Energy Reviews 2 (2023) 100039

Contents lists available at ScienceDirect

Energy Reviews

journal homepage: www.journals.elsevier.com/energy-reviews

Full Review Article

Digital twin in power system research and development: Principle, scope, and challenges

Mohammed A.M. Yassin [*], Ashish Shrestha, Suhaila Rabie

Department of Electrical Engineering, Information Technology and Cybernetics, University of South-Eastern Norway, Porsgrunn, N-3918, Norway

ARTICLE INFO

Keywords:
Communication channel
Cyber-physical systems
Digital twin
Internet of things
Machine learning

ABSTRACT

In order to address the issues that arise in modern power systems, such as system dynamics, stability, control, efficiency, reliability, economy, planning and policy, and so on, efforts have been made to develop new tools and techniques, components, methodologies, and scientific innovations in a variety of fields. These efforts have been undertaken to address these issues. The term "digital twin" (DT) refers to one of the most reliable and rapidly developing technologies that have recently been incorporated into a variety of applications, platforms, and real-time projects. The authors of this study offered a scoping review of DT technologies with a primary emphasis on power systems. It has been established that the underlying notion behind this technology, as well as its operating principle, types, communication channels and protocols, and standards, have all been thoroughly examined. In addition, the possibility of integrating other technologies with DT has also been considered, along with the potential benefits of doing so and the potential difficulties that may arise. Based on the information gained from the current projects, the finished projects, the research publications, as well as the research and industry insights, a critical discussion has been made.

1. Introduction

1.1. Background

With the introduction of rapidly growing power electronic converter (PEC)-based technologies and information and communication technologies (ICTs), the modern power system is adopting a significant transformation in the generation, transmission, and distribution processes, as well as in utilization levels. This is being done in order to tackle the associated problems such as cost, reliability, system dynamics, stability, control, efficiency, security, and so on [1]. It is presumed that the power/energy systems will be able to handle the difficulties that have been described as a result of these changes; nevertheless, these transformations have brought complications with their operation, transmission, storage, and even security concerns [2]. The contemporary power system is a complex system, and appropriate tools and methodologies are necessary to assess the power/energy systems both during the design phases and the operation stages.

To handle the difficulties that come up in contemporary power systems, efforts have been made to create new tools and methods, components, methodologies, and scientific inventions in a range of domains. These innovations have been produced in an attempt to meet the issues that come up in modern power systems. There are several tools and techniques that have been developed using the most up-to-date concepts and that cover the majority of the ground in terms of research, implementation, and operation while delivering satisfactory results. Machine learning (ML), blockchain technology, the internet of things (IoT), big data (BD), and cyber-physical systems (CPS) are a few of the prominent techniques that have been combined with power system research and implementations, which have been widely employed in the last decade. All of these technologies give chances for the integration of the physical world and the digital world, which is an unavoidable development that must be addressed to meet the expanding complexity and high market expectations [3,4].

The digital economy and internet applications are gradually taking over various sectors. Numerous significant strategic actors will step up their efforts in search of novel solutions as a result of the need to enhance consumer engagement, product distribution, and operational efficiency in retail, service, and other sectors [5,6]. Numerous variables may contribute to lengthier analysis times and slower digital rollout timelines across numerous industries. The conversion point from data into useable information still appears to be more manual than automated, despite the

* Corresponding author.
E-mail address: mohammed.yassin@usn.no (M.A.M. Yassin).

https://doi.org/10.1016/j.enrev.2023.100039
Received 6 March 2023; Received in revised form 22 July 2023; Accepted 23 July 2023

fact that a digital strategy is in place and a team of professionals is being organized to tackle these problems. These issues include but are not limited to, the fact that the data is dispersed across the business, is of low quality, and lacks context (i.e., the capacity to translate and correlate the available data) [7,8]. With the fast expansion, various problems occur, particularly in the energy industry. The penetration of intermittent renewable energy sources is one example of this difficulty, as is the high estimated future energy consumption (which is expected to rise by 50% by 2050), the deployment of new equipment and controllers, and financial and regulatory restrictions [9,10]. These difficulties are causing the global energy business to relentlessly look for greener, more dependable, cost-effective, self-healing, and more secure energy operations. One possible answer to these problems is to use "digital twin" DT technology to help power systems switch quickly and make them more flexible [8,9].

1.2. Literature review

The necessity to access and examine satellites after they had been launched into orbit led NASA to use the word "Digital Twin" for the first time in 1970 [11]. Dr. Michael Grieves first proposed the DT concept in 2002 [6,12]. By including "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", Dr. Grieves' presentation went beyond the traditional Product Life-cycle Management (PLM) model [13]. This indicates that the currently used methodologies (i.e., simulation and modeling) need to take a more comprehensive approach by obtaining real-time feedback from the physical system, including it in the simulation, processing the data, and feeding the system with the newly processed data. Since Dr. Greives's presentation, the work in the DT sector has advanced, concentrating on this two-way relationship between the simulation and physical components [14–17]. DT technology is now a hot topic in research and is recognized by Gartner, Inc., a leading worldwide provider of research and consulting services [18,19], as one of the most touted technologies of the 2020s. A comprehensive analysis of the databases (Scopus, ScienceDirect, Google Scholar, and Web of Science) shows that there is still debate about a single definition of DT technology. In Ref. [5], six distinct definitions of DT are provided, while [20] has sixteen further meanings. The precise definition, however, depends on the application area and shares similar key terms and aims (a virtual equivalent or a dynamic digital representation of a genuine system) [21]. Here are two examples of "generic" and "accurate" definitions to provide a better idea of what they mean [22] have defined the DT as "a digital representation of an active unique product (a real device, object, machine, service, or intangible asset) or unique product-service system (a system consisting of a product and a related service) that comprises its selected characteristics, properties, conditions, and behaviors by means of models, information, and data within a single or even distributed computing environment." On the flip side, [23] has presented twenty-two different definitions with a focus on DT concepts on process heat, energy, and decarbonization. A more specific definition in the context of power systems derived from the literature list would be: in power systems, DT is a visual copy of the power grid used to monitor and simulate the power system to maximize the components' performance, reduce safety risks, predict power outages, optimize the economy, and comply with requirements [24–26].

In the last two decades, DT has been implemented in several industries such as manufacturing [27,28], smart cities and healthcare [29,30], agriculture and smart farming [31], automobiles and smart manufacturing [32], 3D printing [33], product design and development [34,35], and several others. On the contrary, in the power system and energy industry, the implementation of DT is still limited [9,23,36,37]. Although the implementation of DT is still in its infancy stage, the research platforms are showing steady growth. A search of the keyword "digital twin'' and "digital twins" on Scopus (limited to abstract, title, and keywords) for the last ten years (2014–22/05/2023) revealed a total of 14,180 documents on several research fields, as shown by Fig. 1 (a). As evidenced by Fig. 1 (a), the publication rate has been exponentially on the rise in the last five years. In 2019, the number of publications has tripled and has had a steady increase of around 70% in 2020 and 2021. By May 22, the number of publications for 2023 is on track with 1,688 publications. When the publications are analyzed by the origin countries, China is identified as the leader. For simplicity, the authors just took the top ten countries that publish scientific papers on DT. After China, Germany, the USA, the UK, and Italy are the leading countries that contribute publications on DT technology. The overall distribution of these ten countries is given in Fig. 1 (b). Similarly, Fig. 1 (c) provides the distribution of the publications concerning the subject area, which indicates that most of the DT-based publications were based on the engineering domain. The main concern of the authors is power or/and energy application; the focus area is energy. When the data is categorized for this domain, the application of DT technologies seems to be increasing significantly, as shown in Fig. 1(d). In this study, the author considered the publications which are directly inclined with energy; 1,681 publications related to energy are considered out of the 14,180 documents.

1.3. Research gap and contributions

In the realm of research and development, the concept of DT has emerged as a significant and promising tool, capturing the attention of both academia and industry. However, despite its potential, the development of DT technology is still in its nascent stages. A lack of standardized definitions, protocols, and implementation frameworks persists [38]. Furthermore, existing studies on DT have revealed a deficiency in

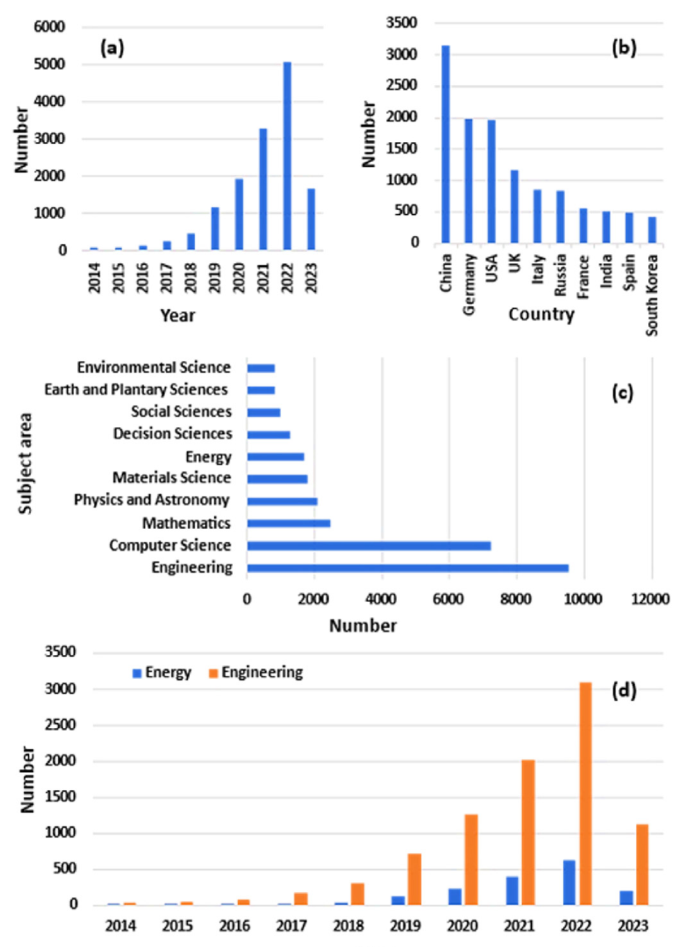

Fig. 1. Trend on DT-based research works (2014–22/05/2023).

comprehensive and in-depth investigations, particularly in terms of ideas, technologies, and industrial applications. Although DT's use is currently limited, its growth is evident, particularly within the power system research and development field, demanding careful exploration in the near future.

With a specific focus on power and energy systems, the authors of this manuscript aim to examine and utilize DT technology. The incorporation of a growing proportion of PEC into the grid adds complexity to today's power infrastructure. This integration, among other factors, necessitates the modification of power system operational principles to align with the dynamics and characteristics of RES. The authors express concern about the future direction and safety levels of power system operation. This article primarily delves into the underlying concept of DT, exploring its various types, operating principles, communication channels, protocols, and industry standards. Additionally, it contemplates the feasibility and implications of combining DT with other technologies. Through detailed analysis, the paper offers the following key contributions:

a) An up-to-date overview of DT-based research, categorized by date, country, and research area. The focus lies specifically on the application of DT technologies within energy and power systems, providing insights into the current status and emerging trends based on comprehensive research database analysis.
b) In-depth exploration of the working principles, communication channels, protocols, and standards of DT technologies within power systems. The study investigates the importance and potential integration of concepts such as the Internet of Things (IoT), Big Data (BD), Cyber-Physical Systems (CPS), and Machine Learning (ML).
c) A critical analysis, leveraging the authors' expertise and an extensive review of relevant literature, to discuss and examine the various aspects of DT technologies.

1.4. Paper organization

In the beginning, this paper discusses the problems and significance of modern energy/power systems as well as the difficulties associated with system dynamics, stability, control, efficiency, dependability, economics, planning and policy, and other factors. The processes used to conduct this assessment are thoroughly described in section 2. Section 3 introduces the core idea of DT technologies with an emphasis on the power system. This section has covered several DT technology categories and how they relate to other ideas like the IoT, BD, CPS, ML, and standards and regulations. In Section 4, a thorough explanation of previous research and potential future applications of DT technologies on the power system has been covered. Section 5 summarizes the challenges and research gaps of DT within the power systems domain based on the research material. Based on the research materials that were used and the authors' expertise, a critical analysis has been conducted highlighting the future recommendation in Section 6. Finally, depending on the current limits, conclusions have been discussed in Section 7.

2. Methodology

To gather insights from the latest advancements in the field, we employed a hierarchical approach known as a Systematic Literature Review (SLR) [39]. The SLR involves a series of sequential steps, which encompass: (a) defining the research scope, (b) formulating the research question, (c) devising the search strategy, (d) establishing inclusion and exclusion criteria, (e) conducting screening and selection, and (f) performing data extraction and quality assessment.

Initially, we delineated the scope of our research as "DT technologies in power and energy systems." Within this defined scope, we formulated our research question as follows: "How does DT technology contribute to the modern power system, which is predominantly dominated by PEC-based technologies?" As outlined in subsection 1.2, we conducted a search on Scopus using the keywords "digital twin" and "digital twins" limited to the abstract, title, and keywords fields, spanning the past ten years (2014–22/05/2023). This search yielded a total of 14,180 documents across various research domains, as illustrated in Fig. 1. However, our primary focus was on the modern power system. Therefore, we categorized the database into different topics, revealing 1,681 publications directly related to energy/power systems, as depicted in Fig. 1(d).

Although sifting through 1,681 relevant documents seemed like a formidable task, we began by manually screening a subset of records. By reviewing the titles, abstracts, and keywords, we selected the relevant documents. During the screening process, we considered factors such as duplication of publications, language (English), availability of open-access publications, and direct relevance to our research interests. Through these steps, we ultimately identified 141 documents for our final evaluation. Additionally, we also considered online information from technology companies and governmental policies to gather updated information, protocols, rules, and regulations. These sources provided valuable insights to complement our literature review.

Fig. 2 presents a detailed outline of the process we followed with the selected number of documents, while Fig. 3 visually represents the key terms extracted from our chosen documents. The font size in Fig. 3 reflects the probability of word occurrence, with larger font sizes indicating higher probabilities.

3. Fundamental concept of digital twin with a focus on the power system

Increased interconnection and intelligent automation have been introduced in response to the complexity of the energy market, economic volatility, rising demand, and inclination to delocalize production. The Fourth Industrial Revolution, often known as Industry 4.0, is defined by these answers [40,41]. This has led to the development of several technologies, including the IoT, BD, and CPS. The major technologies of Industry 4.0 have been identified and are the subject of much discussion [42]. DT technology has benefited from the development of the aforementioned three technologies (IoT, CPS, and BD) [43]. First off, IoT systems enable massive amounts of data to be collected from physical systems and sent in real-time, enabling seamless integration between them [44]. The CPS technology, which functions at virtual and physical levels, interacting with and regulating physical devices, perceiving the environment, and taking appropriate action, enables us to obtain a deeper understanding of the data related to physical assets [42,45]. Thirdly, BD technologies include Hard-loop and Cloud-Based Analytics, which may assess data collection and generate projections, optimize digital twins based on data acquired, and calibrate the general model and its particulars. Industry 4.0 opens the door to real-time connectivity and the synchronization of physical actions with the virtual environment in this way [46].

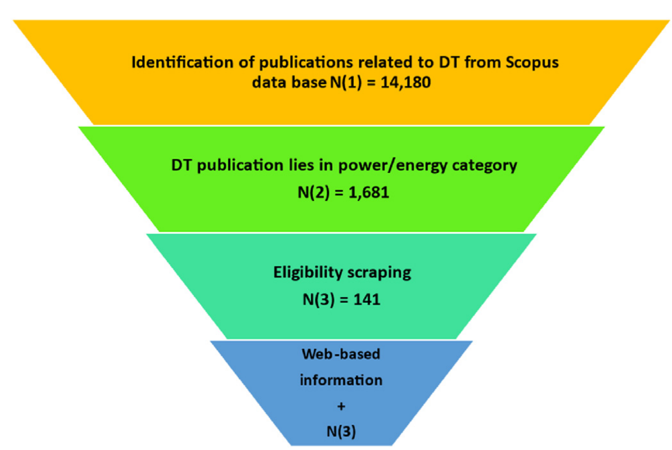

Fig. 2. The adopted process of systematic literature review.

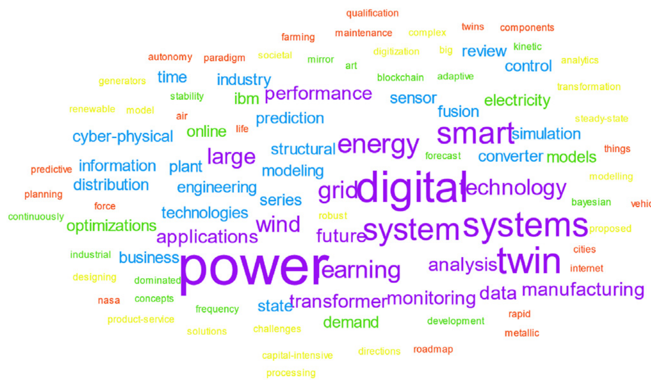

Fig. 3. Word cloud of the keywords form the selected documents.

As proposed by Dr. Greives, DT was defined to include three layers: a) the physical product, b) the virtual product, and c) their connections in the form of data and information. Two more layers have recently been added to form the five-dimensional layers of DT. The two added layers are data and services [46–53]. Fig. 4 shows a simplified representation architecture of the five-dimensional layers from a power system DT perspective. Each layer plays a distinct role in enabling a comprehensive digital representation and management of a power system. A detailed overview of the technologies utilized in each layer of the presented architecture is described below [3,54–58]:

(a) **Physical Layer:** The physical layer is the representation of the objective existence of the power system. It encompasses a variety of features, including system behavior, rules, and data regarding physical space. This layer makes use of a variety of cutting-edge technologies, such as the Supervisory Control and Data Acquisition (SCADA) system, IoT devices, and the Geographic Information System (GIS). SCADA systems provide for real-time monitoring and control of the processes involved in the generation, transmission, and distribution of electrical power. They collect data from remote devices, which enables operators to monitor the performance of the system and respond to events in an effective manner. The architecture of the electricity system is littered with IoT devices, such as sensors and smart meters, in order to collect real-time data on variables such as voltage, current, temperature, and environmental factors. GIS technology, as a final point of consideration, records and evaluates spatial data connected to the infrastructure of power systems. It offers a graphical depiction of the physical network, which is comprised of power plants, substations, transmission lines, and distribution networks.

(b) **Virtual Layer:** The virtual layer acts as a reflection or model of the physical layer. It is similar to the physical layer in many ways. It does this by employing cutting-edge simulation and modeling techniques to produce a digital copy of the power system. The power system simulation software and DT technology are both important technologies that are utilized at this tier. The operation of the power system is simulated using these various software tools, which are guided by mathematical models and equations. They make it possible for engineers and operators to study the dynamics of the system, carry out contingency analysis, and optimize the operation of the system. In a similar manner, DT technology integrates real-time data with simulation models to produce a digital representation of the physical power system. It makes it possible to synchronize the virtual and physical systems, which in turn makes it easier to perform real-time monitoring, predictive analysis, and scenario testing.

(c) **Connection Layer:** The connection layer creates a communication link that can travel in both directions between the digital representation of the power system and the physical power system. Communication protocols and data collection systems are involved in this process. The transfer of data between devices, control centers, and the DT is made possible by a variety of communication protocols. Some examples of these protocols include IEC 61850, DNP3, and Modbus. These protocols ensure that the various components of the power system can integrate with one another and work together without any problems. On the other hand, data acquisition systems are responsible for the collection, preprocessing, and real-time transmission of data from the physical layer to the digital counterpart. They make it easier to extract essential information and allow for decisions to be made on time.

(d) **Data Layer:** The data layer is responsible for managing the massive amount of data that is transferred between the physical and digital layers. This makes use of several technologies for the processing, storing, and analyzing of data, such as BD analytics

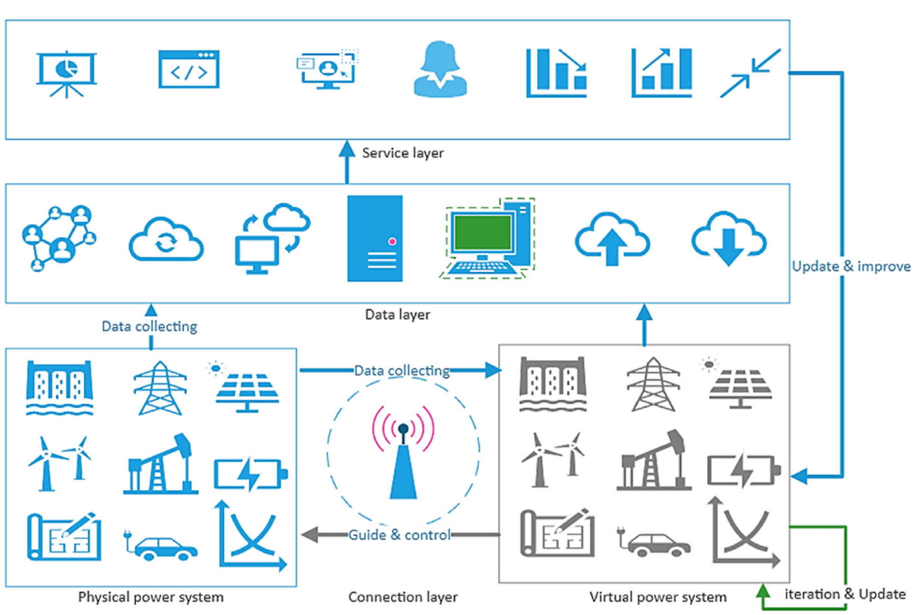

Fig. 4. Simplified architecture of DT technology in power system.

and a data management system. For processing and analyzing massive volumes of real-time and historical data obtained from the physical layer, approaches from BD analytics are utilized. To accomplish this, data must first be cleaned, then aggregated, patterns must be recognized, and lastly, ML techniques must be applied. Likewise, reliable data management systems, which may include databases and data warehouses, are used to store and organize the data that has been acquired. These technologies assure the integrity of data, as well as its security and accessibility, for a variety of applications operating inside the DT framework.

(e) **Service Layer:** The service layer enables decision-making, and control of the physical power system based on specified goals, and it also provides security for the other layers. Technology such as advanced analytics and optimization, as well as control systems, are utilized in its operation. The processes of decision-making can benefit from the application of advanced analytics techniques such as ML, optimization algorithms, and AI. They do data analysis on the data layer and provide insights that can be used to improve system performance, boost productivity, cut down on interruptions, or save expenses. On the other hand, control systems are constantly receiving updated parameters and instructions that are derived from the virtual model and analytics tools. They are responsible for putting control plans into action, regulating system components, and managing operational facets of the power system following the planned outcomes.

The power system DT framework offers greater monitoring, analysis, decision-making, and management of the physical power system. This, in turn, leads to improvements in the system's efficiency, dependability, and resilience. The framework works through the iterative interplay of these layers and the technologies deployed within them. The following subsections describe variants, integrated technologies, communication channels, protocols, and standards for additional information on their respective subjects:

3.1. Classification of DT variants

There is a possibility that a uniform definition of DT has not yet been agreed upon. Nevertheless, each description acknowledges that the connection/integration layer is an essential part of the process of defining the DT. The classification of DT based on modelling techniques can be done in several ways, considering the level of detail, the purpose of modelling, and the availability of data used. The following classifications of DT variants provide a framework for understanding the different modelling techniques used in DT implementations. However, it's important to note that the boundaries between these categories are not always strict, and hybrid approaches that combine multiple techniques are common in practice. Here are some classifications of DT:

(a) **Physics-Based Modelling:** The physics-based modelling can be two types such as static models and dynamic model. The static DTs use geometric and physical properties to create a static representation of the physical object or system. They focus on capturing the structure, dimensions, and material properties of the entity. An example of is shown in Ref. [59], where the article investigates the use of graphene nanoplatelets (GNPs) nanofluids in enhancing the performance of thermoelectric generators (TEGs) and thermoelectric coolers (TECs). A numerical model is developed to analyze the effects of nanofluid weight concentration and Reynolds numbers on heat transfer, electricity generation, and cooling capability. Whereas the dynamic DTs incorporate the physics and dynamics of the physical object or system. They simulate the behaviour, motion, and interactions of the entity over time, considering forces, constraints, and environmental factors, as shown in Ref. [60]. In this article, the authors discuss the implementation of a consistency retention method for a CNC machine tool digital twin (DT) model. The DT model is a high-fidelity replica of the physical machine tool that can provide a time-varying representation of its performance.

(b) **Data-Driven Modelling**: The data-driven modelling also can be of two types such as data replica models and statisticalmodels. The data replica DTs are created by replicating and synchronizing the data from the physical object or system. They focus on capturing and analysing real-time data streams, allowing for monitoring, analysis, and prediction based on historical patterns. [61] provides a historical perspective on the evolution of manufacturing data and discusses the data lifecycle in manufacturing. Similarly, the statistical DTs use statistical techniques and algorithms to model the behaviour of the physical object or system based on historical data. They focus on identifying correlations, trends, and patterns to make predictions and optimize performance[62]

(c) **Hybrid Modelling:** The hybrid modelling is of two types: Integrated and Multi-Level. The integrated DTs combine physics-based models and data-driven models to create a comprehensive representation of the physical object or system. They leverage the strengths of both approaches to provide a more accurate and realistic simulation. Several articles ([63,64]) have been identified discussing this category. On the other hand, Multi-Level DTs employ multiple modelling techniques at different levels of detail. They may use physics-based models for macro-level behaviour and data-driven models for micro-level analysis, allowing for a holistic understanding of the entity. For instance, Ref. [65] focuses on modelling the proportional-integral control link of a voltage source converter (VSC) and uses the time convolution neural network (TCN) algorithm to accurately describe the high-frequency switching states of power electronic devices and the operation states of renewable energy units.

(d) **Domain-Specific Modelling:** In the context of power systems domain, several articles are discovered on three levels of the power system DT modelling: (a) Product Twins, (b) Process Twins, and (c) System Twins.

For the detailed analysis and classification, the authors categorized the research articles that based in different applications and listed in section 4.

3.2. IoT communication channels and their protocols

In conjunction with the different sensing technologies, the connection layer serves as the fundamental building block of the IoT in DT. This layer necessitates a high-fidelity connection between IoT devices in order to ensure that information is sent accurately and on time [66,67]. As can be seen in Fig. 5, the connection layer is responsible for the collection and transmission of data coming from and going to the physical layer. Using technologies such as radio frequency identification devices (RFID), cameras, sensors, software application programming interfaces (APIs), QR codes, open database interfaces, and other IoT technologies [68], real-time data from the physical system and its subcomponents are being sensed in this connection. The transmission of data is the second fundamental component of the IoT, and it supplies data to both the data layer and the virtual system. This transmission makes use of a variety of communication technologies, protocols, and standards so that it may interact with transmissions on higher levels, which may include wired and wireless transmissions. Some examples of technology for transmitting data across wires include twisted-pair cable transmission, symmetric cable transmission, coaxial cable transmission, and fiber optic transmission [68].

The protocol that is used to link physical sensors to DT data across wires depends on the interfaces and communication capabilities that the sensors themselves offer. Such frequently used physical sensor wired-based protocols are: (a) Modbus that allows for reading sensor data and sending control commands over a serial connection, such as RS-485;

(b) the 4–20 mA current loop where the output is converted to a current signal, where 4 mA represents the lowest value and 20 mA represents the highest value. This current is then measured by the receiving device, typically a data acquisition system or a controller; (c) Highway Addressable Remote Transducer (HART) which allows for simultaneous analog signal transmission (typically 4–20 mA) along with digital data encoded in the signal. HART-enabled sensors can provide additional information beyond the analog value, such as diagnostics, calibration data, and configuration parameters; (d) Controller Area Network (CAN) which allows for reliable communication between multiple devices over a shared bus. CAN is often utilized for integrating sensors into DTs in scenarios where sensors support the CAN interface; (e) Ethernet/IP that enables communication between sensors, actuators, and control systems over Ethernet networks. It provides real-time control and data exchange capabilities and is commonly used in automation and manufacturing environments [32].

Similarly, wireless transmission technologies that could be used for CPS include Wi-Fi, Bluetooth, Zig-Bee, Ultra-Wideband (UWB), and Near Field Communication (NFC), as well as General Packet Radio Service/ Code-division Multiple Access (GPRS/CDMA), digital radio, spread spectrum microwave, wireless bridge, satellite communication, machine-to-machine (M2M) communications, and supervisory control and data acquisition (SCADA) [67,68]. On the back end of these different technologies, different protocols can be identified, such as Hypertext Transfer Protocol (HTTP), REpresentational State Transfer (REST), WebSocket, Simple (or Streaming) Text Oriented Messaging Protocol (STOMP), Simple Object Access Protocol (SOAP), Message Queuing, Telemetry Transport (MQTT), Open Platform Communications Unified Architecture (OPC UA), and so on. A comprehensive overview of the transmission protocols and their standards together with vulnerability and attack possibilities could be found in Refs. [69,70]. Data is being stored using BD technologies such as distributed file storage (DFS), NoSQL database, NewSQL database, and cloud storage [68,71]. Further, the data is processed (normalized and cleaned) with the help of ML algorithms [72]. After that, the analyzed, normalized, and cleaned data is forwarded to the service layer for further utilization.

3.3. Machine Learning integration in DT technology

ML is a branch of AI that is used to instill learning behavior in computers through the use of a software model that improves its capabilities through training on historical data [73]. Fig. 6 represents a simple visual of ML-integration into DT highlighting the main learning techniques summarized from the literature list. As can be seen in Fig. 6, ML algorithms have been divided into distinct groups depending on the learning techniques that they employ: supervised learning, unsupervised learning, semi-supervised learning, reinforced learning, deep learning, transfer learning, ensemble learning, and online learning [74–76]. In this straightforward design, the ML integration in DT is denoted by the symbol shown in Fig. 6. Depending on the kind of result that is required, input from the physical world is compiled and fed into the ML algorithm. After the historical and real-time data have been processed (normalized, cleaned, and compressed) [74,77], the data is then used to train and evaluate the model [78]. This processed data is used by the virtual system in order to iterate, update, and test the functionality of the physical system in a variety of unexpected scenarios. After that, real-time data from physical systems and outcomes from virtual systems are compared at the service layer [79], where they are employed even further. The virtual system is adjusted and modified appropriately in accordance with the desired output, which may include visualization, prediction, optimization, adaptability, or control. Last but not least, the actuators are used to bring the physical system up to date and regulate it.

Machine learning integration techniques in DT technology involve the application of various ML algorithms and approaches to enhance the functionality and performance of DT. Depending on the data type, the availability of data, and the particulars of the issue, several ML algorithm approaches might be used. Some of the detailed descriptions are given as follows:

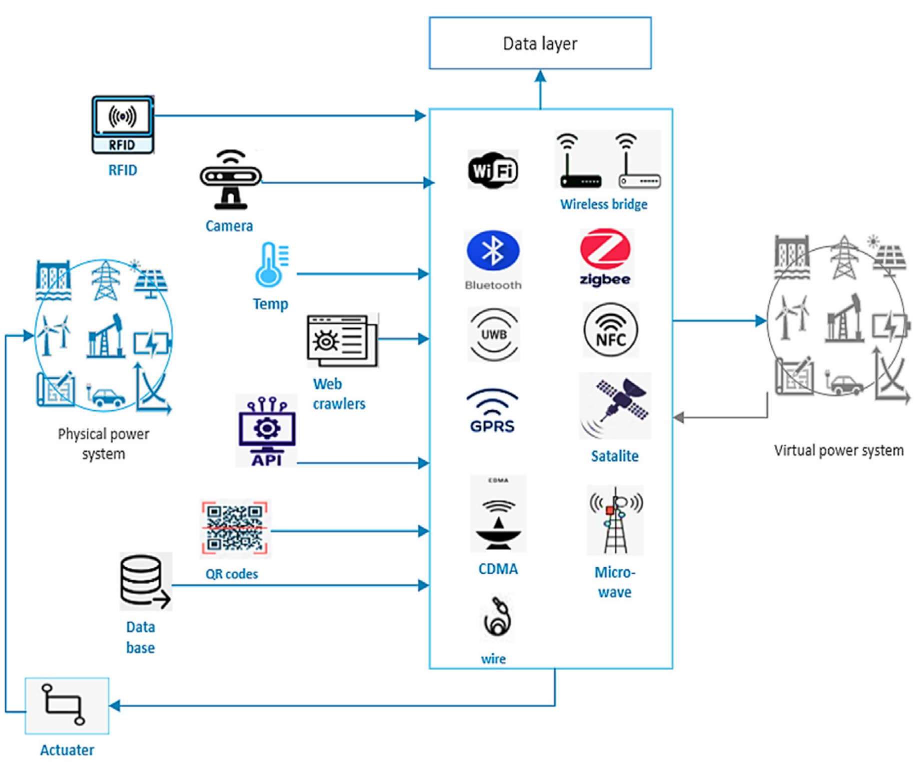

Fig. 5. Communication channels in DT technology.

(a) **Supervised learning:** Supervised learning algorithms are used when historical data with known labels or outcomes is available. These algorithms learn from the labelled data to make predictions or classifications. In the context of DT, supervised learning can be employed to develop models that predict system behaviour, detect anomalies, or optimize system performance based on labelled training data [80]. By analysing data from IoT sensors and using ML algorithms, the DT can predict the risk probability of accidents in oil pipelines [81]. Prognostic algorithms are used to detect failure precursors by estimating risk conditions based on pressure data. Clustering techniques are then applied to identify abnormal pressure behaviour. The extracted features are evaluated using a kernel-based Support Vector Machine (SVM) algorithm to provide control actions in real-time.

(b) **Unsupervised learning:** Unsupervised learning techniques are used when there is no labelled data available. These algorithms aim to discover patterns, structures, or clusters in the data without prior knowledge of the outcomes. Unsupervised learning can be applied in DT to identify hidden patterns, detect anomalies, or segment data for further analysis [82]. In this particular scenario, the authors of [83] explore the effects of DT deployment strategies on predictive maintenance activities in a distributed collaborative prognosis framework. Collaborative prognosis is a technique that allows assets to learn from similar assets in a fleet and improve their prognosis models. The study analyses the performance of distributed and heterarchical multi-agent system architectures for large fleets of assets with varying failure rates and noise levels in the failure data.

(c) **Semi-supervised learning:** Semi-supervised learning is a ML technique that combines labelled and unlabelled data to improve model performance [84]. In the context of DT, semi-supervised learning can be utilized when a limited amount of labelled data is available, but there is a larger amount of unlabelled data. This technique can be particularly useful when it is expensive or time-consuming to obtain labelled data [74]. [85] discusses the application of cluster-adaptive active learning to structural health monitoring (SHM) strategies for aircraft experiments. SHM involves observing a structure over time to determine its health status. However, obtaining diagnostic labels for the measured data is often costly and impractical. The researchers applied the cluster-adaptive active learning method to measured data from aircraft experiments and found that it successfully demonstrated the advantages of using active learning tools for SHM.

(d) **Reinforcement learning:** Reinforcement learning involves training an agent to make decisions and take actions in an environment to maximize a reward signal [76]. In the context of DT, reinforcement learning can be used to develop control policies that optimize system behaviour. The DT can simulate the environment, and the reinforcement learning algorithm can learn from trial and error to determine the best actions or policies for achieving desired outcomes [86]. Several issues within DT application such as the requirement for a feedback loop in predictive maintenance approaches to change dynamically with the asset could be solved by employing reinforcement learning techniques like Hidden Markov Models [71].

(e) **Deep learning:** A subset of machine learning, utilizes artificial neural networks with multiple layers to learn complex patterns and representations from data. Deep learning algorithms, such as convolutional neural networks (CNNs) or recurrent neural networks (RNNs), are powerful tools for tasks like image recognition, natural language processing, and time series analysis. Deep learning techniques can be applied in digital twins to analyze sensor data, images, or textual information for various applications such as anomaly detection, predictive maintenance, or optimization. Examples of this learning technique ([9,24,65,87]) are discussed in detail in section 4.

(f) **Transfer learning:** Transfer learning involves leveraging knowledge or models learned from one domain to another related domain. In DT, transfer learning can be beneficial when data is limited or scarce. Pre-trained models from similar systems or domains can be used as a starting point and fine-tuned using available data. It can accelerate the development and improve the performance of machine learning models within digital twins. [88] presents several use cases that demonstrate the potential of cross-phase industrial transfer learning using intelligent digital twins. These use cases include training deep neural networks, deploying algorithms, injecting rare faults, and enabling reinforcement learning.

(g) **Ensemble learning:** Ensemble learning combines multiple ML models to make more accurate predictions or classifications. Different models or algorithms are trained on the same data or subsets of data, and their outputs are combined to generate a final

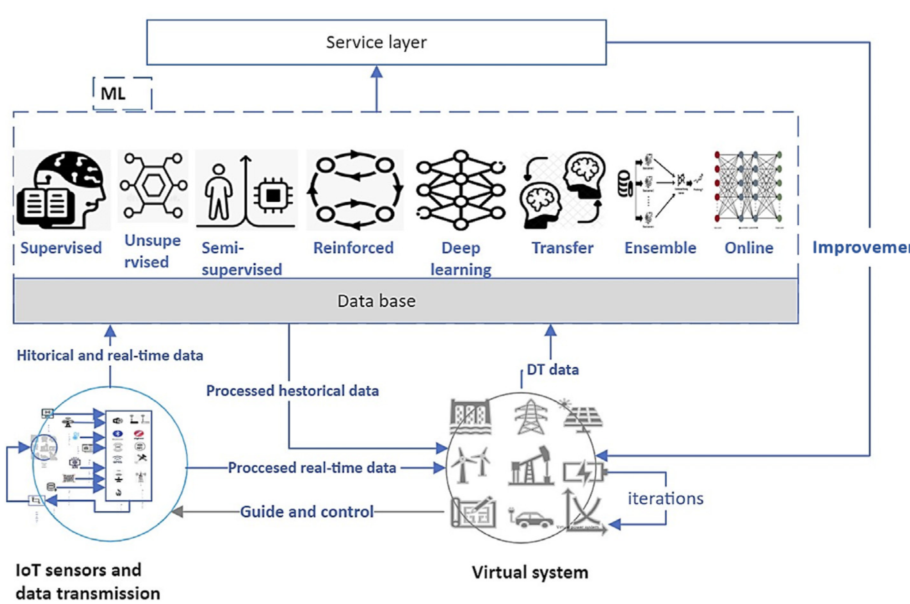

Fig. 6. ML integration with DT.

prediction or decision. Ensemble learning techniques, such as bagging, boosting, or stacking, can be employed in digital twins to improve prediction accuracy, reduce model bias or variance, and handle uncertainty [89]. [90] proposed approach combines DT technology with multiple time series stacking (MTSS) to improve the accuracy and timeliness of pavement performance prediction. The approach includes the establishment of an MTSS prediction model with multiple component learners, the extraction of multiple time series features, and the optimization of hyper-parameters. The results demonstrate the feasibility and effectiveness of the prediction method based on DT and MTSS.

(h) **Online learning:** Also known as incremental learning, enables the model to continuously update and adapt to new data as it becomes available. In DT, online learning can be valuable when the system dynamics change over time or when real-time data streams need to be processed. The model can be updated with new observations, allowing the digital twin to adapt and improve its predictions or control strategies [91].

Research articles [66,71,74,79], provide a comprehensive overview of the implementation of ML algorithms in DT, which you can read more about here.

3.4. Standards and regulations

A DT of a power system acts as a mirror image of an extremely large number of the system's sub-systems and individual components. Each component of the DT has to be able to share information with its physical counterpart, which necessitates interoperability, which in turn necessitates the cooperation of several different technologies and tools. In order to accomplish this goal, it is necessary to standardize data and models and provide them in a manner that is compatible with other protocols and standards [68]. Even though the DT first appeared as a tool for monitoring and managing distant physical items as early as 1970 (i.e., NASA), the worldwide formats and standards are still in the process of being developed and are not known to the general public for general uses [32,66,92]. To the best of the authors' knowledge, there were no standards discovered that was specifically devoted to the power systems area. Nevertheless, the International Organization for Standardization (ISO) has produced a standard for four-series DT for use in production; this standard is known as ISO 23247 [93]. This series offers a framework and accompanying papers to assist in the creation of observable manufacturing DT by regularly updating the data about its employees, equipment, materials, manufacturing processes, facilities, and environment. This framework does not define data formats or communication protocols, which is something that should be brought to your attention. In addition, the international organization IPC published an international standard called IPC-2551 at the beginning of 2021. This standard is made up of the DT product framework, as well as the manufacturing and life-cycle frameworks [94]. At the moment, the technical body ISO/IEC JTC 1/SC 41 is working on DT standards, and the primary areas of attention for these standards are the DT concept, nomenclature, and application cases [95].

4. Digital twin in power system research and development

Research in digital twin technology is critical for advancing knowledge, driving innovation, solving complex problems, validating models, fostering interdisciplinary collaboration, generating economic benefits, and shaping policies and standards. It is through research that we can unlock the full potential of digital twin technology and its transformative impact on various industries and domains. As discussed in the preceding sections, DT research on power systems is still in the preliminary stages of development. In the context of progressing research in the field of DT, various power systems companies, utilities, and research institutions have recognized the potential of digital twins and have initiated projects and collaborations to develop tools/platforms and implement them. These initiatives focus on areas such as grid optimization, asset management, renewable energy integration, and operational efficiency. Table 1 provides case studies of power system DT implementations in different regions of the world. These case studies highlight the diverse approaches and applications of power systems DT across different regions. They demonstrate how cultural and technological differences shape the implementation strategies, emphasizing factors such as renewable energy integration, grid reliability, resilience, and efficient energy management in specific regions.

Similarly, several articles are discovered on the application of DT on three levels of the power system: generation, transmission, and distribution system. These scientific works can be categorized into three groups such as monitoring, visualizing, analysis, and prediction; optimization processes; and tools and platforms, as shown in Fig. 7. For the detailed analysis and classification, the authors categorized the research articles that based in different applications.

Fig. 8 provides an overview of research articles focusing on monitoring, visualization, and prediction within the power system using digital twin (DT) technology. The articles can be classified into four categories, as depicted in Fig. 8.

In one study [102], an online analysis digital twin (OADT) approach is proposed to enhance power grid online analysis, with a specific focus on the Chinese national power grid. The approach utilizes a Complex Event Processing engine to support both model-driven and data-driven online analysis applications. It successfully tracks the operation state of the power grid with a sub-second delay. Another article [103] presents the OADT method for power grid online analysis, employing advanced modeling techniques, in-memory computing, grid stability assessments, and complex event processing engines. The goal is to detect anomalies and potential failures, thereby improving power grid reliability and resilience. For power system simulations, a real-time interactive simulation architecture based on DT technology is introduced [104]. This architecture incorporates twin bodies for power systems, voltage and current sensors, and control units. It provides a framework for the application of digital twins in power systems and highlights potential benefits for the wider power industry. A measurement-based dynamic model identification technique using artificial neural networks (ANNs) is proposed [91]. This method focuses on developing a digital twin that models the dynamics of smart grids. The literature also mentions other applications, such as OADT approaches for improving power grid online analysis, the use of Complex Event Processing engines for situation awareness analysis, integration of advanced modeling techniques, in-memory computing, and grid stability assessments, as well as the application of machine learning-based techniques for fast security assessment and anomaly detection. Furthermore, it emphasizes the importance of tracking the power grid's operation state and detecting anomalies or potential failures.

In another study [105], an advanced digital twin artifact system (DTAS) technology is introduced to enhance the resilience and plasticity of systems by integrating physical and numerical models. This includes an inspection technique for detecting material degradation and optimizing inspection timings. DTAS is particularly useful for evaluating the structural integrity of various artifacts, ranging from nuclear power plants to home appliances. A DT modeling method is proposed for monitoring and diagnosing power electronic transformers using a real-time field-programmable gate array-digital twin (FPGA-DT) technique [106]. The method demonstrates effectiveness and accuracy in analyzing and identifying faults in power electronic transformers. The literature also highlights other applications, such as the development of advanced DTAS technology for evaluating structural materials, the integration of physical and numerical models for monitoring and detecting material degradation, the optimization of inspection timings and modification of operational plans, and the applicability of DT technology to various artifacts.

In [107], a DT model derived from Dynamic Digital Mirroring (DDM)

Table 1
DT implementation case studies in power system domain by country.

General application trends and support	Application scenarios	Reference
Germany showcases expertise in renewable energy and advanced grid management. The country emphasizes environmental sustainability and cross-border collaboration.	Wind farm optimization, remote monitoring, condition-based maintenance.	[96]
The United States rapidly transitions towards green energy reliance. Companies like General Electric (GE) pioneer DT technology, optimizing wind farms. The country focuses on grid modernization and resilience against natural disasters.	Wind farm optimization, cloud-based DT platforms, grid reliability improvement.	[97,98]
The Netherlands relies on DT to predict environmental issues like water problems. Collaborations between companies like Siemens and IBM optimize service lifecycle management.	Environmental monitoring, water condition prediction, asset management.	[99,100]
China's cultural perspective emphasizes technological advancement, data-driven decision-making, and integration of AI and IoT. The adoption of DT aligns with China's ambitions to become a global technology leader.	Coal-fired power plant optimization, thermal efficiency improvement.	[101]
Finland focuses on increasing renewable energy generation and reducing carbon emissions. Citizen participation and engagement in the energy sector are emphasized. Siemens' DT applications improve automation, data utilization, and decision-making.	Power system optimization, energy-efficient asset maintenance.	[34,35]

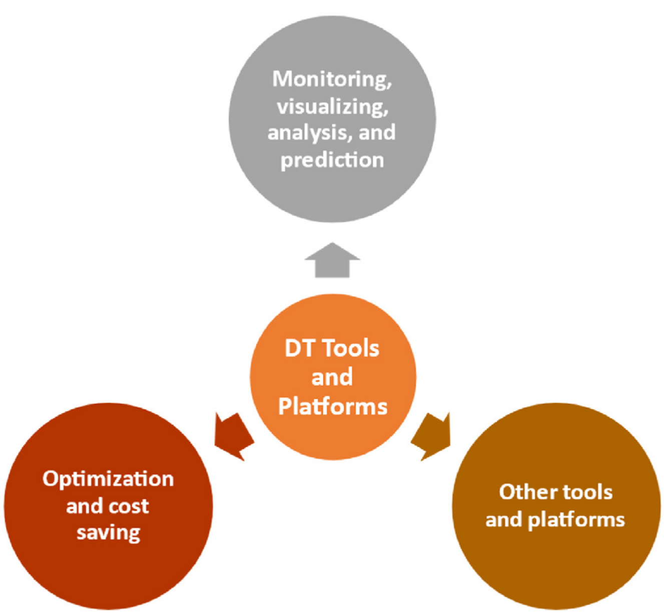

Fig. 7. Categories of the DT based scientific works.

is proposed for real-time simulation, fast system analysis, and control feedback in power system assets. This approach enables advanced analytics beyond standard SCADA databases by reflecting the real-time operating condition of assets. A hybrid modeling and simulation DT method is introduced for the thermal system of in-service thermal power plants [64]. This method leverages system models and historical operation data to achieve high precision in simulation and support the development of digital twins. Other applications discussed in the literature include the use of dynamic digital mirroring (DDM) modeling for real-time simulation, system analysis, and control feedback in power system assets, hybrid modeling methods combining operation data and first-principle mechanisms for performance monitoring of control stage systems, calculation of flow rate and efficiency characteristics in control stages of steam turbines, and the development of control stage digital twins for online performance monitoring.

A review of DT in power plants is provided in Ref. [9], along with a DT for predicting power plants using dynamic system models (DSM), anomaly detection, deep learning, and distributed sensor networks. The proposed 5-level autoregressive DT architecture has the potential to transform the energy production industry and improve energy efficiency. In Ref. [24], deep learning convolutional neural networks are integrated into the Automatic Network Guardian for Electrical systems (ANGEL) DT environment to detect faults in power systems. The framework exhibits high accuracy in fault detection and can be scaled up for larger power systems. The literature mentions various applications, including the use of DT frameworks for predicting power plant performance and optimizing cost savings, the incorporation of dynamic system models, anomaly detection, deep learning, and distributed sensor networks, consideration of energy system cybersecurity, and the integration of all components for a robust digital twin. The potential of these applications to revolutionize the energy production industry and enhance energy efficiency is also highlighted.

Similarly, DT offer significant potential in optimizing operations and reducing costs across various industries. One of the key applications is in the field of power systems, where DT models enable optimization and cost reduction strategies. A detailed information is listed in Table 2. For instance, in solar power plants, DT models of power inverters can be created to compare and analyze their efficiency and economic benefits. This allows for the identification of more efficient inverters that can provide economic advantages, particularly during periods of high electricity prices. Additionally, DT can be utilized in power networks to predict grid conditions, balance grids, and prevent blackouts, leading to improved operational efficiency and cost savings. In the construction of nuclear plants, DT can help save expenses, avoid unexpected outages, and optimize maintenance. By simulating and analyzing different scenarios, DT enables informed decision-making and cost-effective strategies. Furthermore, DT facilitates the optimization of energy demand and utilization in Net Zero Energy Buildings (ZEB) by integrating energy-saving improvements and renewable technologies, resulting in reduced energy costs. Overall, the use of DT in optimization and cost reduction applications holds immense potential for enhancing operational efficiency and achieving substantial savings across various industries within the power systems domain.

On the other hand, Table 3 provides a comprehensive analysis of the controlling and testing applications of DT in power systems. It includes key features, advantages, and challenges associated with each work. The key features highlight the unique aspects and technologies employed in each application, while the advantages showcase the benefits and improvements brought by the use of DT. The challenges column addresses the potential obstacles and areas that require attention for successful implementation. This table offers a detailed overview of the various works, enabling a comprehensive understanding of the controlling and testing applications of DT in power systems.

These tables provide evidence that the DT technologies are being strongly used for research and development operations within the power system domain, even though the technique and the objectives are distinct from one another. After a careful inspection, it is observed that there are many ways to make use of it. For the sake of convenience, the tools and platforms that were utilized in these research works can be categorized into several distinct areas, including monitoring, visualization, analysis,

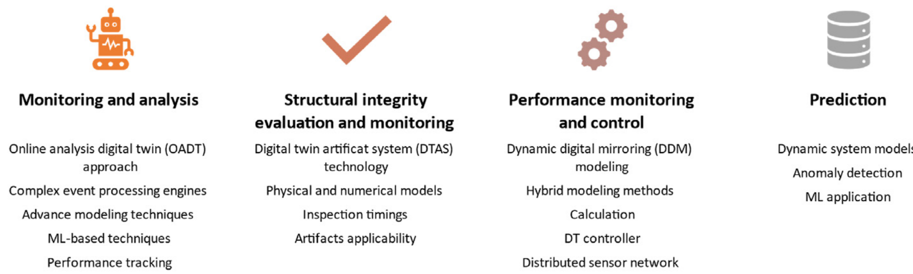

Fig. 8. Overview of DT applications.

prediction, optimization, and cost-saving applications. Creating, managing, and making use of DT for power systems has inspired the development of several commercial tools and platforms with the goal of providing full solutions for these challenges. For example, there are some tools and platforms which were developed to monitor, analyze, predict and visualize the power system states: (a) Oracle provides a cloud-based DT simulator where configurable live data could be generated, alerts, and events for these simulated devices [122]; (b) Beijing BKC Technology Co., Ltd. developed an intelligent power plant management and control system based on a five-dimension DT [96]; (c) ETAP provides a DT platform for real-world power systems under various physical and operational conditions [123]; (d) SEWIO provides Ultra-wideband based hardware and software DT platform for real-time monitoring and prediction of assets [124]; (e) Functional Mock-up Interface (FMI) is an open-source platform supported by 170+ tools allowing the creation, storage, exchange, and (re-) use of dynamic system models of different simulation systems for cyber-physical systems, and other applications [125]; (f) PTC has developed an IoT-based DT platform called ThingWorx IIoT platform [126]. On the other hand, Signify Philips is investing in developing DT for lighting systems. They claim that the DT will continuously optimize lighting to improve occupant comfort, energy efficiency, or safety. In addition, they provide DT for biomedical equipment such as Magnetic Resonance Imaging (MRI), and computerized tomography (CT) scans to get early signs of warning regarding technical issues [127]. Among the reviewed scientific works, some documents [28,66,128] mention other important and emerging platforms such as: (a) Ansys Twin Builder, provided by Ansys, Inc., (b) Altair ONE TOTAL TWIN, provided by Altair Engineering Inc., (c) 3Dexperience, provided by Dassault Systems, (d) Unity Pro, provided by Unity Software Inc., (e) APEX, provided by BP, and so on.

5. Challenges and research gaps of DT in power systems

Stakeholders in the power system sector are working feverishly to improve flexible power plant operations, cut downtime, lower O&M costs, and boost efficiency, productivity, and profitability. In this framework, the DT technology is presented and used (as indicated in section 3) in the literature list as a crucial enabling technology to accomplish these objectives. Even though there has been a noticeable increase in the research of DT over the last ten years, there are still several obstacles that need to be overcome before DT can be successfully realized and implemented across a variety of different sectors. According to Dr. Greives' explanation, the universal DT is composed of the same fundamental building blocks regardless of the industrial area it is applied to. However, during the phase of implementation, the domain-specific DT will face several challenges, including the following: degree of complexity; integration challenges; the number of components; required resources; data scale; performance evaluation metrics; interoperability issues; feasibility; and domain expertise [66]. In addition to this study [66], different articles [28,47,129,130] have analyzed and discussed the universal difficulties associated with DT modeling in a variety of contexts. An article [32], describes some of the challenges that may be encountered in the manufacturing sector. Similarly, challenges are explored in Ref. [131] concerning both the healthcare industry and smart cities. Challenges and a paradigm based on standards are discussed in Ref. [132] with regard to the shipping sector. The difficulties that DT creates in supply chains and food logistics are discussed in Ref. [133]. The application of DT is still in the theoretical phase globally in the power systems domain, and as a result, this domain shares many of the issues that are faced in other domains. The difficulties in using DT technology within the power systems domain are outlined in Fig. 9, along with the research gaps that exist in this area.

(a) **Modeling and simulation:** ML models used in digital twins may produce complex and non-intuitive outputs; Model interpretability and explainability. Understanding and explaining how these models arrive at their predictions or decisions is crucial, especially in critical applications where human operators need to trust and comprehend the reasoning behind the model's behavior. Lack of multi-physics modeling knowledge and complexity of large power systems and components represent obstacles in implementing DT for monitoring and maintenance [10,46]. The time-consuming process of accepting and replacing old ones is considered a social challenge facing DT [46,129]. The lack of a generic model building and validation criteria is another challenge facing DT. Many studies have investigated specific parts of the DT (modeling, IoT, ML, cloud computing, visualization), but an ideal, unified architecture of DT is still yet to come [66,131].

(b) **Connectivity and processing:** Interoperability with existing technologies. A delay in implementation might occur due to the incompatibility of data acquiring (IoT), speed of communication channels, processing infrastructure (ML), and the interaction between the sub-systems in the existing facilities with DT [9,130, 134,135]. Scaling ML models to handle such volumes of data (large-scale power systems) in real time can be computationally intensive and may require distributed computing architectures or specialized hardware. For large-scale power systems, the twinning and bidirectional data flow and synchronization require domain knowledge, resources, and high-stream IoT connection [66,136]. In the research sector, a common understanding of what AI/ML can achieve in DT and how to use them generically poses some challenges for implementing DTs. For example, it might be cost added and less valued by using advanced ML technologies for research of DT for monitoring [23,66].

(c) **Standardization:** Many DT studies (including studies in other domains) have underlined the necessity of having global standards and a consistent framework for building a robust DT. This will help overcome many of today's challenges such as IoT infrastructure, interoperability of sub-systems, information exchange, transparency, data analysis, privacy, and security. Data quality and reliability: ML models heavily rely on the quality and reliability of the data they receive. In digital twins, ensuring the accuracy, completeness, and consistency of data can be challenging, as sensor measurements may be noisy, missing, or subject to various uncertainties [9,23,66,137].

Table 2
DT-based publications in the optimization and cost saving applications.

Application	Summary	Contributions	References
Solar power plant	DT model of a three-phase dual system power inverter (DSPI) for solar power plants.	DSPI has higher efficiency (0.22–0.27% higher) compared to the conventional inverter. DSPI provides economic benefits during daylight hours. Incorporating DSPI simplifies filter systems and improves power system quality.	[108]
Power network	DT for optimizing power networks in various industries.	DT allows predicting grid conditions, balancing grids, and preventing blackouts. Challenges include lack of standards, regulations, and security concerns.	[96]
Nuclear plants	DT to save expenses, avoid outages, and optimize maintenance in constructing new nuclear plants.	DT helps save costs, prevent outages, and optimize maintenance in nuclear plant construction.	[109]
Net zero energy	DT/BIM study of the techno-economic feasibility of a Net Zero Energy Building (ZEB).	DT/BIM model shows a 6.76% reduction in energy demand and feasibility of renewable technologies. Clear definitions, site-to-source factors, and government support are needed.	[110]
Green hydrogen	DT for optimizing the operation of an alkaline water electrolysis (AWE) system for green hydrogen production.	Optimal operating pressure for AWE process is between 10 and 30 bar considering hydrogen compression. Critical to consider hydrogen compression to storage pressure when determining optimal conditions.	[111]
Load balancing	DT algorithm for optimizing load balancing of simulation computing tasks in multi-energy system DT cloud clusters.	Algorithm balances heavy simulation tasks among available nodes, resulting in improved matching and accelerated simulation computation.	[112]
AC/DC hybrid	DT model for characterizing unmodeled dynamics and uncertainty of AC/DC hybrid interconnection systems in renewable energy systems.	Hybrid-driven model combines linearized modeling mechanisms with deep learning methods. Time Convolution Neural (TCN) network provides accurate and efficient data-driven models. Highly accurate and robust against validation sample sets.	[113]
Seaport energy	DT for energy-saving and increased energy efficiency in a seaport, using wind and solar energy.	Solar and wind energy can fully cover the port's energy requirement. CO2 emissions are reduced. Integration of multi-scale digital data sources, BIM, and GIS enables simulation for achieving a Zero Energy District.	[114]

(d) **Security and privacy:** Today, DTs are faced with cybersecurity challenges as it links multiple industrial sectors. The same applied on the IoT components level, where real-time data from the sensors could be leaked. Protecting sensitive data within digital twins is crucial, as they may deal with intellectual property, trade secrets, or personal information Ensuring robust security and privacy mechanisms for ML models and data is a challenge [66,137]. The Authentication process of the sender poses a challenge in today's communication channels and protocols of IoT resource-constrained devices; possible threats registered like Sybil attacks [69,137].

6. Observations and future recommendations

Many benefits of DT implementations within the power systems domain have been discussed, such as less planning & designing time, prediction & monitoring, better visualization, better control & testing, easier optimization & cost reduction mechanisms, and so on. However, a spontaneous observation is that DT is far from being globally categorized as a plug-and-play technology as neither the academic nor the industrial sector has yet agreed on a unified definition or generic architecture. In the last ten years, however, segment-level progress in DT realization has been observed. In the area of modeling and simulation, it has been observed that relying either only on research or industry in conceptualization and design (DT) is a challenging, time-consuming track and doesn't address the rapid transformation of power systems. To overcome this issue, several experts (hardware, software, operations, and business) must work together. This means boosting industrial and academic collaboration is the fastest track toward the fast implementation of a holistic DT. Advancing research on explainable AI techniques for digital twins is essential. This includes developing methods to explain ML model outputs, provide insights into decision-making processes, and build trust between human operators and the digital twin.

The current practical utilization of DT in power systems is mainly for monitoring, visualizing, analysis, and prediction maintenance. On the component level, wind turbines, as a representative of green power, are the most used component in DT research. In addition, photovoltaics applications and transformers share a considerable portion of the DT research. For large power grids, some progress was observed in monitoring and online analysis. However, many research areas such as components modeling, real-time data acquisition, and processing, IoT sensing devices, components aging, etc. should be considered. A good approach for unlocking DT for large power grids is to practice microgrids. To that end, several papers for microgrid, DT had found promising results. Nevertheless, detailed optimization techniques and generic architecture are worth further research. GE and Siemens were at the forefront of implementing DT in wind farms and machine-human interfaces in power systems in the industrial sector. However, it is a competitive environment in which techniques and methods are restricted to the public and research domains. Investigating privacy-preserving ML techniques can enable secure data sharing and collaborative modeling within digital twins while preserving the privacy of sensitive information. Techniques such as federated learning and differential privacy can be explored. In addition, integrating human expertise and feedback into the digital twin environment can improve model performance and decision-making. Research should focus on developing human-in-the-loop approaches that facilitate effective collaboration between humans and ML models.

Connectivity and processing are crucial defining factors of DT. In power grids, the number of components and the complexity of a huge amount of real-time data sensing and processing place the DT in the theoretical phase. Many studies have managed to establish this bidirectional interaction between the physical and virtual systems. However, on the one hand, challenges such as sensor failure (i.e., damaged data), subsystem communication, or network speed are worth further research. Some studies suggest developing specific sensors considering the aging of the existing ones. Other research suggests that the 5G network and

Table 3
DT-based publications in the controlling and testing applications.

Objective	Summary	Key Features	Advantages	Challenges	References
Nuclear Power Plant Control and Testing	Highlights the benefits of using DT in nuclear power plants for controlling, testing, and diagnosing plant equipment.	Optimal control theory, fuzzy logic and machine learning.	*Improved system design, safety, and efficiency. *Reduced need for costly physical testing.	*Lack of knowledge about neural network decision-making. *Safety concerns.	[115]
Integrated Nuclear Digital Environment (INDE)	Conceptual framework for an INDE connecting prototype design, operation, decommissioning, storage, and waste disposal.	Computational modeling, data acquisition, high-performance computing systems.	*Shortened development times, reduced costs, increased credibility, operability, reliability, and safety.	*Technological gaps in implementing INDE.	[116]
Adaptive Control in Wind Turbine Systems	Adaptive control system based on DT for pitch angle control in wind turbines.	Software-in-loop (SIL), hardware-in-loop (HIL), active disturbance rejection control (ADRC), deep deterministic policy gradient (DDPG)	*Improved settling time and overshooting, better control performance, *Enhanced DT-based system compared to state-of-the-art schemes	*Need for fine-tuning parameters *Requirement of real-time computational.	[87]
IoT-based Digital Twin for Microgrid Management	An IoT-based DT model for the communication topology of a cluster of microgrids.	IoT, cloud computing	*Improved energy cyber-physics systems (ECPS) functionality *Enhanced intelligent and efficient operation of microgrids	*Stability, reliability, and resiliency of interconnected power systems *Integration of deep learning for situational awareness	[36]
Virtual Laboratory for Microgrid Management	Virtual laboratory framework for developing, testing, and debugging tools for microgrid management.	Virtual laboratory framework for microgrid management	*Optimized grid operation *Cost reduction through flexibility analysis *Seamless information sharing between geographically separated nodes	*Coordination of various technologies and modules *Integration of communication services	[117]
Fault Diagnosis in Building Integrated PV	Estimation, fault signature calculation, fault isolation	DT-based fault diagnosis approach for building-integrated photovoltaics (BIPV).	*Early fault detection and isolation *Improved performance and safety of distributed PV systems	*Generation of accurate error residuals and fault signatures	[118]
Real-Time Simulation of Combustion Engine Plants	Real-time simulation of a combustion engine-based power plant with battery storage and grid coupling.	Real-time simulation, physics-based modeling	*Self-optimizing grid-power plant control *Superior efficiency and grid response time control strategies beyond conventional approaches	Real-time simulation challenges for combined engine-electrical models	[119]
Multiscale Fusion Simulation for GIS Faults	Multiscale fusion simulation method for analyzing the influence of temperature on GIS insulation void defects	Micro-level streamer simulation, macro-level circuit simulation	Comprehensive and precise online monitoring, controlling, and optimization of GIS condition	Integration with online monitoring and control systems	[120]
DT Model for Power Transformer Fault Diagnosis	DT model for fault diagnosis of power transformers using the LabView platform	Data gathering, simulation, performance verification	Investigation of automated DT diagnostics techniques for electrical equipment	Selection of appropriate model coefficients	[121]

Fig. 9. Challenges and research gaps of DT in the power systems domain.

vehicular networks will support bidirectional communication. On the other hand, a common understanding of AI and ML methods and their capabilities should be addressed. In the future, more research on M2M communication should be conducted to pave the way for quick DT implementation. Another major obstacle observed is the lack of framework and common standards in building a holistic DT for power systems considering existing facilities such as new renewable energy penetration, autonomous operation, energy storage, load management, etc. As a starter, a reference framework for M2M communication and CPS integration and fusion of data are agreed on in many studies as power system DT enablers. Exploring distributed ML techniques and edge computing architectures can address scalability and real-time processing challenges in digital twins. Efficient utilization of computational resources and minimizing data transfer can enable real-time decision-making in distributed systems.

Like any emerging technology, DT is surrounded by privacy and security concerns. This topic is barely discussed in detail in the power system DT. Data leakage and cyber-attacks are examples of these concerns. Some studies suggest multi-layered active security systems for DT, meaning the DT itself can monitor and mitigate cyber hazards. Other studies suggest processing the data locally near the physical system before transmitting it further. It has also been observed that blockchain technology and federated learning, and secure multi-party computation can enable collaboration and data sharing while preserving the privacy of sensitive information. These methods should get more research attention as they could provide privacy solutions in IoT-based applications. From all the above, it's clear to see that transparency and standardization are the key words in overcoming most of the challenges observed.

7. Conclusions

This article presents an in-depth examination and analysis of the use of Digital Twin (DT) technology in power systems. It has provided numerous helpful insights and outlined some significant problems. In order to overcome these obstacles and make further progress in the implementation of DT, certain ideas that can be put into practice are offered. First and foremost, it is necessary to focus research efforts on comprehending the core concept and application framework of DT in power systems. It is possible to build a strong foundation for the successful implementation of this plan by putting more emphasis on research in these areas. Second, the establishment of global standards is absolutely necessary in order to facilitate the wide-scale implementation of DT. It will be much easier to achieve seamless integration and interoperability if industry players, researchers, and regulatory agencies work together to develop standardized methodologies in modeling, communication protocols, data storage and interchange, and privacy protection. Thirdly, it is essential to provide opportunities for collaboration between the scientific community and industry. It is possible to build validation and verification criteria for DT models through the formation of partnerships and the exchange of expertise. This will increase the reliability and accuracy of these models, particularly when they are applied to large-scale power systems. In addition, it is encouraged to support commercially available tools and platforms that make DT adoption easier. Accelerating the adoption of DT in the power sector will require both the encouragement of its development and the maintenance of interoperability with various modeling and AI methodologies. In conclusion, it is essential to make investments in the modeling of major power systems using the DT framework. It is possible to create more accurate simulations and predictions if research efforts are concentrated on resolving the complexities and difficulties that are unique to power grids. The modeling of large-scale systems requires specialized knowledge that can be gained through collaborative efforts with the scientific community. The identified problems can be effectively overcome by applying these practical recommendations, which will enable the realization of the full potential benefits of DT technology in power systems. This will lead to increased levels of standardization, collaboration, and innovation in the power industry, which will ultimately result in increased levels of efficiency, reliability, and sustainability. The advancement and successful integration of DT in power systems will be driven by further research, collaboration with industry, and the creation of best practices for DT; this will shape the future energy landscape.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] A. Shrestha, B. Ghimire, F. Gonzalez-Longatt, A Bayesian model to Forecast the time series kinetic energy data for a power system, Energies 14 (11) (2021) 3299.
[2] A. Shrestha, F. Gonzalez-Longatt, Frequency stability issues and research opportunities in converter dominated power system, Energies 14 (14) (2021) 4184 [Online]. Available: https://www.mdpi.com/1996-1073/14/14/4184.
[3] M. Liu, S. Fang, H. Dong, C. Xu, Review of digital twin about concepts, technologies, and industrial applications, J. Manuf. Syst. 58 (2021) 346–361.
[4] T.B. Malla, A. Bhattarai, A. Parajuli, A. Shrestha, B.B. Chhetri, K. Chapagain, Status, challenges and future directions of blockchain technology in power system: a state of art review, Energies 15 (22) (2022) 8571.
[5] C. Brosinsky, X. Song, D. Westermann, Digital twin-concept of a continuously adaptive power system mirror, in: International ETG-Congress 2019, ETG Symposium, 2019, pp. 1–6. VDE.
[6] T. Liu, et al., Research and application of digital twin technology in power grid development business, in: 2021 6th Asia Conference on Power and Electrical Engineering (ACPEE),, IEEE, 2021, pp. 383–387.
[7] C. Loebbecke, A. Picot, Reflections on societal and business model transformation arising from digitization and big data analytics: a research agenda, J. Strat. Inf. Syst. 24 (3) (2015) 149–157.
[8] Y. Cui, F. Xiao, W. Wang, X. He, C. Zhang, Y. Zhang, Digital twin for power system steady-state modelling, simulation, and analysis, in: 2020 IEEE 4th Conference on Energy Internet and Energy System Integration (EI2), IEEE, 2020, pp. 1233–1238.
[9] A.K. Sleiti, J.S. Kapat, L. Vesely, Digital twin in energy industry: proposed robust digital twin for power plant and other complex capital-intensive large engineering systems, Energy Rep. 8 (2022) 3704–3726.
[10] A. Ebrahimi, Challenges of developing a digital twin model of renewable energy generators, in: IEEE 28th International Symposium on Industrial Electronics (ISIE), 2019, IEEE, 2019, pp. 1059–1066.
[11] M. Shafto, et al., Modeling, simulation, information technology & processing roadmap, Nation. Aeronautics Space Administ. 32 (2012) (2012) 1–38.
[12] L. Tao, X. Yuan, C. Jian, W. Ke, Exploration of smart grid planning in large cities, 南方能源建设 7 (S1) (2020) 13–17.
[13] 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, 2012, p. 1818.
[14] R. Rosen, G. Von Wichert, G. Lo, About the Importance of Autonomy and Digital Twins for the Future of Manufacturing, IFAC-PapersOnLine, 2015.
[15] Z. Liu, N. Meyendorf, N. Mrad, The role of data fusion in predictive maintenance using digital twin, in: AIP Conference Proceedings, AIP Publishing LLC, 2018 020023, 1949, no. 1.
[16] A.M. Madni, C.C. Madni, S.D. Lucero, Leveraging digital twin technology in model-based systems engineering, Systems 7 (1) (2019) 7.
[17] P. Wang, M. Yang, Y. Peng, J. Zhu, R. Ju, Q. Yin, Sensor control in anti-submarine warfare—a digital twin and random finite sets based approach, Entropy 21 (8) (2019) 767.
[18] M. Bertoni, A. Bertoni, Designing solutions with the product-service systems digital twin: what is now and what is next? Comput. Ind. 138 (2022) 103629.
[19] S.V. Fernandes, D.V. João, B.B. Cardoso, M.A. Martins, E.G. Carvalho, Digital twin concept developing on an electrical distribution system—an application case, Energies 15 (8) (2022) 2836.
[20] E. Negri, L. Fumagalli, M. Macchi, A review of the roles of digital twin in CPS-based production systems, Procedia Manuf. 11 (2017) 939–948.
[21] Y. Zheng, S. Yang, H. Cheng, An application framework of digital twin and its case study, J. Ambient Intell. Hum. Comput. 10 (3) (2019) 1141–1153.
[22] R. Stark, T. Damerau, Digital twin, in: S. Chatti, T. Tolio (Eds.), CIRP Encyclopedia of Production Engineering, Springer Berlin Heidelberg, Berlin, Heidelberg, 2019, pp. 1–8.
[23] W. Yu, P. Patros, B. Young, E. Klinac, T.G. Walmsley, Energy digital twin technology for industrial energy management: classification, challenges and future, Renew. Sustain. Energy Rev. 161 (2022) 112407.
[24] W. Danilczyk, Y.L. Sun, H. He, Smart grid anomaly detection using a deep learning digital twin, in: 2020 52nd North American Power Symposium (NAPS), IEEE, 2021, pp. 1–6.
[25] W. Danilczyk, Y. Sun, H. He, Angel: an intelligent digital twin framework for microgrid security, in: 2019 North American Power Symposium (NAPS), IEEE, 2019, pp. 1–6.
[26] J. Huang, L. Zhao, F. Wei, B. Cao, The application of digital twin on power industry, in: IOP Conference Series: Earth and Environmental Science, IOP Publishing, 2021 012015, 647, no. 1.
[27] A.-R. Al-Ali, R. Gupta, T. Zaman Batool, T. Landolsi, F. Aloul, A. Al Nabulsi, Digital twin conceptual model within the context of internet of things, Future Internet 12 (10) (2020) 163.
[28] F. Tao, B. Xiao, Q. Qi, J. Cheng, P. Ji, Digital twin modeling, J. Manuf. Syst. 64 (2022) 372–389.
[29] A. Fuller, Z. Fan, C. Day, C. Barlow, Digital twin: enabling technologies, challenges and open research, IEEE Access 8 (2020) 108952–108971.
[30] P. Augustine, The industry use cases for the digital twin idea, in: Advances in Computers, Elsevier, 2020, pp. 79–105, 117, no. 1.
[31] C. Verdouw, B. Tekinerdogan, A. Beulens, S. Wolfert, Digital twins in smart farming, Agric. Syst. 189 (2021) 103046.
[32] 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. Integrated Manuf. 61 (2020) 101837.
[33] T. Mukherjee, T. DebRoy, A digital twin for rapid qualification of 3D printed metallic components, Appl. Mater. Today 14 (2019) 59–65.
[34] F. Tao, H. Zhang, A. Liu, A.Y. Nee, Digital twin in industry: state-of-the-art, IEEE Trans. Ind. Inf. 15 (4) (2018) 2405–2415.
[35] C. Lo, C. Chen, R.Y. Zhong, A review of digital twin in product design and development, Adv. Eng. Inf. 48 (2021) 101297.
[36] A. Saad, S. Faddel, O. Mohammed, IoT-based digital twin for energy cyber-physical systems: design and implementation, Energies 13 (18) (2020) 4762.
[37] G. Zhang, C. Huo, L. Zheng, X. Li, An architecture based on digital twins for smart power distribution system, in: 2020 3rd International Conference on Artificial Intelligence and Big Data (ICAIBD), IEEE, 2020, pp. 29–33.
[38] D.M. Botín-Sanabria, A.-S. Mihaita, R.E. Peimbert-García, M.A. Ramírez-Moreno, R.A. Ramírez-Mendoza, J.d.J. Lozoya-Santos, Digital twin technology challenges and applications: a comprehensive review, Rem. Sens. 14 (6) (2022) 1335.
[39] D. Gough, J. Thomas, S. Oliver, An introduction to systematic reviews, Intro. Syst. Rev. (2017) 1–352.
[40] 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.
[41] L.J. Wells, J.A. Camelio, C.B. Williams, J. White, Cyber-physical security challenges in manufacturing systems, Manufact. Lett. 2 (2) (2014) 74–77.
[42] M. Brettel, N. Friederichsen, M. Keller, M. Rosenberg, How virtualization, decentralization and network building change the manufacturing landscape: an Industry 4.0 Perspective, Int. J. Inform. Commun. Eng. 8 (1) (2014) 37–44.
[43] J. Lee and B. Bagheri, "Et KAO, Hung-An," A Cyber-Physical Systems Architecture for Industry, pp. 18-23.
[44] S. Sarma, The networked physical world-proposal for engineering the next generation of computing, commerce and automatic-identification. http://www.autoidcenter.org/research/MIT-AUTOID-WH-001.pdf, 2000.
[45] R. Baheti, H. Gill, Cyber-physical systems, Impact Control Tech. 12 (1) (2011) 161–166.

[46] H. Mohammadi Moghadam, H. Foroozan, M. Gheisarnejad, M.-H. Khooban, A survey on new trends of digital twin technology for power systems, J. Intell. Fuzzy Syst. 41 (2) (2021) 3873–3893.
[47] R. da Silva Mendonça, S. de Oliveira Lins, I.V. de Bessa, F.A. de Carvalho Ayres Jr., R.L.P. de Medeiros, V.F. de Lucena Jr., Digital twin applications: a survey of recent advances and challenges, Processes 10 (4) (2022) 744.
[48] P. Palensky, M. Cvetkovic, D. Gusain, A. Joseph, Digital twins and their use in future power systems, Digital Twin 1 (4) (2022) 4.
[49] E.J. Tuegel, A.R. Ingraffea, T.G. Eason, S.M. Spottswood, Reengineering aircraft structural life prediction using a digital twin, Int. J. Aerospace Eng. 2011 (2011).
[50] X.C. Wenhu Tang, Qian Tong, Gang Liu, Mengshi Li, Licheng Li, Technologies and applications of digital twin for developing smart energy systems, Strategic Study Chinese Acad. Eng. 22 (4) (2020) 74–85, https://doi.org/10.15302/j-sscae-2020.04.010.
[51] H. Pan, Z. Dou, Y. Cai, W. Li, X. Lei, D. Han, Digital twin and its application in power system, in: 2020 5th International Conference on Power and Renewable Energy (ICPRE), IEEE, 2020, pp. 21–26.
[52] T. Wenhu, C. Xingyu, Q. Tong, Technologies and applications of digital twin for developing smart energy systems [J], Strategic Study of CAE 4 (2020) 1–12.
[53] W. Tang, X. Chen, T. Qian, Technologies and applications of digital twin for developing smart energy systems, Strategic Study of CAE 22 (2020) 74–85.
[54] S.M. Bazaz, M. Lohtander, J. Varis, 5-dimensional definition for a manufacturing digital twin, Procedia Manuf. 38 (2019) 1705–1712.
[55] A.A. Smadi, B.T. Ajao, B.K. Johnson, H. Lei, Y. Chakhchoukh, Q. Abu Al-Haija, A Comprehensive survey on cyber-physical smart grid testbed architectures: requirements and challenges, Electronics 10 (9) (2021) 1043.
[56] C. Cimino, E. Negri, L. Fumagalli, Review of digital twin applications in manufacturing, Comput. Ind. 113 (2019) 103130.
[57] N. Bazmohammadi, et al., Microgrid digital twins: concepts, applications, and future trends, IEEE Access 10 (2021) 2284–2302.
[58] M. Jafari, A. Kavousi-Fard, T. Chen, M. Karimi, A Review on Digital Twin Technology in Smart Grid, Transportation System and Smart City: Challenges and Future, IEEE Access, 2023.
[59] H. Ruan, et al., Numerical investigation and comparative analysis of nanofluid cooling enhancement for TEG and TEC systems, Case Stud. Therm. Eng. 27 (2021) 101331.
[60] Y. Wei, T. Hu, T. Zhou, Y. Ye, W. Luo, Consistency retention method for CNC machine tool digital twin model, J. Manuf. Syst. 58 (2021) 313–322.
[61] M.G. Kapteyn, D.J. Knezevic, D. Huynh, M. Tran, K.E. Willcox, Data-driven physics-based digital twins via a library of component-based reduced-order models, Int. J. Numer. Methods Eng. 123 (13) (2022) 2986–3003.
[62] S.A. Niederer, M.S. Sacks, M. Girolami, K. Willcox, Scaling digital twins from the artisanal to the industrial, Nat. Comput. Sci. 1 (5) (2021) 313–320.
[63] J. Yu, P. Liu, Z. Li, Hybrid modelling and digital twin development of a steam turbine control stage for online performance monitoring, Renew. Sustain. Energy Rev. 133 (2020) 110077.
[64] J. Yu, N. Petersen, P. Liu, Z. Li, M. Wirsum, Hybrid modelling and simulation of thermal systems of in-service power plants for digital twin development, Energy 260 (2022) 125088.
[65] J. Zhou, et al., Hybrid data-driven modeling for AC/DC power system considering renewable energy uncertainty, Front. Energy Res. 179 (2022).
[66] A. Sharma, E. Kosasih, J. Zhang, A. Brintrup, A. Calinescu, Digital twins: state of the art theory and practice, challenges, and open research questions, J. Ind. Inform. Integrat.. (2022) 100383.
[67] M.A. Razzaque, M. Milojevic-Jevric, A. Palade, S. Clarke, Middleware for internet of things: a survey, IEEE Internet Things J. 3 (1) (2015) 70–95.
[68] Q. Qi, et al., Enabling technologies and tools for digital twin, J. Manuf. Syst. 58 (2021) 3–21.
[69] A.O. Bang, U.P. Rao, A. Visconti, A. Brighente, M. Conti, An IoT Inventory before Deployment: A Survey on IoT Protocols, Communication Technologies, Vulnerabilities, Attacks, and Future Research Directions, Computers & Security, 2022 102914.
[70] S. Al-Sarawi, M. Anbar, K. Alieyan, M. Alzubaidi, Internet of things (IoT) communication protocols, in: 2017 8th International Conference on Information Technology (ICIT), IEEE, 2017, pp. 685–690.
[71] R. van Dinter, B. Tekinerdogan, C. Catal, Predictive Maintenance Using Digital Twins: A Systematic Literature Review, Information and Software Technology, 2022 107008.
[72] A. Malekloo, E. Ozer, M. AlHamaydeh, M. Girolami, Machine learning and structural health monitoring overview with emerging technology and high-dimensional data source highlights, Struct. Health Monit. (2021), 14759217211036880.
[73] T.M. Mitchell, T.M. Mitchell, *Machine Learning* (No. 9), McGraw-hill, New York, 1997.
[74] A. Malekloo, E. Ozer, M. AlHamaydeh, M. Girolami, Machine learning and structural health monitoring overview with emerging technology and high-dimensional data source highlights, Struct. Health Monit. 21 (4) (2022) 1906–1955.
[75] B. Mahesh, Machine learning algorithms-a review, Int. J. Sci. Res. 9 (2020) 381–386 *[Internet]*.
[76] A. Marahatta, Y. Rajbhandari, A. Shrestha, S. Phuyal, A. Thapa, P. Korba, Model predictive control of DC/DC boost converter with reinforcement learning, Heliyon (2022) e11416.
[77] Y. Cai, B. Starly, P. Cohen, Y.-S. Lee, Sensor data and information fusion to construct digital-twins virtual machine tools for cyber-physical manufacturing, Procedia Manuf. 10 (2017) 1031–1042.
[78] Q. Min, Y. Lu, Z. Liu, C. Su, B. Wang, Machine learning based digital twin framework for production optimization in petrochemical industry, Int. J. Inf. Manag. 49 (2019) 502–519.
[79] D. Pandey, K. Niwaria, B. Chourasia, Machine learning algorithms: a review, Mach. Learn. 6 (2) (2019).
[80] N.K. Chauhan, K. Singh, A review on conventional machine learning vs deep learning, in: 2018 International Conference on Computing, Power and Communication Technologies (GUCON), IEEE, 2018, pp. 347–352.
[81] E. Priyanka, S. Thangavel, X.-Z. Gao, N. Sivakumar, Digital twin for oil pipeline risk estimation using prognostic and machine learning techniques, J. indust. Inform. Integrat. 26 (2022) 100272.
[82] K. Alsabti, S. Ranka, V. Singh, An Efficient K-Means Clustering Algorithm, 1997.
[83] M. Dhada, M.P. Hernández, A.S. Palau, A.K. Parlikad, Comparison of agent deployment strategies for collaborative prognosis, in: 2021 IEEE International Conference on Prognostics and Health Management (ICPHM), IEEE, 2021, pp. 1–8.
[84] Y. Rajbhandari, et al., Impact study of temperature on the time series electricity demand of urban Nepal for short-term load forecasting, Appl. Syst. Innov. 4 (3) (2021) 43.
[85] L. Bull, K. Worden, G. Manson, N. Dervilis, Active learning for semi-supervised structural health monitoring, J. Sound Vib. 437 (2018) 373–388.
[86] L.P. Kaelbling, M.L. Littman, A.W. Moore, Reinforcement learning: a survey, J. Artif. Intell. Res. 4 (1996) 237–285.
[87] M. Jahanshahi Zeitouni, A. Parvaresh, S. Abrazeh, S.-R. Mohseni, M. Gheisarnejad, M.-H. Khooban, Digital twins-assisted design of next-generation advanced controllers for power systems and electronics: wind turbine as a case study, Inventions 5 (2) (2020) 19.
[88] B. Maschler, D. Braun, N. Jazdi, M. Weyrich, Transfer learning as an enabler of the intelligent digital twin, Procedia CIRP 100 (2021) 127–132.
[89] I. Syarif, E. Zaluska, A. Prugel-Bennett, G. Wills, Application of bagging, boosting and stacking to intrusion detection, in: Machine Learning and Data Mining in Pattern Recognition: 8th International Conference, MLDM 2012, Springer, Berlin, Germany, 2012, pp. 593–602. July 13-20, 2012. Proceedings 8.
[90] G. Yu, S. Zhang, M. Hu, Y.K. Wang, Prediction of highway tunnel pavement performance based on digital twin and multiple time series stacking, Adv. Civ. Eng. 2020 (2020) 1–21.
[91] P.T. Baboli, D. Babazadeh, D.R.K. Bowatte, Measurement-based modeling of smart grid dynamics: a digital twin approach, in: 2020 10th Smart Grid Conference (SGC), IEEE, 2020, pp. 1–6.
[92] K.E. Harper, C. Ganz, S. Malakuti, Digital twin architecture and standards, IIC J. Innovat. 12 (2019) 72–83.
[93] T. I. O. f. S. (ISO), ISO 23247-4:2021 Automation systems and integration Digital twin framework for manufacturing Part 4: information exchange. https://www.iso.org/standard/78745.html accessed).
[94] IPC, IPC releases IPC-2551, international standard for digital twins [Online]. Available: https://shop.ipc.org/2551-0-0-english.
[95] ISO, Under development standards of DT [Online]. Available: https://www.iso.org/search.html?q=Digital%20Twin&hPP=10&idx=all_en&p=0&hFR%5Bcategory%5D%5B0%5D=standard.
[96] M. Singh, et al., Applications of digital twin across industries: a review, Appl. Sci. 12 (11) (2022) 5727.
[97] G.R. Energy, Digital Wind Farm: the Next Evolution of Wind Energy, May, 2016.
[98] P. G. a. E. Company. "Application of pacific gas and electric company (U 39 E) for approval of its 2021 - 2025 electric program investment charge investment plan " chrome-extension://efaidnbmnnnibpcajpcglclefindmkaj/https://www.pge.com/pge_global/common/pdfs/about-pge/environment/what-we-are-doing/electric-program-investment-charge/EPIC-4-Application-PGE.pdf (accessed.
[99] IBM. "How the Port of Rotterdam is using IBM digital twin technology to transform itself from the biggest to the smartest." https://www.ibm.com/blogs/internet-of-things/iot-digital-twin-rotterdam/(accessed.
[100] I.a. Siemens, Siemens and IBM deliver service lifecycle management solution. https://newsroom.ibm.com/2020-06-17-Siemens-and-IBM-Deliver-Service-Lifecycle-Management-Solution.
[101] B. Xu, et al., A case study of digital-twin-modelling analysis on power-plant-performance optimizations, Clean Energy 3 (3) (2019) 227–234.
[102] M. Zhou, J. Yan, D. Feng, Digital twin framework and its application to power grid online analysis, CSEE J. Power Energy Syst.. 5 (3) (2019) 391–398.
[103] M. Zhou, J. Yan, X. Zhou, Real-time online analysis of power grid, CSEE J. Power Energy Syst. 6 (1) (2020) 236–238.
[104] C. Wang, J. Xu, K. Wang, SoC-based digital twin of power system simulation, in: 2020 5th Asia Conference on Power and Electrical Engineering (ACPEE), IEEE, 2020, pp. 185–191.
[105] T. Okita, T. Kawabata, H. Murayama, N. Nishino, M. Aichi, A new concept of digital twin of artifact systems: synthesizing monitoring/inspections, physical/numerical models, and social system models, Procedia Cirp 79 (2019) 667–672.
[106] J. Xiong, H. Ye, W. Pei, L. Kong, Q. Huo, Y. Han, A monitoring and diagnostics method based on FPGA-digital twin for power electronic transformer, Elec. Power Syst. Res. 210 (2022) 108111.
[107] C. Brosinsky, D. Westermann, R. Krebs, Recent and prospective developments in power system control centers: adapting the digital twin technology for application in power system control centers, in: 2018 IEEE International Energy Conference (ENERGYCON), IEEE, 2018, pp. 1–6.
[108] J. Vaicys, P. Norkevicius, A. Baronas, S. Gudzius, A. Jonaitis, D. Peftitsis, Efficiency evaluation of the dual system power inverter for on-grid photovoltaic system, Energies 15 (1) (2021) 161.

[109] P. Apte, Digital Twins of Nuclear Power Plants, American Society of Mechanical Engineers, 2021.
[110] S. Kaewunruen, P. Rungskunroch, J. Welsh, A digital-twin evaluation of net zero energy building for existing buildings, Sustainability 11 (1) (2018) 159.
[111] Y. Shin, J. Oh, D. Jang, D. Shin, Digital twin of alkaline water electrolysis systems for green hydrogen production, in: Computer Aided Chemical Engineering, Elsevier, 2022, pp. 1483–1488, 49.
[112] X. Tang, Y. Ding, J. Lei, H. Yang, Y. Song, Dynamic load balancing method based on optimal complete matching of weighted bipartite graph for simulation tasks in multi-energy system digital twin applications, Energy Rep. 8 (2022) 1423–1431.
[113] J. Zhou, et al., Hybrid data-driven modeling for an AC/DC power system considering renewable energy uncertainty, Front. Energy Res. 10 (2022) 179.
[114] S. Agostinelli, F. Cumo, M.M. Nezhad, G. Orsini, G. Piras, Renewable energy system controlled by open-source tools and digital twin model: zero energy port area in Italy, Energies 15 (5) (2022) 1817.
[115] V. Volodin, A. Tolokonskii, Concept of instrumentation of digital twins of nuclear power plants units as observers for digital NPP I&C system, in: Journal of Physics: Conference Series, IOP Publishing, 2019 012083, 1391, no. 1.
[116] E.A. Patterson, R.J. Taylor, M. Bankhead, A framework for an integrated nuclear digital environment, Prog. Nucl. Energy 87 (2016) 97–103.
[117] G. Fernández, et al., Development and Initial Testing of a Virtual Laboratory for the Build-Up and Testing of Microgrid Management Algorithms, Renewable Energy and Power Quality Journal, 2022.
[118] 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 Electron. 35 (1) (2019) 940–956.
[119] E. Söderäng, S. Hautala, M. Mikulski, X. Storm, S. Niemi, Development of a digital twin for real-time simulation of a combustion engine-based power plant with battery storage and grid coupling, Energy Convers. Manag. 266 (2022) 115793.
[120] H. Song, Z. Zhang, J. Tian, G. Sheng, X. Jiang, Multiscale fusion simulation of the influence of temperature on the partial discharge signal of GIS insulation void defects, IEEE Trans. Power Deliv. 37 (2) (2021) 1304–1314.
[121] I.E. Kolesnikov, A.V. Korzhov, K.E. Gorshkov, Digital program for diagnosing the status of a power transformer, in: 2020 Global Smart Industry Conference (GloSIC), IEEE, 2020, pp. 315–321.
[122] Oracle, Developing applications with Oracle internet of things cloud service. https://docs.oracle.com/en/cloud/paas/iot-cloud/iotgs/use-oracle-iot-digital-twin-simulator1.html accessed).
[123] ETAP, ETAP digital twin platform. https://etap.com/products/etap-digital-twin accessed).
[124] SEWIO. "Digital Twin for Maximizing Optimalization." https://www.sewio.net/digital-twin-for-maximizing-optimalization/?utm_source=google&utm_medium=cpc&utm_term=digital%20twin&utm_campaign=google_digitaltwin&gclid=CjwKCAjwsMGYBhAEEiwAGUXJaYp5gd3wKIeVPP-OmV1g2tL3vanqEqvngVMFtTL8hh8EK2zCYIKEFBoC0MQQAvD_BwE ((accessed).
[125] FMI, Functional mock-up interface. https://fmi-standard.org/ accessed).
[126] PTC, ThingWorx IIoT. https://www.ptc.com/en/products/thingworx accessed).
[127] Philips, Digital twins: what do they mean for lighting?. https://www.lighting.philips.co.uk/oem-emea/stay-connected/digital-twins accessed).
[128] Y. Fu, Y. Huang, F. Hou, K. Li, A Brief review of digital twin in electric power industry, in: 2022 IEEE 5th International Electrical and Energy Conference (CIEEC), IEEE, 2022, pp. 2314–2318.
[129] A. Rasheed, O. San, T. Kvamsdal, Digital twin: values, challenges and enablers from a modeling perspective, IEEE Access 8 (2020) 21980–22012.
[130] D. Jones, C. Snider, A. Nassehi, J. Yon, B. Hicks, Characterising the Digital Twin: a systematic literature review, CIRP J. Manufact. Sci. Tech. 29 (2020) 36–52.
[131] S. Mathupriya, S.S. Banu, S. Sridhar, B. Arthi, Digital twin technology on IoT, industries & other smart environments: a survey, Mater. Today: Proc. (2020).
[132] Í.A. Fonseca, H.M. Gaspar, P.C. de Mello, H.A.U. Sasaki, A standards-based digital twin of an experiment with a scale model ship, Comput. Aided Des. 145 (2022) 103191.
[133] J.L. Vilas-Boas, J.J. Rodrigues, A.M. Alberti, Convergence of distributed ledger technologies with digital twins, IoT, and AI for fresh food logistics: challenges and opportunities, J. Ind. Inform. Integrat. (2022) 100393.
[134] 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.
[135] M.W. Grieves, Virtually Intelligent Product Systems: Digital and Physical Twins, 2019.
[136] M. Grieves, Digital Twin: Manufacturing Excellence through Virtual Factory Replication-A Whitepaper by Dr. Michael Grieves, White Pap, 2015, pp. 1–7.
[137] K. Hribernik, G. Cabri, F. Mandreoli, G. Mentzas, Autonomous, context-aware, adaptive Digital Twins—state of the art and roadmap, Comput. Ind. 133 (2021) 103508.