case of large investment, it is suggested to use a DT that can provide you with an efficient model that can guarantee to start the production, which incurs better use of raw material, cost, and time of development.

Cyber-physical systems (CPS), often known as CPS, are systems that are made up of both physical systems (also known as hardware) and software systems, as well as maybe other kinds of systems (e.g., human systems). A system for the control and protection of a physical infrastructure that makes use of sensors, actuators, control units, and other physical items.

These are intricately connected and networked with one another to produce some global behavior. Because a failure might have serious repercussions, it is vital to defend it from any malicious assaults that may be launched against it.

A CPS will often function in some kind of hostile environment, in which it may not be easy to replace energy supplies and nodes may be vulnerable to attack.

A computerized payment system is a mechanism that is managed or monitored by computer-based algorithms and is strongly connected with the Internet and the users of the Internet.

Some of the features that define it are**:**

1. The link between cyberspace and the actual world, driven by new requirements and applications

Capabilities in cyberspace embedded in every physical component

Large-scale networking through wired and wireless connections

Linked over a multitude of sizes, some of which are quite large

2. Systems of systems

New restrictions based on both space and time

Complex across numerous temporal and geographical scales

Reorganizing and reconfiguring in real time conventionally unconventional computational and physical substrates

3. Unprecedented interconnections among communications, computing, and control systems

Control loops need to be closed at all scales notwithstanding the high degree of automation.

Large numbers of users who lack technical knowledge participating in the control loop

4. The proliferation of ubiquity creates unprecedented demands on both privacy and security

Reliability and, in certain instances, certification are prerequisites for operation.

14.1.8.1 Cyber-physical system requirements

1. Safety—All of these systems have some kind of interaction with their surroundings. Failure of a system may have devastating repercussions.

   The correctness of a system is contingent not only on the logical findings but also on the time at which those conclusions are delivered (real time).
2. Although the most important need is safety, we still have to meet a certain level of performance standards.

   A great number of systems are limited by their resources (in either weight, power, cost, etc.)
3. Interoperability

   Independent subsystems linked to one another via public protocols

14.1.9 Cyber-physical system and its principles

The integration of applications from the fields of engineering and the physical world with those of computer engineering hardware and computer science cyber worlds is the central tenet of CPS. The aspects of physics, modeling, and intangibles of the actual world, such as risk and uncertainty, are all included in the fundamental principles of the physical universe. Embedded systems, networking, programming, and algorithm development are all topics that are being tackled concurrently in the fields of computer engineering and computer science. CPS education thus extends beyond the exposure to the standard dynamical systems models, such as simple differential or difference equations, to include an awareness of the physical repercussions that occur not only at the physical layer but also across the physical-cyber interface.

One example of a hardware bridge that connects the real and digital worlds is represented by sensors. They are the key instruments responsible for gathering data from the physical environment, which is then utilized as input in the digital world. It is essential to have a solid understanding of the characteristics and working principles of sensors, as well as the methods for using them in a way that takes into account the limits imposed by both the sensors themselves and the actual environment. Sadly, high-level abstractions, which are supposed to facilitate system development, sometimes have the unintended side effect of concealing crucial physical world principles that programmers need to be aware of in order for the CPS they create to function correctly. After the data have been acquired in their raw form, they are next subjected to various signal processing procedures. A linear signals and systems theory, analog and digital filtering, time and frequency domain analysis, convolution, linear transforms such as the discrete Fourier transform and the fast Fourier transform, noise and statistical characterization of signals, machine learning, and decision and sensor fusion are the required principles of signal processing. In CPS, considerations of the implementations of these signal processing techniques on embedded CPUs, running in real time and with safety critical implications, are required, as is the topic of sensor reliability. Typically, these issues are not taken into consideration in classical signal processing courses.

CPS is based on the principle of control. Stability and optimization, as well as control methods in the context of networks, hybrid systems, stochastic systems, and digital systems, are important aspects of control theory. There are significant consequences for control of distributed systems and the inherent delays they impose in cyberspace.

CPS engineers must be familiar with the basic concepts of today's networked, wireless, and real-time environment, as well as our economy and society's increasing reliance on CPS. Students require this information in the following areas:

Networking and communication. For CPS to work, one must have a firm grasp on the fundamentals of wireless communication, from the physical layer all the way up to protocols and layered structures.

On-the-spot real-time scheduling theory, program temporal semantics, and network clock synchronization must all be grasped.

Multi-tiered architectures CPS education should include the dispersed and networked character of CPS in many of the applications of interest. Despite the fact that distributed systems and networking are addressed in standard engineering and computer science programs, these courses frequently do not address the CPS challenges. For the CPS system to work, hardware and software must work together in a real-world environment.

Integrated circuits. The creation of stable and high-quality cyber components of a CPS system requires a good education and expertise in embedded software concepts, the numerous principles of programming, algorithms, software design, formal techniques, and platforms (architectures and operating systems).

Properties of the physical world. The physical features of the surroundings and hardware platforms must be understood and modeled. To provide safety, dependability, real-time performance, risk management, and security, software design concepts must address the realisms of the physical world.

Interaction with others. Many CPS place a high value on human factors design, human-in-the-loop control, and a grasp of and accounting for human behavioral reactions. One of the most significant aspects of CPS design is making it simple for people to use, control, and maintain. Hands-on projects and multidisciplinary cooperation are essential in learning and seeing key ideas used, as they are in other engineering fields.

14.1.10 Digital–physical mapping in digital twins

Data from the physical model, sensor updates, operational history, and other sources are all included into the DT simulation process, which then maps out the whole lifecycle of the matching physical equipment in virtual space.

As DTs progress, their goal is to offer a complete physical and functional description of an object. Create high-fidelity virtual models that faithfully mimic the physical world's geometry, attributes, behaviors, and laws as the first and most critical stage in the process. Aside from their geometric and structural accuracy, these virtual models are also capable of simulating the actual components' spatiotemporal state, behaviors, and functionalities. As a result, there is a strong resemblance between the virtual models and the real-world counterparts. It is also possible to directly improve operations and change the physical process via input from digital models. With bidirectional dynamic mapping, real and virtual models change together. As a result, there is a one-to-one correlation between the real and digital worlds of a DT's mapping relationship. A virtual model is a representation of a real entity that includes its shape, structure, behavior, laws, and functional qualities.

14.1.10.1 Cyber-physical system and digital twins are under control

Keeping a system's operational normality at an acceptable level in the face of disruptions is the goal of control systems. CPS and DTs are all about gaining and maintaining control. The cyber-physical connection of CPS, for example, is of paramount significance. Product or system lifecycles influence the evolution of DTs' virtual models and physical processes. Cyber/digital representations of physical assets or processes may be controlled, as well as the control of physical assets or processes impacting cyber/digital representations. A dynamic physical environment means that an entity might have various attributes at different periods. This is part of the control. Sensors take real-time data from the physical world and send it to the cyber/digital world to keep the cyber/digital components operating in sync with the physical world. Real-time data from a DT drives the virtual models specifically to imitate the actual process and its development. The cyber/digital world utilizes this data to calculate the control output and transmit it to the actuators for physical implementation in the later phase of the control. It is possible to foresee future statuses and faults using mathematical models and associated computational technologies, for example. This allows for better service and control solutions to be produced in advance. Through cyber-physical interactive control, risks of an unanticipated and harmful character may be eliminated.

14.2 Digital twin-based smart factory cyber-physical system modeling

The latest industrial revolution, Industry 4.0, with advanced digital technologies challenged the manufacturing industry and led to transformation in many governments with their own strategic programs. Many large-scale industries are still in early stages of transition. Smart intelligent technologies like IoT, cloud computing, artificial intelligence, and big data analytics make the inspired smart factory automation with the integration of CPS. DT and CPS' integration gained attention by industry practitioners for their efficiency, resilience, and intelligence. IoT is to link the physical assets using sensors to perform data transmission. It plays a vital role in improving the information and dynamic data processing capabilities, which influences not only decision makings but also enhances the global economic systems. The CPS is another technology revolution, proposed to bring the physical and the virtual world together (Fig. 14.3).

Cyber physical systems is an embedded application that brings huge economic benefits and changes the industrial operations. A collaborating manufacturing system that is fully integrated to respond in real-time changes in factories is said to be a smart factory system. A smart factory system is a system that connects to the global network of same production system or cyber world based on IoT infrastructure. To understand smart factory, it is essential to understand the concept of digital twin as it plays a role in connectivity and sensor networking, which is an essential factor in the physical and cyber world. Important active components of DT are sensors and actuators from the physical world, integration, data, and analytics from the cyber worlds.

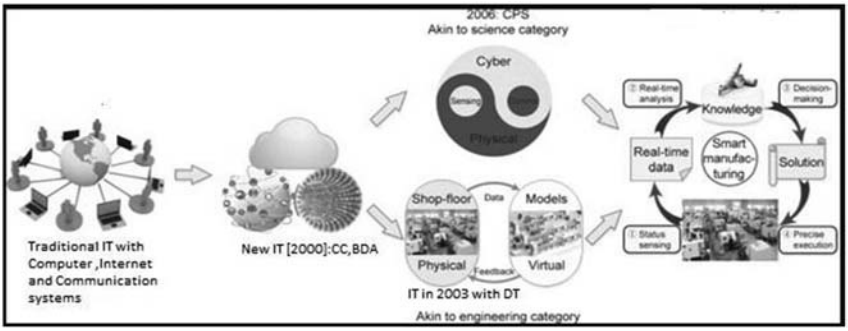


Figure 14.3 Origin of cyber-physical system and digital twins for smart manufacturing.

14.2.1 Integration of cyber physical systems and digital twins

Cyber-physical system is an embedded system of physical and computational processes and DT is an usage of digital copy of a physical system to perform real-time optimization. In factories during manufacturing process both CPS and DT are involved to utilize the physical and cyber part. According to the figure shown, the manufacturing operations are performed by the physical parts like human/machine/material/environment. The cyber world consists of different apps and services that incorporate data management, data analytics, and computational power. The cyber world smart applications and services are used to increase productivity and the physical world makes decisions based on the sensed and collected data. Also CPS analyzes, processes the collected data, and also makes decisions (Fig. 14.4).

For instance, in the Wise-Shop Floor, the CPS gives clients a natural shop-floor climate in which continuous checking and controller are undertaken. The Java 3D model, which gives clients perception according to different viewpoints, is driven by constant sensor signals. Approved clients have some control over genuine gadget controls and view the run-time status of the controlled gadget (e.g., a PC mathematical control machine).

14.2.2 Hierarchical Model of cyber-physical system and digital twins in manufacturing

Smart manufacture is a worthwhile creation process from product design to production, coordinated factors, and administration, in which multiple subjects partake. According to the point of view of hierarchy, CPS and DTs can be separated into three unique levels based on magnitude: the unit level, framework level, and system of systems (Fig. 14.5).

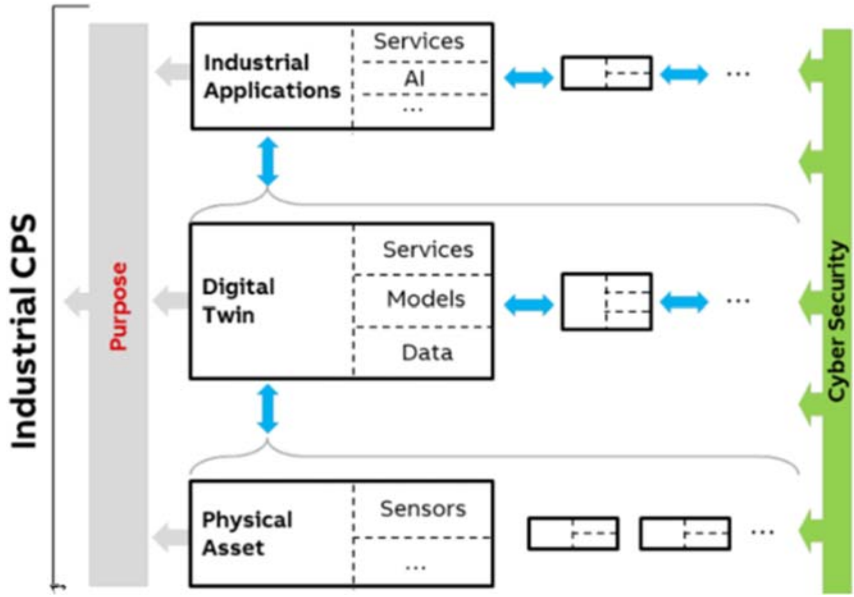


Figure 14.4 Integration of cyber physical systems and digital twins.

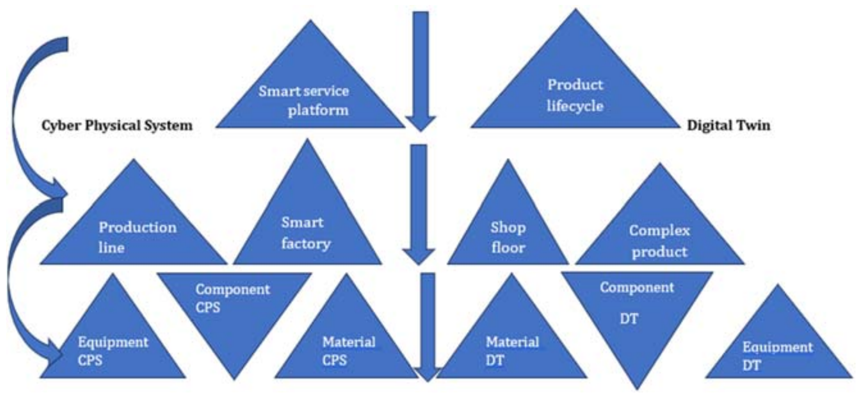


Figure 14.5 Hierarchical levels of cyber-physical system and digital twins in manufacturing.

14.3 Digital twin in cyber-physical system-based production systems

14.3.1 Cyber-physical system—an overview

Cyber-physical system and DT grabbed the attention of researchers and industrialists within a few days by its enormous features. To do anything digitally connected as well as communicated these two plays a major role.

Cyber-physical system from the name indicates the integration of the cyber world and the dynamic physical world. It focuses on multi-dimensional data through the integration and collaboration of computing, communication, and control. It also performs real-time sensing, information feedback, and dynamic control of the devices through the internet, which is highly interdependent. CPS is a semi-autonomous device that plays a major role to bring a closer connection than ever between the industry's digital and physical worlds.

Major advantage of CPS along with DT is: we can trace a working process of the devices through its entire lifecycle. Nowadays, people are getting close with 3D and even more advancement; it's very easy to achieve this by means of DT when it's connected with AR and VR. By this captured dataset; optimization and decision-making would be easy and it's being updated in real time.

14.3.2 Correlating cyber-physical system and digital twin

Cyber-physical system and digital twin are not same in many cases including their origin, application perspectives, and development. Let's start with a scenario. You have devised an algorithm to control the operations of the car, for that instead of doing it on an on-road; you have decided to do virtually first then you will test it on the road. For testing virtually, you have to combine sensor networks with embedded computing to monitor and control the working of the car based on the predefined conditions. Later for simulation you have to create a virtual view of a car and do performance testing. If a car performs well then go for on-road checking.

In the above said scenario; testing virtually with predefined conditions is done by CPS and creating a virtual view of a car is achieved by DT. Therefore, DT is a subgroup under CPS.

14.3.2.1 Bonding between physical and cyber (digital) world in cyber-physical system and digital twin (DT) or bridging the physical-digital divide by DT

Cyber-physical system is nothing but the mapping of physical processes with IoT and performing computations for automation. Whereas DT is coined for digitized form of those physical components. Physical components include man or material, which are all viewable in the real world; it is used for collecting the data from the resources and DT includes smart applications, data management, and decision-making and analyzing those

Figure 14.6 Connection between physical and digital world.

applications using machine learning techniques. To improve the productivity and more secure architecture DT is used along with the CPS (Fig. 14.6).

The bonding between physical and digital components in DT is one to one; using mapping and connectivity they involve strong association and they perform simulation with the data analysis; but the mapping in CPS is one to many so they involve generalized connectivity with the components and they perform only computations.

14.3.3 Cyber-physical system architecture

Cyber-physical system is a complex architecture to design because of its challenges pertaining to security and data-driven techniques. The above given architecture describes the process of data storage and how it's been processed. First, data is being collected from the sensors; the devices without DT will capture only the 2D data like depth, height, volume, torque, thickness, etc. It's not enough to realize the objects in the real world; so devices with DT sensors have been introduced and they capture critical inputs (i.e.) how the devices work in certain conditions like extreme pressure, heavy traffic, overload, etc. Then these inputs are communicated with the ERP systems and get augmented for the next level of processing. During the data process the main thing to be considered is security. Once

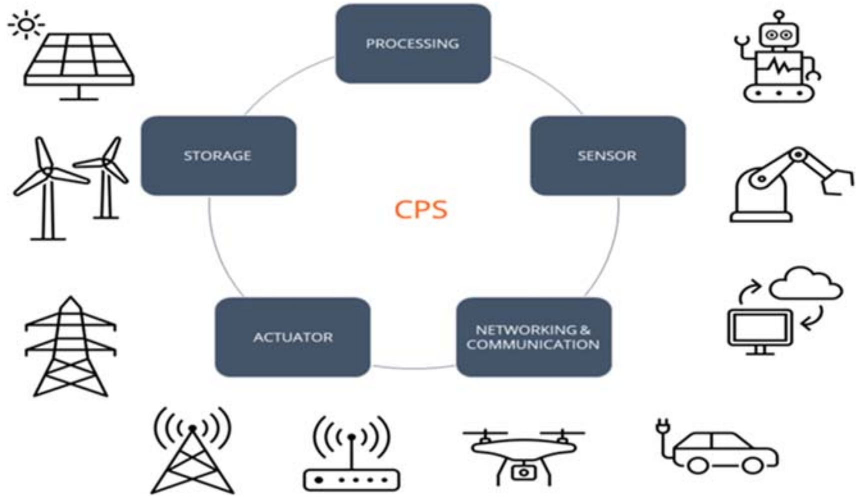


Figure 14.7 Cyber-physical system architecture.

it's done; the secured data is augmented with an artificial intelligence model for analytics (Fig. 14.7).

14.3.4 Cyber-physical system-based production systems

Connected things through the IoT are making drastic changes in human life. Examples include Alexa, Autonomous Car, Smart lock, Smart watches, Smart cities, Industrial IoT, etc. Main applications of CPS come here. Along with IoT, CPS plays a major role in the digital world. In the manufacturing industry the main goal is to reduce the cost of a machine, controlling of sensors, and also to reuse the components whenever we need; it's achieved by CPS production system.

By means of CPS in the production line; the industrialist will get benefited and remove the errors when the sensor detects the failure before the product gets implemented; also in means of car automation if the sensor alerts the user based on the previous information the driver will get helpful.

As manufacturers are facing numerous problems in the real world during productivity; to reduce the cost DT is used to prepare BOM (Billing of Material) with the data collected during the production stage. BOM contains the list of items required to build a product like parts, assemblies, connection between the parts, instructions to construct a product, etc. DT when used for BOM preparation has reduced the rework. Thus, DT captures live data throughout the lifespan of the product; so manufacturers can easily store the as on-data of BOM, Error, Design, and workflow.

14.3.4.1 The brand new manufacturing based on cyber-physical system

It's a main sector in which CPS gets associated easily with all the sub-branches and also gets through the entire process. Mainly CPS is used for reuse, safety, improving efficiency & throughout, and for decentralization. A CPS based manufacturing system has to be introduced such that it should be transformed from closed loop (i.e.) divided from system to an open loop that uses cloud as a storage. To achieve this integrated system with IoT based architecture has to be implemented in the industry.

14.3.4.2 Components of cyber-physical system for manufacturing

Olden days it's too difficult to propose an unmanned device because of its unlikeliness. Therefore, a hybrid model has been introduced by using CPS, which is composed of all connected Physical level Component (PC), Cyber (digital) Component (CC), and Human (Manual level) Component (HC) in every individual level of operations. Later, CPS with the help of DT proposes a new model which collaborates CC and PC which will be managed by HC. Later to achieve feasibility, the connection between CC, PC, and HC has been introduced and produced an unified system (Fig. 14.8).

14.3.4.2.1 Human component

Human Component is basic in CPS manufacturing system; due to sudden increase in customer demands for the personalized products and the rapid changes in machinery manufacturing the workforce has to adapt for the needs. The work force of a company is one of the most important resources to make an industry fly at a high level.

HC includes learning models and human models. To meet the industry expectations and to meet higher needs there should be a drastic change in the workers skill. DT & CPS and AR & VR are emerging techniques so the skills of an employee must meet that level.

14.3.4.2.2 Cyber component

Second important component is CC; it focuses on storage, file management, failure detection throughout the lifecycle, cyber-related threats, and processing of the data. Cloud-based Service Oriented Architecture is used

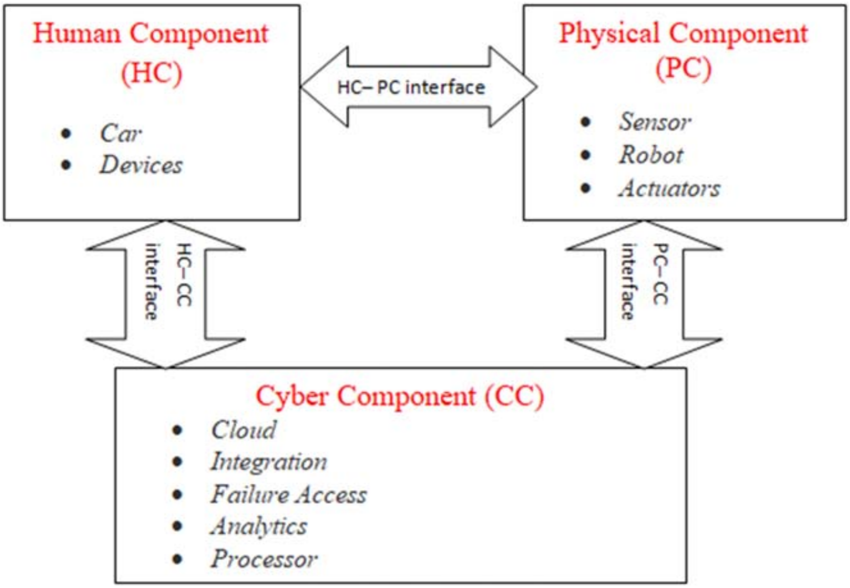


Figure 14.8 Components of cyber-physical system and its relationship.

for secure and fast retrieval of data. Three tier architecture is used for Data Management System; in the middleware machine learning techniques are used for prediction.

To predict the failure in advance an intelligent ramp up technique is being integrated along with the sensors. Numerous CC architecture is available based on the applications of the suitable architecture has been chosen. For future prediction cloud-based CPS is used. Multiagent System architecture is used for multiple decision-making and independent problems.

14.3.4.2.3 Physical component

PC is the very low level of component in the design. It uses only the hardware components. Here the communication between two physical components takes place; also cyber and sensor gets connected here. Other than connection; communication between two machines or between sensor and device takes place here.

The connection between components (HC, CC, and PC) is very important; it has to be strong and dependency should be high. If a manufactured device is said to be more convenient for a customer then it should have a good user interface. Any person without the process knowledge has to operate without any difficulties; so correlation between human and digital should be high. When DT came into the role; then machine had to communicate with the internet by means of IOT it's been done by RFID.

Example devices for human and machine interconnections are smart glass, wearable devices, and sensor-based helmets.

14.3.5 Challenges to cyber-physical system for manufacturing

Implementing CPS is not too easy because of a drastic change from physical to digital world. In manufacturing, the first thing to be noted is *Productivity*. Even an efficient machine will fail if it is not used by a customer or due to sudden change in requirement, decrease in market value, cost of a machine, etc.

Second challenge is dynamic reconfiguration; it needs recent approaches to do dynamic changes in the parts when and where it's needed. In CPS, it's required to combine more techniques for monitoring the errors through the lifespan. Whenever a failure is found, correcting those errors without affecting the efficiency becomes unavoidable for longer parts, and also to reduce high costs. Automation and self-optimization is a high degree of flexibility after repairing and it requires more human components; this causes major restriction.

Later standardization becomes tedious; it includes quality service, support service, and quality standards. IEC 61131 and IEC 61499 these standards tell about the challenges of automation systems. Next major challenges are related to information technology; it deals with how to assemble and maintain hardware parts in the machines using development in IT. To represent the data in the form of digital, understanding and communication between components by means of sensors, learning modern software tools is also a drawback in CPS manufacturing systems.

14.3.6 Cyber-physical system for smart cities (modern city)

In the digital era, people are shifting their lives towards smart devices because of their easy usability. CPS plays an important role in making smart cities and to connect the devices and make them communicate using the internet. By means of smart city, people are feeling comfortable and cost benefited. In smart cities; physical and digital data are collected through sensors and they are processed using CPS (Fig. 14.9).

Figure 14.9 Smart city.

While constructing a smart city, we have to take care of people living in that area, their own problems like transport, sanitation, waste management, hospital management, pollution, water, economy, and at last electricity. Also innovative solutions must be included in the city that should reduce the energy resources, decentralization, parking, healthcare, and education.

The people in the smart cities are expecting that everyday activities should be done with the help of IoT devices. For example, if a person wants to book an appointment in a hospital it can be done by means of their smartphone and they can consult doctors based on that information. They can travel through smart trains by getting the location through the sensors implemented in it.

Application of CPS in smart cities

- Energy infrastructure
- Mobility
- E-governance
- E democracy
- Surveillance
- E-finance
- Smart construction

14.3.6.1 Next-generation smart cities

In the modern trend of rapid advancement, smart cities are helping us to grow high. The vision is to create cities that allow citizens to work, play, interact, and travel by using modern tools as much as possible. World's first and foremost smart city is *Shanghai*. It has around 1000 ready services to access by its people; it costs around USD 70 billion for implementing smart devices. When coming to India, the survey says Bhopal became the first city in completion of smart city projects with 92%; Surat takes next to it with 82% completion, followed by Udaipur, Bhubaneswar, Indore, Varanasi, and Ahmedabad.

The project was started in 2015 and it's going on with eco-friendly implementation and comes to an end in 2023. Apart from industries; government is also providing fullest support to complete the mission for the miserable countries.

Smart Cities 1.0; at first when we start to move towards smart cities it's very much difficult for both citizens as well as devices. They don't know about the changes, development of apps, how it will work and affect their lifestyles, mainly the economy of the people. It's developed by industries like IBM, Cisco. When moving towards *Smart Cities 2.0*, it focuses on how the smart cities are taken care of by the government rather than by the industrialists. Ministries help the people how the city could change their life; what are their roles in deployment. For example, if there's any cyclone or landslide occurring then how the sensors and IOT devices will help to recover the people from disasters. Whereas in *Smart Cities 3.0*, citizen had put their efforts into creating a smart cities model. For example, if we take an online food ordering system; the customer is the fullest support needed to raise the quality of the system and improve the underlying resources.

14.3.7 Research challenges and future trends

CPS with respect to big data has challenges in handling huge amounts of data (volume), and for processing it has to collect data from various sources (variety) with proper authentication and authorization (veracity) also it has to deliver data rapidly (velocity) without any repetition. So new technology has to handle these issues with the help of CPS.

Cyber-physical system in cloud computing must be able to handle transparent and on-demand low-cost resource access. Cloud computing is the backbone for integrating cyber and physical components in the real world that includes challenges like data collection and analysis using machine learning algorithms, low latency, and processing. Major bottleneck is integrating data servers with high end cloud; that needs dynamic attention to avoid overloading problems. So in future scalable systems must be discovered in order to handle various data and that can be easily interconnected with the cloud.

Cyber-physical system in IOT; the challenge is how to handle physical components in the IOT environment. Services for software based are used to enhance the applications. Those applications must be self-optimized to provide good customer needs and user interface.

14.4 Case studies

One of the applications of CPS is Autopilot. It works on the principle of CPS; autopilot monitor and control aircraft as well as marine craft. It won't fully replace human work; instead it helps the pilot to track the process digitally so that the pilot will take care of weather monitoring, altitude checking, etc. One such autopilot method is Traffic Collision Avoidance System (TCAS). This study explains the traffic between the flights in the air. During the Second World War period; there was not much advancement in aircraft. Pilots need to access the control of flight continuously and safe landing is much more important; so TCAS is very helpful during that time. Later, computer algorithms were designed to control sensors and made the work reliable. By means of a sensor it alerts the pilots and sometimes it resolves the solution by providing some other routes or some changes the pilots can do to avoid accidents. TCAS uses transponders to monitor the climate, weather condition, previous condition when collision occurs and it alert the pilots. If suppose the opposite flight does not have transponders then TCAS uses RADAR to predict the collision.

Next major area in which CPS shows its growth is healthcare. Medical imaging like X-ray, MRI, ultrasounds are used to create visual representations of the interior of the body for clinical analysis and medical intervention of complex diseases in a short period of time to help the diagnostic to enhance patient care. Traditional medical imaging systems provide 2D visual representations of human organs where advanced digital medical imaging systems (e.g., X-ray CT) with the help of CPS can create both 2D and in many cases 3D images of human organs. With the current system we are able to only view the exterior part of the cells; if we moved towards CPS; then it would be easy to recognize the disease and that would be helpful for young surgeons to diagnose the type of disease. VR-based 3D medical modeling platform is used for creating patient-specific 3D models, importing volumes, and handling 2D and 3D drawing tools to select and segment individual body parts. Using computer software we can track the models and analyze the result easily.

With the help of information retrieved by sensors; the high-end surgical planning, guiding, and patient care are ultimately improved. Also, while recognizing dangerous diseases like cancer and brain tumor with the help of CPS, the region of interest (ROI) can be segmented easily.

This page intentionally left blank

Index

Note: Page numbers followed by "*f*" and "*t*" refer to figures and tables, respectively.

K

L

T

U

V

DIGITAL TWIN FOR SMART MANUFACTURING

Edited by Rajesh Kumar Dhanaraj, Ali Kashif Bashir, Rajasekar Vani, Balamurugan Balusamy, and Pooja Malik

Digital Twin For Smart Manufacturing provides detailed descriptions of how to integrate and optimize novel digital technologies for smart manufacturing. Digital twins combine the industrial internet of things, artificial intelligence, machine learning, and software analytics with spatial network graphs to create living digital simulation models that update and change as their physical counterparts change. The book also provides an effective way to integrate technologies such as cyber-physical systems into a smart manufacturing system, potentially optimizing the entire business process and operating procedure of the manufacturing firm.

Drawing on the latest research, this book addresses the topics and technologies key to successful implementation of a smart manufacturing system, including augmented and virtual reality, big data, and energy management. Broader subjects such as additive manufacturing and robotics are also addressed in this context, covering every aspect of production.

Key features:

- Includes detailed case studies to show how digital twins have been successfully implemented in real life
- Shows how digital twins can be used to improve sustainability through superior energy usage management
- Outlines potential future uses of the digital twin, pointing the way for future research directions

About the editors:

Rajesh Kumar Dhanaraj is a Professor at Symbiosis International (Deemed University), Pune, India.

Ali Kashif Bashir is a Reader at the Department of Computing and Mathematics of Manchester Metropolitan University, United Kingdom.

Rajasekar Vani is an assistant professor at the Department of Computer Science and Engineering at Kongu Engineering College, India.

Balamurugan Balusamy is an Associate Dean-Student Engagement at Shiv Nadar Institution of Eminence, Delhi-National Capital Region (NCR), India.

Pooja Malik is an assistant professor at the Department of Computer Science and Engineering at Shiv Nadar Institution of Eminence, India.

ISBN 978-0-323-99205-3

9 780323 992053

ELSEVIER

ACADEMIC PRESS
An imprint of Elsevier
elsevier.com/books-and-journals