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Digital Replica and Twin Systems for Cyber-Physical Power Systems: Technology Development and Foresight

Neha Kumari
Indian Institute of Technology, Jodhpur
Email id. P24ee0012@iitj.ac.in

Abstract— ***Digital Twin (DT) technology is emerging as a transformative force in the modernization of cyber-physical systems (CPSs), enabling seamless integration between physical infrastructure and its virtual counterpart. This paper presents a comprehensive review of DT concepts, historical evolution, and enabling technologies—such as the Internet of Things (IoT), artificial intelligence (AI), machine learning (ML), and cyber-physical systems to support real-time monitoring, predictive maintenance, and system optimization. The paper begins with foundational frameworks for modelling digital replica modules and cooperative operation as twin systems. It discusses the application of DTs in improving monitoring, control, system resilience, network integration, component tuning, and managing decentralized edge-based cyber-physical systems is explored in depth. The paper draws attention towards the applicability of digital replica and twin system technology in the power grid as an evolving cyber-physical system. It also includes key challenges like data accuracy, communication latency, and system interoperability in terms of digital twin operation and management.***

Keywords—: *Digital Replica, Digital Instances, Digital Twin, Cyber-Physical System, Smart Grid, Artificial intelligence (AI), and machine learning (ML).*

I. Introduction

A. Digital Twin Technology

Digital twin (DT) technology has been one of the most prominent fields of study over the last few decades, and it is now growing and changing at a fast pace. DT mirrors the entire existence cycle of the equivalent physical item and allows for the mapping of virtual to physical space. Many other types of industrial applications have found success using DT technology. These include electric cars, intelligent manufacturing, energy conversion, space missions, and many more. Electrical systems gain from DT development when considering both the impacts that have been accomplished and the potential that is yet to be attained. In this digital age, many ideas and technologies are revolutionizing the built environment by incorporating smart features into buildings, houses, and cities for the benefit of their inhabitants. A project's and the built environment's performance can be improved with use of digital technology [1]. IT processes, intelligence, and automation make up the numerous the foundations that support this digital transformation process, which also includes training the workforce for this change. In their assessment of companies that have successfully undergone a digital shift, McKinsey outlined the digital technology, tools, and processes that these companies used to reach their digital transformation objective. Beginning with cloud-based services, which enable the expansion of firm assets and reachability to workers and consumers, and traditional online and mobile technology deployment are at the top of the list. The second step is to use Big Data infrastructures and analytic methodologies to derive business choices. This involves integrating IoT technology to gather data from any chosen source. In addition, by producing insights, anticipating trends, and discovering connections, use of AI and ML algorithms may improve transformation process. Augmented reality is the last pillar; it improves digitalization and gives consumers an immersive experience with their equipment. Data visualization, monitoring, operation, and other applications can benefit from DT's ability to digitally represent real-world items and create a two-way relationship between them. To create digital entities and transfer data from physical to digital realm, DT employs a variety of technologies, including as building information modeling and the IoT. The technology it can interface with and the jobs it can complete determine DT's capabilities.

The rapidly developing technology of DTs has potential applications in many different industries for things like lifecycle management and predictive analysis. People and businesses can benefit from this technology because it reveals important details about the inner workings of a system, such as its relationships and future behaviour. There is an increasing interest in development and use of digital technologies across several sectors, including smart cities, metropolitan areas, logistics, healthcare, engineering, and automobile industry. Today,

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the fuel and energy industry are actively using DT technology to address a range of technical and technological issues. Traditional control and monitoring systems may miss anomalies in industrial equipment's performance because they may not yet impact the equipment's state. However, the digital twin enables exceptionally sensitive detection of such deviations [2].

B. DT in the Power Industry and Future Power System

The majority of the power industry's digital twin research has concentrated on the following areas: evaluating the technical status of power equipment [3-5], controlling the modes of operation of the power system, optimizing energy consumption, and solving the technical problems associated with integrating renewable energy sources [6-8]. Research on electrical network digital twins using an ontological approach is presented in the paper [9]. To examine the modes of functioning of the power system and guarantee its security, the suggested method employs digital twin technology. In [10], scenarios for the implementation of DT technology at the Cai-Lun substation in China are presented.

- Simulating the system in real or quasi-real-time
- Ensuring data transmission between the digital twin and the ontology-based system are the major requirements given forth in the design of the digital twin.

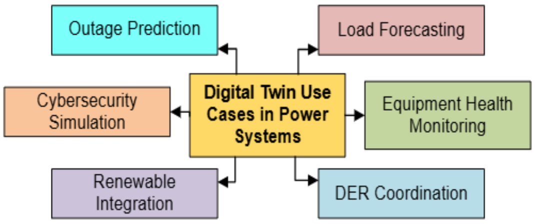

Fig.1 Digital Twin Use Cases in Power Systems.

This approach relies on establishing links between different forms of information in the digital realm. Consideration of the system's uncertainty due to the existence of different generators, consumers, and the likelihood of power equipment failure is included into the DT utilized for the study of the simulated system [11]. In [12] presents a study on the application of the digital twin concept to the development of an intelligent system to assist in the operation and maintenance of a photovoltaic power plant, utilizing 3D modeling technologies. The development of tidal power plants is predicted using digital twin technology in [13].

Future power system will have to change its operating approach drastically to accommodate active prosumers and dispersed renewable energy resources. Its uncertainty and grid-connected power electronic converters potential to provide both random and planned disruptions to system are two concerns. Additionally, grid stability is at risk when natural energy reserves disappear primarily a result of increasing withdrawal of traditional synchronous generators, which substantially lowers system's available inertia. Due to their flexibility, rapid response, and local control over production and consumption, distributed power converters provide significant efficiency and financial advantages. Various storage systems and renewable energy sources will constitute production, while economic dispatch and peak shaving are instances of consumption strategies that may be customized to satisfy particular local and individual requirements. Accessing current environmental, economic, and operational data on the interconnected system and its actors is essential for addressing the challenges of the transition and leveraging its transformative opportunities. CPSs has gained a popularity in recent years. Combining both physical and computational components into a virtual environment maximizes real-world processes and to build strong energy systems at all levels with intelligence, dependability, and security [14].

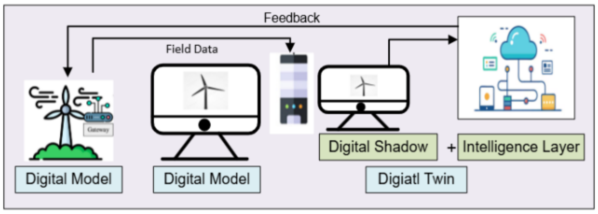

Fig.2 Wind Turbine as a Model for Digital Twin [41].

DT technology is needed in future power systems to manage complexity and demands of modern energy networks. By simulating physical assets and systems, DTs provide real-time monitoring, predictive maintenance, and grid efficiency. This enhances grid dependability and resilience, enabling utilities to proactively identify defects and avert outages. DTs facilitate the incorporation of renewable energy sources by modeling their fluctuations and optimizing the equilibrium between demand and supply. Moreover, they are crucial in overseeing decentralized grids, including microgrids, and enable peer-to-peer energy transactions. Through the enhancement of asset management, the reduction of operational inefficiencies, and the improvement of cybersecurity, digital technologies substantially decrease costs while guaranteeing system sustainability and adherence to environmental objectives. Moreover, digital twins allow the evaluation of novel technologies and situations inside a risk-free virtual setting, hence expediting innovation and grid modernization. Modern modeling tools and systematic investigation of the interaction between cyber and physical systems are foundation of integration [15]. A popular and effective approach for attaining CPS is the use of DTs, which are grounded on physical system models and include processing, connectivity, and data storage capabilities. A vital facilitating instrument for cyber-physical power systems, DT may gather, predict,

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and represent virtual or real conditions for human-system interaction and autonomous functioning [16].

II. DIGITAL TWIN CONCEPT AND FRAMEWORK

A. Origin of DT

In the 1960s, NASA used DT in Apollo program to build physical replicas of Earth that aligned with their systems in space for the first time. This methodology was used to simulate several situations, allowing for evaluation of system behaviour and performance under diverse settings. It escalated when twin interfered to handle technological challenges of the Apollo 13 mission, which engineers on Earth had tackled by testing potential solutions on terrestrial twin. Before Michael Grieves introduced virtual factory models in the early 2000s for operational monitoring, failure prediction, and efficiency enhancement, idea of DTs had not been considered in manufacturing sector.

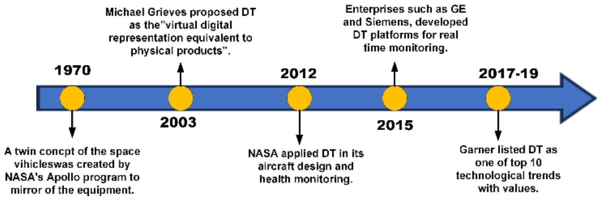


Fig.3 Development of DT Timeline.

This concept's increased visibility and impact were reinforced by prominent companies such as Siemens [17] and General Electric [18], as well as Gartner's classification of it as one of the top 10 significant technology trends of 2017.

B. Types, Advantages and Characteristics of DT

Different types of DTs can be classified based on various factors, such as their development time, level of integration, applications, hierarchy, and maturity. Considering these factors, some researchers have suggested different ways to categorize DTs.

1. DT Creation Time

Grieves and Vickers [53,54] proposed that DTs fall into two main categories based on the product's development stage: design phase (before the prototype is built) and production phase.

- *Digital twin instance (DTI):* It is a type of DT that represents its physical version throughout its entire life [55]. This means that DT is affected by any changes or evolutions that occur to the physical twin, and that its status is constantly tracked as shown in Fig. 4.

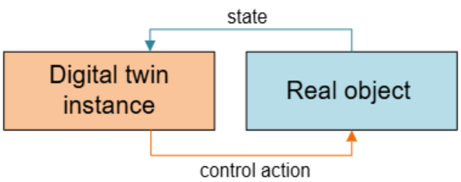


Fig.4 DT Instance.

- *Digital twin prototype (DTP):* It is helpful for product development and production because it captures and stores crucial information about the physical twin. Before simulating production conditions, the DTP may conduct evaluation, validation, and quality control testing in accordance with DT standards as shown in Fig. 5.

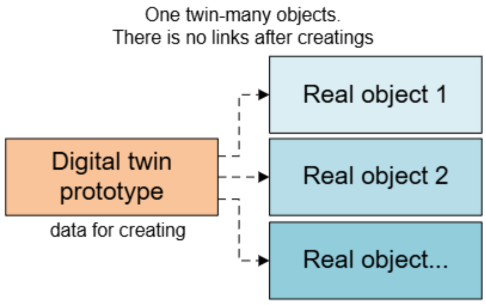


Fig.5 DT Prototype.

- *Digital twin aggregate (DTA):* The aggregate is a combination of digital twin instances. It receives data from many physical objects as shown in Fig. 6.

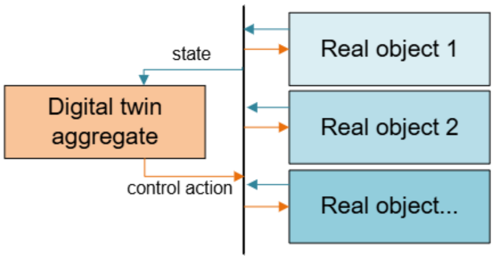
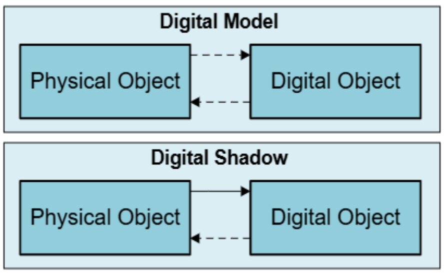


Fig.6 DT Aggregate.

2. Level of Integration

Based on how well DTs were integrated, Kritzinger et al. [56] split them into three groups:

- *Digital Model:* In this type of DT, data is transferred manually between physical and digital objects. This means any changes to physical object do not instantly update in the digital version, and vice versa.
- *Digital Shadow:* In this type of DT, when physical things undergo alterations, their digital replicas are updated immediately. But changing the digital version doesn't easily affect real object.



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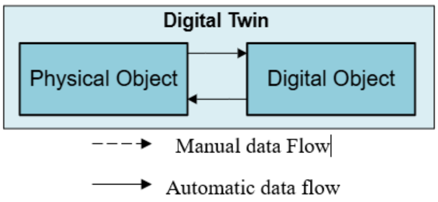

Fig.7 Data Flow in DT at Different Subcategories.

- *Digital Twin:* In this type of DT, data flows automatically between physical and digital versions. Changes in one always lead to changes in the other as shown in Fig. 7.

3. Hierarchy

Implementation of DTs is a highly intricate and tedious process. Hierarchical structure suggests that DT can be completed in three phases. The first stage is to construct the DT at the unit level [57]. By using the DT unit, we can enable smart monitoring, control, and equipment health management. The next step is building a system-level DT, where multiple units combine to support smart manufacturing. Finally, the SoS level [58] is reached by integrating both unit-level and system-level DTs shown in Fig. 8.

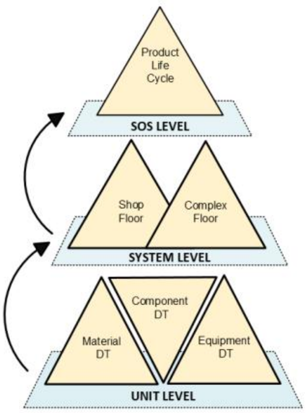

Fig.8 Hierarchical Levels of DTs in Manufacturing [57].

4. Recapitulation

Implementing DTs is a complex and time-consuming task. A hierarchical structure divides process into three phases. First, DT is built at unit level, enabling smart monitoring, control, and equipment health management. Next, multiple units combine to form system-level DT, supporting smart manufacturing. Finally, SoS level is reached by integrating both unit-level and system-level DTs [59].

5. Level of Maturity/Sophistication

Complexity of a DT depends on how much and how well data is collected from its physical counterpart and surroundings. This helps categorize DTs into different types [60]: *Partial DT:* It provides a limited set of data points that may be used to ascertain connection and performance of DT; these data points may include things like pressure, temperature, humidity, and so on. *Clone DT:* It includes all the important and necessary product/system data that may be utilized to create prototypes and organize development stages. *Augmented DT:* By the application of algorithms and analytics, it draws from asset data and its historical data to extract and correlate valuable information. The acquisition of more datasets throughout operational periods may enhance the complexity level of DT. In the view of Azad M. Madni et al. [61], the degree of development of DT includes not only the data but also the degree of complexity of the model or virtual representation.

6. Advantages of DT

A few benefits of DT technology have led to its positioning as a cornerstone in Industry 4.0. These include the fact that it can improve the efficiency, accuracy, and cost-effectiveness of any system or process. It also breaks down conventional industrial systems' separation and divisionism, which helps streamline processes and organizations.

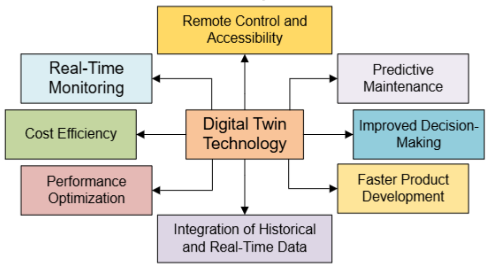

Fig.9 Advantages of DT.

A few of the benefits that have been mentioned for DT are:

- Redesigning products and speed prototyping: Prototyping and redesigning become more simpler and quicker when using simulations to examine several situations; this is because the design and analysis cycles are shortened. Once put into place, DT may be used throughout several phases of product design, beginning with ideation and continuing through testing [62]. In addition, it opens the way for the possibility of tailoring products to individual customers by collecting and analysing data on their wants and product use. Engineers and product designers may reevaluate their methodology in product development, since a DT remains linked to its physical twin, influencing both its present and future performance.
- **Affordable:** Over a time, cost of prototyping decreases as digital technology mostly utilizes virtual resources. In contrast, using digital technology, items may be reconstructed and subjected to destructive testing without additional material expenses, resulting in significant time savings compared to

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conventional prototyping techniques. This is due to conventional prototyping's need on physical materials and labor, which may be costly and time-intensive. Through digital testing, products may be economically evaluated under many operating settings, even adverse ones.

- **Improving Maintenance and Optimizing Solutions:** Traditional maintenance methods are more reactive than proactive because they follow general rules and worst-case assumptions rather than considering each product's specific material, design, and usage [63]. On the other hand, DT can predict production system failures and plan maintenance in advance. With DT's scenario-based solutions and strategies, maintaining products and systems becomes much easier. Additionally, DT's physical counterpart can be used in a continuous feedback loop to constantly improve and validate the system's processes.
- **Training:** DT can help create better safety training programs with clearer examples than traditional methods. Operators may be DT-trained before operating potentially dangerous equipment or at a high-risk location; this will help them feel more prepared to handle real-life events by exposing them to and teaching them various techniques. New hires in the mining industry, for instance, may learn how to operate heavy gear and respond to various emergencies with the help of DT.

III. DIGITAL TWIN IN POWER SYSTEMS

Since its origin in 2002, [19] a concept of a DT has been used across several industries with diverse interpretations. Due to their many conceptual applications in sectors such as industry, aviation, health, and energy, digital twins are seen in various manners. Although there may be minor differences on specifics, the three main aspects of the DT concept that are widely accepted are: The phrase "two-way data flow" [20] denotes the bidirectional connection between a virtual representation of a physical asset and asset itself. From this underlying principle, two categories of definitions emerge: Two primary perspectives exist on this subject: one that focuses on specific components of Figure 10 and another that seeks to include all subsystems dependent on the program to provide the requisite functionality for DT.

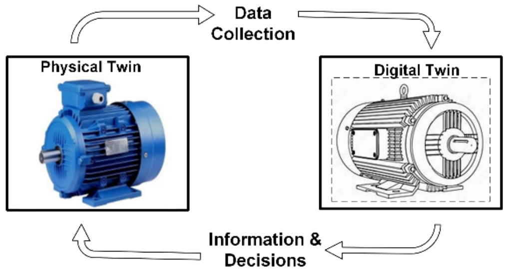

Fig.10 DT Process: from Physical to Virtual.

Research on DT's potential uses in simulating power system dynamics is sparse. Nevertheless, DTs have found use in dynamic modeling in various fields, including simulations of big plants and manufacturing. When it came to DT of power systems, Siemens' PSS®ODMS was the market leader. Using the CIM as a guide, Siemens® created the system. Grid modeling relies on this technology, which links the created models to actual data in real time. American Electric electricity's DT project and the electricity transmission network in Finland both make use of it. As a replacement for the existing architecture of web analytics, Zhou et al. [21] have presented a conceptual approach. A technological need of real-time simulation capabilities has mainly prompted efforts to improve processing speed. As a result of Zhou's research, the potential for ANN modelling has been discovered. A conceptual approach for a power system mirror that continuously adjusts with dynamic power system models has been outlined by authors in [22]. Models based on physics and ANNs have been proposed in the study. For gas turbine system-specific plant duplication applications, GE offers the Analytical Engine. Physical and ANNs are employed to implement dynamic modelling methodologies. In [23], modern technologies such as AI, cloud computing, big data analytics, and IoT have substantially increased development of smart manufacturing. Manufacturers are increasingly implementing cyber-physical integration, which is a critical prerequisite for smart manufacturing.

The fuel and energy industry are now making extensive use of DT technology in order to address a wide range of technical and technological issues. The DT makes it possible to detect deviating parameters in the operation of industrial equipment with an unusually high level of sensitivity. The enabling technologies that support DT's features are the backbone of DT's origins and developments. Their capabilities cover all bases, including ensuring that measurements are coordinated, models are correct, communication is real-time, and services can analyse massive volumes of data. Enabling technologies are outlined in this section in the following order: data acquisition, modelling, communication, computation, and data analysis.

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A. Data Acquisition

Measurement and sensing devices provide real-time data to DT functions, acting as a bridge between the digital and physical realms. It is important that the data collection interfaces be consistent and that the protocols employed offer sufficient transmission speeds to keep the DTs synchronised. This is especially true since various applications have varying needs when it comes to transmission delay.

SCADA/PMU: The Supervisory Control and Data Acquisition (SCADA) system is a typical way of exchanging data between a control/monitoring unit and the associated devices. Modern SCADA systems may wirelessly communicate with microprocessors to collect data from faraway units or controllers; however, this data is not time stamped and updates at a slow pace [24]. Power system control centres are increasingly utilising Phasor Measurement Units (PMUs) for real-time identification and monitoring, improving condition monitoring, and fault detection and diagnosis. PMUs are multifunctional signal acquisition systems with a significantly larger sample rate than SCADA [25]. For large-scale power systems, PMUs based on the Global Positioning System (GPS) can provide locally synchronised phasors of phase voltages and currents over a large geographical area. This makes them useful for detecting transient events, particularly stability-related issues where quick decisions are needed to prevent fault propagation [26].

Combining SCADA and PMU in DT offers a potential foundation for an adaptive and automated control system for energy systems [27], even if the ideal location of PMUs to balance hardware investment costs and complete estimating capabilities is still an open research subject [28]. Over an extended length of time, condition monitoring may provide an estimate of the asset's condition. For such sluggish jobs, the typical update rate of SCADA systems—on the range of minutes [29]—is more than enough. Lower latency and quicker computational execution are critical for other DT applications like asset optimisation methods. It is recommended to use a PMU system for data collection.

B. Modeling Technologies

Developing a reliable virtual representation capable of providing simulation results or predictions in real-time poses the greatest challenge to the modelling issue since it is a crucial component of DTs. Despite its long history of study, the question of how to accurately and affordably model complicated, large-scale power systems still needs answering. In this case, DT technology can help with both system identification and model reduction.

System identification: In order to accurately and continuously portray the physical system, it is necessary to update the models to account for changes or deterioration caused by factors like ageing. System identification updates the mathematical description of the dynamical system's properties using measurable input–output data. DT models may be classed into three categories based on system understanding and applications: white box, grey box, and black box. Data dependability rises when previous knowledge of the physical system structure diminishes. Interactions between sub models may cause assumptions and simplifications to worsen overall behaviour, even if individual sub models are accurate and perform well.

Model reduction: Higher system complexity means more model states and greater computing effort for simulation. DTs of large-scale power systems may use model reduction to speed up simulations while maintaining anticipated realism. If physical processes or components have little impact on the system, excluding or simplifying them reduces model order. Thus, any model must balance modelling depth, simplicity, simulation accuracy, and speed. There are known mathematical order reduction techniques such balanced truncation, Krylov subspace, singular value decomposition, and orthogonal decomposition for linear and nonlinear systems [30]. A reduced-order model of the complete system may increase simulation errors, particularly during disturbances. In problematic situations, moving to full models from reduced models might enhance performance. DTs for power electronic devices also use model partitioning before order reduction to speed up simulation.

C. Communicating Technology

In order to fully use the data that has been measured and collected locally, it is essential that communication technologies provide access to higher-level or worldwide data. Thus, data-based holistic system modelling and identification tools need this. The growing volume of data transmitted in DT, whether locally or across adjacent DTs, strains communication capacity and speed of traditional technologies [31].

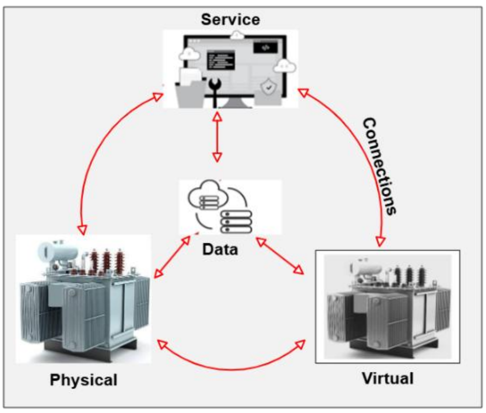

Fig.11 Five-dimensional DT model as proposed in literature [31].

Author (year)	Application area	Methodology	Contribution	Implementation	Limitations
Sifat et al. (2024) [41]	Grid network	ML for state modeling with key features	Developed a DT foundation for DTEG	Applied to a microgrid	Principal component only
Jiang et al. (2022) [42]	Smart gird, system level and subsystem	A DT body of model OKDD is proposed	supports hierarchical complex system building	SG equipment: a 35 kV distribution network and a vacuum circuit breaker, 110 kV substations	lack of a functional application architectural model.
Fernandes et al. (2022) [43]	Distribution network	3D asset modeling	Physical asset virtual dynamic modelling using images	Densest region of Brazil	Interdisciplinary integration
Shen et al. (2023) [44]	Power system	Virtual Testbed Creation	Testbeds allow realistic digital twin generation	To accelerate development of DT-enabled applications in power systems	Not performed: DT adaptation, PT fault discovery, what-if scenario testing, online decision-making.
De lópez diz et al. (2022) [45]	Monitoring of three-phase power electronics converters	Particle swarm optimization and a genetic algorithm	Attained a low-cost and robust parallel digital-twin model	Application for a three Leg Neutral Point clamped converter is demonstrated	Data accuracy
Gui et al. (2023) [46]	Hierarchical coordinated control strategy for PV inverters in the low voltage grid	Automatic voltage regulation, VAR controller	Optimizes PV inverter reactive power outputs and grid voltage.	Low-voltage feeder located in Denmark	Communication connection failures, cyber-physical power grid assaults, and outside attack vectors
Yu et al. (2024) [47]	Grid connected photovoltaic systems	Swarm intelligence and grey wolf optimization algorithm	Tracks parameter changes to monitor PV grid-connected inverter health	PV system simulation, power forecast, and condition monitoring	Estimation methods of coupling parameters
Baboli et al. (2020) [48]	Smart grid	Artificial Neural Networks	Analyses time-varying load dynamics by system identification and nonlinear numerical optimization	Distribution grid	Requirement analysis, Trade-off analysis
Saad et al. (2020) [49]	Power system components and the communication topology	Amazon Web Service	Both low-bandwidth and high-bandwidth DT replicated CPS live status precisely	Cloud data management	Data Dependency and scalability
Peng et al. (2019) [50]	DC-DC power converters	PSO algorithm	Non-Invasive Monitoring, Experimental Validation	Capacitors and MOSFETs	Measurement and limitation error
Shajahan et al. (2022) [51]	Power System Protection	Deep learning-based differential protection using Convolutional Neural Networks (CNNs)	Developed a deep learning-based protection scheme that avoids feature engineering	Simulated using MATLAB/Simulink and Python	Real-time implementation challenges; generalization to multiple faults not tested
Maslo et al. (2024) [52]	Power System Training & Simulation	Dispatcher Training Simulator (DTS), Dynamic Model of Electric System (DMES)	Verified DMES against Digital Twin criteria for real-time simulation	Used by Czech TSO with real SCADA	Lack of full cyber-physical integration and digital twin scalability beyond training simulators

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IV. APPLICATIONS AND CHALLENGES OF DIGITAL TWIN

A. Applications

- *Automation:* Despite a growth in the application of DT principles, the majority of the current literature focuses on prototype testing and automobile production processes. The notion of the DT is an important facilitator of data-driven production. Important advantages include "increased productivity, reduced complexity, time savings, reduced cost, improved quality," as stated by the authors in [64]. Model-based systems engineering's functional representation of the vehicle is based on functional prototype twins wins.
- *Manufacturing:* The most recent developments in manufacturing are characterized by what is referred to as Industry 4.0, the fourth industrial revolution. By creating virtual replicas of their production lines and factories, DTs allow companies and industrial systems to test, improve, and optimize their operations in real time without interrupting output.
- *Education:* As a result of the COVID-19 outbreak, students and teachers throughout the globe have scrambled to find ways to keep learning even when schools are on lockdown. A large number of institutions eventually adopted the DT idea for education, which enabled students from across the globe to participate in a whole new paradigm of learning, but initially, the problem was substantial since not all institutions had platforms to support a digitalized education process. Smart learning environments with integrated data mining tools [60], customized adaptive learning frameworks, and the integration of IoT technologies are just a few of the solutions that have been suggested for the deployment and enhancement of digital twins in education.
- *S*mart Cities and Infrastructure: Using DTs in urban planning, building management, disaster response, and simulation of city infrastructure can optimize traffic flow, reduce congestion, and increase sustainability. Smart buildings also use DTs for energy efficiency, maintenance, and security.

B. Challenges:

1. Complexity and expense: Building and maintaining an electronic model of a power transformer might be a time-consuming and difficult task that calls for expert-level software and hardware. Therefore, it can be too expensive and not practical for certain power transformers, especially smaller or older ones. The *software for creating the DT, the software for integrating it, and the expense of education and training are all variables that affect the total cost of the DT.*
2. *Problems with communication networks:* Faster and more efficient communication technologies like 5G are urgently needed. According to [67], 5G is essential for smart cities as it connects more devices, offers high-speed internet, enhances reliability, and saves energy. It also enables real-time data sharing and improves operational efficiency for the DT.
3. *Concerning data availability and quality:* For a DT to function effectively, real-time data is essential for accurate simulation and prediction. If the data used is outdated, incomplete, or low quality, the DT's accuracy may suffer. Additionally, without real-time data, its usefulness decreases. A key challenge in the DUET Digital Urban Twin project was collecting the required data. Limited access to federal government data and privately owned datasets created hurdles in acquiring the necessary information.
4. *Existing-system integration:* To get most out of DTs, they can be combined with other systems like control and monitoring systems. However, this may require major system changes, which can be complicated and costly.

V. CONCLUSION

In recent years, DT technology has attracted substantial attention from both academia and industry. This technique is defined differently in the literature since it is used to describe diverse areas of study in different fields. The term "digital twin" refers to a system where data from both the physical and virtual parts of a machine are seamlessly integrated. In the aerospace and astronautics industries, NASA first used DT technology on the Apollo 13 lunar exploration mission and the Curiosity Mars Rover. The literature study demonstrates that digital twins are a rapidly expanding IT solution in many sectors due to their expanding scope and effect. By providing intelligent control, predictive analytics, and real-time monitoring, DT technology is quickly becoming an essential tool for updating power systems. Particularly important as power grids move towards distributed and renewable energy sources, DTs improve system dependability, efficiency, and flexibility by connecting the digital and physical realms. Digital twins are revolutionising grid operations and asset management with the help of technologies like the internet of things (IoT), AI, and cloud computing. However, there are still major obstacles to widespread adoption, including complicated integration, huge data needs, and insecurity concerns. Future work should concentrate on creating safe data handling procedures, scalable systems, and standardised frameworks. In order to construct power networks that are smarter and more robust, DTs need to be further studied, collaborated with, and supported by regulators.

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