International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(8s) 2026 pp. 242-262
https://doi.org/10.70917/ijcisim-2026-3231
Article

Review on Application of digital twins in the electrical power system

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Abstract: Recent years have seen the electrical power system an area of rapid change due to the significant interleaving electric vehicles. This complexity has grown to the point where there is an increasing need for intelligent solutions that can enhance the monitoring, operation and maintenance of the system. The review covers the research done in the past five years and gives a detailed summary of the Digital Twin concept applied in Electrical Power Systems industry. They can be combined to enable a wide range of applications such as real-time monitoring of systems, predictive maintenance, fault diagnostics, asset management, integration with renewable energies, and intelligent decision-making during operation.The reviewed studies prove advantages such as better operation efficiency, higher reliability of the grid, better planning of maintenance, lower operating costs and higher sustainability of the power system infrastructure. However, there are still a number of technical challenges that limit the widespread deployment, such as maintaining high quality data, cyber security, interoperability between different platforms, computational needs, as well as common standards to follow when putting it in place and integrating with legacy systems.
Keywords: Digital Twin; Electrical Power Systems; Smart Grid; Internet of Things (IoT); Artificial Intelligence; Predictive Maintenance; Renewable Energy Integration.

1. Introduction

Recent developments, including renewable energies, smart grid, DERs, EVs, and intelligent monitoring, have made power networks far more complicated. The era of traditional monitoring and maintenance, which is mostly based on off-line simulations and periodic inspection, is no longer enough to ensure reliable, efficient and resilient power system operation. In this context, the key requirements of electrical infrastructure are advanced digital technologies that enable real-time monitoring, predictive analysis and intelligent decision support (Dong, Luo and Meng, 2019; Zhou, Fu and Yang, 2016).

Digital twins continuously update their virtual models based on the changing operating conditions, allowing for real-time monitoring, fault diagnosis, predictive maintenance and system optimization, as opposed to traditional simulation models (Grieves and Vickers, 2017; Fuller et al., 2020; Barricelli, Casiraghi and Fogli, 2019).

Digital twin technology was born in manufacturing and product lifecycle management and has grown quickly to a number of engineering fields such as aerospace, healthcare, transportation, and energy systems. Digital twins for electrical power systems are now being employed in the modeling of generators, transformers, substations, transmission networks, distribution systems, renewable energy plants and smart grids. They are capable of integrating data from the sensors with artificial intelligence (AI), machine learning (ML), cloud computing, and the Internet of Things (IoT) to enhance asset management, operational efficiency, and system reliability (Tao et al., 2019; Correa-Florez, Michiorri and Kariniotakis, 2022).

The benefits of this are the ability to detect faults early, considerable saving on maintenance costs, increased equipment life and reduced unexpected outages. Moreover, digital twins can be used to enhance renewable energy integration through accurate energy generation prediction, energy management and grid stability under variable operating conditions (Wang et al., 2019; Zhao et al., 2023; Yang, Zhang and Wang, 2022).

These benefits, however, come with certain drawbacks such as cybersecurity concerns, data quality, interoperability, cost of implementation and integration with existing power systems (Khajavi et al., 2019; Mchirgui et al., 2024). So, it is important for researchers or utility operators to have a full grasp of digital twin technology.

This review chapter provides a complete survey of the digital twin applications in EPS. It includes an overview of the basic concepts, enabling technologies, key applications, advantages, challenges, and future research trends, offering a short overview of the current research and future potential opportunities of intelligent and sustainable power systems.

2. Fundamentals of Digital Twin Technology

2.1 Definitions of Digital Twin

A digital twin continuously synchronizes with the physical asset, with real-time data that allows continuous monitoring, analysis, prediction and optimization across various operating conditions, in contrast to traditional simulation models that are typically static and created for a particular operating scenario. Having sensing technologies, communication networks, computational models, and intelligent analytics allows digital twins to be a virtual living replica of a physical entity, as opposed to a traditional engineering model (Grieves and Vickers, 2017; Barricelli, Casiraghi and Fogli, 2019).

Operational parameters like voltage, current, temperature, vibration, pressure, frequency and environment are constantly gathered by sensors attached to physical equipment. These data are sent via communication systems to computational systems running mathematical models, artificial intelligence algorithms and simulation engines that physical asset. Digital Twins are intelligent decision making support systems that, through continuous feedback cycles, can boost operational efficiencies and decrease uncertainty (Fuller et al., 2020; Rasheed, San and Kvamsdal, 2020).

For electrical power systems, digital twins go beyond models of individual components, such as a transformer or a generator. They can simulate substations, transmission lines, distribution lines, renewable energy generators, battery storage facilities, microgrids, and even entire power systems. These comprehensive virtual environments provide real-time visualization of system dynamics and help utility operators assess operational strategies, optimize resource usage, and quickly and effectively react to unforeseen disturbances without causing disruption to real-world system operations (Correa-Florez, Michiorri and Kariniotakis, 2022; Zhang et al., 2022).

2.2 Evolution of Digital Twin Technology

Initial engineering models were mostly simulation models of physical systems under predefined operating conditions performed in an offline manner. These models were helpful for system design but couldn't reflect the changes of the system condition throughout the operational life time (Negri, Fumagalli and Macchi, 2017), and did not have the ability to update themselves with real time operational condition.

The idea was reinforced with the aid of aerospace technology, as a digital replica of spacecraft was created to enhance the performance of mission planning, maintenance, and fault detection. With the development of the Internet of Things (IoT), cloud computing, artificial intelligence, wireless communication and high-performance computing, the range of applications for digital twins has broadened considerably for various sectors in the manufacturing industry, transportation, healthcare, construction and energy industry (Glaessgen and Stargel, 2012; Grieves and Vickers, 2017).

Digital twin research was further spurred by the shift from Industry 4.0 to intelligent, cyber-physical production systems, which has made it possible to continuously interact with the virtual models and the physical production assets. Thus, digital twins have gradually developed into autonomous systems that can predict, optimise, diagnose and make intelligent decisions (Liu et al., 2021; Tao and Qi, 2019; Qi and Tao, 2018).

This growing digitalisation of power networks, the increasing number of smart sensors and the use of intelligent electronic devices in widespread use, as well as resources, paved the way for digital twin technology to be applied to contemporary power networks. Recent studies are pointing towards the construction of digital twins that can model the entire smart grid and at the same time incorporate operational, environmental, economic and cybersecurity data and information into a single platform for decision support (Song et al., 2023; Mchirgui et al., 2024).

2.3 Characteristics

Digital twins have a number of distinguishing features from traditional simulation models and other digital engineering technologies.

One of the differences that make digital twins unique is real-time synchronisation. By having continuous data acquired by sensors and a communication network, the virtual model will be true to the current operating condition of a physical asset. This real-time data sharing helps operators keep track of the system's ongoing operation and makes better decisions (Fuller et al., 2020).

However, a bidirectional flow of information is also another important feature. Digital Twins can not only pass the data from their physical counterparts, but also send the optimisation suggestions or control instructions to the physical systems. This interaction enables the operation of systems without the need of humans, intelligent control, and adaptive optimisation, especially in smart grid applications (Othman et al., 2023).

Predictivity is no exception for digital twins either. They estimate future operating conditions with a combination of historical operating data, machine learning algorithms, and physical system models, predicting equipment degradation, and even making predictions of possible failures before they occur. This predictive intelligence can enable utilities to transform from being reactive to condition and predictive maintenance programmes (Wang et al., 2019; Zhao et al., 2023).

Scalability is another important attribute. This flexibility enables utilities to implement digital twins as needed for their operations, and ensures interoperability at various levels of infrastructure (Correa-Florez, Michiorri and Kariniotakis, 2022).

2.4 Core Components of a Digital Twin

2.4.1 Physical Asset

The physical asset can be anything that is being monitored in the real world. Physical assets in electrical power systems are such as transformers, generators, transmission lines, substations, circuit breakers, PV systems, wind turbines, battery storage systems, and distribution systems. They continuously generate data in the form of operational data by embedded sensors and intelligent monitoring devices (Mansour et al., 2023).

2.4.2 Data Acquisition Layer

This layer will guarantee continuous collection of the set of electrical, mechanical, thermal and environmental parameters necessary to keep physical and virtual systems synchronized (Dong, Luo and Meng, 2019).

2.4.3 Communication Infrastructure

Stable communication networks are used to quickly transmit data from sensor to computation platform between physical assets. To enable low latency, secure data exchange, modern digital twins employ technologies like fibre-optic communication, wireless sensor networks, 5G communication, industrial Ethernet and cloud-based networking (Kabir et al., 2024).

2.4.4 Virtual Model

Combines mathematical equations, simulation algorithms, finite element models, machine learning models and operational databases, to accurately simulate the system's behavior. By continually updating the virtual model, the condition of the physical infrastructure is maintained in the virtual model (Thelen et al., 2022a).

2.4.5 Analytics and Intelligence Layer

It identifies abnormalities, can estimate the remaining useful life of the elements; it can predict the failures and recommend maintenance actions; it can optimise the operation of electrical networks (Arraez, Molina and Corchado, 2022).

2.4.6 Feedback and Decision Layer

The last piece allows to transform the analytical findings into decisions for action. Recommendations can be delivered to operators via dashboards and/or executed automatically via intelligent control systems depending on system configuration. To optimize the system in a way that can adapt to the changing environment and enable autonomous operation of future smart grids, it is essential to have continuous feedback (Yang et al., 2022).

2.5 Working Principle of Digital Twins in Electrical Power Systems

A closed-loop process that continuously collects data, models the virtual environment, analyzes the data intelligently, makes decisions and provides feedback. First, sensors placed throughout the electrical assets are constantly collecting data on the operational components, including voltage, current, frequency, power quality, temperature, vibration, insulation condition and environmental information. These measurements are sent to a RTI through secure communication systems to cloud or edge computing systems where the digital twin reflects changes in the virtual model in real time (Mansour et al., 2023).

Operating conditions are compared with historical data, engineering models and pre-defined operating limits to analyse the behaviour of the systems when synchronised, and then incorporate this into an artificial intelligence and simulation program. Anomalies are detected if the behavior differs from what is expected, allowing to determine the degradation of the equipment or instability of the system in early stages. Predictive algorithms also forecast future operating circumstances, enabling utilities to prepare for failures and optimise maintenance scheduling in advance of any critical failures (Zhao et al., 2023).

The digital twin then simulates various operational scenarios, without impacting the physical power system, to assess their performance. Before putting these or other maintenance plans, load balancing methods, renewable energy dispatch plans or emergency restoration techniques into practice, operators can test them in the virtual environment. This feature can greatly reduce the operational risk and enhance the reliability, efficiency, and resilience of electrical power systems (Kumari et al., 2023; Mchirgui et al., 2024).

Table 1. Fundamental Characteristics of Digital Twin Technology

Characteristic	Description	Significance in Electrical Power Systems
Real-time Synchronization	Continuous updating using live sensor data	Accurate monitoring of grid conditions
Bidirectional Communication	Data exchange between physical and virtual systems	Enables intelligent control
Predictive Analytics	Forecasts failures and equipment degradation	Supports predictive maintenance
AI Integration	Machine learning for intelligent decision-making	Improves fault diagnosis and optimisation
Scalability	Models individual assets to complete power grids	Flexible deployment across utilities

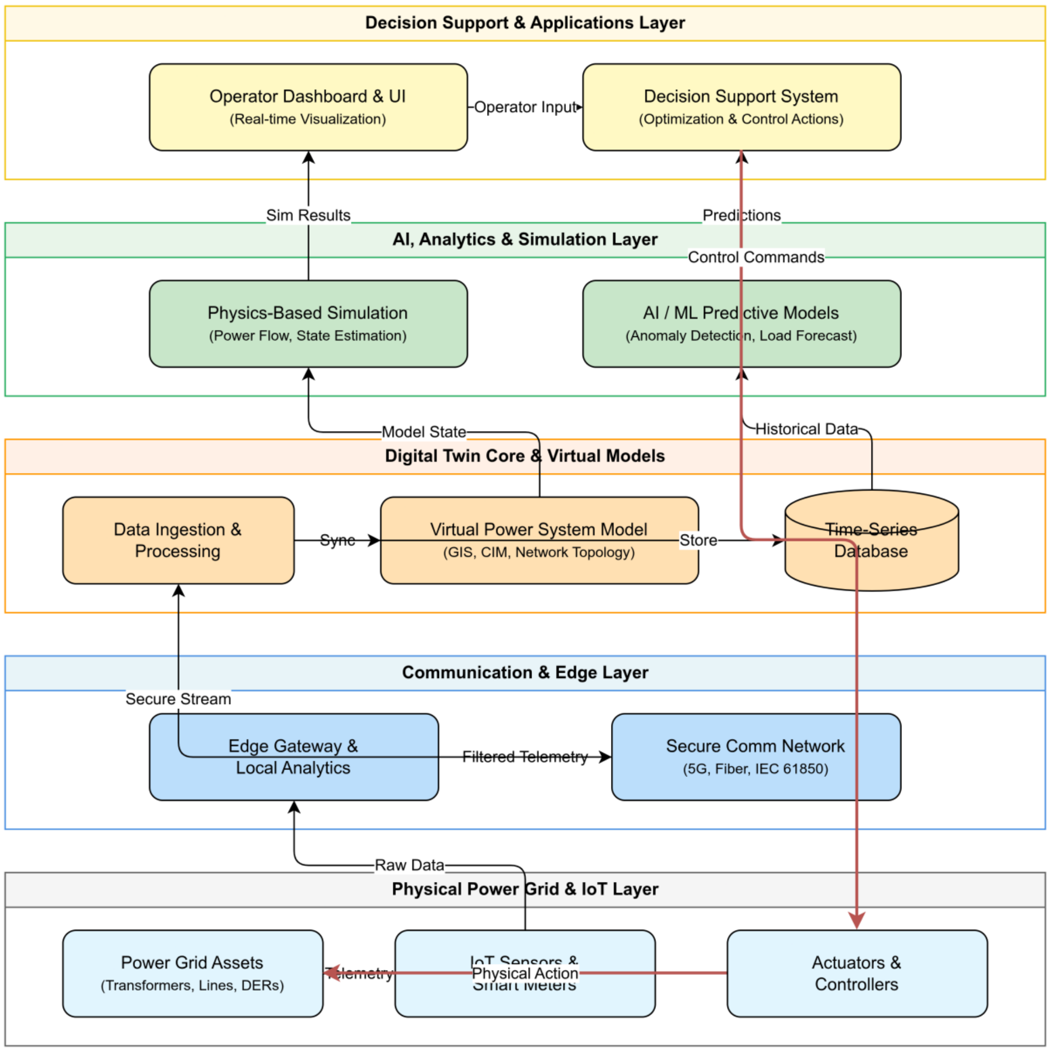

Figure 1. General Architecture of a Digital Twin for Electrical Power Systems

3. Enabling Technologies for Digital Twins in Electrical Power Systems

The success in an electrical power system relies on the ability to integrate different sensing technologies, communication networks, computational infrastructure, data analytics, and intelligent decision-making algorithms into a unified system. These enabling technologies enable continuous monitoring, real time data exchange, predictive analysis and autonomous operation between the generation, transmission and distribution and consumption stages of the electrical grid (Fuller et al., 2020; Rasheed, San and Kvamsdal, 2020).

Digital twins need a strong technological basis that can manage vast amounts of data, including heterogeneous data, while ensuring reliability, scalability and cybersecurity, especially as power systems are becoming more decentralized with the rise of renewable energy resources, distributed energy resources (DERs) and electric vehicles (EVs).

3.1 Internet of Things (IoT)

Digital twin continuously receives signals from parameters like voltage, current, frequency, power factor, temperature, vibration, humidity, insulation resistance, and environmental conditions, which are then synced with the physical infrastructure and provided to computational platforms.The signals received by the digital twin are: voltage, current, frequency, power factor, temperature, vibration, humidity, insulation resistance and environmental conditions, which are then synced with physical infrastructure and provided to computational platforms.

By implementing IoT, utilities can gain continuous visibility into conditions of their equipment and dramatically improve their situational awareness. In contrast to traditional inspection techniques that are based on maintenance programmes, IoT technology-based monitoring can alert utilities at the moment they detect the abnormal operation of equipment, which means a shorter outage duration and avoiding catastrophic equipment failure. Also, IoT can enable condition-based maintenance by providing real and precise operational data that is needed for predictive maintenance and remaining useful life estimation (Kabir et al., 2024).

But as more devices connect to the network, there are also significant volumes of diverse data which present issues of cybersecurity, power usage, device compatibility, and communications reliability. Thus the coordination and security of data transfer are significant issues in the successful implementation of IoT (Mohammadi et al., 2021).

3.2 Artificial Intelligence

AI algorithms convert these data into meaningful insights that can be used to help with operational decisions, predict failures, and optimize system performance.AI algorithms turn these data into meaningful insights that can help with operations decisions, predict failure and optimize system performance.

Machine learning algorithms look at past and current operating data and discover hidden relationships, categorize operating conditions, predict equipment health, predict electrical demand, and detect anomalies. Additionally, deep learning models can be used to learn complex nonlinear relationships that analytical models typically cannot, enhancing the accuracy of the predictions. Digital twins will continuously receive information from sensors and AI models will be able to retrain themselves as they receive new data, gradually increasing the accuracy of the predictions made (Arraez, Molina and Corchado, 2022).

In electrical power systems, AI-powered for variety of transformer fault diagnosis, load forecasting, predicting renewable generation, assessing voltage stability, performing dynamic security assessments, monitoring power quality, and intelligent energy system management. One of the most successful applications of AI in predictive maintenance is the use of algorithms to predict when and what type of maintenance or repairs are required before the equipment fails, which helps to reduce maintenance costs and increase system reliability (Yang, Zhang and Wang, 2022; Zhao et al., 2023).

Explainable artificial intelligence (XAI) is also seeing more important advances in recent years, especially in critical infrastructure where engineers demand visibility and not just a black-box prediction. The use of XAI in digital twins is increasing trust, increasing regulatory compliance and making easier for the operators of the utility network to adopt XAI (Arraez, Molina and Corchado, 2022).

3.3 Cloud Computing

A modern electrical grid has terabytes of information flowing through it each day and this information is generated by a variety of things, such as IoT sensors, smart meters, PMUs, SCADA systems, and weather monitoring stations. Cloud platforms provide scalable computing resources that will be able to process these data, and have remote access and centralized system management (Fuller et al., 2020).

Through the cloud, digital twins can allow utilities to bring together data gathered from assets in remote locations into a virtual environment. System-wide tracking and reporting of substations, transmission corridors, renewable energy plants and distribution systems are performed by engineers remotely without the need to be on site. Moreover, cloud computing can enhance the collaborative decision making process as it enables all parties to access the same operational information at any time (Khajavi et al., 2019).

However, these benefits come with certain drawbacks, such as latency concerns, data privacy issues, bandwidth requirements, and reliance on internet connectivity. Recent restrictions have spurred the research of alternative computing models and approaches that can process data near physical resources.

3.4 Edge Computing

For power systems, some of the operational decisions have to be made in milliseconds to ensure the stability of the system. These include protective relay operation, fault location, frequency control and voltage control.

Edge computing processes data at its point of origin to decrease communication delays, relieve network congestion and allow quick response in emergency operating conditions. The information is then summarized or relevant and passed on to cloud platforms for long term storage and sophisticated analysis. The distributed computational approach enhances overall efficiency and minimizes bandwidth usage (Kabir et al., 2024).

3.5 Big Data Analytics

Big data platforms give utilities the capability to analyze patterns of equipment degradation, customer demand, renewable energy variability, system disturbances and more over a range of temporal and spatial scales (Zhou, Fu and Yang, 2016).

Combining historical data with current measurements, advanced analytics can be used to complement predictive maintenance, energy forecasting, asset health monitoring, risk assessment, and operational optimization. Thus, big data is now an essential part of digital twin systems to intelligent power system management (Mohammadi et al., 2021).

3.6 Communication Technologies

In all digital twin applications, a reliable communication infrastructure is the foundation. Operational data needs to be transmitted without interruption to be synchronized continuously between physical assets and virtual models, thus securing, high-speed, low latency communication networks are required.

Today's electrical power systems use several sensor networks, industrial Ethernet, Wi-Fi, cellular communication and the new 5G communication systems. Compared to the fourth generation, the fifth generation of communication technology offers much larger bandwidth, ultra-low latency, increased reliability, and massive device connectivity, which is well suited for smart grid applications with thousands of devices that are connected simultaneously (Othman et al., 2023).

In addition to being used for data transfer, reliable communication is also necessary to provide geographically distributed control, operation, synchronized measurement and protection of electrical infrastructure.

3.7 Cyber-Physical Systems (CPS)

Computational elements interact continuously with the physical system via sensing, communication and intelligent controlling. Physical electrical equipment and digital computational models in CPS are not separate but rather a system.

The cyber layer is used for computation, communication, optimization and decision making and the physical layer is used for actual electrical operations. These layers interact continuously to allow the CPS to adapt autonomously to varying operating conditions and thus provide the crucial base for a smart grid that is intelligent (Al Faruque and Ahourai, 2015; Yang et al., 2022).

In a digital twin context, the CPS architecture allows the implementation of autonomous fault detection, adaptive voltage management, distributed energy management and intelligent recovery after disturbances.

3.8 Simulation and Mathematical Modelling

The mathematical representations model the behavior of the electrical system based on physical phenomena, including power generation, transmission, distribution, electromagnetic phenomena, thermal phenomena and mechanical dynamics.

Digital twin simulations are different to traditional simulations, which run separately of the actual system, as they continually adjust model parameters with real-time measurements taken during operation. This ongoing synchronization helps to make more accurate predictions and allows utilities to test a variety of modeled scenarios in advance to make decisions for the physical infrastructure (Thelen et al., 2022a).

Using a simulation-based digital twin, engineers can conduct contingency analysis, power flow optimization, transient stability analysis, fault propagation analysis and planning for integrating renewable energy without impacting real-time system operations.

3.9 Cybersecurity Technologies

Digital twins can be compromised as can the physical infrastructure that they represent due to unauthorized access, data manipulation, ransomware attacks, communication failures, and false data injection.

To achieve confidentiality, integrity and availability of operational data, modern digital twin architectures integrate techniques such as encryption, secure authentication protocols, blockchain-based identity management systems, intrusion detection systems, access control mechanisms, etc., and continuously monitor cybersecurity issues (Bécue, Praça and Gama, 2020).

The next generation of digital twin platforms will be enhanced by AI-powered cybersecurity solutions that will be able to identify advanced cyber threats at real-time and swiftly trigger counter-measures.

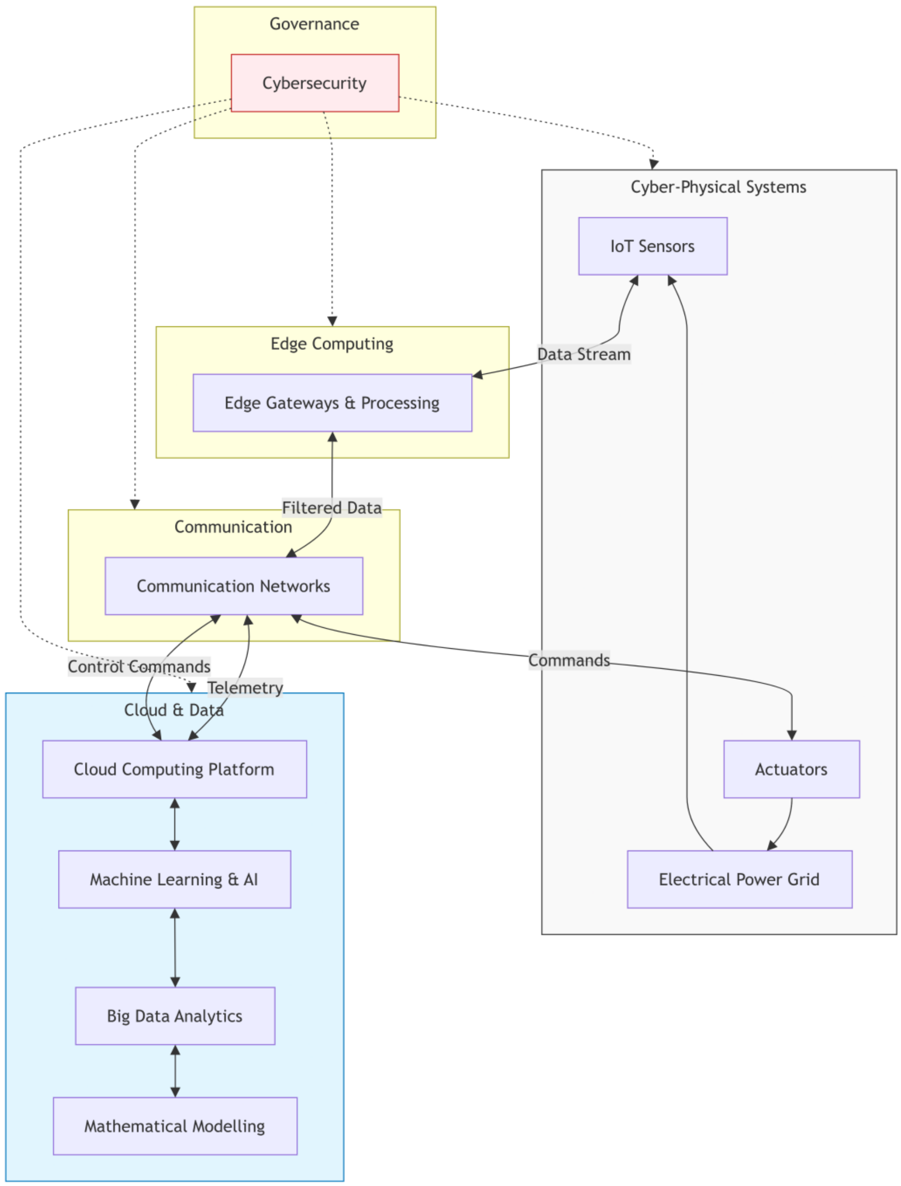

Figure 2. Enabling Technologies Supporting Digital Twin Implementation in Electrical Power Systems

4. Applications of Digital Twins in Electrical Power Systems

As electrical power systems become more digital an increasing number of digital twins are not just used for monitoring, but as smart platforms to support real-time operation, predictive maintenance, system optimisation, and autonomous decision making. Combining real-time sensor data, artificial intelligence, communication technologies and high fidelity simulation models, digital twins create a holistic virtual space that reflects the status of real power infrastructure in operation. These features have facilitated their adoption in most phases of the electrical power system, from power generation, power transmission, power distribution, integration of renewable energy, microgrids, electric vehicles, asset management, and predictive maintenance, among others (Correa-Florez, Michiorri and Kariniotakis, 2022; Mansour et al., 2023).

Conventional monitoring systems are reactive, as they only look for problems that have already happened; digital twins continuously monitor operational behaviour, predict future conditions of the system, assess the operating capabilities and put forward recommendations for optimal operating actions before problems arise. Thus, they have emerged as one of the critical enabling technologies that facilitate the shift towards smart grids that are becoming intelligent, resilient, and sustainable (Song et al., 2023).

4.1 Digital Twins in Smart Grid Management

Digital twin technology is expected to be an application hotspot, among others, in the smart grid. Smart grids nowadays incorporate distributed energy resources, renewable energy generation, and smart substations, advanced communication networks and consumers' engagement into a highly coupled cyber-physical system. Maintaining the control and monitoring of such complex infrastructure necessitates a continuous monitoring and controlling process which is often difficult to achieve with traditional supervisory systems.

These virtual models continuously monitor the grid conditions, estimate the health of the equipment, predict congestion, analyse voltage stability, evaluate multiple scenarios of operation before taking control action in the physical grid (Zhang et al., 2022; Othman et al., 2023).

In addition, digital twins can make electricity demand predictions, analyse consumption patterns and optimise the dispatch of electricity use over distributed resources, enhancing the effectiveness of demand-response programmes. An operator using scenario analysis can have a greater confidence that their scenario-based contingency plans would work in the event of contingency (whether it is extreme weather, equipment failure or sudden fluctuation in renewable energy supply) and so enhance the resilience and operational reliability of the grid (Mchirgui et al., 2024).

4.2 Applications in Power Generation Systems

Monitoring is a continuous process in power generation facilities that is necessary to optimize their efficient, reliable and safe operation. Traditional maintenance approaches are typically based on periodic checks and may lead to an absence of identifying any potential equipment issues or to conducting maintenance tasks that are not required. Digital twins mitigate these challenges by continuously analysing equipment behaviour based on operational data that is collected from generators, turbines, boilers, cooling systems and auxiliary equipment.

Thermal and hydroelectric power plants of track conditions like vibration, temperature, lubrication condition, rotational speed, pressure, and fuel use. Machine learning algorithms analyze the existing conditions and performance history to detect signs of mechanical wear and tear and efficiency decline early. This allows for maintenance personnel to carry out targeted maintenance before equipment failure before and decreases downtime and operation costs (Wang et al., 2019).

Weather forecasts along with equipment performance models can be combined to optimize power generation, schedule equipment maintenance and enhance the accuracy of power forecasting (Yang, Zhang and Wang, 2022).

4.3 Applications in Transmission Networks

Transmission assets are exposed to environmental effects and these are spread across a large geographic area, thus necessitating continuous monitoring to ensure reliability of the system.

Digital twins allow to continuously acquire electrical and environmental data and monitor transmission lines, towers, insulators, circuit breakers, transformers and substations in real time. Conductor temperature, line sag, wind speed, ambient temperature, current loading, vibration and insulation condition are among the parameters that are constantly analysed, giving an indication of asset health and operational risk (Mansour et al., 2023).

Dynamic line rating, for example, is one of the most important applications, in which the digital twin estimates the actual transmission capacity of an overhead line under real conditions, instead of the conservative static line ratings. This method can help utilities to achieve maximum transmission capacity with operation safety.

In this way the grid operators can be able to assess the restoration plan prior to the implementation of corrective measures, thereby minimizing the risk of widespread power outages (Correa-Florez, Michiorri and Kariniotakis, 2022).

4.4 Applications in Distribution Systems

The distribution networks are facing a lot of changes as distributed generation, rooftop solar schemes, battery storage, electric vehicles and smart meters have been increasingly penetrating the network. All of this has resulted in higher complexity and crossed power flows, making the traditional distribution management methods more difficult to apply.

Digital twins enable utilities to achieve full visibility of their distribution networks, as they continually connect all the data on these elements such as transformers, feeders, voltage regulators, protection devices, distributed generation, and consumer loads. Virtual models numerically simulate the voltage profiles, feeder loading, fault propagation and switching operations under various operating conditions (Dong, Luo and Meng, 2019).

With digital twins, engineers can test their expansion plans for networks, see which feeder configuration is best, optimise equipment placement, and determine the impact of predicted future growth in electricity demand, without harming existing infrastructure. Similarly, digital twins can aid in outage management by quickly pinpointing the fault location and suggesting best management strategies for restoration in order to minimize outage durations (Zhang et al., 2022).

4.5 Renewable Energy Integration

Digital twins are used to enhance renewable energy integration, leveraging historical energy generation data, real-time operational measurements, machine learning algorithms, and meteorological forecasts to predict future energy generation. Virtual simulations are used to test various dispatch methods, battery charging plans, and grid balancing approaches prior to their deployment in the real grid (Chavhan, Venkatesh and Singh, 2022).

Moreover, digital twins enable the best coordination of renewable power generation, battery storage and traditional power generation systems. The coordinated operation reduces renewable energy curtailment, stabilises voltages, increases the reliability of the grid and helps national decarbonising targets (Yang, Zhang and Wang, 2022; Kumari et al., 2023).

4.6 Microgrids and Distributed Energy Resources

Microgrids are small-scale power grids that can be used to generate electricity in a specific area or integrated into a larger network. This rise in their popularity has led to new opportunities for implementing digital twins as they are required to coordinate intelligently among the distributed energy resources.

Digital Twins continually monitor and control PV systems, wind turbines, diesel generators, battery storage systems, controllable loads, power electronic converters in a micro-grid. Digital twins can emulate various operating conditions to optimize energy scheduling, battery utilization, frequency control, and voltage control, as well as economic dispatch (Kumari et al., 2023).

A digital twin helps the operators to keep the system stable during an islanded mode by predicting the future load demand, renewable generation and battery state of charge. These capabilities greatly enhance the resilience of microgrids in the event of a utility outage or emergency operating condition.

4.7 Electric Vehicle Infrastructure

Electric vehicles (EVs) are being introduced which creates considerable uncertainty in the electricity demand because charging EVs occurs concurrently with other load demands and the charging process is a high power event. Digital twins offer smart solutions that enable the efficient management of EV charging infrastructure and reduce the negative effects on electrical distribution networks.

Digital twins incorporate live charging station data, electricity rates, battery specifications, traffic and weather information, and renewable energy sources to schedule charging and minimize peak demand. The utilities can then simulate future charging scenarios, see what network constraints may arise, and get an idea of the best places to install new charging infrastructure before deployment (Song et al., 2023).

4.8 Predictive Maintenance

One of the most useful areas of electrical power systems for predictive maintenance has become the digital twin. Typical preventive maintenance programs fail to take into account the condition of equipment, causing unnecessary maintenance or equipment failures.

Operational measurements taken from transformers, generators, motors, circuit breakers, cables and switchgear are continuously monitored through digital twins to monitor asset health. The machine learning algorithms include the use of vibration, temperature, dissolved gas analysis, electrical loading, insulation characteristics, and historical maintenance records to estimate equipment degradation (Wang et al. 2019).

The models are predictive and estimate critical equipment, allowing team to focus on the maintenance activities that are actually necessary rather than those based on a fixed maintenance schedule. Therefore, utilities save on maintenance expenses, save on equipment lifespan, increase reliability, and minimise outages (Zhao et al., 2023).

4.9 Asset Management

Utility companies today have thousands of assets that are connected and spread out over vast geographical areas. Managing assets effectively means continually evaluating the condition of the equipment, the risk of its operation, maintenance records, the cost of replacement and its service life.

Digital twins combine existing asset maintenance history with operational data and engineering models to produce complete health indices for assets. These indices are useful for utility managers to prioritize their equipment replacement efforts, allocate maintenance budgets and optimize long-term investment strategies (Mansour et al., 2023).

Continuous monitoring of equipment performance allows utilities to optimise the return on investment on equipment and lower equipment life cycle costs. In addition, virtual simulation helps to gauge possible maintenance strategies prior to implementation to enhance financial decision making.

4.10 Fault Detection and System Diagnostics

Protective schemes designs used in traditional fault detection rely on threshold methods which are able to detect a fault once the abnormal operating conditions are met.

By constantly comparing the behaviour of the system against the expected performance, based on virtual models, digital twins improve fault detection. Artificial intelligence algorithms detect very minor changes that often can indicate growing equipment defects, insulation deterioration, abnormal heating, PD activity or mechanical wear well before the equipment catastrophically fails (Arraez, Molina and Corchado, 2022).

Digital twins can also conduct root cause analysis, as they can simulate various failure scenarios in virtual environments, making it possible to evaluate multiple scenarios. Engineers can thus assess what is most likely to be wrong with the equipment and what the corrective action should be, before applying it to actual infrastructure, saving time and money in diagnostics and maintenance.

Table 2. Major Applications of Digital Twins in Electrical Power Systems

Application Area	Primary Objectives	Key Benefits
Smart Grid Management	Real-time monitoring and control	Improved grid reliability and resilience
Power Generation	Equipment performance optimisation	Increased efficiency and reduced downtime
Transmission Systems	Asset health monitoring	Dynamic line rating and contingency analysis
Distribution Networks	Network optimisation	Faster fault restoration and voltage management
Renewable Energy	Generation forecasting	Improved renewable integration

Microgrids	Energy scheduling and islanding support	Enhanced resilience and operational flexibility
Electric Vehicles	Charging optimisation	Reduced peak demand and grid congestion
Predictive Maintenance	Failure prediction	Lower maintenance costs and improved asset life
Asset Management	Lifecycle optimisation	Better investment planning
Fault Detection	Early anomaly identification	Faster diagnosis and reduced outage duration

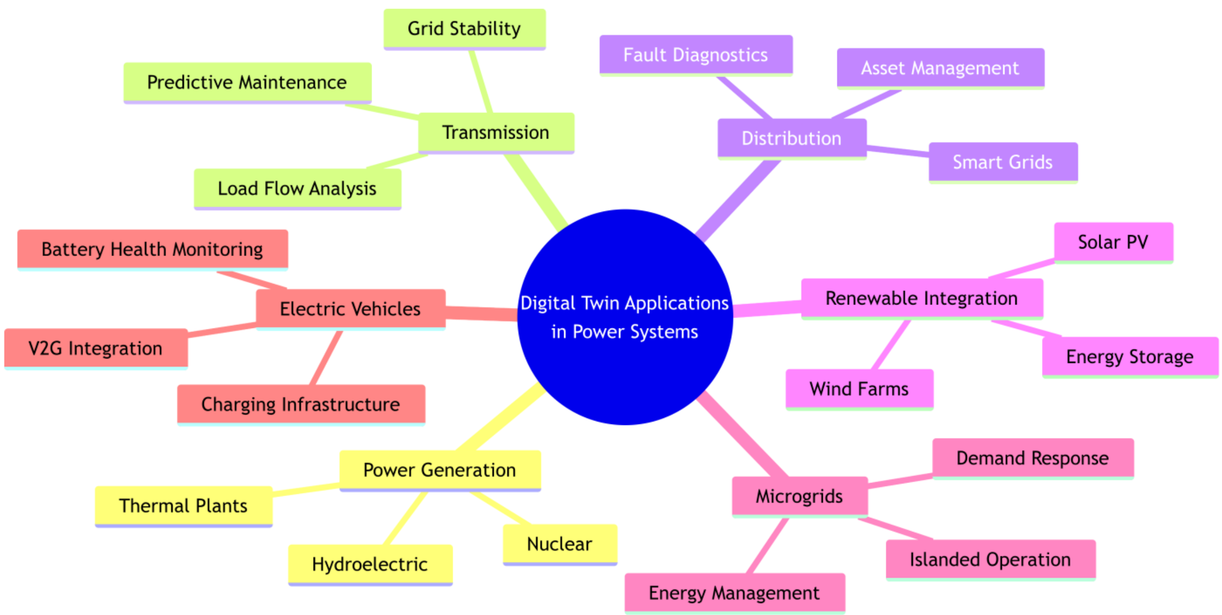

Figure 3. Major Applications of Digital Twins Across Electrical Power Systems

5. Benefits and Opportunities of Digital Twins in Electrical Power Systems

Technology has rapidly developed to revolutionize the way electrical power systems operate and are managed, offering utilities intelligent, data-driven tools to enhance efficiency, reliability, sustainability and decision making. Digital twins differ from traditional monitoring systems, which mostly record or capture live data, in that they produce constantly updated virtual environments, which allow for predictive analysis, optimisation of operations and autonomous management of the system. Therefore, utilities are increasingly finding digital twins as an important technology to support the digital transformation of a modern power infrastructure (Correa-Florez, Michiorri and Kariniotakis, 2022; Song et al., 2023).

They help save money in the economy by reducing maintenance expenses, they are environmentally friendly because they use resources efficiently, they make operations more resilient in case of emergency and in future they will allow for planning the grid when needed.

5.1 Real-Time Monitoring and Situational Awareness

The modern power network is comprised of geographically distributed assets in a highly dynamic environment. Monitoring with traditional methods is becoming more challenging as more and more devices are connected and generating a lot of operational data.

This simultaneous model helps operators have a view of the conditions of the equipment, track the power flow, analyse the voltage profile, identify abnormal operation and evaluate system performance at a central point (Mansour et al., 2023).

Real-time monitoring also helps to gain operational transparency, as it enables the engineer to be aware of the potential problem at an early stage and take appropriate action before it becomes a serious fault. Continuous visibility helps to facilitate quicker operational decisions, minimise uncertainty and ultimately improve the reliability of the grid (Fuller et al., 2020).

5.2 Predictive Maintenance and Reduced Downtime

Traditionally there have been two types of maintenance management strategies: corrective and preventive.Corrective or preventive strategies have always been used for maintenance management, and they are both limited. There is a possibility of unexpected equipment failures and extended outages associated with corrective maintenance, while preventive maintenance can involve replacing parts that are still operating.

The degradation and remaining useful life (RUL) of equipment are estimated by analysing operational variables like temperature, vibration, concentration of dissolved gases, electrical loading, the condition of the insulation and mechanical wear (Wang et al., 2019).

The early warning of failing equipment enables maintenance staff to plan for maintenance activities before equipment fails. This results in utilities with reduced unplanned outages, cost savings on maintenance, asset uptime, and extended asset lifecycle (Zhao et al., 2023).

Moreover, predictive maintenance reduces the need for uncalled-for inspections and enhances staff deployment as it allocates maintenance efforts to the parts with the greatest chance of failing.

5.3 Improved Operational Efficiency

The operational efficiency of the electrical power system is an important factor that digital twins can help with, as it can continuously optimise the performance of the equipment and the operation of the system. By simulating and analyzing, in real time, several operating scenarios without stopping physical infrastructure, utilities can assess a variety of scenarios.

The optimisation can minimize technical losses, optimize power quality, improve the use efficiency of equipment and increase the efficiency of the system (Yang, Zhang and Wang, 2022).

In addition, simulation based optimisation can be used to test a variety of operational options prior to implementation, thus minimising the uncertainty of operation and enhancing the quality of decision making (Correa-Florez, Michiorri and Kariniotakis, 2022).

5.4 Enhanced Asset Management

Electrical utilities have thousands of assets, with high valuations, spread out over large geographical areas. These assets need to be well managed and information about the condition of the equipment, its service life and history, and maintenance costs is essential.

Digital twins combine operational and engineering models and asset maintenance databases to deliver asset health assessments. Instead of just periodic inspections to assess asset performance, asset managers can make continuous evaluations which can lead to better informed decisions on asset maintenance schedules, equipment replacements and long-term infrastructure investment (Mansour et al., 2023).

Estimating RUL can help utilities to prolong the useful life of their equipment and not replace them too early. Thus, lifecycle management can be more cost effective and be integrated to the long-term investment planning.

5.5 Improved Grid Reliability and Resilience

As electric load keeps increasing, renewables keep coming onto the grid, climate-related disasters are becoming more common and the threat of cyber attacks is rising, power system reliability is becoming a more critical issue. Digital twins help to make things reliable, resilient, and helps to keep them monitored, analyzed and planned proactive.

Virtual simulations enable operators to assess several contingency scenarios, such as transmission line outages, transformer failures, fluctuations in renewable generation, cyber-attacks and natural disasters, prior to when they happen in real life infrastructure. This scenario analysis can help in effective emergency preparedness and speed up the post-disturbance restoration process (Mchirgui et al., 2024).

Moreover, digital twins can enhance the ability of smart grids to be self-healing by detecting abnormal operation conditions in a timely manner and suggesting corrective measures without affecting the stability of the smart grid system (Othman et al., 2023).

Table 3. Benefits of Digital Twins in Electrical Power Systems

Benefit	Description	Impact on Power Systems
Real-time Monitoring	Continuous synchronization with physical assets	Improved situational awareness
Predictive Maintenance	Early prediction of equipment failures	Reduced downtime and maintenance costs
Operational Efficiency	Intelligent optimisation of system performance	Lower energy losses and improved productivity
Asset Management	Continuous equipment health assessment	Extended asset lifespan
Grid Reliability	Faster fault detection and contingency planning	Improved resilience and service continuity

6. Challenges and Limitations of Digital Twins in Electrical Power Systems

The successful implementation of a precise and real-time digital copy of complex electrical infrastructure involves the merging of many technologies: IoT, artificial intelligence, cloud computing, communication networks, cyber security mechanisms and mathematical modelling. However, there are considerable challenges in implementing these technologies, especially in a large-scale utility network with thousands of interconnected assets, (Fuller et al., 2020; Rasheed, San and Kvamsdal, 2020).

A digital twin approach has shown some potential in predictive maintenance, asset management, and operational optimisation but there are many power utilities in the early stages of digital twin adoption because of implementation costs, data quality, interoperability, cyber-security, computational needs and organisational preparedness concerns. Solving these problems is crucial to enable the large-scale implementation and realize the potential of digital twin technology in future intelligent power systems (Mchirgui et al., 2024).

6.1 Data Quality and Availability

Digital twins continuously update with data from physical assets which means errors or incomplete data from sensors have a direct impact on predictions and reliability of decisions. The datasets are frequently missing, and may have communication delays, inconsistent sampling frequencies, measurement noise, and calibration errors, which can cause inaccuracies in the model (Kabir et al., 2024).

6.2 Integration with Legacy Power Infrastructure

A lot of electric power companies are still using old plant and equipment which were built well before the dawn of Industry 4.0 technologies. Proprietary communication protocols and only limited digital connectivity are sometimes implemented in existing transformers, substations, protection systems or distribution equipment.

These transitions to digital twin platforms are challenging technologically, as they need to be integrated. When using equipment from a variety of manufacturers with different levels of compatibility, utilities often experience problems. Lack of standardized interfaces makes the system more complicated and implementation costs are higher (Khajavi et al., 2019).

Adopting IoT sensors, intelligent controllers and communication gear for older infrastructure can also cause intermittent service disruptions, which could make the implementation massive in scale difficult for utilities whose operations are mandated to keep the lights on.

6.3 Cybersecurity and Data Privacy

Threats can include unauthorized access to the system, malware or ransomware attacks, false data injection, denial-of-service attacks, communication interception and modification of sensor measurements. Inaccurate virtual models, incorrect operational decisions, equipment damage or large-scale power outages, in the event of a successful attack, could lead to errors and damage to the system (Bécue, Praça and Gama, 2020).

6.4 Computational Complexity

This computational need is a significant challenge, especially for utilities with a national transmission network and/or large smart grid infrastructure.

Real-time synchronization demands high-speed processing of thousands of sensor measurements, frequent updates to mathematical models and the implementation of predictive analytics without compromising significantly the real-time performance. Increasing the complexity of the system, the virtual representation of it becomes more expensive in terms of computing resources, memory, and communication bandwidth (Thelen et al., 2022a, Kabir et al., 2024).

6.5 Model Accuracy and Validation

Electrical power systems have a highly non-linear behaviour that can be affected by varying loads, variability of renewable generation, equipment aging, changing environment and network topology changes. It is essential to include these dynamic interactions in the analysis by combining physics-based models with data-driven machine learning techniques, and to maintain consistency across the physics-based and machine learning modelling approaches (Thelen et al., 2022b).

6.6 Lack of Standardization

There are also no standards that are widely accepted that can be used to implement a digital twin in electrical power systems. Architectures and communication protocols, modelling approaches, and data formats may be proprietary and vary across a range of different utilities, equipment manufacturers, software vendors and research organisations.

Digital twin systems can be provided by a particular vendor for equipment from that vendor, but utilities will find themselves in a situation where digital twin systems by a different vendor are not readily able to communicate with systems from a different vendor (Mchirgui et al., 2024).

6.7 Economic and Financial Constraints

Sensors, IoT devices and communication systems, cloud platforms, cyber security, software development, computational power and staff training are the investments utilities must make.

However, small-scale utility companies, especially in the developing world, may have trouble financing the modernisation of existing infrastructure. Thus, cost benefit analysis is a crucial factor to be considered prior to the implementation on large scale (Khajavi et al., 2019).

Table 4. Major Challenges Associated with Digital Twin Implementation

Challenge	Description	Potential Mitigation Strategy
Legacy Infrastructure	Limited digital connectivity	Gradual infrastructure modernization
Cybersecurity	Vulnerability to cyber-attacks	Encryption, authentication, intrusion detection
Computational Complexity	Large-scale real-time processing requirements	Hybrid cloud-edge computing
Model Accuracy	Difficulty representing dynamic system behaviour	Continuous model updating and validation

Lack of Standards	Poor interoperability among platforms	International standardization initiatives
High Implementation Cost	Significant investment requirements	Phased deployment and cost-benefit analysis

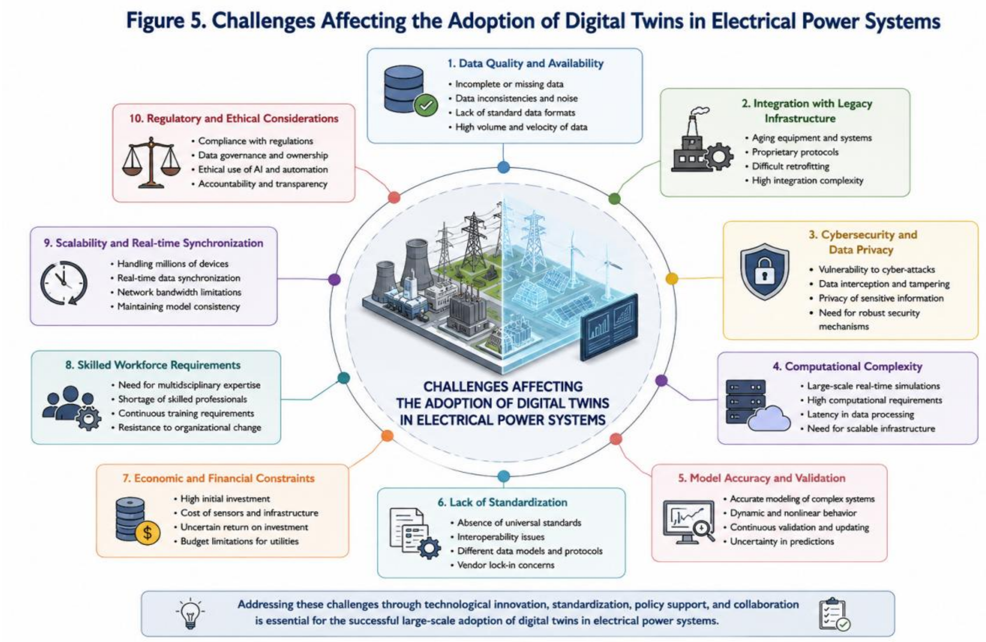

Figure 4. Challenges Affecting the Adoption of Digital Twins in Electrical Power Systems

7. Future Research Directions

Digital twin technology is rapidly developing and building a solid foundation for digital transformation of electrical power systems. But, the current implementations are mainly designed for monitoring equipment, predictive maintenance and visualization of operation. With the increasing decentralization, autonomy and data-richness of smart grids, future research needs to tackle the current technological challenges and investigate new solutions that can enable smart grids for intelligent, secure and sustainable energy. Potential revolutionary new technologies like explainable AI (XAI), federated learning, blockchain, quantum computing, edge intelligence, and Digital Twin as a Service (DTaaS) will also have an impact on the future of digital twin platforms (Song et al., 2023; Mchirgui et al., 2024).

7.1 Artificial Intelligence-Driven Digital Twins

AI has already made a crucial contribution to the digital twins by providing intelligent data analysis, anomaly detection, forecasting and predictive maintenance. But the future digital twin is likely to be more than a decision support system, as it will become autonomous and learn and adapt for optimization.

AI-based digital twins will develop analytical models continuously, based on the data fed to them in real time from operational data of electrical infrastructure. Without the need of pre-defined operational rules, reinforcement learning algorithms can optimise power dispatch, voltage regulation, battery scheduling and network reconfiguration. Likewise, the deep learning architectures that are able to process large scale heterogeneous data can provide much better predictions on equipment failures, renewable energy generation and electricity demand forecasting (Arraez, Molina and Corchado, 2022).

Another research area will be to design light weight AI algorithms for deployment on edge devices so that intelligent analysis can be performed nearer to the physical assets, which will help to reduce the latency of communication.

7.2 Explainable Artificial Intelligence (XAI)

While deep learning models have achieved great success in prediction, many models are considered "black-box" models in which the reasoning behind the decision is not easily understood. This lack of transparency is a great challenge for safety-critical applications like electrical power system operation.

The key to future digital twins is to take into account the Explainable Artificial Intelligence (XAI) techniques that will allow them to explain predictions, maintenance recommendations and operational decisions in a way that is understandable. The use of transparent AI models would help build operator trust, make the engineering of automated recommendations (Arraez, Molina and Corchado, 2022) easier and more straightforward, and aid in regulatory approval.

What is anticipated to be a crucial aspect of explainable AI is that the AI makes a decision, and the engineer can understand the reasoning behind that decision before the decision is put into practice in the application, such as in the case of an autonomous fault diagnosis, emergency restoration, protective relaying or intelligent control.

7.3 Federated Learning for Distributed Power Systems

The future electrical grids will be made up of millions of geographically spread intelligent devices producing vast amounts of data from their operation. The support of all these data in the cloud platforms can bring up some privacy issues, communication problems, and computation restrictions.

A potential alternative approach is federated learning, which enables the training of machine learning models locally at distributed substations, renewable energy and/or microgrids, but would only exchange and upload model parameters instead of raw operational data. This allows for the protection of data privacy, minimisation of communication needs and allows for collaborative learning between multiple utility organisations (Kabir et al., 2024).

Federated learning combined with digital twins could mean much more robust predictive maintenance models, and keep vital operational data close to the utility infrastructure.

7.4 Blockchain Integration

With the increasing exchange of operational data between digital twins according to interconnected electrical infrastructures, it is becoming more important to guarantee data integrity and safe information sharing.

Distributed ledger mechanisms provide a decentralised and tamper-resistant data management solution with blockchain technology. A digital twin platform could be used to validate equipment history, secure equipment maintenance records, ensure that measurements from sensors are trusted, and allow for trusted information sharing among utilities and renewable energy providers, regulators and consumers, in the future (Othman et al., 2023).

Digital twins based on the blockchain technology could be used to facilitate the trading of energy between two parties, decentralised electricity markets and secure coordination of distributed energy resources, while minimising the risk of data manipulation.

7.5 Digital Twin as a Service (DTaaS)

DTaaS allows utilities, especially SMEs to subscribe to cloud services for advanced simulation, predictive analytics, AI and visualization services. This approach saves on implementation costs, decreases software maintenance and increases scalability (Khajavi et al., 2019).

7.6 Integration with 6G and Advanced Communication Networks

While 5G (5th generation) communication systems make a significant contribution to the performance of digital twins with their increased bandwidth and decreased latency, future power systems will make use of communication technologies of the 6th generation (6G).

The 6G Networks will bring ultra-low latency, intelligent communication, integrated sensing, massive device connectivity and advanced edge intelligence. These features will enable the real-time synchronisation of physical assets to digital twins and the ability to operate the grid without human control and with significant dynamics (Kabir et al., 2024).

Future studies are needed into the communication architectures that can provide reliable synchronization for millions of electrical devices that are interconnected and spread across a national power grid.

7.7 Large Scale Optimisation using Quantum Computing

The modelling related to unit commitment, economic dispatch, transmission expansion planning, optimal power flow and contingency analysis can be very complex and often the answers yield a vast number of variables to solve. When working with very large-scale interconnected systems, conventional computation methods can be very time consuming.

While still in its infancy, quantum computing could be able to solve some optimisation problems much faster than classical computing. The ability to consider multiple operating scenarios at once with the help of quantum optimisation methods may also help enhance the decision-making speed and solution quality for complex power system management tasks in the future digital twins (Song et al., 2023).

7.8 Autonomous Self-Healing Smart Grids

The future digital twins are likely to incorporate AI, Edge computing, Distributed control systems, and sophisticated communication networks to constantly monitor system status, forecast disturbances, isolate faults, automatically restore power supply and optimise network operation (Yang, Zhang and Wang, 2022).

Table 5. Emerging Future Research Directions for Digital Twins

Research Area	Expected Contribution	Potential Impact
AI-Driven Digital Twins	Autonomous learning and optimisation	Intelligent grid operation
Explainable AI (XAI)	Transparent decision-making	Improved trust and regulatory compliance
Federated Learning	Privacy-preserving collaborative learning	Secure distributed analytics
Blockchain Integration	Secure and tamper-resistant data management	Enhanced cybersecurity and trust
Digital Twin as a Service (DTaaS)	Cloud-based digital twin platforms	Reduced implementation costs
6G Communication	Ultra-low latency synchronization	Real-time autonomous control
Quantum Computing	High-speed optimisation	Faster large-scale power system analysis
Self-Healing Smart Grids	Autonomous fault detection and restoration	Improved resilience

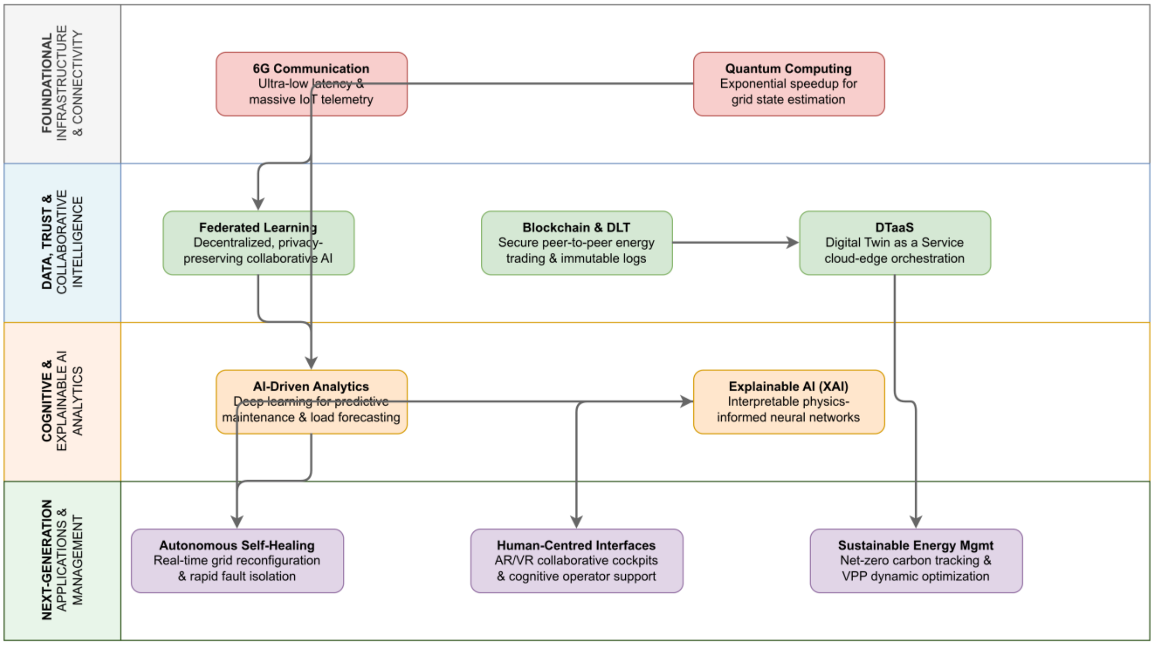

Figure 5. Future Research Roadmap for Digital Twins in Electrical Power Systems

8. Conclusion

However, with the advent of Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning (ML), Cloud Computing, Edge Computing, Big Data Analytics, and Cyber-Physical systems, the digital twin has moved beyond simulation as a tool to include an intelligent platform that can support the overall lifecycle of Electrical infrastructure (Fuller et al., 2020; Correa-Florez, Michiorri and Kariniotakis, 2022). The advantages of these applications are numerous, such as better situational awareness, better predictive maintenance, greater equipment reliability, lower operating costs, more efficient use of renewable energy, more optimal use of assets, and more intelligent engineering decision making (Mansour et al., 2023; Song et al., 2023).

The computational tools that are required for an accurate real-time representation of complex electrical systems are made available by advanced sensing technologies, high-speed communication networks, cloud-edge computing architectures, intelligent data analytics, and sophisticated mathematical models. These enablers are continually developing at a fast pace, and new opportunities for building increasingly intelligent and autonomous digital twin platforms (Kabir et al., 2024) are emerging.

Despite these benefits, there are still some problems which prevent the widespread use of these in realistic application scenarios. Topics on data quality, interoperability, integration with legacy systems, cyber security, computational complexity, model validation, standardisation, implementation cost, staffing up and regulatory compliance are current research areas. This will demand the joint effort of researchers, equipment manufacturers, software developers, utility companies, and regulatory bodies to ensure the adoption of common standards, greater interoperability, enhanced cyber security, and cost-effective implementation strategies (Khajavi et al., 2019; Mchirgui et al., 2024).

The review also highlighted a number of new research topics that are likely to guide future advancements for electrical power systems. The synergy of explainable AI, federated learning, blockchain, quantum computing, advanced communication and autonomous self-healing architectures in the electric grid has tremendous potential for enhancing the intelligence, scalability, transparency, security, and sustainability of the electric grid. Such new technologies are anticipated to change the digital twins from advanced decision support tools to fully functional operational platforms that can be used to manage increasingly complex electrical energy infrastructures with limited human involvement (Arraez, Molina and Corchado, 2022; Yang, Zhang and Wang, 2022).

In the future, digital twins are believed to be an important tool for smart grids, which will include renewable and distributed power generation, battery storage systems and electric vehicles, and will help to make energy systems more sustainable and carbon neutral. They are able to marry up operational awareness in real-time with predictive intelligence, making them important technologies for overcoming the technical, economic and environmental challenges of the next generation of electrical power networks.

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