Energy Conversion and Management: X 24 (2024) 100715

Contents lists available at ScienceDirect

Energy Conversion and Management: X

journal homepage: www.sciencedirect.com/journal/energy-conversion-and-management-x

Advancements in digital twin technology and machine learning for energy systems: A comprehensive review of applications in smart grids, renewable energy, and electric vehicle optimisation

Opy Das [a], Muhammad Hamza Zafar [a], Filippo Sanfilippo [a,b,*], Souman Rudra [a], Mohan Lal Kolhe [a]

[a] Department of Engineering Sciences, University of Agder, Grimstad 4879, Norway
[b] Department of Software Engineering, Kaunas University of Technology, Kaunas 51368, Lithuania

ARTICLE INFO

Keywords:
Digital twin
Machine learning
Smart Grid
Real-time data communication
Power system digital twin
Renewable energy
Electric vehicle

ABSTRACT

The growing interest in Digital Twin (DT) Technology represents a significant advancement in academic research and industrial applications. Leveraging advancements in Internet of Things (IoT), sensors, and communication devices, DTs are increasingly utilised across different sectors, notably in the energy domain such as Power Systems and Smart Grids. DT concepts facilitate the creation of virtual models mirroring physical assets, streamlining real-time data management and analysis. Driven by the potential of DTs to revolutionise energy systems, this paper offers a comprehensive review of DT applications in the power sector, specifically within next-generation energy systems like Smart Grids. TThe integration of DT technology with Machine Learning (ML) algorithms is highlighted as a key factor in significantly enhancing the performance and capabilities of these advanced energy systems. In contrast to prior reviews, our study meticulously investigates all of the crucial components of energy systems, including forecasting, anomaly detection, and security, which are fundamental for improving the management of operational grids. In addition, the study examines the seamless incorporation of Renewable Energy into current grids and investigates how DT technology could contribute to Electric Vehicles for increased sustainability and reliability within the Smart Grid framework. This review underlines that DTs significantly enhance the management of real-time data and analysis, consequently improving operational grid management. There are ample opportunities into further research and development to design a more advanced and digital system as compared to conventional power systems. The findings are presented in clear and concise tables, highlighting current limitations, proposing effective solutions, and identifying potential future research directions in academia and industry.

1. Introduction

The energy sector is currently undergoing a massive technological transition becoming more sustainable, reliable, and efficient. There is a greater emphasis on renewable energy to combat climate change. Smart Grids (SGs), Electric Vehicles (EVs), Grid Management Systems (GMS) are merging mainstream research topics. Additionally, the application of Digital Twins (DTs) in these areas is gaining substantial attention due to their ability to facilitate faster decision-making through comprehensive and optimal management. The method of power generation has remained largely unchanged over the past century, with coal, nuclear, or hydro-power plants transmitting electricity to substations and transformers via transmission lines. Because energy travels at close to the speed of light, every kilowatt must be used as soon as it is generated. For utilities, this requires balancing enormous loads to match supply with demand quickly and effectively. When demand surpasses supply, power outages occur, requiring backup power plants to provide electricity at short notice. Keeping these power plants operational was once the most expensive aspect of electrical grid. Since the 1980s, conditions have changed, and the power system has become smarter, with utilities installing sensors in key locations. These sensors provide real-time data regarding energy consumption, providing utilities with insight into the supply and demand sides of the equation. As sensors become more affordable and technologies such as the internet and wireless

* Corresponding author.
E-mail address: filippo.sanfilippo@uia.no (F. Sanfilippo).

https://doi.org/10.1016/j.ecmx.2024.100715

Available online 20 September 2024

communication become more widely available, utilities are connecting more sophisticated sensors to the grid, resulting in a growing volume of data. This inundation of data is utilised to locate power outages and enhance the efficiency of electricity transitions, resulting in more streamlined and effective energy management overall. This shift in the energy sector introduces technological advancements such as Digital Twins (DTs).

Michael Grieves first presented the concept of a DT during his partnership with NASA's John Vickers. Grieves introduced this new notion of 'Digital Twin' in 2003 during a lecture on product life-cycle management [1] and the last decade has seen rapid advancements in DT technology. The initial application of Digital Twins (DTs) was in the aerospace industry. The concept of the 'twin' was first implemented by NASA's Apollo space programme. Two comparable space vehicles were constructed for the purpose of mirroring, simulating, and predicting the conditions of the other vehicle in space. The vehicle that remained on Earth was an identical twin of the vehicle that carried out the space mission [2].

The integration of cutting-edge sensor technology and advanced analytical methods, such as Machine Learning (ML) and Artificial Intelligence (AI) has facilitated the adoption of Digital Twin (DT) technology within power systems. DTs offer promising solutions to core issues faced by power systems, significantly enhancing their resilience, efficiency, and reliability. The evolution of electrical grids into smart grids, which enable bidirectional communication between grid networks and consumers, relies heavily on the implementation of DT technology. In smart cities, where Distributed Energy Resources (DERs) are prevalent, DTs are crucial for efficient management. They play a vital role in improving forecasting accuracy for intermittent renewable energy sources and detecting faults within Smart Grids (SGs). However, the increasing number of sensors introduces significant cybersecurity concerns. Integrating ML algorithms with DT technology provides the capability to detect anomalies in real-time, thereby mitigating potential hazards associated with cyber attacks. Ensuring effective communication between users and grids is also essential to optimize the functionality of smart grids. DTs empower customers to make informed decisions about their use of electrical equipment based on personal preferences and requirements. Moreover, this advanced approach is utilized for grid management, power system control and analysis, and health condition assessment of power tools. With the growing emphasis on sustainable energy sources, the transportation sector is also undergoing significant changes. The introduction of Electric Vehicles (EVs) has led to a substantial shift in people's perception of transportation. DT technology is employed to enhance the management of EVs, including optimizing charging processes, conditioning battery health, and predicting the State of Charge (SOC) and State of Health (SOH) of batteries.

1.1. Motivation

The current study presents a critical review of recent researches conducted on DT applications within the Energy Sector, encompassing both conventional power systems and smart grid systems. Significant gaps exist in the existing research on DT applications in the energy sector, as Table 1 illustrates. Previous studies often lack a comprehensive approach, failing to address the full spectrum of the energy sector, including the rapidly growing fields of renewable energy and electric vehicles. Furthermore, not enough research has been done on the potential integration of DT and ML in critical domains like forecasting, fault detection, grid security, and grid management. This article thoroughly examines the utilisation of DT technology alongside ML in this domain. By offering an extensive overview of the dynamics of the current energy system and the breakthroughs made possible by the application of DT in conjunction with ML, our research aims to bridge these gaps. Our study aims to provide a thorough analysis and synthesis of the current state and possible future advances in DT applications by spanning the whole energy sector, including renewable energy and electric vehicles. In doing so, it will be possible to steer future research and implementation efforts towards the creation of more robust, efficient, and intelligent energy systems by highlighting accomplishments as well as identifying areas that require additional investigation.

1.2. Contributions and paper organisation

An exciting opportunity has emerged to create Power System Digital Twin (PSDT) by combining existing digital twins. PSDT can revolutionise various aspects of smart grid management. The key contributions of this research are:

- Offers an in-depth analysis of Digital Twin applications within the energy sector, encompassing renewable energy and electric vehicles;
- Identifies critical gaps in existing research, especially the lack of a comprehensive approach in utilising DT technology across the energy sector;
- Highlights unexplored areas where DT can significantly enhance forecasting, fault detection, grid security, and grid management;
- Investigates the synergy between Digital Twin and Machine Learning to advance predictive analytics and optimise system performance;
- Suggests a framework for future research and implementation, directing efforts towards creating more robust, efficient, and intelligent energy systems;
- Explores the potential benefits of DT applications in boosting the reliability and efficiency of energy infrastructures;
- Provides valuable insights into how integrating DT with RE and EVs can contribute to a sustainable energy future.

Table 1
Research gap in the prior research works.

Year	Reference	Forecasting	Fault Detection	Security of Grid	Grid Management	RE	EV
2023	[3]	✓	✓	✓	✓		
2017	[4]		✓				
2020	[5]	✓				✓	
2020	[6]		✓				✓
2019	[7]	✓		✓	✓		
2021	[8]					✓	
2021	[9]			✓			
2020	[10]			✓			✓
2022	[11]			✓	✓		
2021	[12]		✓	✓	✓		
2021	[13]				✓		
2021	[14]						✓
2020	[15]				✓		
2022	[16]				✓		
2023	[17]				✓	✓	
2024	Presented	✓	✓	✓	✓	✓	✓

The paper is structured as follows. Section 2 provides an overview of DT technology, while Section 3 delves into the various types of ML techniques commonly associated with DT. Section 4 presents the application of DT in Power Systems, followed by a brief discussion on the potential applications of DTs in smart grid realms in Section 5. Section 6 addresses the challenges associated with the development of DTs. Finally, Section 8 presents the conclusion. The structure of this work is depicted in Fig. 1.

2. Digital twins

There has been a significant increase in interest in DT technology over the past few years, both in academia and industry. This has resulted in an expansion of relevant publications, processes, and concepts developments. DT technology is a groundbreaking innovation that creates a bridge between the physical and digital worlds [18]. It involves the creation of a digital replica of a physical entity or system. This digital replica can simulate, predict, and analyse behaviours and dynamics in the physical counterpart, offering insights that were previously difficult or impossible to obtain [19]. The key concepts around DT technology are summarised in the following:

- **DT Prototype:** it consists of all the crucial and pertinent virtual data regarding the physical qualities of a prototype product—properties, designs, parameters, etc.—to facilitate the production of the digital twin.
- **DT Instances:** DT instances are specific instances of a product that are usually linked to its physical counterpart for the course of the physical counterpart's life.
- **DT Aggregates:** the DT aggregate is a compilation of all DT instances and aggregates.

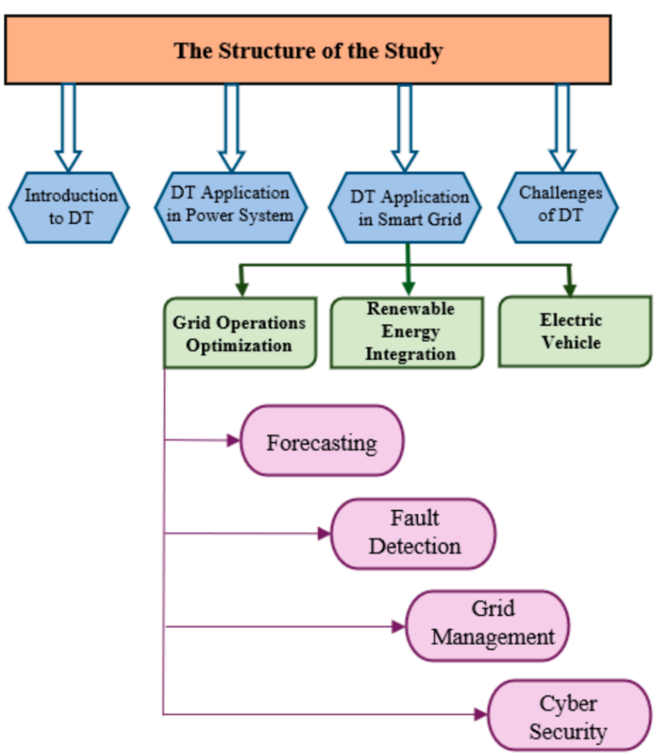

Fig. 1. Structure of the Study on Digital Twin Technology Applications in Power Systems, including Key Areas of Grid Operations Optimisation, Renewable Energy Integration, and Electric Vehicles, with Focus on Forecasting, Fault Detection, Grid Management, and Cybersecurity.

- **DT Environment:** it consists of all the hardware and software components employed to simulate the virtual designs of the physical models [20].

The fundamental principles behind DT technologies, as explained above, are visually depicted in Fig. 2. This figure depicts the interconnections between various components, including the DT Prototype, DT Instances, DT Aggregates, and DT Environment. Notably, DT prototypes and DT instances incorporate files in Extensible Markup Language (XML) and JavaScript Object Notation (JSON) formats, enabling enhanced data management for digital twins.

A DT is a coordinated representation of the digital model or pattern which reflects a particular phase in the life cycle of a physical system. In the field of renewable energy, detecting faults in solar photovoltaic (PV) cells is an essential issue in increasing system efficiency. PV system defects may be caused inadvertently by a number of factors, including cell degradation, mismatched modules or cells, and deterioration of encapsulation materials [21]. Monitoring these issues within specific solar systems provides a better understanding of overall system performance. A detailed model of the PV system can be developed by constructing digital instances of individual modules or cells and combining them into a DT environment. This approach allows for the early detection of defects in PV systems, enhancing overall system reliability and performance.

DT technology leverages Internet of Things (IoT) data, artificial intelligence (AI), machine learning (ML), and analytics to provide real-time and predictive data analyses. Core Components of this technology are elaborated below:

- **Data Integration:** data is the fundamental element of a DT. For the purpose of gathering comprehensive data for the DT, it is advisable to select sensors, gauges, Radio Frequency Identification (RFID) tags and readers, cameras, scanners, and other similar devices. The data should be transmitted promptly, either in real-time or with little delay;
- **Simulation and Modelling:** uses advanced simulation tools to model behaviours under various scenarios. DT simulation allows for bidirectional interaction between virtual models and physical entities in real time;
- **Analytics and Intelligence:** applies AI and ML for predictive analysis, anomaly detection, and optimisation;
- **Visualisation:** offers user-friendly interfaces and visualisation tools to interpret the data and simulation results.

Fig. 3 depicts the extensive relationships between physical assets and the DT idea, offering important understanding of the interactions and coordination of various sub-systems. In the context of real-world assets and systems, this visual representation provides a fundamental framework for understanding the dynamics and complexities associated with DT technology. The integration of DT into the domain of the power sector or smart grid has increased the compactness of the systems. The power system is inherently complex, and the addition of numerous new technologies and sensors makes it even more challenging to monitor. However, the primary consideration regarding the Power System is to ensure reliability in all situations. In the past, monitoring and control of this exceedingly intricate systems were extremely laborious. With the integration of DT and the powerful analytical capabilities of ML, new possibilities have emerged to enhance and strengthen it. Also, as the energy system is currently shifting towards renewable energies, there is a substantial need to effectively incorporate these green energy sources into the existing energy sources. The primary challenges related to renewable energy sources lie in their intermittent nature. Fortunately, the use of DT technology now allows for more accurate prediction and forecasting, but it still needs a lot of improvements, and a significant amount of research has already been done in this area.

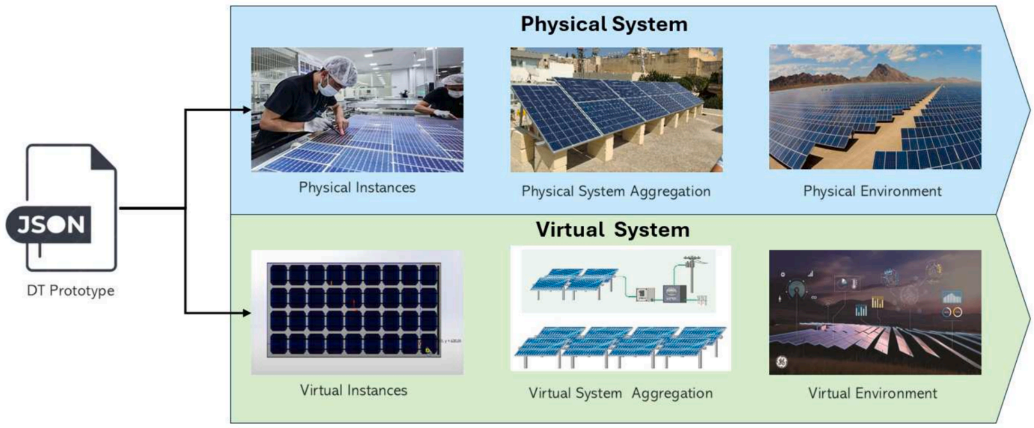

Fig. 2. Key Concepts of Digital Twin Technology in Physical and Virtual Systems which demonstrates the relationship between physical systems (instances, aggregation, environment) and their corresponding virtual systems (instances, aggregation, environment).

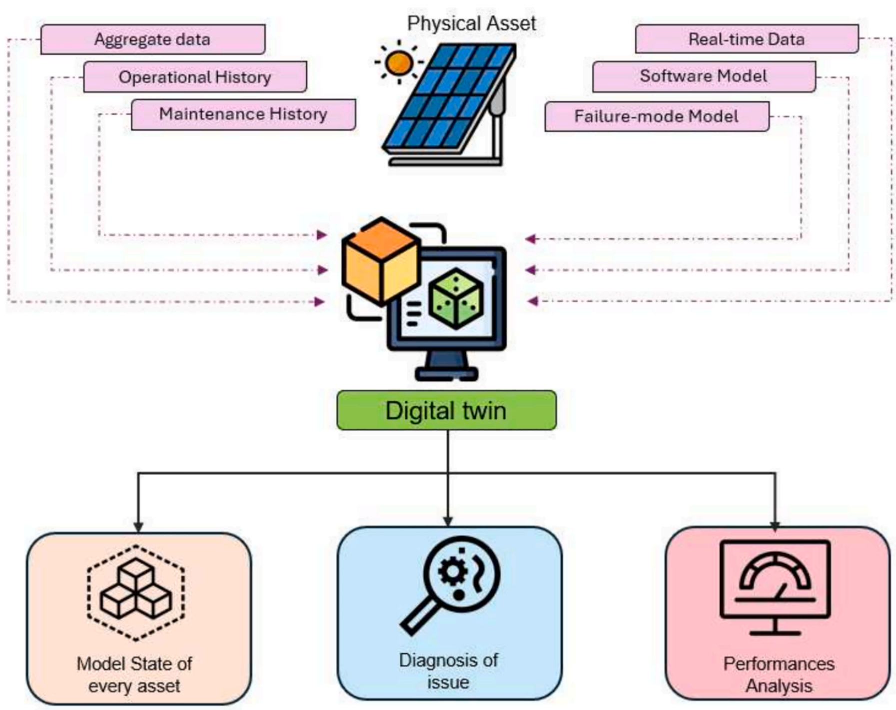

Fig. 3. Relationship between physical asset and Digital Twin concept highlighting how data from physical assets, including operational and maintenance history, real-time data, and failure models, are integrated into a Digital Twin for asset modelling, issue diagnosis, and performance analysis.

3. Machine learning in digital twin

The power sector is undergoing significant changes in accordance with developments observed across various industries. Researchers are currently involved in developing predictive models to facilitate the transition to a digital era for the entire power system. Due to the large amount of data in power systems, there has been a significant focus on using ML methods to efficiently handle big data challenges. ML has the unique capacity to examine large datasets and identify patterns, trends, and anomalies that might otherwise go undetected using traditional methods. The integration of machine learning with DT technology increases its impact by enabling instantaneous monitoring, analysis, and optimisation of power systems. ML algorithms also play a crucial role in optimising grid operations and energy management. Through the analysis of historical data in conjunction with up-to-date information, machine learning plays a role in improving the efficiency of power generation, distribution, and consumption. There are different types of ML algorithms like Supervised, Unsupervised, Neural Network, and Reinforcement Algorithm that are being used in power systems and smart grids.This review paper mentions numerous algorithms, which are categorised by their machine learning types in the Table 2.

3.1. Supervised learning

Supervised Learning (SL) is a machine learning approach in which a model acquires knowledge from a dataset that has previously been labelled with precise responses. This approach employs a dataset that comprises input–output pairings. The input is represented as a feature vector that reflects the data, while the output provides the appropriate category based on those features. The model uses this labelled dataset during training to learn the correlation between inputs and outputs. Over time, the model fine-tunes its internal parameters to minimise the

Table 2
Types of machine learning algorithm used in power system.

Supervised	Unsupervised	Neural Networks	Reinforcement Learning
Decision Tree Classifier (DTC)	Modified Mutual Information (MMI)	Factored Conditional Restricted Boltzmann Machine's (FCRBM)	Model-Free Reinforcement Learning (RL)
Logistic Regression (LR)	K-means clustering	Modified Teaching–Learning Algorithm (MTLA)	Proximal Policy Optimisation (PPO)
Support Vector Machines (SVM)	Hidden Markov Model (HMM)	Temporal Convolution Network (TCN)	Interpretable Machine Learning
Naïve Bayes (NB)	Principle Component Analysis (PCA)	Long Short-Term Memory (LSTM)	
K-Nearest Neighbor (KNN)	Ensemble Learning	Stacked Denoising Auto-encoders (SDAs) with Support Vector Regression (SVR)	

discrepancy between its predictions and the actual labels in the training data. This repeated approach enables the model to acquire knowledge and enhance its capacity to make precise predictions or classify new data. Various algorithms and computations techniques are used in supervised machine learning processes. Some of them are discussed following:

- **Decision Tree Classifier:** Decision Tree Classifiers (DTC) operate in an approach that is analogous to flowcharts. The process starts at the root node and advances through decision points, which divide into two leaf nodes that represent different outcomes. These decisions can also serve as decision nodes, branching out further until they reach final outcomes. Decision trees are easily comprehensible and may be visually represented, which helps in understanding the process of making decisions;
- **Support Vector Machines:** Support Vector Machines (SVM) are multi functional learning algorithms that are applied to tasks involving both classification and regression. In order to distinguish between classes, they determine which hyperplane maximises the distance between the closest data points of opposing classes. This hyperplane is crucially determined using support vectors, which consist of data points that are closest to the decision boundary. SVM handles high-dimensional data exceptionally well and can account for both linear and nonlinear relationships;
- **Naïve Bayes:** Naïve Bayes (NB) is a popular classification algorithm based on Bayes' theorem with the assumption of independence among predictors. Naïve Bayes algorithms calculate the probability of a data point belonging to a particular class based on the observed features. The algorithms use Bayes' theorem to calculate the posterior probability of the class given the features. Naïve Bayes often performs well in practice, particularly in text classification tasks such as sentiment analysis, spam detection, and document categorisation;
- **K Nearest Neighbour:**In classification scenarios, K Nearest Neighbour (KNN) computes the class label of a new data point by evaluating the class labels of its closest k neighbours. The label appearing most frequently among these neighbours is then allocated to the new data point. In regression problems, KNN estimates the value of a new data point by averaging the values of its k-nearest neighbours. The choice of k value is critical in KNN since it determines the complexity and smoothness of the decision boundary or regression functions;
- **Logistic Regression** The Logistic Regression (LR) method is applied to the forecasting of categorical outcomes. The process involves developing a linear model to predict the log-odds, denoted as logit, of a positive class instance. The logistic function, which is also referred to as the sigmoid function, converts the output of the linear model into probability estimates. By mapping these estimates between 0 and 1, the probability of belonging to a particular class is then denoted. Smart grid applications make extensive use of logistic regression, specifically for fault classification and cyber security duties.

3.2. Unsupervised learning

Unsupervised learning is a machine learning methodology in which algorithms identify patterns solely from unlabeled data, in contrast to supervised and semi-supervised learning approaches. These algorithms aim to identify hidden frameworks, relationships, or patterns in datasets that lack predetermined labels or target variables. Unsupervised learning tasks include grouping, reduction of dimensionality, and anomaly detection. It is useful when labelled data is missing or when investigating data for underlying ideas and trends. Unsupervised learning has a wide range of applications in smart grids, including grid line failure and detection of anomalies, load monitoring, and power quality monitoring:

- **K-means Clustering:**K-means clustering is a prevalent unsupervised machine learning technique that partitions a dataset into a predefined number of clusters. The process commences by randomly assigning K centroids from the cluster to the feature space, where K represents the desired number of clusters. Subsequently, it assigns every data point to the closest centre and modifies the placements of the centres. This process is iterated until reaching convergence, leading to the formation of K clusters;
- **Principal Component Analysis:** Principal Component Analysis (PCA) is a technique that decreases the dimensionality of datasets by extracting key features and removing redundant information. PCA uses a linear transformation to generate new data representations known as "principal components." The first main component captures the dataset's highest variance. Subsequent principal components maximise variance while remaining orthogonal to one another, maintaining independence. This iterative procedure continues, resulting in orthogonal orientations that maximise variance in the dataset;
- **Modified Mutual Information:** Modified Mutual Information (MMI) is important in the field of smart grid load forecasting since it extracts critical data and features required for short-term load prediction. MMI is intrinsically connected to mutual information, a concept used to measure the amount of information exchanged between two stochastic variables. Mutual information measures the reduction in uncertainty for one variable when knowledge of the other variable is accessible. This measure provides useful insights into the relationships and dependencies between variables in a dataset, allowing for better understanding and prediction of future load requirements in smart grid systems.

3.3. Neural networks

In machine learning, a neural network is a computational model based on the structure and functioning of the human brain's neural networks. It is composed of interconnected nodes known as neurons or units that are organised into layers. Typically, there is an input layer, one or more hiding levels, and one output layer. Each artificial neuron in a neural network receives input, executes computations with weights and thresholds, and produces an output. The output of one neuron is used as the input for the next neuron in the network. The strength and significance of neural connections are determined by their weights and thresholds. These networks are trained with training data to learn and improve their accuracy over time. Neural networks have numerous applications in the smart grid domain:

- **Long Short-Term Memory:**Long Short-Term Memory (LSTM) is a specific form of Recurrent Neural Network (RNN) that is specifically built to detect and understand long-term connections in sequential data. LSTMs, or Long Short-Term Memory units, are able to selectively retain or delete information over time by utilising memory cells and gating mechanisms. This makes them highly suitable for tasks that necessitate memory and knowledge of context. LSTMs are employed in the smart grid field for tasks such as load forecasting, consumption of energy prediction, anomaly detection, and grid optimisation. This utilisation leads to enhanced efficiency and dependability;
- **DEEP Belief Network:** It has two phases: pre-training and fine-tuning. During pre-training, layers learn representations of data independently. Fine-tuning involves adjusting parameters for specific purposes. DBNs are taught layer-by-layer using unsupervised learning, such as Restricted Boltzmann Machines (RBM), and then fine-tuned using supervised learning techniques.They are trained using unsupervised learning techniques such as RBMs and have applications in load forecasting, fault detection, and energy optimisation in smart grids, which improves management and efficiency;
- **Convolutional Neural Network:** A Convolutional Neural Network (CNN) is a fundamental architecture in Deep Learning (DL), especially prevalent in Computer Vision, a field within Artificial Intelligence focused on interpreting visual data. CNNs are comprised of layers including the input layer, Convolutional layer, Pooling layer, and fully connected layers. In the smart grid domain, CNNs find applications in areas such as image-based fault detection, where they can analyse images captured by sensors to identify anomalies or faults in power grid infrastructure. Additionally, CNNs can be utilised for image classification tasks in smart grid monitoring systems, aiding in the identification of different components or equipment.

3.4. Reinforcement learning

Reinforcement learning is a sub field of Machine Learning that prioritises the optimisation of decision-making processes in order to maximise rewards in a certain context. Contrary to supervised learning, which relies on labelled data for model training, reinforcement learning functions without explicit replies. Conversely, agents acquire knowledge by engaging in a process of experimentation and making mistakes, while receiving feedback in the form of incentives or penalties contingent upon their activities. The goal is for the agent to create a strategy that maps states to actions in order to maximise the total rewards received over a period of time. This approach is extensively employed in diverse applications, facilitating software and machines to ascertain the optimal course of action in intricate settings.

4. Digital twin application on power sector

Technological advancements such as IoT, improved sensors, and efficient converters have considerably increased the complexity of power systems. Conventional computational and analytical frameworks have experienced difficulties in analysing the complexity of these physical systems. As a result, there is a growing demand among power system engineers for DT technology. DTs are becoming more prevalent because they make it easier to make effective decisions by providing a virtual representation of the complex and dynamic power system environment. Leveraging DT technology to manage smart power systems advances the entire system into the realm of Industry 4.0. Efficient power system management necessitates the development of a complete model that incorporates many complexities, such as data management, storage, rapid response, computing needs, and scalability. DTs also play a crucial role in facilitating predictive maintenance by constantly monitoring and analysing vital elements, such as power semiconductors, to determine their remaining lifespans. Extensive study has been carried out in recent years on the digitisation of the power sector and the investigation of DT applications. This section will delve into the most recent studies and advancements in the adoption of DTs in the power industry.

Though DT technology originated in the aerospace and aviation industries, it has rapidly extended its applications to fields such as manufacturing [22–24], petrochemical [25,26], automotive systems [27], urbanisation and smart cities [28,29], and the power industry [30–32]. Similar to other industrial sectors, power system operations are increasingly moving towards automation, driven by extensive digital transformation [33]. The authors of the paper [30] suggest that the DT application on the power grid is primarily a challenge of large-scale software development. In terms of software development, an Online Analysis Digital Twin (OADT), which is mostly a software platform, has been introduced. They stated that DT is primarily a virtual model (software model) that replicates the real-time complicated physical system from several perspectives and is capable of addressing specific challenges. The authors primarily focus on online power grid analysis using a new methodology tested on a large-scale network model. It allows tracking of any operation status without a second delay. In the future, there will be DTs that will interface with both the physical power grid and IT applications. In [34]Digital Twin (DT) is defined as the virtual representation of a physical object within the electrical power system, making the provided data useful for various purposes in the control centre.Several companies are now incorporating digital twinning (DT) into their solution plans after realising the potential benefits of this approach. Companies like Rolls-Royce, Siemens, ABB, and General Electric (GE) are at the forefront of this initiative. A DT interface with a graphical user interface (GUI) by GE is presented at [35] for managing wind farms, featuring digital representations of wind turbines, environmental information, control icons indicating operating conditions, and control features to optimise wind farm performance. Siemens and ABB are pioneers in adopting Digital Twin technology across various sectors, with Siemens developing the ELVIS digital grid model for Finland's transmission system and collaborating with American Electric Power (AEP) for network model coordination, while ABB uses DT for remote monitoring and predictive maintenance in marine systems, significantly reducing the need for onboard visits [36].

The work in [37] examines the impact of Industry 4.0 on the development and adoption of the Digital Twin simulation modelling paradigm through multiple real-life R&D case studies, highlighting differences in adoption challenges and methodologies between large companies and SMEs (small and medium-sized enterprises), and emphasising the need for academic-industry collaboration. The evolution of the Digital Twin (DT) paradigm over the years is depicted in the Fig. 4 adapted from [37,38]

These technologies are anticipated to significantly elevate Digital Twin (DT) applications in energy systems by enabling more sophisticated data integration, predictive analytics, and real-time decision-making capabilities. In [39] the authors suggested that the main application sectors of DT in power system could be:

- Monitoring system for power;
- Control of the pitch angle of a variable-speed wind turbine;
- Prognosis and Management of Health DT model;
- Management of the underground pipe network visualised.

In recent years, DT has been applied in a wide range of fields, most notably in space applications. But it is now feasible to develop a new PSDT (Power system Digital Twin) by combining DTs based on the existing model [40]. The concepts of PSDT can be depicted as presented in Fig. 5. However, the specific model space environment and software implementation should be determined by the power system's specific applications. The PSDT system is designed in this manner to reduce reliance on physical models. It also enables real-time comparison of real data throughout operation, ensuring the stability of both virtual and real systems. The PSDT should also be able to execute multi-scenario

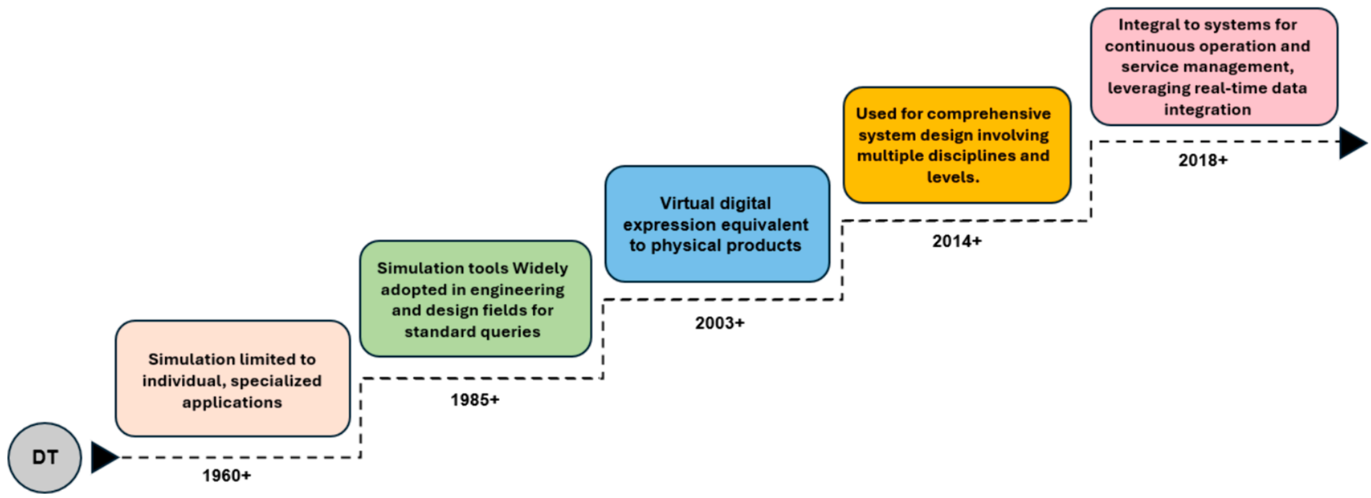

Fig. 4. Digital twin development process; the evolution of Digital Twin (DT) technology from the 1960s to the present, highlighting key milestones.

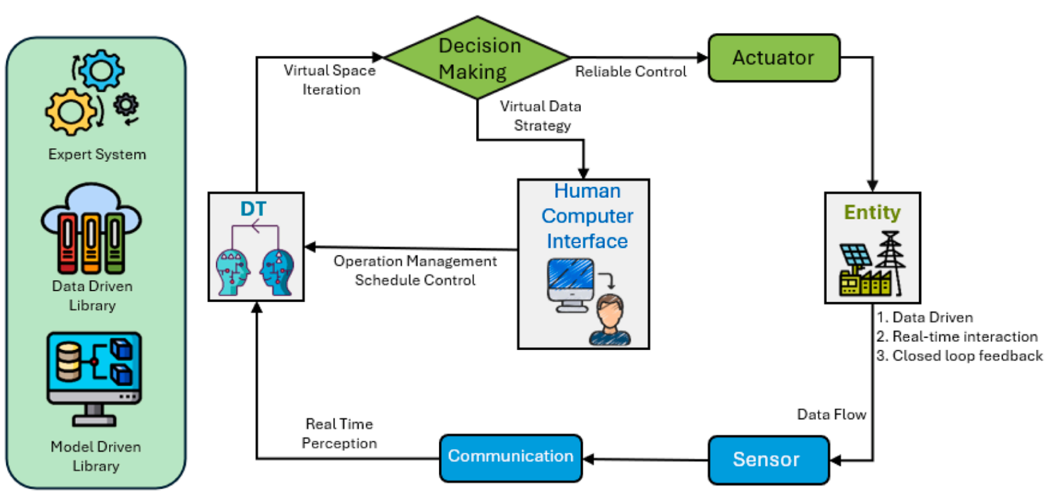

Fig. 5. A Power System Digital Twin that illustrates the architecture and data flow of a Power System Digital Twin (DT). The system includes an Expert System with Data-Driven and Model-Driven Libraries, physical Entities representing assets like power plants, Sensors for real-time data collection, and a Communication network for data transmission. The Human–Computer Interface facilitates operator interaction, while the Decision Making component analyses data for reliable control. Actuators implement control decisions, ensuring efficient, reliable, and responsive power system operations.

simulations from many perspectives, as the power system faces several types of uncertainty, such as generation and load of new energy, time, place, type, and severe AC system failure. As a result, the PSDT should incorporate a multi-dimensional, multi-probability, multi-scale simulation approach [39]. PSDT is more than just a simulation tool or a cyber physical system. PSDT is a real-time, smooth, and dynamic data-driven connection between the digital and physical worlds [31]. PSDT is, therefore, an essential component of any future grid management system. Existing models have some shortcomings, including the fact that they are restricted to specific applications. Since the power system is a complicated model with thousands of components and consumers, flexibility in modelling becomes imperative for comprehensive and effective grid management. In [41], a PSDT modular architecture is presented. They stated that it will be able to achieve one to one DT of any power grid and will have distinct domains to facilitate multiple services and users. Each module is constructed independently, allowing for potential modifications, replacements, or exchanges with other modules according to particular components and applications. DT is also applicable to the most often used Power Factor analysis and some common application cases. This requires a high-dimensional evaluation. In [42], the authors stated that, a feasible choice in power system applications is the implementation of a DT open architecture framework. They demonstrates a framework consists of DT technology stack (D-Arc) coupled with information flow, sequence, and object diagrams. These elements serve as valuable resources for energy industry engineers and researchers, enabling them to engage in prospective studies across various DT platforms. Control room assistance, education and training, and post-mortem examination, long-term asset management, model predictive operations, and collaborative decision making among stakeholders could be the future DT applications in PS [43].

As interest in PSDT has increased, research has shifted its focus to the more fundamental development of DT's core technology, which demands the use of virtual reality and data-driven, real-time monitoring. If PSDT is closely integrated with big data mining and analysis technologies, it has the potential to greatly reduce reliance on physical entities and enhance the data-driven model. This integration can help address the relative uncertainty problem in the power sector and improve error handling capabilities [39]. It will be possible to create a quick start for DT using only the data that has been observed, which will make DT significantly more readily available and spare us from the need to rely on physical markers [31].

The most recent innovation in the power industry is the introduction of smart grids. These sophisticated, interconnected networks provide an innovative approach for managing and optimising the complex processes involved in generating, transmitting, and distributing power. Smart grids utilise advanced technologies to enable more efficient and adaptable administration of the entire power system. The smart grid utilises information and communication technologies (ICT) to facilitate real-time monitoring, control, and communication between different components of the power system, such as generators, consumers, and grid operators. The utilisation of DT technology significantly improves the efficiency of smart grid systems. In the next section we will describe how the implementation of DT has improved the performance of smart grid operations.

5. DT and ML application on Smart Grid

A smart grid is an improved electricity network that incorporates digital technologies and bi-directional communication to optimise the efficiency, dependability, and sustainability of the electrical power system. The Smart Grid, similar to the Internet, includes a comprehensive integration of controls, computers, automation, and novel technologies and equipment. But in this scenario, these technologies work with the electrical grid to digitally respond to our rapidly fluctuating electricity demands. The Smart Grid is about providing everyone with the information and tools required to make energy-related decisions, not only utilities and technologies.

The integration of DT technology into smart grids represents a transformative approach of managing and optimising the complex dynamics of modern energy systems. This technology has found a particularly compelling application in the realm of smart grids, where it serves as a bridge between physical operations and digital analysis, enabling unprecedented levels of system monitoring, analysis, and prediction. In the context of smart grids, DTs can be created for a wide array of components, from individual wind turbines and solar panels to entire substations and distribution networks. These digital replicas collect real-time data from their physical counterparts through a network of sensors and IoT devices, ensuring that the virtual model remains an accurate, up-to-date reflection of the physical system's state. This real-time data collection is crucial for the dynamic modelling of energy flow, demand response, and network stability, allowing operators to simulate scenarios, predict outcomes, and make informed decisions.

The application of DT technology in smart grids offers several key benefits. Firstly, it enhances operational efficiency by enabling the precise modelling of energy supply and demand, which helps in optimising grid operations and reducing energy wastage. For instance, DTs can simulate the impact of integrating renewable energy sources into the grid, assisting in the management of variable outputs from solar and wind power. This capability is essential for maintaining grid stability and ensuring a reliable energy supply.

Moreover, DTs contribute significantly to predictive maintenance within smart grids. By continuously monitoring the health and performance of grid components, these virtual models can predict failures before they occur, thereby minimising downtime and extending the lifespan of physical assets. This approach not only reduces maintenance costs but also enhances the reliability of the energy supply, a critical factor for both utilities and consumers.

In addition to operational efficiencies and maintenance improvements, DTs play a crucial role in enhancing the resilience of smart grids against external shocks, such as natural disasters or cyber-attacks. By simulating these events in the virtual environment, grid operators can identify vulnerabilities and implement strategies to mitigate risks, ensuring that the grid can withstand and quickly recover from such incidents. The deployment of DT technology in smart grids also facilitates better integration of consumer-side technologies, such as smart meters and home energy management systems. By creating DTs of these consumer technologies, utilities can gain deeper insights into consumer behaviour, enabling more effective demand response strategies and personalised energy services. This not only improves customer satisfaction but also encourages more efficient energy use, contributing to overall sustainability goals.

A smarter grid will enable unprecedented levels of customer participation. Customers would no longer have to wait for their monthly bill to figure out how much electricity they use. With a smarter grid, they can get a clear and timely picture of it. "Smart meters," among other approaches, will allow customers to know how much electricity they use, when they use it, and how much it costs. Users will be able to save money by using less power when electricity is most expensive when combined with real-time pricing. The Smart Grid's Distributed Energy Resources concept, which integrates physical entities, virtual entities, decision-making bodies, and customers, is depicted in Fig. 6. Reliability, safety, adaptability, self-sufficiency, and optimality are important aspects of smart grid performance. A lot of research has been carried out regarding improving smart grid performance, but using the DT process as a tool for smart grid analysis, design, control, and growth is an entirely new area of study. In this section we will try to find out the relevant potential applications of DT and ML in smart grid and recent studies conducted in this field.

5.1. Forecasting

In the context of a power grid or smart grid, forecasting is the process of predicting future generation, demand, and other relevant factors for electricity. It involves the use of a range of analytical and statistical methods to predict changes and patterns in the behaviour of the grid. In smart grid load forecasting, various models and techniques are implemented, including price forecasting, electricity load forecasting, short term load forecasting, long term load forecasting, and real time load forecasting. In [44], a novel ordinary differential equation (ODE) solver of class Deep Learning (DL) is introduced for the purpose of short term load forecasting. The method is assessed using a real-world, data-driven computational benchmark case in order to demonstrate its numerical efficacy. Another accurate and efficient layout for short-term load prediction is presented in [45], using Modified Mutual Information (MMI) to extract previous data and then factored conditional restricted Boltzmann machine (FCRBM) to predict loads. The recommended modified teaching–learning algorithm (MTLA) ensures the overall effectiveness is

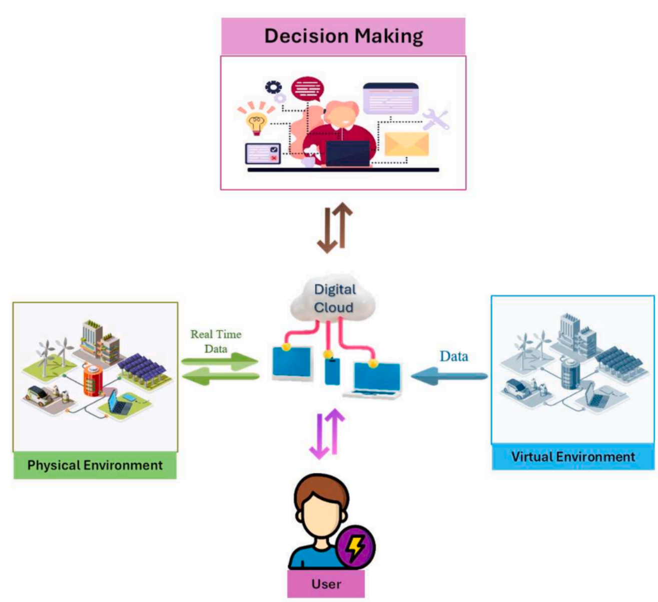

Fig. 6. Digital Twin concept within a Smart Grid illustrating interaction between the Physical Environment and the Virtual Environment through real-time data exchange facilitated by the Digital Cloud.

optimised. The paper [5] provides a brief overview of three important technologies utilised in forecasting: i) machine learning algorithms; ii) ensemble-based techniques; and iii) artificial neural networks. The characteristics of these cutting-edge models, as well as how these models enable the development of more accurate prediction models, have also been described. The decision tree classifier (DTC) algorithm of ML outperforms other models including logistic regression (LR), support vector machines (SVM), naïve Bayes (NB), K-nearest neighbour (KNN), and neural networks (NNs), as demonstrated in [46]. This paper presents a comprehensive comparative comparison among machine learning methods for short-term load forecasting. The prediction of electricity generation from renewable energy sources, including solar and wind, is one way to utilise DT technology in smart grid forecasting. DT can predict the future power output of renewable energy systems by incorporating real-time data from weather conditions, previous energy production patterns, and other pertinent elements [47]. A deep belief network (DBN)-based model for short-term electricity consumption forecasting is presented in paper [48]. The model undergoes parameter fine-tuning using supervised back-propagation training, following to the layer-by-layer unsupervised training process. The DBN model has demonstrated superior performance compared to the alternative traditional model utilised for the Macedonian system operator (MEPSO). A DRNN-GRU (Deep Recurrent Neural Network - Gated Recurrent Unit) model with a one-hour resolution to forecast the load demand of residential buildings over a short to medium period is proposed in [49]. The proposed DL model excels in accurately forecasting both aggregated and dis-aggregated load demand for residential buildings while effectively filling missing data through learning from historical data. District heating and smart building energy management are integral components of the smart grid, which employs digital technologies to optimise electricity production and distribution. The paper [50] introduces linear regression-based building energy models to generate the energy characteristics of buildings and heating systems. These models depend on the heat provided to the heating system and the weather conditions outside the building, such as temperature, wind speed, and solar insulation. The result is an energy model for the structure expressed as the equivalent external temperature. The dynamics of heat loss in District Heating System are frequently neglected due to the higher computational costs involved. Machine learning offers a significant opportunity to decrease complexity in thermal dynamics models [51]. The paper [52] presents ensemble forecasting of weather in district heating operation by developing a heat load forecast model that incorporates time-varying weather uncertainties.

Fig. 7 demonstrates the integration of digital twins with machine learning for predictive analysis in the energy industry, particularly in the context of wind farms. The concept entails the creation of a virtual model of a wind farm, where data from wind turbines is accumulated and communicated to a central hub. Subsequently, this data undergoes processing through machine learning models in order to improve the precision of predicting. The digital twin facilitates continuous monitoring and preemptive repair, enhancing operational efficiency and dependability.

The unpredictability of wind speed is the greatest challenge to the growth of such zero-carbon-emission energy sources. In [53], the design of a 5G-NG-RAN Framework is presented, which enables the virtual prediction of wind speed and power curves without the requirement for physical presence at the location. A temporal convolution network (TCN) is utilised in conjunction with a k-nearest neighbour (KNN) regression to form the architecture. In order to assess the effectiveness of this model, it has been implemented on onshore wind farms and the results are more effective to those of other traditional prediction models. In [54], the authors presented a principal component regression (PCR)-based method for predicting the weather-dependent dynamic thermal rating (DTR) of lines for an existing power grid. Two Long Short Term Memory (LSTM) algorithms: 1) standard LSTM and 2) LSTM-based Sequence to Sequence (S2S) architecture based on DL is proposed for load forecasting in [55]. In [56], the authors offer a model that combines stacked denoising auto-encoders (SDAs) with Support Vector Regression (SVR) to improve day-ahead total electricity load forecasting. It improves features using SDAs on historical power load and temperature data before employing an SVR model for prediction and classification. The model improved the accuracy of load tendency forecasting, as abstract features derived by SDAs demonstrate greater performance with lower errors. In [57], a hybrid forecasting model is proposed that utilises

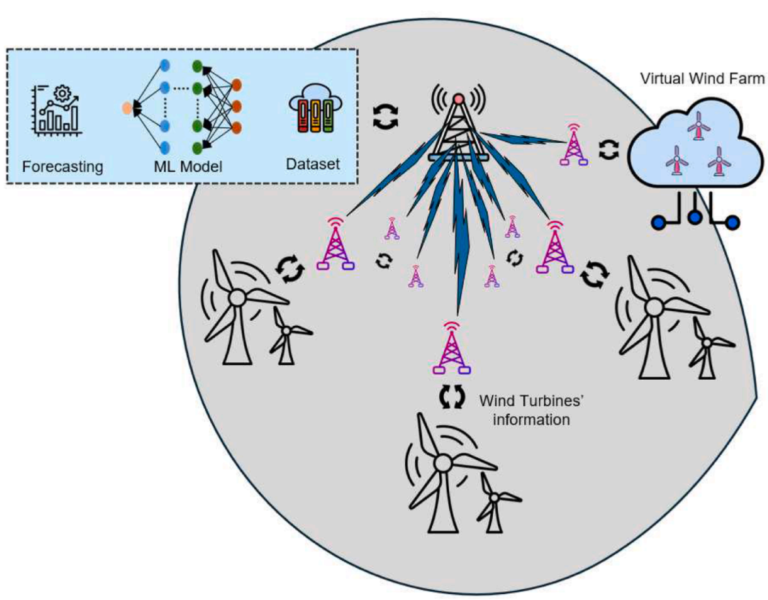

Fig. 7. A framework of forecasting in Smart Grid that demonstrates the integration of digital twins with machine learning models for predictive analysis in wind farms, a virtual wind farm model in which real-time data from wind turbines is collected and communicated to a central hub, and the data is processed using machine learning models to enhance forecasting accuracy.

DL and consists primarily of interval probabilities. The model is constructed applying Restricted Boltzmann Machines and real-valued inputs to acquire robust feature knowledge from the probability distributions of wind data. A DNN (Deep Neural Network)-based technique for estimating short-term wind and PV power is proposed in [58]. Because of the great compatibility of diverse ML algorithms, these algorithms may be used in DT to almost precisely predict the real-time forecasts of various intermittent renewable energy sources. It will also allow the smart grid system to work properly because load variability and demand can be predicted efficiently. An overview of current research on Forecasting smart grids utilising the DT technique is presented in Table 3.

5.2. Fault detection

In smart grids, fault detection includes the use of modern technology to quickly find and localise abnormalities in the electrical power system. Smart grids use a variety of sensors to continuously monitor characteristics like as voltage, current, temperature, and frequency. Faults are a fundamental characteristic of every electrical system, and their presence in a particular region of the system can cause substantial difficulties throughout the system. As a result, quick or real-time detection will assist in preventing irreversible damage to these issues. Faults might be short circuits, equipment failures, voltage fluctuations, or aberrant currents. Smart grids have become more complicated as power technology advances, with many sensors being used, making fault identification more challenging. These sensors offer data that is communicated to central control systems via communication networks, allowing for rapid investigation of inconsistencies from typical operational conditions. Intelligent algorithms, which often incorporate machine learning and artificial intelligence, are used to find out the inaccuracies. Grid operators can preserve grid stability and minimise power supply disruptions by recognising and diagnosing faults as soon as they occur. DTs can be used in the context of smart grid to construct real-time representations of the smart grid, including its components and their interactions, since it allows for the tracking and monitoring of real-time data. This permits realistic modelling and simulation of the smart grid's behaviour, allowing flaws and anomalies to be detected. In addition, the integration of distributed energy resources and renewable energy sources requires advanced algorithms to deal with their intermittent nature. DT's multidimensional characteristics provide the real-time detection of faults in the smart grid, improving its reliability and stability throughout operation.

Fig. 8 depicts a comprehensive method for identifying faults in power distribution networks by combining digital twin technology and machine learning. It shows the basic structure of DT in fault detection that comprises of five layers: Physical, Sensing, Data Transmission and Storage, Model Evaluation, and Maintenance. Every layer has a crucial function in guaranteeing the effective and dependable functioning of power distribution networks. By integrating these levels, the system establishes a complete structure for identifying and handling faults, greatly improving the robustness and effectiveness of power distribution networks. The combination of digital twins and machine learning in this integrated strategy is a major step forward in the energy sector's capacity to effectively handle and reduce defects.

In [67], an ongoing study demonstrating the capability of attaining near-real-time fault identification in smart grid operations is presented, which is accomplished through the use of a hybrid DT model resembling the physical system. A data-driven machine learning subsystem and a discrete deterministic subsystem comprise the model. In [68], the authors presented a DT-assisted deep transfer learning method for accurate machine fault diagnosis. This strategy is based on the novel sparse denoising auto-encoder (NSDAE) model, which has been developed with an improved activation and cost function. The goal of this strategy is to accomplish accurate machine fault diagnosis regardless of whether there is inadequate measured fault condition data. A case study of triplex pump fault diagnosis is used to validate the provided method. A digital framework comprised of DL convolutional neural networks (CNN) as a module within the Automatic Network Guardian for ELectrical systems (ANGEL) is presented in [69], to detect physical problems in power systems. It is mainly designed for use in distributed power systems to

Table 3
An analysis of recent research trends in DT/ML-based approaches to Forecasting in Smart Grid Domain.

Year	Reference	Method	Application
2019 Ordinary differential equation (ODE) a class of DL; DRNN-GRU	[44] [49] Residential Load Demand Forecasting		
2019;2022	[5] [46]	Comparison among ML algorithms (KNN, NN,SVM,DTC,LR)	Short-, medium- and long-term forecasting in the RE usage and energy demand requirement
2017	[47]	Feed-forward Deep Neural Network (FF-DNN) and Recurrent Deep Neural Network (R-DNN)	Short term bulk power load forecasting
2016;2017	[48] [59]	Deep Belief Network composed of multiple restricted Boltzmann machines; Online SVR	Short-term electricity load forecasting
2019	[60]	Bayesian deep learning	Probabilistic forecasting of load
2017	[61]	Combined CNN with K-means Clustering	Power industry load forecasting
2022	[62]	Temporal Fusion Transformer (TFT)	Daily, weekly, and monthly energy consumption prediction
2019	[63]	Enhanced Convolutional Neural, Network (ECNN) and Enhanced Support Vector Regression (ESVR), Grid Search (GS) for tuning	Electricity load and Price Forecasting
2017	[64]	IoT-based Deep Learning System	Electricity load forecasting
2016	[54]	Principal component regression (PCR)	The weather dependent dynamic thermal rating (DTR)
2022	[53]	5G-NG-RAN Framework	Wind speed and predict the generated power
2016	[55]	Long Short Term Memory (LSTM) algorithm	Building level energy load forecasting
2017	[56]	Stacked denoising auto-encoders (SDAs) with support vector regression (SVR)	The day-ahead electricity load
2019	[57]	Interval probability distribution learning (IPDL)	Wind speed forecasting
2019	[65]	Elman Neural Network (ENN) driven Wavelet Transform (WT-ENN)	Hourly solar irradiance forecasting
2017	[66]	GCA and PCA for Feature Selection, Coupled with Differential Evolution (DE)-Based SVM Optimization	Electricity Price Forecasting

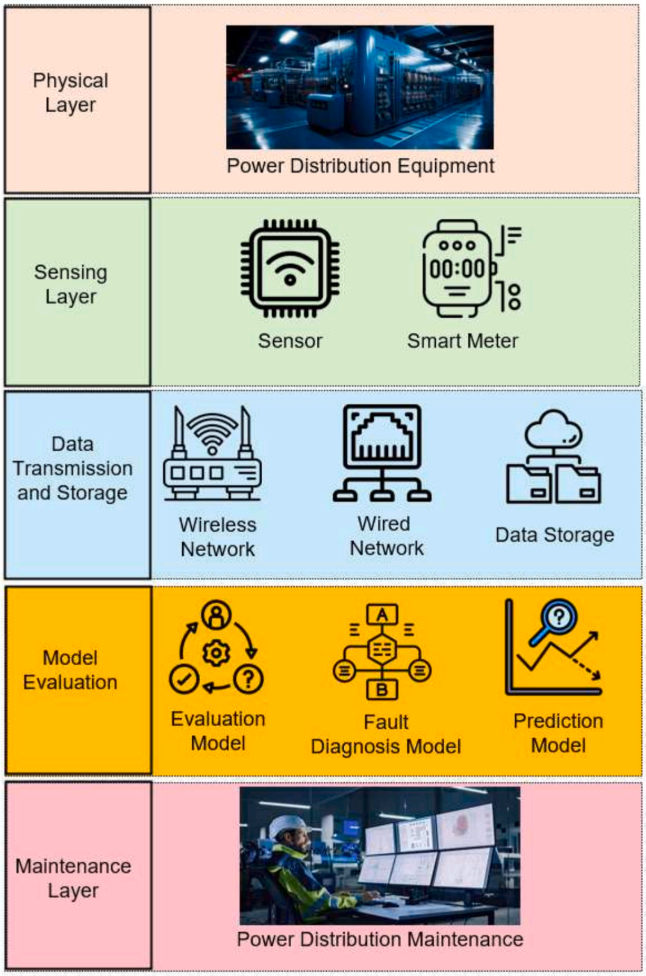

Fig. 8. A layered framework for fault detection in power distribution systems, comprising physical equipment, sensing technology, data transmission and storage, model evaluation, and maintenance processes.

detect defects in fractions of a second. In [4], the categories and new requirements of autonomous fault detection are discussed. A cloud-edge based hybrid smart grid defect detection system has been generated to address the flexibility and optimal performance issues of edge based systems while also overcoming the requirements of enormous quantities of data in cloud based systems. The developed system is a computational resource allocation approach for cloud-edge smart grid fault detection systems. A support vector machine (SVM)-based solution for classifying islanding and grid fault occurrences in a low voltage distribution grid is proposed in [70]. Subsequently, the model has been tested for evaluating parameters of a real-life practical PV plant, and it produced significantly better results than the previous existing approaches. In [71], a matching pursuit decomposition (MPD) for fault detection, identification, and location in smart grid using Gaussian atom dictionary, hidden Markov model (HMM) of real-time frequency and voltage variation features, and fault contour maps produced by machine learning algorithms are presented. In [72] the researcher analyses a five-layer DT technology architecture used in the power grid's distribution field. It provides an overview of the state of research today, highlighting advantages in areas including fault prediction and real-time monitoring. The difficulties in developing this technology caused by the integration of many different sensors, algorithms, and modelling standards are also thoroughly discussed.

The use of machine learning algorithms for quick anomaly detection in smart grids has recently been a popular research area. A lot of relevant work is being done in this field. For microgrid protection, an intelligent Fault Detection (FD) system based on local measurements and machine learning (ML) approaches employing robust communication protocols has been proposed in [73]. The intelligent FD system, which consists of four phases, can be implemented on any microgrid for its unique methodology. For intelligent Fault detection and diagnosis (FDD), three ensemble learning techniques (EL) that combine the benefits of Support Vector Machine (SVM), K-Nearest Neighbour (KNN), and Decision Tree Classifier (DTC) are presented in [74]. Using the collected raw data, it will provide more accurate performance than a single learner in distinguishing between the various PV system operating modes. In [75], grid search (GS) model selection method based on the Support Vector Machines (SVM) classifier is proposed. In [6] the authors investigated the classification of various fault scenarios within a comprehensive framework that incorporates system-level applications, such as transmission, distribution, commercial, Distribution Grid, and EV. Machine learning technique based on principle component analysis (PCA) can also be introduced to address the issue of Fault Detection and Diagnosis (FDD) in Grid-Connected photovoltaic (GCPV) systems [76]. A supervised machine learning (ML) model is proposed for extracting anomaly information from high-frequency measurements of electrical quantities in Power Line Communication (PLC) signals in [77]. In [78] the authors proposed DL techniques, specifically employing Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) models for detection of fault. The objective is to precisely identify and pinpoint Fault Disturbances Events (FDEs) by utilising a constrained dataset of Rate-Of-Change-Of-Frequency (ROCOF) time-series obtained from a few Phasor Measurement Units (PMUs). In [79], techniques for detecting, categorising, and pinpointing faults is proposed in a radial distribution grid. The system employs machine learning methods and advanced signal processing techniques, notably utilising the discrete wavelet transform (DWT), to extract features from three-phase current waveform collected at the transmitting end both before and after a failure occurs. Faults in smart grids are common due to the immense size and complexity of electricity networks. In recent decades, there has been an enormous enhance to digitise entire smart grid systems to enable rapid identification of faults. This includes incorporating sensors across the grid, establishing reliable communication networks, and utilising data analytics and machine learning to detect problems quickly. The goal is to improve the efficiency and reliability of power systems by resolving errors quickly. An overview of recent developments in DT-based approaches to Fault Detection in Smart Grid Domain is presented in Table 4.

5.3. Security of grid

Cyber Security (CS) in the context of smart grid primarily focuses to protect the digital infrastructure and data against cyber threats and attacks. The consequences of cyber-attacks on smart grids can be significant, including power supply outages, compromise of important data, and physical harm to the grid infrastructure. This includes assuring the integrity of the system, protecting data from unauthorised access or manipulation, securing communication networks, and protecting connected devices. The most crucial factor in destroying the impact of a cyberattack is to shorten the detection time. In addition, identifying intrusions in the microgrid is also indispensable. Thus, it is one of the major research topics in this realm on which researchers are currently focusing. Smart grid components can be protected against cyber-attacks by the implementation of secure device design, multi-factor authentication, and access control regulations. Cyber security incidents can be prevented quickly and effectively with incident response plans and periodic inspections. The application of machine learning-based algorithms and DT technology is growing in the domain of CS. Because of the ease that DT permits real-time monitoring of data and systems, this can help mitigate the risk of potential attacks. As machine learning-based algorithms and DT technology become more widely used in cyber security. The accompanying Fig. 9 provides a real-world example of DT

Table 4
An analysis of recent developments in DT/ML-based approaches to Fault Detection in Smart Grid Domain.

Year	Reference	Method	Application
2021	[68]	DT and deep transfer learning	Fault Detection of machine
2023	[69]	Incorporating a DL CNN module into the ANGEL Digital Twin	Automatic Physical Fault detection in Power Network
2019	[70]	Support Vector Machine	Grid Fault detection and Islanding
2014	[71]	Gaussian atom dictionary, hidden Markov model (HMM)	Fault identification and location
2020	[73]	Local measurements of Fault detection using ML	Microgrid Fault Detection
2021;2020	[74]76	Ensemble learning is comprised of SVM, KNN, and DT; Feature Extraction by PCA and Classification by ML classifiers	Fault Detection in Grid Connected PV systems
2020	[77]	A supervised machine learning (ML)	Identifying Anomaly of electrical quantities in power line communication
2021	[78]	Deep Learning using Recurrent Neural Network	New England 39-bus, IEEE 14 bus systems, and modified IEEE 118-bus system
2020	[80]	Gradient Boosting Trees	Detect and localise single-phase-to-ground and three-phase faults in LV smart distribution grids.
2020	[79]	Discrete wavelets transform (DWT)	Radial distribution grid
2022	[81]	Cloud-edge based hybrid system using Embedded devices	Real time fault detection in Smart Grid
2021	[82]	Privacy reinforcement learning	To detect anomaly patterns in a distributed and heterogeneous energy environment
2020	[83]	Maximal Overlap Discrete Wavelet Transform (MODWT)	Microgrid protection scheme (MPS)
2017,2018	[84]85	Smart Meter	High impedance fault (HIF) in smart grid
2022	[72]	Five-layer architecture of DT technology	Power distribution grids

concept in the Security domain of smart grid.

By analysing huge amounts of data gathered from sensors and network components, machine learning algorithms enable the identification of patterns, anomalies, and potential cyber-attacks within the shortest possible time [86]. The European Union Agency for Network and Information Security (ENISA) published a list of the 15 most significant threats that took place between January 2019 and April 2020 [87]. The threats categorised as: " Distributed Denial of Service (DDoS), identity theft, data breach, insider threat, botnets, physical manipulation, damage, theft and loss, information leakage, ransomware, and cyberespionage." For efforts to improve the cyber security of physical systems, it is necessary to create a distinct physical test bed that can address the challenges related to the scalability and modification of the physical configuration of a smart grid. In a secure setting, this will enable the training and testing of cyberattack simulations [88]. The integration of thousands of sensors and measurement devices within smart grid infrastructure necessitates the management of significant amounts of data, thereby increasing the vulnerability to false data injection in systems. Different ML techniques proven to be a better approach for dealing with False Data Injection Attacks (FDIA) [89]. In [90], to address the issue of intermittent wind energy, a CS assessment employing Deep Reinforcement Learning (DRL) and an adapted Common Vulnerability Scoring System (CVSS) is presented to assess the cyber physical security of power systems. DRL can also be employed in an online method to improve safety features for Distributed Energy Resources (DER) [91]. The combination of DT technology and algorithms based on machine learning improves the efficiency and effectiveness of cyber threat detection, prevention, and response. To make human judgement more certain, machine learning is a feasible technique to provide accurate decision assistance to power system operators on whether the system is under attack [92]. For smart grids, a universal robust online detection algorithm based on the model-free reinforcement learning (RL) framework is proposed for partially observable Markov decision processes (POMDP) [93]. Unsupervised Offline techniques with real-time data monitoring can be an efficient solution for large smart grid anomaly detection that can distinguish between actual fault and a disturbance, and an intelligent cyber-attack [94]. In [95], a cutting-edge technique called iForest-based unsupervised scheme is proposed for detecting covert data integrity attacks (CIAs) in SG communications networks using unlabelled data.An overview of recent developments in DT-based approaches to Security in Smart Grid Domain is presented in Table 5. (see Table 6).

5.4. Management and monitoring

Smart grids demand extensive measurement, control, and monitoring of critical parameters due to their large scaling and multidimensional functionalities. The management of smart grids involves controlling and coordinating various aspects, such as integrating renewable energy sources, implementing demand response strategies, and managing energy storage. Control and energy management systems rely on measurement data to make the right decisions for optimal

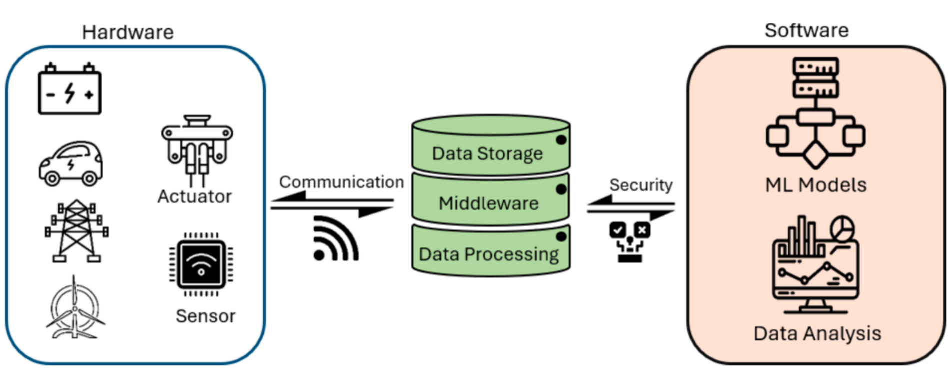

Fig. 9. An example of Digital Twin concept using Machine Learning algorithms in Security domain depicting the hardware components, including actuators and sensors, that collect data and communicate it through middle-ware for processing and storage. The software side applies ML models and data analysis tools to ensure security, enhancing the overall management and protection of the system.

Table 5
An analysis of recent developments in DT/ML-based approaches to Security of Smart Grid.

Year	Reference	Method	Application
2020	[90]	Deep reinforcement learning (DRL) and an adapted Common Vulnerability Scoring System (CVSS)	Wind integration in Electric Power System
2018	[93]	Free Reinforcement Learning (RL) for Partially Observable Markov Decision Process	Online cyber attack detection in Smart Grid
2019	[94]	Symbolic Dynamic Filtering	Unsupervised cyber attack detection at large scale
2022	[86]	Smart Meter System as DT	Protection of physical devices through virtual device interactions
2022	[96]	Data Centric Approach to generate invariants in Cyber physical systems	Anomaly detection and providing cyber security to the smart grid.

Table 6
An analysis of recent developments in DT/ML-based approaches to RE systems.

Year	Reference	Focus
2021	[8]	To analyze and demonstrate how artificial intelligence (AI) can mitigate the integration costs associated with variable renewable energy (VRE) sources in the power sector
2022	[107]	A comprehensive review of the synergy between optimisation methods and machine learning techniques in the context of integrated energy systems (IES)
2017	[116]	To review the present state and limitations of realistic simulation and Hardware-in-the-Loop (HIL) approaches used for smart grids.
2023	[17]	To investigate the shift from centralised to decentralised techniques in the electrical business, with a focus on the role of machine learning (ML) developments in allowing renewable energy sources and improving grid management.
2021	[108]	An overview of machine learning (ML) applications in diverse manufacturing industries, including renewable energies, smart grids, catalysis, and power storage and distribution, with a focus on sustainability and the environment.

performances. However, ensuring optimal decision-making at the energy management level poses challenges due to potential errors in data measurement from measurement devices. Smart grid management and monitoring involve gathering and analysing real-time data about how much energy is being produced, used, and distributed. This helps keep a good balance between the amount of energy available and the amount needed, lessens pressure on the grid, and makes things more efficient overall. It also helps identify precisely and resolve problems like changes in voltage, deviations in frequency, and equipment malfunctions, making sure that the power supply is dependable. A lot of efforts have been made in this sector so far to make the whole smart grid management smoother and more reliable. This section focuses on the importance of utilising DT for monitoring and management of smart grids. Supervisory Control and Data Acquisition (SCADA) systems have gained popularity for their ability to remotely control and monitor renewable energy sources (RES). These systems have found widespread use in different industries, effectively enhancing the efficiency of various systems. Despite progress in ensuring reliability, safety, and protection for power generation, distribution, and transmission. SCADA systems are commonly utilised in power systems, including those that incorporate Renewable Energy Sources [97,98]. These systems also play a crucial role in monitoring power quality within Smart Grid. The paper [99] is made on an energy management architecture in an educational constructing with an MG Laboratory (Lab) testbed based on a SCADA system.

Information and Communication Technologies (ICT) are essential for performing measurement, control, and monitoring tasks. DT-based systems have proved superior performance compared to traditional systems, enabling effective load sharing, regulation of terminal voltages and frequencies of generators, control of power flow, and detection of faults in specific sections of the grid. In [100], a framework has been proposed for real-time monitoring, condition assessment, visual observation, deductive simulation, and personalised interaction at the distribution side consists of a five-layer architecture in the realm of DT. A systemic review of DT technology application for industrial energy management has been presented in [101]. In [102], the authors of propose Smart Energy Management System (SEMS), an energy management tool designed for smart cities or districts. SEMS facilitates optimal control and coordination of interconnected energy assets while adhering to user-defined objectives. It leverages machine learning-based forecasting and model predictive control techniques to ensure optimal decision-making and maintain system constraints. In [103], a critical review has been conducted, exploring the application of ML in Energy Economics/Finance. The review focuses on the utilisation of ML in various areas such as energy price prediction, demand forecasting, risk management, trading strategies, data processing, and macro/energy trend analysis. The paper provides insights into the achievements and limitations of the literature in this field. As mentioned, DT has the potential to be utilised in predictive data management. By leveraging this technology, it becomes possible to predict the remaining useful life of an offshore wind turbine power converter. A scheduling model for energy storage systems that utilises machine learning techniques to enable digital twin technology in electricity bill management is presented at [104]. One of the main problems associated with the DT application on smart grid is to handle a large amount of data which makes the management of power system more complex. In [105], a comprehensive analysis has been presented of the obstacles and concerns related to integrating significant volumes of data, particularly the utilisation of data centres, in addition to the associated energy-related challenges and uncertainties. To enhance the adaptability and coordination across various energy systems, it is essential to ensure that DTs can be effectively adjusted. The concept of edge-based DTs emerged as a means to create a simulated environment for performance evaluation, with the aim of enhancing the resilience of microgrids [106].

5.5. Integration of renewable energy

As the renewable energy sector experiences rapid growth within the energy industry, ensuring consistent and dependable operations poses escalating challenges. It becomes imperative to maintain real-time visibility of all assets to guarantee seamless and uninterrupted operations. Consequently, renewable energy companies are increasingly adopting DTs as part of their digital transformation efforts. Digitisation allows for enhanced connectivity, intelligence, efficiency, reliability, and sustainability in energy systems. By utilising digital technologies, renewable energy systems can be optimised and managed more efficiently, resulting in improved performance and cost savings. DT applications can enhance the efficiency and reliability of solar panels by allowing for preplanned maintenance and the identification of potential failures before they occur. Through simulations of wind turbine blades and the entire system, optimal power extraction can be achieved even in the presence of intermittent wind speeds. By combining DTs with machine learning, wind farms can make accurate predictions about wind speeds, leading to improved performance. Additionally, DTs enable the reuse of parts from hydro power plants at the end of their life cycle, and the expansion of hydropower plants becomes easier with the use of DTs.

Variability of Renewable energy integration is one of the main concerns now a days. How the use of AI and data driven system can minimise the cost of integration is presented in [8]. The rising popularity of Integrated Energy Systems is attributed to their significant potential for decarbonisation and achieving carbon neutrality. In [107], a review of the crucial energy components, modelling structure, and optimisation applications utilising ML and DL is presented. In [108], the authors have provided an extensive examination of the utilisation of machine learning in the sustainable energy domain, highlighting key factors influencing the increased adoption of ML. These factors include advancements such as the emergence of 5G technology and the growth of fields like big data analytics. The integration of renewable energy into smart grids comes with various challenges, necessitating the implementation of a demand-side energy management system. The incorporation of machine learning in this sector proves instrumental in addressing issues like enhancing energy efficiency, implementing real-time pricing, optimising economic load dispatch, managing optimal power flow, and conducting load forecasting and scheduling [109]. Within the integrated renewable energy sources framework, challenges include storage options, sizing methodologies, and control systems for RE sources, as highlighted in [110]. In [17], the authors explored how the application of ML in incorporating renewable energy into current electric grids transforms the entire electrical power system, shifting it from centralised systems to a network of Distributed Energy Resources (DER). Recently, there has been an increase in the use of both data-driven and model-driven methods to handle uncertainty related to renewable energy sources. Data-driven approaches utilise historical information and machine learning methods, whereas model-driven approaches depend on mathematical models and optimisation techniques. Multiple research have investigated the use of data-driven methods, such as machine learning algorithms, to forecast renewable energy production and handle uncertainty. Conversely, model-driven methods, such as optimisation and robust control techniques, have been employed to create resilient solutions for power system operations. In [111] a method called distributional robust chance constraint (DRCC) is presented that use semidefinite programming to optimise the imbalanced three-phase power flow in distribution networks. The method also aims to efficiently clear energy and flexibility markets.In [112] authors presented the Lossless Coding considering Precision (LCP) method, which is a model-free technique for compressing time series data in smart grids. LCP utilises differential coding, XOR coding, and variable length coding to encode and transmit data points, based on the immediately preceding data point.

Another important use of DT is the integration of renewable energy into the grid. Intermittency of the RE sources creates a number of challenges for integration in the grid. As a result of these challenges, the integration of renewable energy becomes unstable. In [113], to address this issue, the authors propose a mathematical model for controlling the parameters of renewable energy systems to ensure optimal conditions. The study examines the meteorological factors associated with each type of renewable energy, providing valuable insights that can facilitate the integration of renewable energy in the future. Therefore, policy makers and renewable energy developers require reliable and comprehensive best practice information to ensure the feasibility of achieving high levels of renewable energy penetration at specific sites [114]. As of now, renewable energy has paved the path for distributed energy supplies. Additionally, it brings about complicated load dynamics because of the intermittent nature of renewable energy and the newly emerging load pattern brought about by the impact of electric vehicles. The DT technique is one of the best ways to optimise the DER and identify time-varying load. The authors of the research investigated the possibility of using measurement-based system identification with the existing simulation capabilities of a numerical simulations platform [115].

A power system control center with a high profile is also required due to the increasing use of renewable energy, the proliferation of power electronics devices (e.g., rectifiers and converters), the decline of conventional power generation, and the variability of load profiles. An imbalance exists between current technologies and forthcoming demands. The authors discuss in their paper a DT-centric control center architecture as a way of mitigating this issue [32]. DT, which is essentially a dynamic simulation engine, produces near-real-time visualisations of the power system, connecting both the physical and virtual power systems. The implementation of DT as the core component of the power system has the potential to enhance Operational Situational Awareness (OSA) and optimise system performance. The implementation of this unique control center will enable operators to respond promptly and make accurate choices by utilising a wide area monitoring system (WAMS). One potential beneficial application of DT in DER is the Power-Hardware-In-Loop (PHIL) system. Enabling the evaluation of DER integration within microgrids, both locally and globally, is achievable through the real-time simulation integration of Power Hardware in the Loop (PHIL) with DT technology at the target grid. Therefore, the running of probable practical deployment of DRE at the planned site including industrial communication network that improves its reliability and stability. This PHIL DT system provided a demonstration of a case study that involved the integration of a new PV inverter and load into a microgrid with a high percentage of PV cells, which has been regulated by a coordinated voltage control algorithm. This significantly enhances the capacity to modify the topology between the actual hardware and its corresponding virtual representation, without disrupting any of the real-world connections or the operations being carried out [116]. The authors attempted to elaborate on the uses of DT in RE, shipboard, and power electronics equipment utilised in DER systems in this article. The impact of big data analysis, AI, IOT, and 5G networks in various industries is briefly discussed, as well as how these additions make the whole DER an efficient detection system in terms of parameter errors and diagnosis [117]. An overview of recent developments in DT-based approaches to Integration of RE in Smart Grid Domain is presented in Table 7.

5.6. Digital twin application on electric vehicle

The transportation sector is one the main contributor the Greenhouse Gas, accounting for approximately 15% of the total emissions. So the scientists consider Electric Vehicle would be the most viable option to combat with this challenges. Electric vehicles produce fewer emissions compared to conventional internal combustion engine vehicles as they contribute to lower CO_2 emissions. The challenges associated with EVs include the establishment of charging infrastructure, constrained driving range, and the sustainable management of batteries and other components. There is currently a significant focus on making substantial efforts to develop sustainable solutions for the seamless integration of EVs. Consequently, the application areas of DT technology in EVs are experiencing rapid expansion. Fig. 10 illustrates the broad spectrum of Digital Twin (DT) applications within the Electric Vehicle (EV) domain.

Table 7
An analysis of recent developments in DT/ML-based approaches to Electric Vehicle systems.

Year	Reference	Focus
2023	[118]	To explore the application of DT technology in EVs, comparing model-based and data-driven DT approaches.
2019	[120]	An intelligent digital twin (i-DT) in MATLAB/Simulink for the condition tracking and prediction of permanent magnet synchronous motors (PMSM) used in electric vehicles (EVs).
2021	[123]	To incorporate Industry 4.0 technology, particularly the idea of the digital twin and smart materials, in order to solve issues related to the maintenance and repair of the electric vehicle (EV) sector.
2022	[124]	A Digital Twin (DT) for Fuel Cell Hybrid Electric Vehicles (FCHEVs) to characterize vehicle behavior
2021	[126]	To investigate current developments in electric vehicles (EVs) and associated infrastructure, with an emphasis on artificial intelligence's (AI) potential to solve problems and increase EVs' attraction to consumers
2020;2021	[10]128	To create and evaluate a charging management system for electric vehicles (EVs) using machine learning (ML) algorithms. This system aims to reduce distribution system issues arising from numerous EVs charging at the same time.

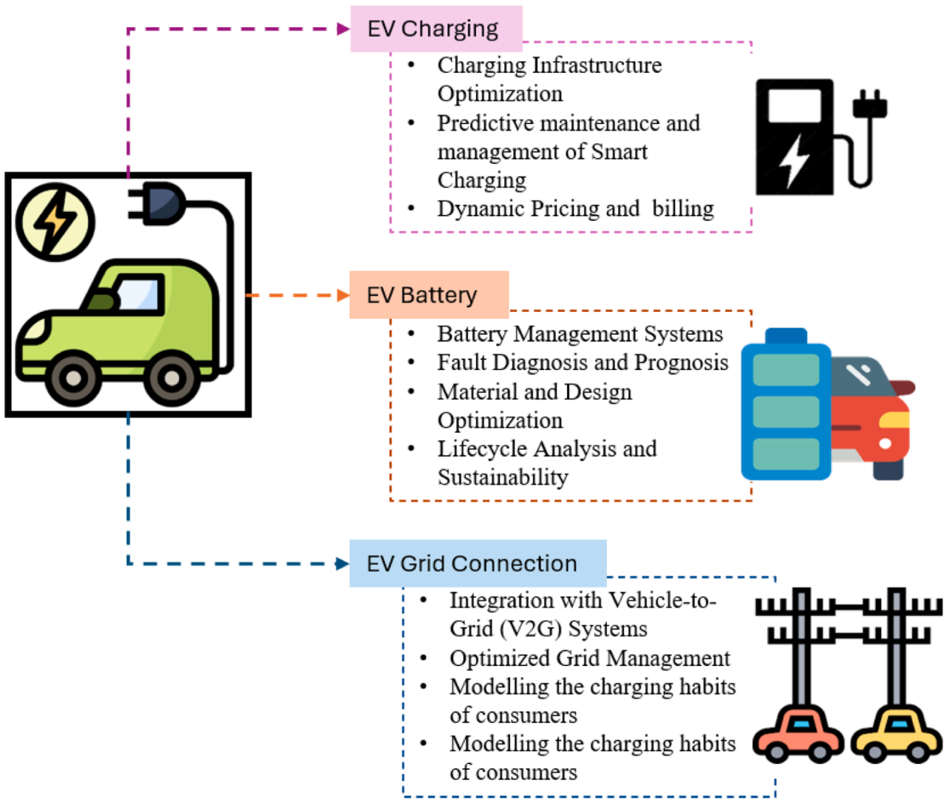

Fig. 10. Applications of Digital Twin in Electric Vehicle charging, battery management, and grid connection, focusing on infrastructure optimisation, predictive maintenance, lifecycle analysis, V2G integration, and consumer charging habits modelling.

The prominence of DT technology in smart vehicles is rising, as it bridges the gap between the physical system and its digitally generated model. This connection facilitates accurate predictions of vital constraints associated with electric vehicles, offering abundant opportunities for the implementation of DT technology in the realm of EVs. In paper [14], the authors provided a concise overview of the application of DT in smart electric vehicles. The review encompasses recent research and contributions in this domain, offering a comprehensive examination of EVs from various perspectives. The authors break down EVs into distinct categories, including autonomous navigation control, advanced driver assistance systems, vehicle health monitoring, battery management systems, vehicle power electronics, and electrical power drive systems. Monitoring real-time conditions and optimising the manufacturing process can serve as a crucial application area for DT in this industry. However, according to the research presented in [118], utilising Data-driven DT might offer greater advantages compared to Model-driven DT in such applications. The utilisation of data-driven DT can contribute to the development of a model-driven DT, enhancing the precision of the energy consumption model for EVs [119]. PMSMs are popular in EV applications because of their excellent efficiency, compact size, and ideal torque-to-weight ratio. These motors provide precise control of speed and torque, a feature essential to obtaining peak performances and range in electric vehicles. The health monitoring and prognosis of Permanent Magnet Synchronous Motors (PMSM) can be achieved through two distinct approaches: 1) In–house health monitoring, and 2) remote health monitoring utilising an intelligent DT [120]. Substantial research efforts are required for the effective implementation of DT technology in electric vehicle (EV) propulsion drive systems [121,122].

Another significant issue related to electric vehicles (EVs) is the repair and maintenance aspect. In [123], the authors suggest that employing DT technology will decrease the service time and associated costs in the servicing and repair processes of EVs. The paper outlines the entire operational procedure involved in creating a DT to facilitate its adoption in the Indian EV industry.

The Fuel Cell Hybrid Electric Vehicle (FCHEV) is the current emerging industry, offering even lower greenhouse gas (GHG) emissions compared to traditional electric vehicles. In [124], the authors introduced a DT for FCHEV to effectively simulate the precise modelling of the vehicle's auxiliary systems. Demand-side management is another crucial aspect of electric vehicles. In [125], the researchers created a ML model that provides consumers with timely charging decisions by considering diverse auxiliary data such as driving patterns, environmental conditions, pricing, and demand time series. The aim is to minimise the overall energy cost of the vehicle in real-time. The implementation of ML and AI in the EV industry enhances the efficiency of charging systems by automating the process of charging stations, managing EV batteries intelligently through functions such as state estimatiion, diagnosis, and charging controls, and integrating EVs with the smart grid. The overall application area of AI in these sectors is briefly reviewed [126]. The overall health of the battery is determined by the battery's State of Charge (SOC). The deterioration of battery quality is quite nonlinear. In [127], six different types of ML algorithms were employed to estimate the SOC of a Lithium Ion Battery. Coordinated charging systems are crucial to improving the efficiency and reliability of electric vehicle charging, enabling the smooth integration of EVs into the broader energy ecosystem. The study [10] compares various ML techniques to identify the most suitable model for enhancing power system stability during the seamless integration of electric vehicles (EVs). Also, adding a lot of electric cars to the smart grid makes the transformers overloaded, causes more power loss, and causes voltage changes. To mitigate these impacts, various ML techniques can be evaluated against one another in terms of their efficacy in order to identify the most optimal model for routing electric vehicles to charging stations [128]. In [129], artificial intelligence (AI) and machine learning (ML) techniques are explored for establishing robust information security in electric vehicles (EVs). In [130] author presented a supervised machine learning-based system for re-training hybrid electric vehicle powertrain control strategies. Successful implementation EVs from business perspectives also requires a well-defined market strategy and targeted consumer acquisition. ML algorithms can be useful for classifying potential electric vehicle (EV) buyers and classify them according to different features[131]. Despite the advancement of DT technology reaching a pivotal stage, its exploration within the automotive industry, particularly in EVs, remains limited. Therefore, there are still noteworthy gaps that necessitate further research to address and resolve. An overview of recent developments in DT-based approaches Electric Vehicle is presented in Table 7.

6. Challenges of DT application in power sector

The energy sector is increasingly recognising the significance of DT technology due to technological improvements. However, despite the potential advantages, there are multiple obstacles associated with the implementation of DTs in power systems. These issues are caused by the complex features of power systems and the various factors involved. This section explores some of the significant challenges faced while implementing DT technology in power systems.

- **Data management:** The DT application at Power Systems or Smart Grid requires a highly advanced virtual environment which facilitates large amount of Data. The collected data from real scenarios is either locally decentralised or centrally stored in a cloud. Technologies like Hadoop Distributed File System (HDFS) and cloud-based storage solutions allow for efficient storage and retrieval of large datasets. Data Base management system (DBMS) can provide structured storage, Amazon S3, Microsoft Azure Blob Storage, or Google Cloud Storage provide reliable and scalable storage options for large datasets [132,133].
- **Modelling and Simulation:** Modelling and simulation perform a crucial role in the creation of a virtual representation of a physical system or object within the framework of DTs. But the physical systems or objects being modelled may exhibit a high degree of complexity, characterised by advanced interactions and behaviours. Power systems are more complex, with interrelated components like generators, transmission lines, substations, and distribution networks. The Smart Grid currently integrates Renewable Energy resources, which are characterised by their significant intermittent and dependence on weather conditions. The development of the virtual representation of these dispersed energy resources is more difficult. It is essential to know and explain the process by which these models generate their predictions or decisions, particularly in important applications where human operators must have trust in and understand the logic behind the model's behaviour [133]. The computational requirements for modelling and simulation are very intensive and need to be very efficient.
- **Connectivity and the processing:** Establishing a connection between the physical system and its virtual counterpart is crucial for the effective implementation of a DT. This connection allows for real-time monitoring, data integration, and the ability to perform remote operations. But since DT is still young, there are still problems with connectivity, like software mistakes and power outages. The latency in data collecting (IoT), the quickness of communication in reaction to real-time events (Sensors), the efficiency of processing algorithms, and the compatibility of interaction speed across various subsystems of DTs may limit the effective implementation of DT [134]. Poor data quality and missing information reduce the possibility of accurate DT execution, which results in inadequate results. The amount and reliability of Internet of Things (IoT) signals are essential factors in determining the effectiveness of DT. Hence, it is essential to apply a technique for identifying and maintaining effective interoperability to prevent data loss [133,135].
- **Privacy and Security:** The protection of privacy and security is crucial in DT applications, as they heavily rely on collecting and exchanging of sensitive data from many sources, such as sensors, IoT devices, and systems. DTs are vulnerable to cyber dangers and attacks due to their connection to networks and systems[136]. Ensuring the security of DTs is crucial in order to prevent unwanted entry, data breaches, and potential interruptions to the physical system. So creating a secured and reliable systems to ensure the data security is one of the main challenges in DT domain. Protecting data security can be achieved through the implementation of robust encryption methods, such as blockchain technology, as well as privacy-enhancing technologies and practices, including data minimisation, anonymisation, and identity theft [133,137].
- **Standardisation:** The diversity of potential DTs for various industries and purposes presents a challenge for standardisation in DT technology. There must be a standardised method from the initial design phase to the simulation of a DT, regardless of whether it is physics-based or design-based [138]. Numerous DT studies as well as those in other fields have emphasised the importance of a consistent framework and global standards for constructing a robust DT. This will help in overcoming numerous modern obstacles, including those related to IoT infrastructure, subsystem connectivity, exchange of information, transparency, analysis of data, privacy, security,quality and dependability of data. These obstacles can be overcome through the implementation of a standard platform, such as the DT definition language. ISO (International Organisation for Standardisation) and other organisations are in the midst of creating frameworks like ISO 23247. Organisations can benefit from improved integration, lower development costs, and greater scalability of DT systems by adopting uniform standards [132].
- **Costing of Development of Digital Twin:** DT incurs significant costs in infrastructure development, mostly due to substantial investments in hardware, software, and networking infrastructure. The process of collecting and combining data is also expensive. Maintaining and ensuring the cybersecurity of systems, as well as periodically upgrading them, is a highly expensive operation. To reduce new costs, use current technologies, data sources, and infrastructure as much as possible. By integrating with present platforms and utilising existing data, the necessity for large data collecting and infrastructure investments can be minimised [132].
- **Scalability:** Large amounts of data are produced by DT systems from a variety of sources, necessitating the use of powerful computers for processing and analysis in real time. It must combine data from several systems and devices, typically using different communication protocols and standards. It is difficult and takes a lot of computer power to manage, process, and analyse this amount of data in real time. This is why using DT in the complicated and extensive present power systems caused issues.

7. Future outlook

The potential of Digital Twin (DT) technology in the energy sector is incredibly encouraging, offering the opportunity to revolutionise multiple facets of power systems and smart grids. Here are some important areas where DT technology is expected to bring about significant advancements and impacts:

- The existing power system grid's viability can be validated using techniques comparable better predictive maintenance and mathematical modelling, which will reduce maintenance costs, increase power system dependability, and minimise downtime.With the help of advanced DT models, power flows can be optimised more effectively, resulting in reduced losses and improved efficiency in power transmission and distribution;

- The potential of Digital Twin DT applications in the transition to a smart grid focused on renewable energy is extensive and revolutionary. DTs will significantly enhance the integration of energy from renewable sources by offering comprehensive modelling techniques and real-time prototypes of solar, wind, and other renewable sources, optimising their performance and predictability;
- Demand response efforts could be changed permanently by DTs, which provide real-time simulations and models of how customers use energy. With this cutting-edge technology, utilities can correctly predict and control demand, changing how energy is distributed based on actual patterns of use. DTs can also help utilities make programmes that are more efficient and effective by maximising the effects of different demand response methods. This feature makes sure that demand response actions are not only specific to the current situation but also perfectly tuned to save the most energy and keep the grid stable;
- IoT devices have the potential to be made more compact, economical, energy-efficient, and resilient. Exploring advanced communication protocols can lead to improvements in both throughput and security. In addition, there is potential for improvement in the monitoring systems of power generation distribution and transmission facilities;
- DTs can allow dynamic modelling and optimisation of EV systems, improving their performance and integration into the wider energy grid. Researching new materials for battery cells will reap significant advantages from DT simulations, resulting in improved efficiency and environmentally friendly EV technologies;
- Machine learning and Edge AI algorithms can be developed to ensure power quality standards in a smart grid by leveraging available data. These algorithms can also be utilised in wind-solar hybrid systems and battery management systems to optimise resource utilisation;
- DT technology is going to implement state-of-the-art cybersecurity measures to safeguard against cyber threats and guarantee the security and privacy of data. Communication systems should be made more efficient and equipped with enhanced protective measures;
- Regulatory frameworks and standardisation efforts are crucial for ensuring a uniform and trustworthy application of DT technologies throughout the energy sector. This will encourage the widespread use and integration of DTs, fostering innovation and maintaining compatibility among various systems and technologies;
- DTs can be utilised for education and training purposes for power system engineers and operators, offering immersive and interactive virtual environments. This will improve the skills and knowledge of the workforce, promoting greater cooperation and decision-making in the energy sector.

8. Conclusion

This study provides a comprehensive review of Digital Twin (DT) applications in power systems and modern smart grids. Extensive research in fault detection, forecasting, cybersecurity, and grid management has been revolutionised by machine learning (ML), enabling rapid responses through data-based analysis. This article summarises key milestones and contributions in these fields, highlighting the progress toward a fully digital power system. DT technology enables the smooth incorporation of distributed energy resources, such as renewable energy, into preexisting power grids. This articles examines numerous applications of DT, with a specific emphasis on effectively integrating intermittent renewable energy sources in a sustainable approach. DTs play a crucial role in evaluating the effectiveness of photovoltaic cells and projecting the long-term expenses of wind farms. They enable the simulation of alternate scenarios including offshore wind farms and floating solar panels, which expands the understanding of potential renewable energy options. DT technology has provided extensive research opportunities in the field of contemporary transportation systems, particularly in the dynamic modelling and optimisation of Electric Vehicle (EV) systems. It supplies information on the prognosis of battery health, smart battery management systems, and even the exploration of materials for battery cells. Since DT is a relatively new technology, it faces obstacles in areas such as data management, storage, and security. Creating an exact duplicate of a physical object and effectively altering its physical characteristics can be a difficult task. However, the knowledge acquired from this technology showcases its substantial suitability in improving the efficiency and dependability of EV systems, hence facilitating the development of greener transportation options. Despite being an emerging technology, we have seen DT encounters challenges such as data management, storage, and security. Developing a precise replication of a physical asset while accurately adjusting its physical parameters can be quite a difficult task. This study stands out by thoroughly analysing every essential aspect of energy systems, encompassing prediction, anomaly detection, security, integration of renewable energy, and optimisation of electric vehicle systems. Future research should focus on current challenges in order to enhance and improve the applications of DTs. Although there are limitations, this review makes a substantial contribution to the subject by providing thorough insights that demonstrate researchers as well as professionals about the potential of DT technology in upgrading energy systems. The rapidly advancing DT technology has resulted in a new era in the energy sector, fostering adaptability and compatibility to create a more resilient and sustainable energy future.

Declaration of Competing Interest

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

Data availability

No data was used for the research described in the article.

Acknowledgement

This research is supported by the Artificial Intelligence, Biomechatronics, and Collaborative Robotics research group at the Top Research Center Mechatronics (TRCM), University of Agder (UiA), Norway. This research is also endorsed by the UiA-CUET CARE project, a partnership between the University of Agder (UiA), in Norway, and Chittagong University of Engineering and Technology (CUET) in Bangladesh.

References

[1] Grieves M. Digital twin: manufacturing excellence through virtual factory replication; a white paper. Melbourne, fl, usa: michael grieves llc; 2014.
[2] Boschert S, Rosen R. Digital twin—the simulation aspect. Cham: Springer International Publishing; 2016. p. 59–74. https://doi.org/10.1007/978-3-319-32156-1_5.
[3] Jafari M, Kavousi-Fard A, Chen T, Karimi M. A review on digital twin technology in smart grid, transportation system and smart city: Challenges and future. IEEE Access 2023;11:17471–84.
[4] Li Q, Deng Y, Liu X, Sun W, Li W, Li J, Liu Z. Autonomous smart grid fault detection. IEEE Commun Stand Magaz 2023.
[5] Ahmad T, Zhang H, Yan B. A review on renewable energy and electricity requirement forecasting models for smart grid and buildings. Sustain Cities Soc 2020;55:102052.
[6] Rivas AEL, Abrao T. Faults in smart grid systems: monitoring, detection and classification. Electric Power Syst Res 2020;189:106602.
[7] Hossain E, Khan I, Un-Noor F, Sikander SS, Sunny MSH. Application of big data and machine learning in smart grid, and associated security concerns: A review. Ieee Access 2019;7:13960–88.
[8] Boza P, Evgeniou T. Artificial intelligence to support the integration of variable renewable energy sources to the power system. Appl Energy 2021;290:116754.
[9] Chehri A, Fofana I, Yang X. Security risk modeling in smart grid critical infrastructures in the era of big data and artificial intelligence. Sustainability 2021;13:3196.

[10] Shibl M, Ismail L, Massoud A. Machine learning-based management of electric vehicles charging: Towards highly-dispersed fast chargers. Energies 2020;13:5429.

[11] Sifat MMH, Choudhury SM, Das SK, Ahamed MH, Muyeen S, Hasan MM, Ali MF, Tasneem Z, Islam MM, Islam MR, et al. Towards electric digital twin grid: Technology and framework review. Energy and AI 2023;11:100213.

[12] T. Cioara, I. Anghel, M. Antal, I. Salomie, C. Antal, A.G. Ioan, An overview of digital twins application domains in smart energy grid, arXiv preprint arXiv:2104.07904 (2021).

[13] M. Lamagna, D. Groppi, M.M. Nezhad, G. Piras, A comprehensive review on digital twins for smart energy management system, International Journal of Energy Production and Management. 2021. Vol. 6. Iss. 4 6 (2021) 323–334.

[14] Bhatti G, Mohan H, Singh RR. Towards the future of smart electric vehicles: Digital twin technology. Renew Sustain Energy Rev 2021;141:110801.

[15] Errandonea I, Beltrán S, Arrizabalaga S. Digital twin for maintenance: A literature review. Comput Industry 2020;123:103316.

[16] Wang Y, Kang X, Chen Z. A survey of digital twin techniques in smart manufacturing and management of energy applications. Green Energy Intell Transport 2022;1:100014.

[17] M. Mohammadi, A. Mohammadi, Empowering distributed solutions in renewable energy systems and grid optimization, arXiv preprint arXiv:2310.15468 (2023).

[18] F. Sanfilippo, R.T. Thorstensen, A. Jha, Z. Jiang, K.G. Robbersmyr, A perspective review on digital twins for roads, bridges, and civil infrastructures, in: Proc. of the IEEE International Conference on Electrical, Computer, Communications and Mechatronics Engineering (ICECCME), 2022, pp. 1–6.

[19] Singh M, Fuenmayor E, Hinchy EP, Qiao Y, Murray N, Devine D. Digital twin: Origin to future. Appl Syst Innovat 2021;4:36.

[20] Jones D, Snider C, Nassehi A, Yon J, Hicks B. Characterising the digital twin: A systematic literature review. CIRP J Manuf Sci Technol 2020;29:36–52.

[21] Jain P, Poon J, Singh JP, Spanos C, Sanders SR, Panda SK. A digital twin approach for fault diagnosis in distributed photovoltaic systems. IEEE Trans Power Electron 2019;35:940–56.

[22] Qi Q, Tao F. Digital twin and big data towards smart manufacturing and industry 4.0: 360 degree comparison. Ieee Access 2018;6:3585–93.

[23] Lee J, Lapira E, Bagheri B, Kao H-A. Recent advances and trends in predictive manufacturing systems in big data environment. Manuf Lett 2013;1:38–41.

[24] Tao F, Zhang M. Digital twin shop-floor: a new shop-floor paradigm towards smart manufacturing. IEEE access 2017;5:20418–27.

[25] Min Q, Lu Y, Liu Z, Su C, Wang B. Machine learning based digital twin framework for production optimization in petrochemical industry. Int J Inform Manage 2019;49:502–19.

[26] E. LaGrange, Developing a digital twin: The roadmap for oil and gas optimization, in: SPE Offshore Europe Conference and Exhibition, SPE, 2019, p. D011S003R001.

[27] Magargle R, Johnson L, Mandloi P, Davoudabadi P, Kesarkar O, Krishnaswamy S, Batteh J, Pitchaikani A. A simulation-based digital twin for model-driven health monitoring and predictive maintenance of an automotive braking system. Modelica. 2017. pp. 132–003.

[28] Mohammadi N, Taylor JE. Smart city digital twins. 2017 IEEE Symposium Series on Computational Intelligence (SSCI). IEEE; 2017. p. 1–5.

[29] R.-M. Soe, Finest twins: platform for cross-border smart city solutions, in: Proceedings of the 18th Annual International Conference on Digital Government Research, 2017, pp. 352–357.

[30] Zhou M, Yan J, Feng D. Digital twin framework and its application to power grid online analysis. CSEE J Power Energy Syst 2019;5:391–8.

[31] X. He, Q. Ai, R.C. Qiu, D. Zhang, Preliminary exploration on digital twin for power systems: Challenges, framework, and applications, arXiv preprint arXiv:1909.06977 (2019).

[32] Brosinsky C, Westermann D, Krebs R. Recent and prospective developments in power system control centers: Adapting the digital twin technology for application in power system control centers. 2018 IEEE International Energy Conference (ENERGYCON). IEEE; 2018. p. 1–6.

[33] Xie L, Weng Y, Rajagopal R. Data Science and Applications for Modern Power Systems. Springer; 2023.

[34] C. Brosinsky, X. Song, D. Westermann, Digital twin-concept of a continuously adaptive power system mirror, in: International ETG-Congress 2019; ETG Symposium, VDE, 2019, pp. 1–6.

[35] A.M. Lund, K. Mochel, J.-W. Lin, R. Onetto, J. Srinivasan, P. Gregg, J.E. Bergman, K.D. Hartling, A. Ahmed, S. Chotai, et al., Digital twin interface for operating wind farms, 2018. US Patent 9,995,278.

[36] Bazmohammadi N, Madary A, Vasquez JC, Mohammadi HB, Khan B, Wu Y, Guerrero JM. Microgrid digital twins: concepts, applications, and future trends. IEEE Access 2021;10:2284–302.

[37] Rodič B. Industry 4.0 and the new simulation modelling paradigm. Organizacija 2017;50:193–207.

[38] Zhang R, Wang F, Cai J, Wang Y, Guo H, Zheng J. Digital twin and its applications: A survey. Int J Adv Manuf Technol 2022;123:4123–36.

[39] Huang J, Zhao L, Wei F, Cao B. The application of digital twin on power industry. In: IOP Conference Series: Earth and Environmental Science, volume 647. IOP Publishing; 2021. p. 012015.

[40] Pan H, Dou Z, Cai Y, Li W, Lei X, Han D. Digital twin and its application in power system. In: 2020 5th International Conference on Power and Renewable Energy (ICPRE). IEEE; 2020. p. 21–6.

[41] Arraño-Vargas F, Konstantinou G. Modular design and real-time simulators toward power system digital twins implementation. IEEE Trans Industr Inform 2022;19:52–61.

[42] Gourisetti SNG, Bhadra S, Sebastian-Cardenas DJ, Touhiduzzaman M, Ahmed O. A theoretical open architecture framework and technology stack for digital twins in energy sector applications. Energies 2023;16:4853.

[43] Palensky P, Cvetkovic M, Gusain D, Joseph A. Digital twins and their use in future power systems. Digital Twin 2022;1:4.

[44] Xie X, Parlikad AK, Puri RS. A neural ordinary differential equations based approach for demand forecasting within power grid digital twins. In: 2019 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm). IEEE; 2019. p. 1–6.

[45] You L, Zhu M. Digital twin simulation for deep learning framework for predicting solar energy market load in trade-by-trade data. Sol Energy 2023;250:388–97.

[46] Alquthami T, Zulfiqar M, Kamran M, Milyani AH, Rasheed MB. A performance comparison of machine learning algorithms for load forecasting in smart grid. IEEE Access 2022;10:48419–33.

[47] Din GMU, Marnerides AK. Short term power load forecasting using deep neural networks. 2017 International conference on computing, networking and communications (ICNC). IEEE; 2017. p. 594–8.

[48] Dedinec A, Filiposka S, Dedinec A, Kocarev L. Deep belief network based electricity load forecasting: An analysis of macedonian case. Energy 2016;115:1688–700.

[49] Wen L, Zhou K, Yang S. Load demand forecasting of residential buildings using a deep learning model. Electric Power Syst Res 2020;179:106073.

[50] Cholewa T, Siuta-Olcha A, Smolarz A, Muryjas P, Wolszczak P, Anasiewicz R, Balaras CA. A simple building energy model in form of an equivalent outdoor temperature. Energy Build 2021;236:110766.

[51] Kudela L, Chỳlek R, Pospíšil J. Efficient integration of machine learning into district heating predictive models. Energies 2020;13:6381.

[52] Dahl M, Brun A, Andresen GB. Using ensemble weather predictions in district heating operation and load forecasting. Appl Energy 2017;193:455–65.

[53] Fahim M, Sharma V, Cao T-V, Canberk B, Duong TQ. Machine learning-based digital twin for predictive modeling in wind turbines. IEEE Access 2022;10:14184–94.

[54] Jiang J-A, Liang Y-T, Chen C-P, Zheng X-Y, Chuang C-L, Wang C-H. On dispatching line ampacities of power grids using weather-based conductor temperature forecasts. IEEE Trans Smart Grid 2016;9:406–15.

[55] Marino DL, Amarasinghe K, Manic M. Building energy load forecasting using deep neural networks. In: IECON 2016–42nd Annual Conference of the IEEE Industrial Electronics Society. IEEE; 2016. p. 7046–51.

[56] Tong C, Li J, Lang C, Kong F, Niu J, Rodrigues JJ. An efficient deep model for day-ahead electricity load forecasting with stacked denoising auto-encoders. J Parallel Distrib Comput 2018;117:267–73.

[57] Khodayar M, Wang J, Manthouri M. Interval deep generative neural network for wind speed forecasting. IEEE Trans Smart Grid 2018;10:3974–89.

[58] Wu W, Chen K, Qiao Y, Lu Z. Probabilistic short-term wind power forecasting based on deep neural networks. 2016 international conference on probabilistic methods applied to power systems (PMAPS). IEEE; 2016. p. 1–8.

[59] Vrablecová P, Ezzeddine AB, Rozinajová V, Šárik S, Sangaiah AK. Smart grid load forecasting using online support vector regression. Comput Electr Eng 2018;65:102–17.

[60] Yang Y, Li W, Gulliver TA, Li S. Bayesian deep learning-based probabilistic load forecasting in smart grids. IEEE Trans Industr Inform 2019;16:4703–13.

[61] Dong X, Qian L, Huang L. Short-term load forecasting in smart grid: A combined cnn and k-means clustering approach. 2017 IEEE international conference on big data and smart computing (BigComp). IEEE; 2017. p. 119–25.

[62] Nazir A, Shaikh AK, Shah AS, Khalil A. Forecasting energy consumption demand of customers in smart grid using temporal fusion transformer (tft). Results Eng 2023;17:100888.

[63] Zahid M, Ahmed F, Javaid N, Abbasi RA, Zainab Kazmi HS, Javaid A, Bilal M, Akbar M, Ilahi M. Electricity price and load forecasting using enhanced convolutional neural network and enhanced support vector regression in smart grids. Electronics 2019;8:122.

[64] Li L, Ota K, Dong M. When weather matters: Iot-based electrical load forecasting for smart grid. IEEE Commun Magaz 2017;55:46–51.

[65] Huang X, Shi J, Gao B, Tai Y, Chen Z, Zhang J. Forecasting hourly solar irradiance using hybrid wavelet transformation and elman model in smart grid. IEEE Access 2019;7:139909–23.

[66] Wang K, Xu C, Zhang Y, Guo S, Zomaya AY. Robust big data analytics for electricity price forecasting in the smart grid. IEEE Trans Big Data 2017;5:34–45.

[67] Tzanis N, Andriopoulos N, Magklaras A, Mylonas E, Birbas M, Birbas A. A hybrid cyber physical digital twin approach for smart grid fault prediction. 2020 IEEE conference on industrial cyberphysical systems (ICPS), volume 1. IEEE; 2020. p. 393–7.

[68] Xia M, Shao H, Williams D, Lu S, Shu L, de Silva CW. Intelligent fault diagnosis of machinery using digital twin-assisted deep transfer learning. Reliab Eng Syst Saf 2021;215:107938.

[69] Danilczyk W, Sun YL, He H. Smart grid anomaly detection using a deep learning digital twin. 2020 52nd North American Power Symposium (NAPS). IEEE; 2020. p. 1–6.

[70] Baghaee HR, Mlakić D, Nikolovski S, Dragicević T. Support vector machine-based islanding and grid fault detection in active distribution networks. IEEE J Emerg Select Top Power Electron 2019;8:2385–403.

[71] Jiang H, Zhang JJ, Gao W, Wu Z. Fault detection, identification, and location in smart grid based on data-driven computational methods. IEEE Trans Smart Grid 2014;5:2947–56.

[72] Zhaoyun Z, Linjun L. Application status and prospects of digital twin technology in distribution grid. Energy Reports 2022;8:14170–82.

[73] Cepeda C, Orozco-Henao C, Percybrooks W, Pulgarín-Rivera JD, Montoya OD, Gil-González W, Vélez JC. Intelligent fault detection system for microgrids. Energies 2020;13:1223.
[74] Dhibi K, Mansouri M, Bouzrara K, Nounou H, Nounou M. An enhanced ensemble learning-based fault detection and diagnosis for grid-connected pv systems. IEEE Access 2021;9:155622–33.
[75] Eskandari A, Milimonfared J, Aghaei M. Optimization of svm classifier using grid search method for line-line fault detection of photovoltaic systems. 2020 47th IEEE Photovoltaic Specialists Conference (PVSC). IEEE; 2020. p. 1134–7.
[76] Hichri A, Hajji M, Mansouri M, Harkat M-F, Kouadri A, Nounou H, Nounou M. Fault detection and diagnosis in grid-connected photovoltaic systems. In: 2020 17th International Multi-Conference on Systems, Signals & Devices (SSD). IEEE; 2020. p. 201–6.
[77] Letizia NA, Tonello AM. Supervised fault detection in energy grids measuring electrical quantities in the plc band. 2020 IEEE International Symposium on Power Line Communications and its Applications (ISPLC). IEEE; 2020. p. 1–5.
[78] Shadi MR, Ameli M-T, Azad S. A real-time hierarchical framework for fault detection, classification, and location in power systems using pmus data and deep learning. Int J Electr Power Energy Syst 2022;134:107399.
[79] Mamuya YD, Lee Y-D, Shen J-W, Shafiullah M, Kuo C-C. Application of machine learning for fault classification and location in a radial distribution grid. Appl Sci 2020;10:4965.
[80] Sapountzoglou N, Lago J, Raison B. Fault diagnosis in low voltage smart distribution grids using gradient boosting trees. Electric Power Syst Res 2020; 182:106254.
[81] Li J, Deng Y, Sun W, Li W, Li R, Li Q, Liu Z. Resource orchestration of cloud-edge–based smart grid fault detection. ACM Trans Sensor Networks (TOSN) 2022; 18:1–26.
[82] Belhadi A, Djenouri Y, Srivastava G, Jolfaei A, Lin JC-W. Privacy reinforcement learning for faults detection in the smart grid. Ad Hoc Networks 2021;119: 102541.
[83] Patnaik B, Mishra M, Bansal RC, Jena RK. Modwt-xgboost based smart energy solution for fault detection and classification in a smart microgrid. Appl Energy 2021;285:116457.
[84] Chakraborty S, Das S. Application of smart meters in high impedance fault detection on distribution systems. IEEE Trans Smart Grid 2018;10:3465–73.
[85] Moghaddass R, Wang J. A hierarchical framework for smart grid anomaly detection using large-scale smart meter data. IEEE Trans Smart Grid 2017;9: 5820–30.
[86] Olivares-Rojas JC, Reyes-Archundia E, Gutierrez-Gnecchi JA, Molina-Moreno I, Cerda-Jacobo J, Méndez-Patiño A. Towards cybersecurity of the smart grid using digital twins. IEEE Internet Comput 2021;26:52–7.
[87] I. ENISA, Smart grid threat landscape and good practice guide; 2013.
[88] Kandasamy NK, Venugopalan S, Wong TK, Leu NJ. An electric power digital twin for cyber security testing, research and education. Comput Electr Eng 2022;101: 108061.
[89] Sayghe A, Hu Y, Zografopoulos I, Liu X, Dutta RG, Jin Y, Konstantinou C. Survey of machine learning methods for detecting false data injection attacks in power systems. IET Smart Grid 2020;3:581–95.
[90] Liu X, Ospina J, Konstantinou C. Deep reinforcement learning for cybersecurity assessment of wind integrated power systems. IEEE Access 2020;8:208378–94.
[91] Bailey T, Johnson J, Levin D. Deep reinforcement learning for online distribution power system cybersecurity protection. In: 2021 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm). IEEE; 2021. p. 227–32.
[92] Hink RCB, Beaver JM, Buckner MA, Morris T, Adhikari U, Pan S. Machine learning for power system disturbance and cyber-attack discrimination. 2014 7th International symposium on resilient control systems (ISRCS). IEEE; 2014. p. 1–8.
[93] Kurt MN, Ogundijo O, Li C, Wang X. Online cyber-attack detection in smart grid: A reinforcement learning approach. IEEE Trans Smart Grid 2018;10:5174–85.
[94] Karimipour H, Dehghantanha A, Parizi RM, Choo K-KR, Leung H. A deep and scalable unsupervised machine learning system for cyber-attack detection in large-scale smart grids. IEEE Access 2019;7:80778–88.
[95] Ahmed S, Lee Y, Hyun S-H, Koo I. Unsupervised machine learning-based detection of covert data integrity assault in smart grid networks utilizing isolation forest. IEEE Trans Inform Forens Secur 2019;14:2765–77.
[96] D. Hudani, M. Haseeb, M. Taufiq, M.A. Umer, N.K. Kandasamy, A data-centric approach to generate invariants for a smart grid using machine learning, in: Proceedings of the 2022 ACM Workshop on Secure and Trustworthy Cyber-Physical Systems, 2022, pp. 31–36.
[97] Sayed K, Gabbar HA. Scada and smart energy grid control automation. In: Smart energy grid engineering. Elsevier; 2017. p. 481–514.
[98] Regula M, Otcenasova A, Roch M, Bodnar R, Repak M. Scada system with power quality monitoring in smart grid model. In: in: 2016 IEEE 16th International Conference on Environment and Electrical Engineering (EEEIC). IEEE; 2016. p. 1–5.
[99] Kermani M, Adelmanesh B, Shirdare E, Sima CA, Carnì DL, Martirano L. Intelligent energy management based on scada system in a real microgrid for smart building applications. Renewable Energy 2021;171:1115–27.
[100] Zhaoyun Z, Linjun L. Application status and prospects of digital twin technology in distribution grid. Energy Reports 2022;8:14170–82.
[101] Yu W, Patros P, Young B, Klinac E, Walmsley TG. Energy digital twin technology for industrial energy management: Classification, challenges and future. Renew Sustain Energy Rev 2022;161:112407.
[102] O'Dwyer E, Pan I, Charlesworth R, Butler S, Shah N. Integration of an energy management tool and digital twin for coordination and control of multi-vector smart energy systems. Sustainable Cities and Society 2020;62:102412.
[103] Zhang Y, Huang T, Bompard EF. Big data analytics in smart grids: a review. Energy informatics 2018;1:1–24.
[104] Park H-A, Byeon G, Son W, Jo H-C, Kim J, Kim S. Digital twin for operation of microgrid: Optimal scheduling in virtual space of digital twin. Energies 2020;13: 5504.
[105] M. Lamagna, D. Groppi, M.M. Nezhad, G. Piras, A comprehensive review on digital twins for smart energy management system, International Journal of Energy Production and Management. 2021. Vol. 6. Iss. 4 6 (2021) 323–334.
[106] Sivalingam K, Sepulveda M, Spring M, Davies P. A review and methodology development for remaining useful life prediction of offshore fixed and floating wind turbine power converter with digital twin technology perspective. 2018 2nd international conference on green energy and applications (ICGEA). IEEE; 2018. p. 197–204.
[107] Alabi TM, Aghimien EI, Agbajor FD, Yang Z, Lu L, Adeoye AR, Gopaluni B. A review on the integrated optimization techniques and machine learning approaches for modeling, prediction, and decision making on integrated energy systems. Renewable Energy 2022;194:822–49.
[108] Rangel-Martinez D, Nigam K, Ricardez-Sandoval LA. Machine learning on sustainable energy: A review and outlook on renewable energy systems, catalysis, smart grid and energy storage. Chem Eng Res Des 2021;174:414–41.
[109] Mohamed MA, Eltamaly AM, Farh HM, Alolah AI. Energy management and renewable energy integration in smart grid system. 2015 IEEE international conference on smart energy grid engineering (SEGE). IEEE; 2015. p. 1–6.
[110] Chauhan A, Saini R. A review on integrated renewable energy system based power generation for stand-alone applications: Configurations, storage options, sizing methodologies and control. Renewable and Sustainable Energy Reviews 2014;38:99–120.
[111] Lu Z, Wang J, Shahidehpour M, Bai L, Li Z, Yan L, Chen X. Risk-aware flexible resource utilization in an unbalanced three-phase distribution network using sdp-based distributionally robust optimal power flow. IEEE Transactions on Smart Grid 2023.
[112] Yan L, Han J, Xu R, Li Z. Model-free lossless data compression for real-time low-latency transmission in smart grids. IEEE Trans Smart Grid 2020;12:2601–10.
[113] Belik M, Rubanenko O. Implementation of digital twin for increasing efficiency of renewable energy sources. Energies 2023;16:4787.
[114] Abdmouleh Z, Alammari RA, Gastli A. Review of policies encouraging renewable energy integration & best practices. Renewable and Sustainable Energy Reviews 2015;45:249–62.
[115] Baboli PT, Babazadeh D, Bowatte DRK. Measurement-based modeling of smart grid dynamics: A digital twin approach. 2020 10th Smart Grid Conference (SGC). IEEE; 2020. p. 1–6.
[116] Nguyen VH, Tran QT, Besanger Y, Jung M, Nguyen TL. Digital twin integrated power-hardware-in-the-loop for the assessment of distributed renewable energy resources. Electrical Engineering 2021:1–12.
[117] H. Mohammadi Moghadam, H. Foroozan, M. Gheisarnejad, M.-H. Khooban, A survey on new trends of digital twin technology for power systems, Journal of Intelligent & Fuzzy Systems 41 (2021) 3873–3893.
[118] Ibrahim M, Rjabtšikov V, Gilbert R. Overview of digital twin platforms for ev applications. Sensors 2023;23:1414.
[119] Zhang Z, Zou Y, Zhou T, Zhang X, Xu Z. Energy consumption prediction of electric vehicles based on digital twin technology. World Electric Vehicle Journal 2021; 12:160.
[120] Venkatesan S, Manickavasagam K, Tengenkai N, Vijayalakshmi N. Health monitoring and prognosis of electric vehicle motor using intelligent-digital twin. IET Electric Power Applications 2019;13:1328–35.
[121] Ibrahim M, Rassõlkin A, Vaimann T, Kallaste A. Overview on digital twin for autonomous electrical vehicles propulsion drive system. Sustainability 2022;14: 601.
[122] Rjabtšikov V, Rassõlkin A, Kudelina K, Kallaste A, Vaimann T. Review of electric vehicle testing procedures for digital twin development: A comprehensive analysis. Energies 2023;16:6952.
[123] S.S. Kamran, A. Haleem, S. Bahl, M. Javaid, D. Nandan, A.S. Verma, Role of smart materials and digital twin (dt) for the adoption of electric vehicles in india, Materials Today: Proceedings 52 (2022) 2295–2304.
[124] Bartolucci L, Cennamo E, Cordiner S, Mulone V, Pasqualini F, Boot MA. Digital twin of a hydrogen fuel cell hybrid electric vehicle: Effect of the control strategy on energy efficiency. Int J Hydrogen Energy 2023;48:20971–85.
[125] López KL, Gagné C, Gardner M-A. Demand-side management using deep learning for smart charging of electric vehicles. IEEE Transactions on Smart Grid 2018;10: 2683–91.
[126] Ahmed M, Zheng Y, Amine A, Fathiannasab H, Chen Z. The role of artificial intelligence in the mass adoption of electric vehicles. Joule 2021;5:2296–322.
[127] Chandran V, Patil CK, Karthick A, Ganeshaperumal D, Rahim R, Ghosh A. State of charge estimation of lithium-ion battery for electric vehicles using machine learning algorithms. World Electric Vehicle Journal 2021;12:38.
[128] M. Shibl, L. Ismail, A. Massoud, Electric vehicles charging management using machine learning considering fast charging and vehicle-to-grid operation, energies 14 (19), URL: https://www.mdpi.com/1996-1073/14/19/6199 (2021).
[129] Mohamed N, Bajaj M, Almazrouei SK, Jurado F, Oubelaid A, Kamel S. Artificial intelligence (ai) and machine learning (ml)-based information security in electric vehicles: A review. 2023 5th Global Power, Energy and Communication Conference (GPECOM). IEEE; 2023. p. 108–13.

[130] Harold CK, Prakash S, Hofman T. Powertrain control for hybrid-electric vehicles using supervised machine learning. Vehicles 2020;2:267–86.
[131] Bas J, Cirillo C, Cherchi E. Classification of potential electric vehicle purchasers: A machine learning approach. Technological Forecasting and Social Change 2021; 168:120759.
[132] Yassin MA, Shrestha A, Rabie S. Digital twin in power system research and development: principle, scope, and challenges. Energy Reviews 2023;100039.
[133] Ebrahimi A. Challenges of developing a digital twin model of renewable energy generators. 2019 IEEE 28th international symposium on industrial electronics (ISIE). IEEE; 2019. p. 1059–66.
[134] P. Almasan, M. Ferriol-Galmés, J. Paillisse, J. Suárez-Varela, D. Perino, D. López, A.A.P. Perales, P. Harvey, L. Ciavaglia, L. Wong, et al., Digital twin network: Opportunities and challenges, arXiv preprint arXiv:2201.01144 (2022).
[135] D.M. Botín-Sanabria, A.-S. Mihaita, R.E. Peimbert-García, M.A. Ramírez-Moreno, R.A. Ramírez-Mendoza, J. d. J. Lozoya-Santos, Digital twin technology challenges and applications: A comprehensive review, Remote Sensing 14 (2022) 1335.
[136] National Academies of Sciences, Engineering, and Medicine and others, Opportunities and challenges for digital twins in engineering: Proceedings of a workshop—in brief (2023).
[137] Fuller A, Fan Z, Day C, Barlow C. Digital twin: enabling technologies, challenges and open research. IEEE access 2020;8:108952–71.
[138] Rasheed A, San O, Kvamsdal T. Digital twin: Values, challenges and enablers, arXiv preprint arXiv:1910.01719; 2019.