Meta-Power: Digitalized Power Systems Driven by Metaverse

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Abstract: Metaverse is a transformative stage in the digital revolution, focusing on the development of an interactive and hyper-spatiotemporal ecosystem. This ecosystem is built upon various technologies, such as digital twins and extended reality. The application of the metaverse in power systems can significantly advance their digitalization level. This paper introduces a novel concept of meta-power to represent digitalized power systems driven by the metaverse. Supported by multiple technologies, the meta-power is a power ecosystem with high interactivity and hyper-spatiotemporal capabilities. The multi-technicity of meta-power enhances the stability, flexibility, reliability, safety, and economy of power systems. Furthermore, its high interactivity improves the convenience and immersion of power system monitoring and maintenance. Additionally, its hyper-spatiotemporal capability overcomes spatial and temporal limitations in power system operations and planning, providing benefits in evaluating and deducing future energy development strategies. This paper presents a comprehensive exploration of meta-power, encompassing its architecture, characteristics, enabling technologies, and application scenarios, aiming to provide theoretical and practical implications, respectively. At the theoretical level, this paper can stimulate research and development efforts in new metaverse technologies for power systems. At the practical level, it serves as a guide for power system digitalization, facilitating the advancement of a sustainable economy while ensuring the reliability and safety of power systems.

Keywords: Artificial intelligence; Digital twins; Extended reality; Internet of Things; Metaverse; Power systems

1. INTRODUCTION

CARBON, in various forms, is widely recognized as having a detrimental impact on the environment. In the pursuit of sustainability, numerous countries have made commitments to achieve carbon peaking and carbon neutrality. The widespread adoption of renewable energy sources and the increasing prevalence of electric vehicles are recognized as pivotal strategies in realizing these dual objectives of carbon peaking and carbon neutrality [1]. However, the widespread deployment of renewable energy sources and electric vehicles necessitates the development of flexible power systems capable of accommodating the intermittent nature of their energy supply [2]. Smart grid, operating as a digitalized power system with bi-directional data transmission and computational intelligence, plays a vital role in enabling the flexible operation necessary for the seamless integration of renewable energy sources and electric vehicles into power systems [3].

The smart grid concept was first introduced in Wired Magazine in 2001, which prompted various countries to initiate research and projects related to the implementation of smart grid technology [4–6]. The advancement of communication and computation infrastructure has enabled power systems to become smarter, allowing for bi-directional data transmission and decision-making based on big data analysis [7]. The smart grid has significantly enhanced the stability, flexibility, reliability, safety, and economy of power systems [8]. However, there is still considerable room for improvement in the digitalization efforts of the smart grid, particularly in two aspects: ubiquitous information visualization and intelligent hyper-spatiotemporal operations. Ubiquitous information visualization is user-oriented digitalization that enhances user convenience and immersion within the power plant environment by providing access to real-time operational information [9]. However, the current level of information visualization in power systems needs to be improved to ensure a seamless and immersive user experience, highlighting the importance of enhancing this aspect. A second improvement that can be made is intelligent hyper-spatiotemporal operation, which belongs to system-oriented digitalization. Currently, the historical and real-time data of the power systems are analyzed, but the data analysis capability under unprecedented conditions is weak, indicating that the analysis capability still needs to be improved [10].

In 2021, the emergence of non-fungible tokens has ushered in a new era for the digital world, providing a means to guarantee the uniqueness and authenticity of digital assets and sparking a surge of interest in the metaverse. The term 'metaverse' is derived from the combination of the prefix 'meta' and the suffix 'verse,' representing a cohesive value system and an independent economic framework that is interconnected with the physical world [11]. Initially introduced in Neal Stephenson's science fiction novel 'Snow Crash,' the metaverse portrays a shared virtual reality inhabited by millions of users, and the concept has subsequently been embraced and further developed in diverse technological and cultural contexts [12]. Recently, the industry has seen rapid progress in applying metaverse, particularly in the Internet, transportation, aerospace, and manufacturing industries [13]. In the Internet industry, Facebook has purchased the Oculus for deeper development of virtual reality and augmented reality, aiming to provide a new customer experience. Microsoft has taken over Activision, one of the biggest developers of online gaming, to prepare for the metaverse [14]. In the transportation industry, the Invisible-to-Visible (I2V) technology, which aims at improving driving safety by providing drivers with imperceptible road information, has been developed [15]. The aerospace industry has also used the metaverse, with Boeing utilizing mixed reality to train personnel to maintain Boeing 737 aircraft [16]. Nvidia has developed the world's first virtual collaboration and simulation platform, called Nvidia Omniverse, which can improve the efficiency of new product development (NPD) in the manufacturing industry.

In addition to the initiation of metaverse-related projects in industry, academic researchers have also actively pursued investigations into the metaverse. These research endeavors encompass a comprehensive exploration of the metaverse, including its definitions, characteristics, architecture, enabling technologies, and application scenarios. Regarding the definition of the metaverse, academia lacks a singular consensus, and Al-Ghaili et al. [17] have compiled and summarized various definitions proposed by scholars. In terms of characteristics, Ning et al. have identified characteristics of the metaverse, including multi-technicity, high interactivity, and hyper-spatiotemporality [18]. As for the architecture of the metaverse, its construction requires five primary modules: reality, virtuality, virtual-reality interaction, intelligent analysis, and human-machine interaction (HMI) [19]. Among these modules, reality serves as a reference for modeling, the virtuality creates either a virtual world that differs from reality or a mirror world that aligns with reality, the virtual-reality interaction facilitates the transfer of information between reality and the virtuality, the intelligent analysis combines and analyzes data from both reality and the virtuality to provide users with analytical results and intelligent decisions, and the HMI enables the transfer of information between the metaverse and its users. Enabling technologies for the metaverse encompass digital twins (DTs), Internet of Things (IoTs), communication networks, big data management, computing strategies, artificial intelligence (AI), and advanced HMI [20–22]. Advanced HMI in the metaverse differs from traditional 2D interfaces and incorporates extended reality, an umbrella term encompassing virtual reality, augmented reality, and mixed reality, enabling users to explore a 3D virtual world with an immersive experience [23–25]. For example, the Microsoft HoloLens headset enables mixed reality for engineering applications [26,27]. The extended reality market is estimated to reach approximately USD 250 billion by 2028 [28]. In terms of application scenarios, the Accelerated Research Foundation has categorized the metaverse into four scenarios: augmented reality, daily recording, mirror world, and virtual world [29]. This paper will explore the application of the metaverse in power systems from these perspectives.

Previous studies have conducted reviews and surveys on various aspects of the metaverse. Dionisio et al. have summarized metaverse development in terms of reality, universality, interoperability, and scalability [30]. Lee et al. have conducted a survey exploring user-centric factors and future research agendas [22]. Khan et al. have investigated wireless communication architectures for the metaverse and discussed its potential impact on improving wireless systems [31]. Falchuk et al. have focused on privacy issues in the metaverse and proposed privacy protection measures for social interactions [32]. Huynh-The et al. have reviewed blockchain technology for the metaverse [33]. While many of these studies concentrated on enabling technologies, networking, security, or privacy concerns associated with the metaverse, few papers have specifically addressed its application in power systems [34]. Currently, there are two papers that touch upon the application of the metaverse in power systems [35,36]. Among them, Abou El Houda and Brik [35] have proposed a concept of next-power, facilitating P2P energy transactions using virtual economic systems and blockchain technology of the metaverse. Zhang and Liu [36] have developed a concept of meta-energy and described its application to power system operations from four aspects: (1) Intelligent monitoring and perception, (2) Intelligent information communication and management, (3) Intelligent modeling and simulation technology, and (4) Intelligent optimization and control. Although these papers have provided the application of some metaverse enabling technologies in power systems, they do not comprehensively cover other aspects such as architecture, characteristics, enabling technologies, and application scenarios. In comparison, this paper offers a more comprehensive review of the application of the metaverse in power systems.

The application of the metaverse in power systems holds the potential to propel the digitalization of the power industry, offering numerous benefits. Leveraging multiple enabling technologies of the metaverse, power systems can experience improvements in stability, flexibility, reliability, safety, and economy. The high interactivity of the metaverse can enhance the convenience and immersion of power system monitoring and maintenance. Additionally, its hyper-spatiotemporality can overcome the spatial and temporal limitations of power systems, expediting the evaluation and deduction processes for future energy strategies. This paper defines the application of the metaverse in power systems as meta-power. Section II provides a conceptual explanation of the meta-power. In Section III, key enabling technologies that can achieve the meta-power are analyzed. Section IV presents application scenarios of the meta-power. Section V discusses the challenges and opportunities associated with the meta-power. Finally, Section VI concludes the paper. The hierarchical structure of the paper is shown in Figure 1.

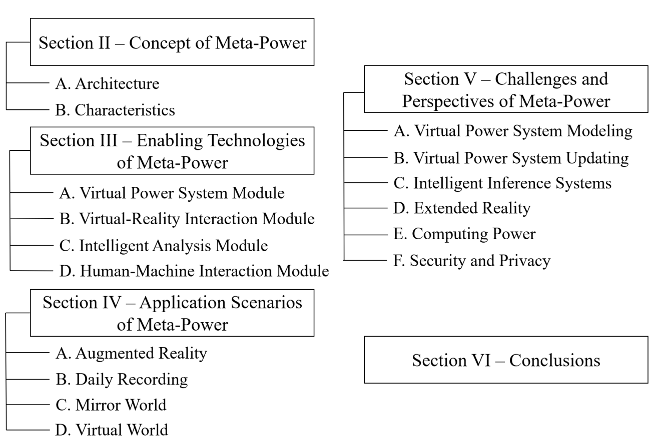

Figure 1. Hierarchical structure of the paper.

2. CONCEPT OF META-POWER

2.1. ARCHITECTURE

Meta-power is the application of the metaverse in power systems, and its architecture encompasses five fundamental modules: real power systems, virtual power systems, virtual-reality interaction, intelligent analysis, and HMI [36]. Within the me-power architecture, the virtual-reality interaction module facilitates bi-directional data transmission, enabling seamless communication between the real and virtual power system modules. The intelligent analysis module merges and analyzes data from both the real and virtual domains, generating valuable information or decisions. The HMI module serves as the interface through which users can access and interact with information pertaining to both real and virtual power systems. The meta-power architecture consists of two layers: the infrastructure layer and the platform layer [11]. The infrastructure layer encompasses the real power system, virtual power system, and virtual-reality interaction modules. Conversely, the platform layer comprises the intelligent analysis and HMI modules, as depicted in Figure 2. In the infrastructure layer, the real power system module forms the essential skeleton for the virtual power system module to build upon. The virtual power system module serves as a digital representation in the meta-power, capable of adapting to dynamic updates from the real power system [37]. The key enabling technology that facilitates the realization of the virtual power system module is DT technology [38]. The virtual-reality interaction module acts as a communication medium between the real and virtual power systems, responsible for collecting, exchanging, and storing information from both real and virtual power systems. Key enabling technologies for realizing the virtual-reality interaction module include IoTs, communication networks, and big data management [39–41]. The intelligent analysis module in the platform layer acts as the 'brain' in the meta-power, enabling intelligent power system operation and its enabling technologies include computing strategies and AI [42,43]. The HMI module serves as the communication bridge between the meta-power and its users, with extended reality technology being the key factor in its realization [24,25].

In the infrastructure layer, the connection between the real power system, the virtual power system, and the virtual-reality interaction modules constitute four scenarios of the meta-power: augmented reality, daily recording, mirror world, and virtual world. Augmented reality is a scenario that enables one-way information flow from the virtual power systems to the real power systems, facilitated by the virtual-reality interaction module. This enables the real power systems to receive virtual data and information to aid in operating real power systems. The scenario of the daily recording involves a two-way information flow between the real and virtual power systems via the virtual-reality interaction module, which records and reproduces abnormal data and events from the real and virtual power systems. In the scenario of the mirror world, there is a two-way information flow between the real and virtual power systems through the virtual-reality interaction module. The virtual power system module acts as a parallel controller. It is responsible for gathering data from the real power system module and analyzing it to issue control commands to the real power system module. In the virtual world scenario, there is a one-way information flow from the real power system module to the virtual power system module through the virtual-reality interaction module. The design of the virtual power system module based on real power systems can provide a virtual power plant environment for designers and interns to assist in power plant design and training.

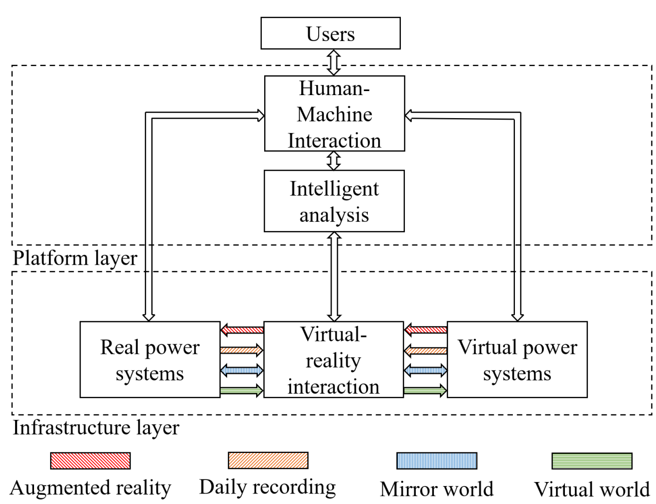

Figure 2. Architecture of the meta-power.

2.2. CHARACTERISTICS

Meta-power is the application of the metaverse in power systems, which shares the common characteristics of multi-technicity, strong interactivity, and hyper-spatiotemporality as the metaverse [17]. The multi-technicity of the meta-power is reflected in its reliance on diverse technologies, including DTs, IoTs, communication networks, big data management, computing strategies, AI, and extended reality [24]. The strong interactivity of the meta-power is evident not only in the interaction between the real and virtual power system modules but also in the emphasis on the interaction between the meta-power and its users. The hyper-spatiotemporality of the meta-power is reflected at both user and system levels. At the user level, the meta-power allows users to learn about and conduct research in power plant environments from the past or future in the temporal dimension. It also enables learning at any virtual power plant in the spatial dimension. At the system level, the meta-power enables the assessment and deduction of future energy strategies in arbitrary multi-operational conditions, especially unprecedented conditions in the spatial dimension [36].

The digitalization of power systems has advanced significantly, enabling stability, flexibility, reliability, safety, and economics in power system operations. Despite these advances, there is still considerable potential for further development of digitalization in power systems, particularly in ubiquitous information visualization and intelligent hyper-spatiotemporal operation. Ubiquitous information visualization is user-centric digitalization that seeks to visualize the operational information of power equipment across power systems and provide users with a convenient and immersive power system environment [30]. Intelligent hyper-spatiotemporal operation is system-centric digitalization that refers to the ability to analyze data from power systems over historical, current, and future periods and under arbitrary operating conditions with AI algorithms [38].

The strong interactivity and hyper-spatiotemporality of the meta-power can effectively address the challenges related to ubiquitous information visualization and intelligent hyper-spatiotemporal operation in current power systems, thereby serving as essential characteristics of digitalized power systems. Implementing extended reality, such as holographic projections, can significantly enhance the convenience and immersion of operation and maintenance tasks. With the extended reality technology, the operators can quickly access operational information about power equipment from any location within the power plant environment and use these technologies to interact with power equipment and achieve ubiquitous information visualization. The virtual power system module based on DT technology is a key enabling module for achieving the hyper-spatiotemporality of the meta-power. By creating virtual power systems that are parallel to real power systems, designers and operators can leverage these virtual systems to simulate and evaluate future energy strategies in the temporal dimension, as well as perform unprecedented scenario simulation to obtain operational dynamics across a vast number of power systems in the spatial dimension, thereby enabling intelligent hyper-spatiotemporal operation [36,37].

3. ENABLING TECHNOLOGIES OF META-POWER

The implementation of the meta-power requires the collaborative operation of a real power system, virtual power system, virtual-reality interaction, intelligent analysis, and HMI modules. Enabling technologies of virtual power systems, virtual-reality interaction, intelligent analysis, and HMI modules play indispensable roles, which have been applied in the generation, transmission, distribution, and consumption parts of real power systems, separately. The following subsections present enabling technologies for these meta-power modules.

3.1. VIRTUAL POWER SYSTEM MODULE

The virtual power system module serves as the digital backbone of the meta-power architecture. It enables power systems to leverage hyper-spatiotemporal characteristics, facilitating intelligent hyper-spatiotemporal operations. While conventional digitalization efforts have primarily focused on the real power system module, the meta-power architecture emphasizes the integration of both real and virtual power system modules. This integration allows for the supplementation of analysis results obtained from real power systems with those derived from virtual power systems, enabling a more comprehensive system analysis under unprecedented conditions. Implementing the virtual power system module relies heavily on DT technology, which is essential for its successful deployment and operation.

DT technology has gained significant recognition and has been listed as one of the top ten strategic technologies for 2018 by Gartner due to its ability to virtually map the operational states of real systems. Rodiv has proposed that DT technology represents the next simulation paradigm, enabling real-time system simulation during both design and service phases [44]. In academia and industry, there is a widely accepted definition of DT: it is an integrated multi-physics, multi-scale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin. The initial concept of DT consisted of three components: physical assets, digital prototypes, and communication between physical assets and digital prototypes, as developed by Grieves and Vickers [45]. Subsequently, Tao et al. have introduced two additional components, DT data and service [46,47]. The architecture of DT with five components is shown in **Figure 3**.

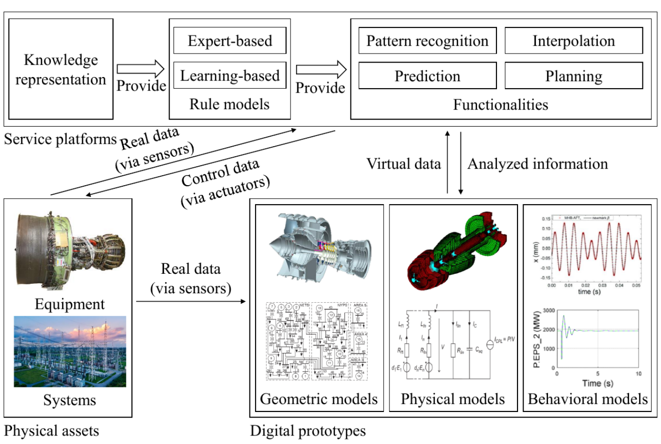

Figure 3. Architecture of the digital twins.

The construction of DT typically involves two steps, which are DT modeling and updating. DT modeling involves four steps, including geometric, physical, behavioral, and rule modeling [48,49]. Geometric modeling primarily describes the structural/topological relationships in the physical assets. In terms of equipment, the geometric modeling tools include AutoCAD, CATIA, and SolidWorks, aiming to describe the shape, size, position, and assembly relationships of equipment elements. In terms of systems, the geometric modeling tools include PSCAD, SIMPOW, and SIMULINK, aiming to describe the network connection between different equipment. Physical modeling mainly includes the fundamental laws of physical assets. For example, the Newton-Euler law is the physical law describing mechanical characteristics, while the impedance law is the fundamental law describing electrical characteristics. Behavioral modeling focuses on describing the responses of physical assets to external drivers or disturbances over time. Rule modeling is a service-oriented process based on users' requirements after geometric, physical, and behavioral modeling. It is an important part of the DT since it can provide different functions (e.g., pattern recognition, interpolation, prediction, and planning) for users. Rule modeling broadly consists of two parts: knowledge management and inference system design, which form the bulk of the DT service. DT updating is also a key part of the DT, as it ensures consistency between the physical assets and digital prototypes. **Figure 4** shows the flowchart of DT updating. DT updating can be divided into two categories based on the updated parts: model update and parameter update. The model update involves a variation in the model structure, while the parameter update involves changing the model parameters. The DT can be divided into two categories based on the update strategy: Cycle-based and event-based updates. The cycle-based update refers to the periodic updating of the models, whereas an event-based update is triggered by the difference between the physical assets and digital prototypes with performance metrics [50].

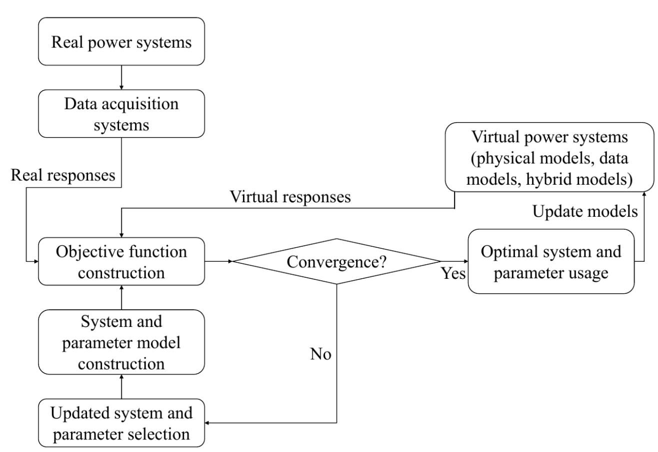

Figure 4. Flowchart of the digital twins updating.

The DT is a versatile technology with various applications in power systems, including three-dimensional visualization for efficient management of power plants, optimization of power plant operation for enhanced performance, health management of power equipment to minimize downtime, construction of genetic grid models for effective planning, grid design to ensure optimal utilization of resources, and asset management for maintenance activities [51–55]. Table 1 lists some applications of DT technology in the generation, transmission, distribution, consumption, and market sectors of power systems. The DT technology can be leveraged to build virtual power systems that accurately replicate the operational conditions of real power systems, offering a low-cost, low-risk environment for operators to perform detailed analysis throughout the lifecycle of the power systems [56]. The technology can facilitate more informed decision-making and enable proactive maintenance, ultimately leading to improved reliability and economy in the power systems. In applying DT to power systems, there are two categories of physics-based models: structure-based finite element modeling and topology-based system dynamics modeling. Structure-based finite element modeling is primarily utilized for simulating virtual power equipment and finds its applications in various subsystems of power systems, such as generation, transformation, transmission, distribution, consumption, and storage [57–60]. Topology-based system dynamics modeling is mainly used for simulating virtual power grids, with the models based on realistic transmission and distribution networks established by IEEE [61,62]. Although physics-based virtual power systems effectively explain various phenomena, this modeling method can be computationally demanding, requiring significant running time. As information and communication infrastructure in power systems undergoes large-scale modeling, researchers are increasingly investigating data-driven models. However, the high-dimensional nature of real power systems presents a challenge for conventional machine learning (ML) models to express virtual power systems accurately. The random matrix can represent data in high-dimensional spaces, while deep learning (DL) can effectively handle the strong nonlinearity of real power systems. Combining these two techniques can offer feasible solutions for developing data-driven models for virtual power systems that can overcome the challenges of the high dimensionality and strong nonlinearity of power systems [63]. The DT technology can simulate both the cyber and physical sides of real power systems, which means that the DT can model the physical infrastructure of real power systems and the associated cyberinfrastructure, including communication and control systems. Several institutions have constructed test platforms capable of simulating the physical and cyber infrastructure of real power systems to facilitate related research about the cyberinfrastructure. These platforms include the hardware loop test platform in the USF Smart Grid lab, the IEC 61850-based Smart Grid test platform, and other test platforms that serve different functions. These test platforms provide researchers and engineers with a realistic environment for testing and evaluating the performance of power systems and energy strategies in a controlled and safe manner [64,65].

Once the virtual power systems have been built, updating them with data from the real power systems is essential, ensuring the accuracy of current virtual power systems. There is already some research on the update of virtual power systems. At the power equipment level, Qin et al. have employed a back propagation neural network to correct the error between the virtual bearing and real bearing [66]. At the system level, Saad et al. have established a physical model to model the physical and cyber-side of the power systems and employed real data to update the parameters of the physical models to achieve an update with an average error of no more than 4% from the real power systems [67].

3.2. VIRTUAL-REALITY INTERACTION MODULE

The virtual-reality interaction module of the meta-power serves as a vital communication interface between real and virtual power system modules. The virtual-reality interaction module relies on IoTs, communication networks, and big data management, facilitating crucial tasks of sensing, transmitting, analyzing, controlling, and managing.

3.2.1. INTERNET OF THINGS

IoTs comprise three fundamental components: the device, the edge, and the cloud. In the context of IoTs, the device refers to a physical endpoint that collects data. Conversely, the edge represents a connected network

Table 1. Application of digital twins in power systems

Real power system sectors	Physical assets	Research objectives	Digital prototypes	Results	References
Generation	Protective coating systems on wind turbines	Prescriptive maintenance planning	Physics-based finite element model	The digital twin can be used to predict the state of assets and future risks, to optimize maintenance intervals, and to develop forecast models.	[68]
	Distributed photovoltaic systems	Fault diagnosis in building integrated photovoltaics	Model-based digital twin estimator of a PV energy conversion unit	The proposed approach demonstrates higher fault detection sensitivity than other existing approaches.	[69]
	Combustion engine-based power plant	Coordinated control of combustion engine-based power plants with battery storage	Physics-based model	The model showed expected functionality and validity within 4% and 8% of the respective measured generator and converter outputs.	[70]
Transmission	Multi-energy system	Dynamic load balancing	62-node multi-energy system and weighted bipartite graph	The response time of optimized task assignment was reduced and the simulation efficiency was improved.	[71]
	Ultra-high voltage direct current systems	Loss measurement	DTformer including random feature extraction, transfer learning, and knowledge distillation	The model has good accuracy, response time, and resistance to the missing data.	[72]
	Internet of Energy	Situation awareness including fault location and stability prediction	Graph digital twin combining graph convolution network	The proposed model can localize the multiple fault components with high accuracy, and can accurately predict the stability of the system.	[73]
Distribution	Power distribution systems	Identify the locations of cyber attacks	Physics-based state space models	The proposed method can distinguish attacks on protective devices and load measurement units and determine the locations of the attacked devices.	[74]
	Networked microgrids	Energy management of networked microgrids	Neural network trained by the data from the different optimal results of unit commitment	The neural network model can interact with the physics-based model in a real-time manner.	[75]
Consumption	Buildings	Net Zero Energy	Building information model	It is possible to achieve Net Zero Energy of existing buildings via balancing out their energy demand from renewable energy.	[76]
		Energy performance certificate for energy efficiency classification	Building information model	This study demonstrates the importance of adapting the energy assessment of buildings for digital assessment with digital twins.	[77]
		City block renovation using renewable energy sources	Multi-objective optimization with goal programming	A hybrid renewable energy source solution, including a PV system and a heating system, is optimal.	[78]

of multiple operating devices linked through logical relationships. Finally, the cloud is a centralized hub for multiple domains and an application-centric integrated IoT service system, enabling efficient data analysis and system control. The IoTs have several applications in power systems, including but not limited to Supervisory Control and Data Acquisition (SCADA), Wide Area Measurement System (WAMS), and Advanced Metering Infrastructure (AMI) [79]. **Figure 5** illustrates the schematic diagram of ubiquitous power IoTs, which are based on SCADA, WAMS, and AMI systems. The SCADA system is a centralized IoT system that employs a main-servant architecture for process control in power systems. The SCADA system primarily comprises intelligent electronic devices (IEDs), remote terminal units (RTUs), programmable logic controllers (PLCs), and monitoring consoles, which are based on the main-servant architecture, database, and communication infrastructure [80]. IEDs are employed to monitor the operational conditions of power equipment, including circuit breakers, transformers, and capacitors. RTUs interact with IEDs, convert the sensor readings into a standard data format, and transmit the sensor data to monitoring consoles. PLCs are utilized for implementing process control, while monitoring consoles are responsible for collecting data from RTUs, performing data analysis, and sending control commands to PLCs. The database plays a crucial role in the SCADA system by facilitating the storage and management of data. The communication infrastructure is an essential component of IoTs, enabling the connection between various subsystems [81]. The WAMS is an IoT that comprises phasor measurement units (PMUs), phase data concentrators (PDCs), and satellites [82–84]. It can provide synchronized phase measurement information every 20ms with a synchronization error of 1ms for each data point. PMUs are considered the key components of IoTs in WAMS. These units are capable of generating voltage, current, frequency, and phase angle signals at a frequency of 60Hz, and some advanced PMUs can even generate electrical signals at a higher frequency of 100Hz. Implementing WAMS has made it possible to analyze the transient stability of power systems with greater accuracy. The conventional smart meter-based IoT system is based on automatic meter reading (AMR) technology, which is designed for one-way communication and can only monitor the distribution network but cannot control it [85]. To address the issue of controlling the distribution network, an advanced metering infrastructure (AMI) system that utilizes bi-directional communication is proposed. Unlike the centralized SCADA system, the AMI system is a distributed IoT system that enables interconnection between smart meters, between smart meters and IEDs, and between smart meters and other control systems [86]. The AMI system has a broad range of applications, including obtaining power quality, electricity consumption, and fault records at the customers' end and monitoring the power generated or stored by distributed energy sources [87–89].

IoTs find applications across various aspects of the power sector, including power generation, transmission, distribution, and consumption. In power generation, IoTs can enhance the efficiency of distributed energy generation and ensure reliable and safe operation. For renewable power plants, IoTs can consider the fluctuations in renewable power generation through cloud computation and weather prediction algorithms. This enables optimal power plant operation and predictive maintenance [90]. With respect to transmission and distribution, IoT can help reduce power losses and electricity thefts by adjusting or detecting electrical parameters such as voltage, current, frequency, and phase [91]. With respect to power consumption, IoT technology is the key driver to the growth of microgrids or nanogrids, smart home energy management systems, and distributed energy storage systems. As a result, consumers gradually become prosumers, which can participate in power exchanges with the electrical network. Examples of scenarios where customers are able to participate in power exchanges with the electric network include smart home energy management and electricity price schemes [92].

3.2.2. COMMUNICATION NETWORKS

The regular communication operation of the IoTs is supported by effective data transmission through communication networks, which can be broadly classified into wired and wireless communication technologies. Some of the commonly employed wired communication methods include power line communication (PLC), digital subscriber line (DSL) communication, and fiber optic communication [93]. The wireless communication networks include ZigBee, wireless mesh networks (such

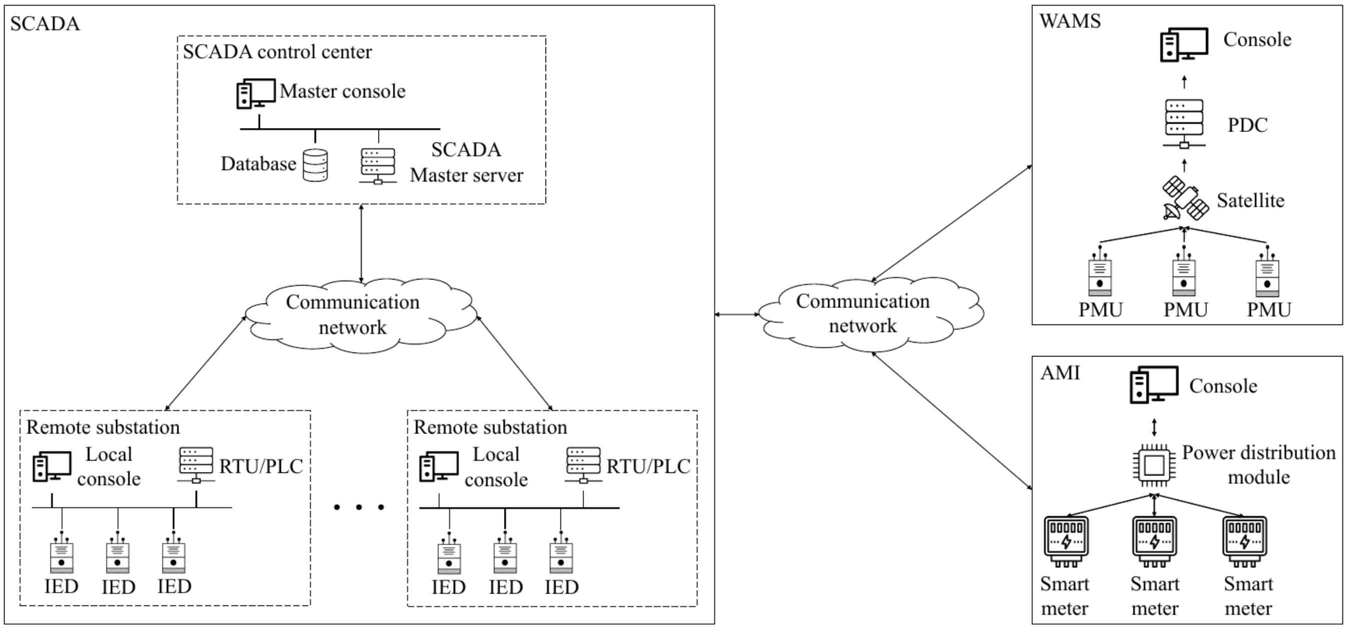

Figure 5. Ubiquitous power internet of things.

as radio frequency networks), and cellular communication networks such as 3G, 4G, 5G, and WiMAX [94–96]. The application of communication networks in the power IoTs has matured due to advancements in the field. The PLC, which operates in the 40-500kHz frequency band, is used in the substations on the high voltage side, the AMI systems, vehicle-to-grid systems, and home energy management systems on the medium and low voltage sides, as well as 1,100kV AC/DC lines [97]. Due to high bandwidth and reliability, DSL and fiber optic communication are utilized in SCADA systems to facilitate communication between substations and dispatch centers.

Due to its low power consumption, low data rate, and low cost, ZigBee is particularly well-suited for applications such as intelligent lighting, electrical automation, and AMR. Wireless mesh networks, including radio frequency networks, can transmit data in the AMI system for smart metering. Cellular communication networks, such as 3G, 4G, and 5G, can also transmit smart meter data. WiMAX networks can be utilized as backhaul networks to connect remote and rural areas to the main grid. Due to its short-range coverage and high data transmission rate, WiFi communication is suitable for user-side applications, such as home energy management systems and vehicle-to-grid systems. Satellite communication can serve as a reliable backup communication solution for power systems, providing redundancy in the event of communication network malfunction. To ensure efficient and secure data transmission in power IoTs, it is essential to consider high-speed, low-latency, and high-performance data transmission protocols such as fiber channel protocol and 5G. Table 2 lists the wireless communication technologies employed in power systems [98]. In addition, quantum transmission technology has the potential to be applicable for communication, including quantum key distribution (QKD), quantum teleportation, quantum secure direct communication (QSDC), and quantum secret sharing (QSS).

Table 2. Application of wireless communication technologies in power systems

Technology	Transmission distance	Cost	Application
Satellite	> 1500 km	High	Wind and solar plants
LTE-M	< 200 km	Moderate	Energy meter
NB-IoT	< 50 km	Low	Grid communication
LoRA	< 50 km	Low	Lighting

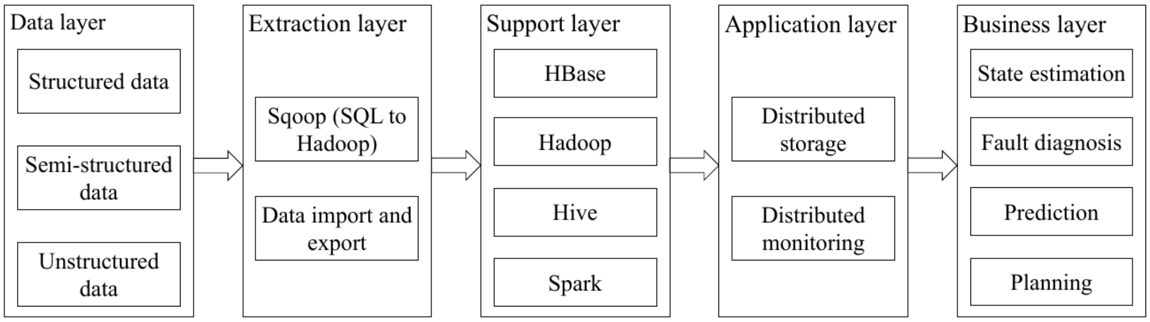

Figure 6. Hadoop-based data management architecture.

3.2.3. BIG DATA MANAGEMENT

Big data management involves two primary strategies: database management and data cluster management. Database management is a strategy that integrates a variety of storage devices to provide data storage and external business access. Data cluster management involves collecting, organizing, and integrating heterogeneous data sources into a new centralized big data source, which is then managed and made available for access.

Two types of databases are relational and non-relational databases. The conventional relational database is not suitable for handling massive data since it requires storing the correlation between data, while non-relational databases do not have a fixed table structure and do not require connections between data, making them more suitable for high-performance read and write operations for massive data and better meeting the data management requirements of power big data era.

Data cluster management primarily utilizes cluster system architecture developed by the Apache Foundation, which includes Hadoop, Storm, Spark, and Drill [99]. The application of Hadoop is mature, and this paper focuses on analyzing the architecture of Hadoop. The Hadoop architecture comprises three components, namely the distributed file system (HDFS), the distributed parallel programming model (MapReduce), and the distributed database (HBase). Among them, the HDFS can effectively store massive data, the MapReduce can perform massive data processing in large cluster sizes, and the HBase is a distributed non-relational database. **Figure 6** is a Hadoop-based data management architecture.

Big data management is a versatile technology that can be effectively applied at both the power equipment and grid system levels to extract meaningful insights from massive data. At the level of power equipment, a significant amount of data support is required for tasks such as wind turbine power forecasting. The application of big data management technology can provide the massive storage, management, and screening capabilities needed for more efficient data collection from wind farms, support the integration of renewable energy sources into the grid, and reduce the data processing costs associated with new energy strategies. Using IEDs, PMUs, and smart meters has significantly increased the volume of power data. The use of non-relational databases and distributed cluster system architectures can effectively integrate and analyze big data at the grid system level.

3.3. INTELLIGENT ANALYSIS MODULE

The intelligent analysis module can be likened to the neural center of the meta-power, as it is tasked with assimilating, manipulating, and scrutinizing information from the real and virtual power system modules. Compared to conventional digitalized power systems that only analyze data from real power systems, the meta-power poses unique challenges in computing resource allocation and implementation of AI, as they require data processing from real and virtual power system modules. The intelligent analysis module, similar to conventional digitalized power systems, relies on computing strategies and AI as its key enabling technologies. The combination of computing strategies and AI allows for real-time analysis of power data while utilizing AI technology to provide accurate decision support.

3.3.1. COMPUTING STRATEGIES

Computing strategies can be categorized into three types: Cloud, edge, and hybrid. Cloud computing involves transmitting all data to a data center for analysis, offering a high computing capability. The key services provided by cloud computing include infrastructure as a service (IaaS), platform as a service (PaaS), and software as a service (SaaS). However, this strategy necessitates all data being uploaded to the data center, significantly burdening the communication networks and potentially causing delays and security issues. Edge computing refers to analyzing data locally, which ensures real-time and secure analysis, but can only be performed on a small scale. Hybrid computing is a strategy involving utilizing local servers and remote data centers to analyze data. This strategy effectively allocates computing resources between the cloud and the edge, improving real-time performance and security in large-scale computing tasks. Such a strategy can be categorized into three types: Distributed computing, hierarchical computing, and federated computing. Each of these strategies involves different approaches to combine different computing resources, but they all aim to leverage the strengths of each computing resource to achieve better performance.

Cloud computing strategy is increasingly being utilized by power companies to perform high-volume and repetitive computing tasks, as well as conduct complex data analysis [100]. Cloud computing strategy can offer high-performance parallel computing capability that can be leveraged to enhance the efficiency of power flow calculation, reliability analysis, and safety assessment [101–103]. By utilizing cloud-based parallel computing, it is possible to achieve improved computational efficiency and increase the belief degree of analysis results. The computational requirement for time-domain simulation on large-scale power systems is considerably high. Using cloud-based high-performance parallel computing can potentially enhance the speed of time-domain simulation for large-scale power systems.

Edge computing is becoming increasingly popular in power systems, as a result of the widespread usage of various edge devices, including intelligent relays, IEDs, smart meters, base stations, drones, and local data centers [104]. The primary objective of edge computing in power systems is to achieve low-latency analysis and control, which can be particularly beneficial in critical situations when fast decision-making is crucial. J. Tong et al. proposed a power protection system that utilized an edge computing strategy [105]. In addition, Peng et al. [106] have employed substation servers as edge computing nodes to locate faults in the grid systems with a trained neural network model.

Hybrid computing is a strategy involving integrating and coordinating cloud computing and edge computing to optimize the performance and economy of computing processes across different devices. Fusing the benefits of strong computing power in the cloud center and efficient low-latency performance in the edge nodes, this computing strategy optimizes the computing resource allocation to achieve optimal performance [107,108]. Liu et al. have employed a hybrid computing strategy and developed a deep reinforcement learning model to effectively manage energy in urban areas. The edge layer of the hybrid computing strategy has two tasks: 1. Collect, pre-process, and transmit power data to the cloud; 2. Request the latest deep reinforcement learning model from the cloud and regulate power flow accordingly. The primary function of the cloud is to utilize power data obtained from the edge layer to train the deep reinforcement learning model, and subsequently send the trained Q-values back to the edge for updating [109].

3.3.2. ARTIFICIAL INTELLIGENCE

AI technology includes expert knowledge and ML, among which ML has attracted widespread attention due to its strong learning capability [110,111]. Based on the learning paradigm, ML can also be categorized into supervised learning, unsupervised learning, and reinforcement learning, which is shown in **Figure 7** [112]. In 2006, DL, which has the automatic learning capability, has been proposed. It improves the modeling capability of complex systems in the real world. In addition to the development of ML models, different learning strategies have been developed for different application scenarios such as single-task learning, multi-task learning, transfer learning, meta-learning, online learning, and continuous learning, as shown in **Figure 8** [113]. ML models and corresponding learning strategies have extensive applications in power systems, including power generation forecasting, energy management, power flow control, equipment health management, and grid fault detection.

With AI, it is possible to forecast power generation from renewable energy sources accurately. In the industry, the WeatherSentry software, a collaborative effort between Vaisala and Schneider Electric, is utilized in the power industry to predict wind turbine power by utilizing data from wind turbine speed and meteorological conditions. In academia, Jiao et al. proposed a wind turbine power forecasting model that combines a stacked auto-encoder, particle swarm optimization, and backward propagation algorithm [114]. There are many DL-based models for photovoltaic power generation for forecasting the power of photovoltaics [115].

In addition to power generation forecasting, AI has the potential to be utilized for load forecasting. The loads are influenced by factors such as electricity price, policy, season, etc., so it is difficult to establish accurate physical models. AI technology, especially DL, with

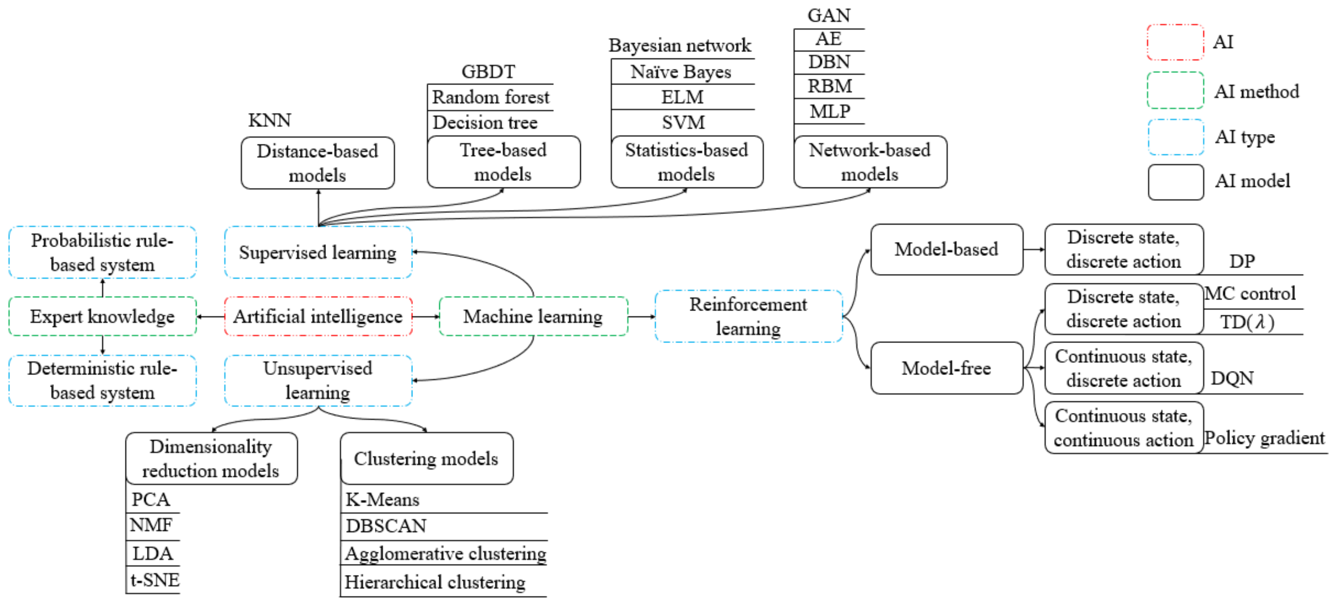

Figure 7. Overview and classification of various artificial intelligence techniques.

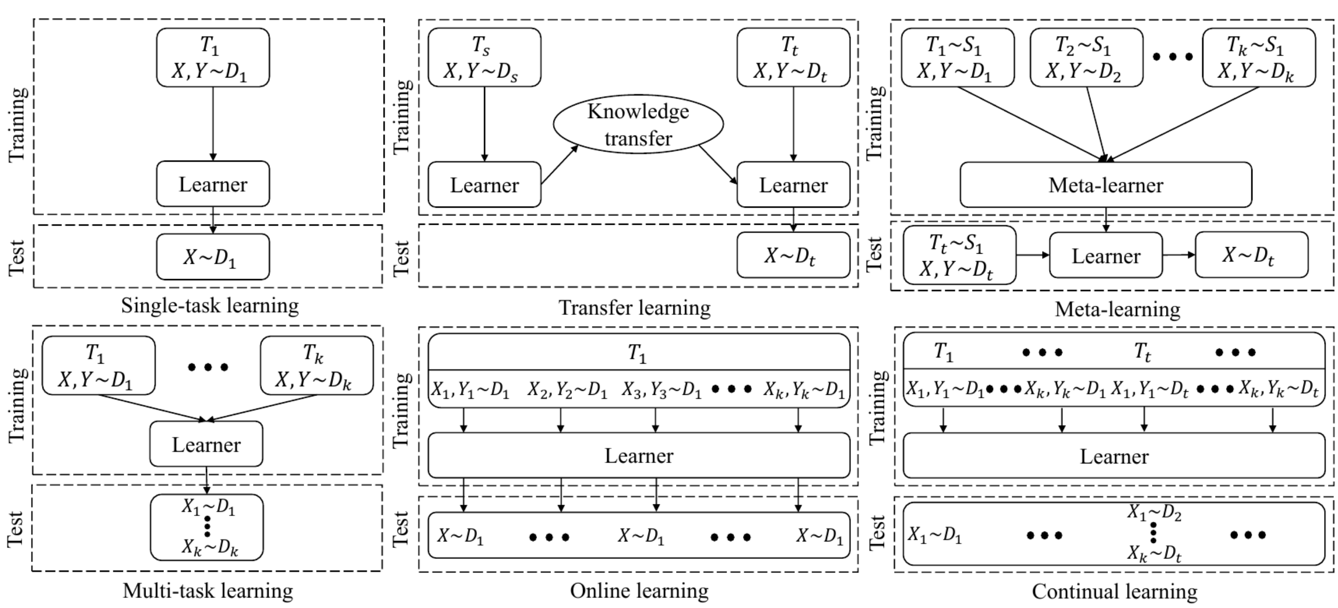

Figure 8. Overview and classification of various machine learning strategies.

its strong nonlinear capability, can effectively fit the relationship between loads and influencing factors to predict future loads. Load forecasting is divided into short-term and medium-to-long-term load forecasting. Kong et al. [116] and Wang et al. [117] utilized long short-term memory (LSTM) networks and attention-based bi-directional LSTM networks to predict short-term load. Rafiei et al. [118] proposed the use of a generalized extreme learning machine to train a wavelet neural network for the prediction of medium-to-long-term loads.

Intelligent control systems can automatically plan the operation of power systems, maximizing the efficiency of renewable energy-integrated power systems. Yin et al. [119] proposed a DL model for achieving optimal control of future grid systems that can be applied to power systems with different topologies. Zhang et al. proposed a consensus transfer Q-learning model for distribution networks, which realizes optimal power generation allocation for decentralized power plants based on the Q-value matrix [120].

The conventional methods to assess the health of power equipment depend on subjective feature extraction. However, the usage of DL, with its strong feature learning capability, has significantly improved health analysis automation. Islam et al. [121] have utilized an ensemble regression neural network to determine the health condition of power transformers, demonstrating its superior accuracy in estimating the health condition of transformers compared to expert knowledge systems.

AI can not only detect faulty power equipment but also identify abnormal operations in the grid systems, such as system fault identification and fault location positioning. Abdelgayed et al. [122] have employed various models such as decision trees, K-nearest neighborhoods, SVM, and naive Bayes to accurately identify fault patterns in a microgrid during system fault identification. The combination of wavelet transformation and SVM has been shown to be an effective model for identifying the fault locations in the transmission lines [123]. Table 3 presents the application of AI in power systems.

Table 3. Application of artificial intelligence in power system

Power system applications	Research objectives	Artificial intelligence models	Evaluation metrics	Results	References
Power generation forecasting	Solar power generation	Extreme learning machine	RMSE and MAE	The proposed model efficiently provides reliable and sharp predictive densities for very short-term power generation.	[124]
	Wind speed forecasting	Interval deep belief network with a fuzzy type II inference system (FT2IS)	RMSE and MAPE	The developed model can obtain more robust deep features as well as interval upper-bound and lower-bound parameters.	[125]
	Wind and solar energy forecasting	Quality-driven loss deep neural networks (QDDNN) and hypernetworks (HN)	PI coverage probability, average PI width, and coverage-width trade-off	Direct PI models (HN and QDDNN) clearly outperform quantile estimation in terms of width and coverage-width ratio.	[126]
Load forecasting	Long-term load prediction	Hierarchical decomposition self-attention network	MSE and MAE	Compared with existing models, the proposed model maintains stable forecasting performance and speed in long-term forecasting services and achieves the most reliable multivariate and univariate forecasting results.	[127]
	Short-term load forecasting in residential buildings	Feed-forward neural network with backtracking adjustment of the learning rate	RMSE and R	The proposed algorithm performs better than the other ML algorithms, revealing smaller RMSE differences compared to the classic Nesterov and DNN.	[128]
	Short-term day-ahead load forecasting	Ensemble deep residual network	MAPE	Comparisons with existing models have shown that the proposed model is superior in both forecasting accuracy and robustness to temperature variation.	[129]

Table 1 (Continued)

Power system applications	Research objectives	Artificial intelligence models	Evaluation metrics	Results	References
Intelligent system control	Transmission and distribution coordination	Multi-agent deep reinforcement learning	Score, deviation, oscillation, and violation	Experiments on integrated transmission and distribution systems demonstrate that the proposed framework can mitigate the impact of system disturbances and thus benefit the system operation.	[130]
	Load shedding	Deep reinforcement learning	Reward, global interpretability, and local interpretability	The proposed DRL model can quantify the importance of input features, which can explain the feature classification and probabilistic analysis of power systems better.	[131]
	Autonomous voltage control	Deep Q-network (DQN) and deep deterministic policy gradient (DDPG)	Reward	The DDPG algorithm has done a wider range of exploration in the beginning stage and demonstrates much better performance after a sufficient number of training scenarios.	[132]
Asset health management	Diagnostics of power transformers	XGBoost	ROC and precision	The proposed Shapley additive explanation method can explain the diagnosis results, which could extract the impacts of fault features on diagnosis and guide to improve the model performance	[133]
	Prognostics of wind turbines	Multivariate time-series (MTS)-based mutual information estimator (MIE)	Misdetection rate, false alarm rate, accuracy, expected calibrated error, and maximum calibrated error	The experimental results show that the proposed approach has a significantly superior calibration performance than the other methods.	[134]
	Predictive maintenance of power transformers	Advantage Actor-Critic (A2C) algorithm	Maintenance and power outage costs	The proposed policy achieves the least cost and power outage compared to the failure-based policy and myopic policies.	[135]
Grid anomaly detection	Transient stability assessment	Deep belief network	False dismissal and false alarm	The proposed method is tested and the result demonstrates that the proposed method can perform rapid, accurate, and interpretable transient stability assessment.	[136]
	Risk assessment of the maximal frequency deviation	Partitioning around medoids-Convex hull (PAM-CH) ensemble learning	Absolute error, relative error, and computational time	The proposed PAM-CH can achieve a high-quality assessment verified with respect to accuracy and efficiency.	[137]
	Power quality disturbance	Incremental neural network	Classification accuracy and learning efficiency	The proposed dynamic incremental learning method can train deep learning models in near real-time and adapt the model to learn new event types anticipated in a modern grid.	[138]

3.4. HUMAN-MACHINE INTERACTION MODULE

The HMI module plays a vital role in the communication between the meta-power and its users, serving as a component in enabling strong interactivity and ubiquitous information visualization in the meta-power. The HMI module in the meta-power utilizes XR and holographic projection technology for displaying information while employing wearable controllers for control.

Extended reality encompasses a range of immersive technologies, including augmented reality, virtual reality, and mixed reality devices. The augmented reality devices utilize sensors and visual interfaces to facilitate user interaction with the real environment, providing them with virtual information [139]. The virtual reality devices are designed to enable users to interact with virtual environments in which the actions of the users are confined solely to the virtual world and have no impact on the real world [140]. Mixed reality devices can enable interaction in both physical and virtual environments. Combined with robots, they can facilitate the manipulation of real-world objects in the virtual world [141]. Laaki et al. have developed a remote surgery system that utilizes mixed reality technology, allowing a surgeon to operate on a digital avatar of the patient, which is then replicated on the patient's physical body through a robotic arm [142]. Holographic projection is an advanced technology that utilizes optical techniques to display highly realistic three-dimensional images of objects, creating a virtual representation that appears to be tangible and interactive [143]. The holographic projection enables the display of three-dimensional images to users, which can be viewed from various angles without the assistance of extended reality devices using the naked eye. The advancement of holographic projection technology has resulted in a merging of the real and virtual worlds, creating a solid basis for realizing ubiquitous information visualization in the meta-power.

The HMI in the power industry has evolved through three generations of transformation. In the first generation, analog signals display information, while mechanical switches such as knobs and blades are employed for operation purposes. The second generation utilizes computer screens to showcase information and computer systems, such as Windows, to perform display and analysis. The third generation employs a mobile device operating system, such as Android, for display and analysis. The fourth generation will incorporate XR devices, holographic projection for display purposes, and wearable controllers for ease of operation. **Figure 9** shows the development of the HMI module in the power industry.

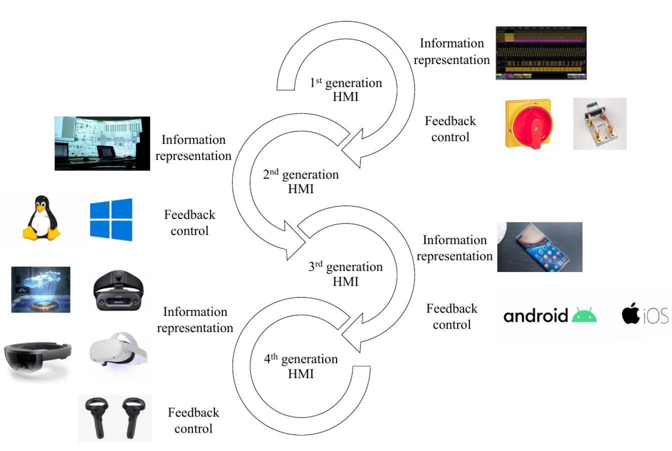

Figure 9. Development trend of human-machine interaction systems in the power industry.

In the meta-power, the HMI module emphasizes the interaction between the operators and the meta-power. Specifically, the meta-power provides immersive visual information to the operators through extended reality devices and holographic projection, and the operators control the meta-power through wearable controllers.

In the meta-power, augmented reality devices can be utilized to provide operators with digital information about real power systems. The augmented reality glasses can be more convenient for operators, eliminating the need to carry additional hand-held devices. For example, Gomes et al. designed an augmented reality device that enables the annotation of real data obtained from transformers, as well as visualization of data from the SCADA system directly on the transformers [144]. The meta-power offers virtual information to operators regarding the power systems through the utilization of virtual reality devices, allowing them to undergo training and gain knowledge. Gorski et al. have created two immersive virtual reality training scenarios designed to teach individuals how to operate switches in virtual substations and connect new cables in the distribution network. In these training scenarios, detailed operating procedures are provided, ensuring that trainees receive a thorough understanding of the processes involved in these tasks [145]. The meta-power utilizes mixed reality devices to deliver digital information about both real and virtual power systems to the operators, thereby enhancing the efficiency of inspections by providing them with more information. The holographic projection technology enables the display of virtual 3D images of power equipment to the operators, allowing them to access operation information without needing to wear extended reality devices.

Once the operators acquire digital information from the meta-power, they must analyze and use the data to inform their decisions and subsequent actions. The initial three generations restricted the operation solely to the real power systems. With the fourth-generation HMI module, the operators can have three operation scenarios: Real power system operation, virtual power system operation, and collaborative virtual-reality operation. The scenario of real power system operation involves using wearable controllers to conduct remote inspections and repair power equipment with the assistance of robots. The scenario of virtual power system operation involves the training of the operators with wearable controllers, where crews can be trained via controlling digital avatars. This scenario can refine the skills of the operators through simulation experience. The scenario of collaborative operation between virtual and real power systems is particularly suitable for emergencies, where the operators are confronted with an unfamiliar operation condition provided by the meta-power. The proposed operation scenario includes three steps: (1) Mapping the current condition of real power systems into virtual power systems; (2) Allowing the operators to perform various experiments within the virtual power system module to derive an optimal plan; (3) Implementing the optimal operation plan obtained from the virtual power systems to the real power systems.

4. APPLICATION SCENARIOS OF META-POWER

The meta-power scenarios embody the link between the three elements in the infrastructure layer, which has been shown in **Figure 2**. The augmented reality scenario of the meta-power facilitates a unidirectional information transfer from the virtual power system module to the real power system module, which can be categorized into data augmentation and information augmentation. The daily recording involves the information transfer from both real and virtual power systems to databases, enabling the creation of a comprehensive historical record of events that can be accurately reproduced. The scenario of the mirror world entails a two-way information exchange between real power systems and their virtual counterpart, serving various purposes such as operational control, information security, health management, and resilience restoration. The virtual world operates as a unidirectional channel where data from real power systems is transmitted to the virtual power systems, which then employ the information to perform design and training solutions for designers and trainers. **Figure 10** shows the four major scenarios of the meta-power.

4.1. AUGMENTED REALITY

Augmented reality can be categorized into two types: data augmentation and information augmentation. The data augmentation is used to generate additional power data by simulating multiple scenarios, including normal, abnormal, and extreme conditions, using a virtual power system module. Data augmentation helps to expand the dataset and improve the accuracy and reliability of ML models. Information augmentation refers to enhancing the information representation related to the current

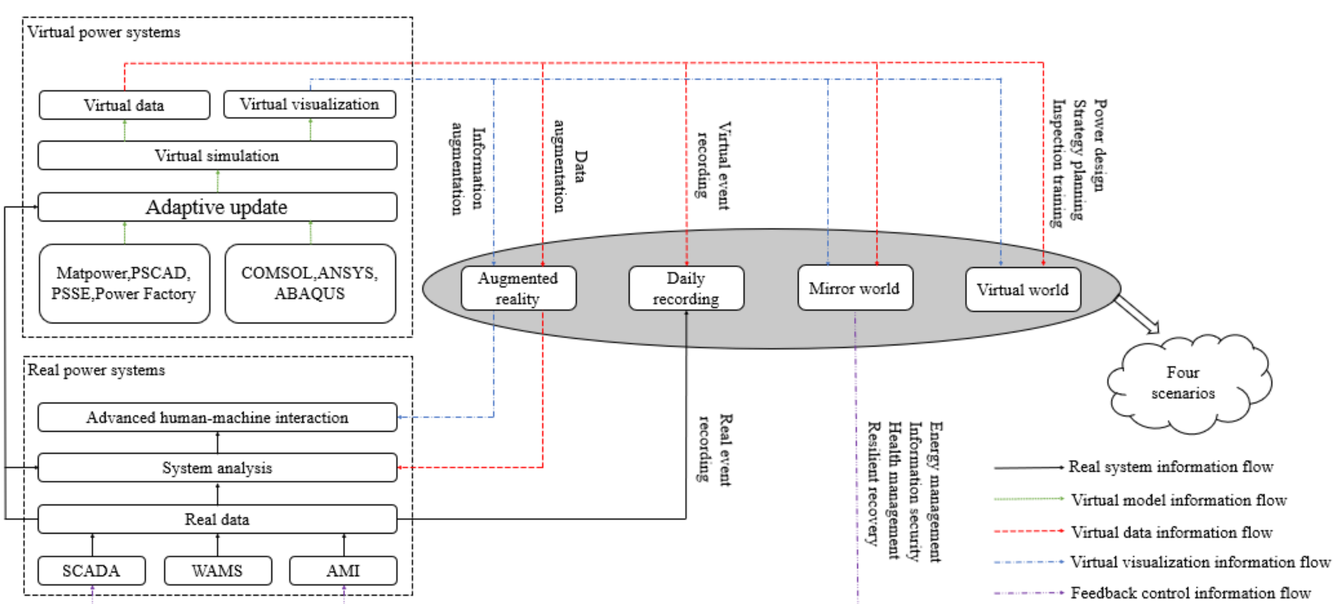

Figure 10. Four application scenarios of meta-power: augmented reality, daily recording, mirror world, and virtual world.

operational conditions of power equipment and grid systems to achieve ubiquitous information visualization.

Data augmentation can be effectively implemented in real power systems to improve the accuracy and reliability of various tasks, such as power generation forecasting, load forecasting, and situation awareness (SA). The virtual power system module can enhance the accuracy of DL models for power generation and load forecasting by simulating various operational conditions, including power generation and user consumption patterns. These simulations increase the data quantity and quality, resulting in more accurate predictions. SA is a term used to express the capacity to perceive and comprehend the current states of real power systems with a high level of resolution [146]. This includes the ability to perceive, understand, and map the processes of power system operation, which can be achieved by a three-step process. By applying data augmentation, the SA of power systems can be improved, enabling them to gain a better understanding of how real power systems behave when subjected to different operational conditions. This is achieved by performing multiple simulations and visualizing the results in various ways, which allows operators to observe the state transition of real power systems in greater detail. To achieve information augmentation in the meta-power, it is necessary to utilize information processing systems and interactive interfaces, such as SCADA systems for supervisory control and data acquisition, WAMS systems for wide-area monitoring and control, and AMI systems for advanced metering infrastructure. These systems work in tandem to enhance data processing and communication, enabling more comprehensive and accurate decision-making in the meta-power.

The conventional interactive interface for power systems is a two-dimensional display screen, which lacks convenience and immersion as an HMI medium. Moreover, it fails to offer real-time operational information on power equipment for inspectors, thus limiting their ability to monitor and maintain the power systems effectively. The implementation of augmented reality devices can enhance power equipment inspection by providing inspectors with real-time and accurate information, displaying operational data clearly, and improving convenience and immersion during the inspection process. Chae et al. have created an augmented reality-based remote monitoring system for the power grid [147]. Augmented reality glasses were integrated with a cluster radio system and RTUs in power systems. This integration enables inspectors to visualize the operational information of power equipment in real-time, as obtained from the cluster radio systems and RTUs, through the augmented reality glasses. The inspection process was recorded on video and subsequently shared with experts for analysis.

4.2. DAILY RECORDING

The meta-power involves the systematic collection and reproduction of historical data and events from both real and virtual power systems, enabling the recording and analysis of past power system operations with greater accuracy.

In the meta-power, the daily recording is reflected in the collection and reproduction of historical data and events from real and virtual power systems, which facilitates the recording and analysis of past power systems. Managing the vast amount of data generated by real and virtual power systems is a crucial challenge in implementing daily recording, and a practical storage and management system must be developed to handle this task efficiently. Although abnormal data is more valuable in power systems, it is typically less abundant than normal operating data due to the usual operation of power systems under normal conditions. Therefore, there is a greater quantity of normal operating data available compared to abnormal data. In power systems, digital fault recorders are commonly used to record information about equipment failures. However, they do not have an automated feature to capture and store the data sequence preceding the occurrence of the faults. One potential direction for expanding the event or fault library of the meta-power in the future is the development of fault recorders equipped with an automatic data storage function for sequences leading up to a fault occurrence. A robust big data management strategy is also crucial for effectively storing operating data from real and virtual power systems. The meta-power database aims to store well-comprehended information rather than raw data. It is a more effective solution for daily records to use big data management technology to process vast amounts of data into easily understandable information for operators before storing it. Several alternative data management schemes can be used for the meta-power, including Hadoop distributed file systems, layered expansion storage mechanisms, micro-storage strategies based on edge devices, and data storage technologies based on cloud platforms [148,149].

Recording historical data and events in the meta-power serves the purpose of facilitating the reproduction of past events or faults that occurred in the real power systems. Virtual power systems in the meta-power can access historical data records from the database that pertain to a particular event that occurred in the real power systems. The aforementioned historical data is utilized as an input to simulate an event or fault in the virtual power system. This enables operating personnel to develop a more comprehensive understanding of the past incidents that took place in the real power systems. To enhance the awareness of operating personnel regarding operational safety, simulations of past incidents, such as the Chornobyl nuclear power plant disaster within a virtual power system environment, can be highly beneficial.

4.3. MIRROR WORLD

The scenario of the mirror world in the meta-power depicts the interaction between the real and virtual power systems, primarily focusing on the analysis and management of the power systems that are currently operational. The real power systems utilize sensors and communication networks to transmit data to the virtual power systems, enabling both systems' seamless integration and operation. The virtual power systems operate in a simulated environment using acquired data and provide a visual representation of operating results to aid operators in making decisions, whether as direct controllers or indirectly, to achieve optimal operation of the real power systems. The scenario of the mirror world has broad applicability in various fields, such as power system control, information security, health management, and resilient recovery [150].

In the scenario of the mirror world, the real and virtual power systems run in parallel. The two power systems aid operators in evaluating both the transient and steady-state performance of the power systems, enabling them to make informed decisions regarding optimal control strategies. The energy and distribution management systems play crucial roles in maintaining a balanced supply-demand by efficiently controlling the transmission and distribution of energy. However, the existing analysis of supply-demand balance in control centers predominantly emphasizes steady-state analysis, whereby the strategy for balancing supply and demand is determined beforehand, and subsequently, the temperature and voltage conditions of the power equipment are assessed to establish the stable operating limits of the power systems [151]. By leveraging the high fidelity and high data rate of the virtual power system, it becomes possible to conduct thorough assessments of the supply-demand balance strategy, allowing for the determination of the transient operating boundaries of the power system. The virtual power system not only provides real-time updates on the current operating state of the power system but also has the capability to simulate and predict future system evolution, thereby enhancing the protection of the power system operations. The virtual power system enables the detection of abnormal operations in the real-time power system through transient and steady-state assessments, allowing for the prompt switching of control strategies to prevent severe damage and provide protection.

Information security is crucial to maintaining the smooth operation of the meta-power. The vulnerabilities present in the communication of the smart grid can be categorized into three distinct groups: device vulnerabilities, network vulnerabilities, and data vulnerabilities. A virtual power system has the capability to simulate various attack scenarios on the actual power system, allowing for the timely detection of potential information leaks, tampering, and intrusions. A. Saad et al. leveraged Amazon Web Services to create a virtual power system platform capable of analyzing the distribution system's security and thwarting potential attacks, including virtual data injection, denial of service, and coordinated attacks [152]. In addition to simulating attack scenarios, the virtual power system can also function as a preventive measure to safeguard the real power system against potential threats or vulnerabilities by identifying and mitigating them before they manifest in the physical system [153]. As an example, physics-based virtual power systems can detect and flag data that violates physical laws, recognize and label data that has been injected by attackers as anomalous, and enhance the security of the real power system operation by preventing the integration of potentially harmful data into the systems.

In real power systems, degradation is an inevitable occurrence that can cause a decline in system performance and an increase in operating costs [154]. Virtual power systems have the capability to monitor the operational condition of power equipment and accurately predict its remaining useful life, thereby allowing for a shift in maintenance strategies from scheduled preventive maintenance to predictive maintenance. This results in more efficient power equipment maintenance and helps optimize equipment uptime while minimizing downtime and maintenance costs. The process of health management utilizing the scenario of the mirror world can be broken down into four steps: (1) The process involves creating virtual models of real power equipment with a high level of accuracy by incorporating detailed information on its geometric structure, materials used, and operational mechanisms; (2) The identification of anomalies in real power equipment, or design defects in virtual power equipment, can be achieved through the analysis of interactions between the real and virtual power equipment; (3) By integrating data from both real and virtual power equipment, it becomes possible to analyze the health status and remaining lifetime of real power equipment; (4) Based on the results of the health analysis, predictive maintenance can be executed and necessary parts can be proactively purchased to minimize downtime [155]. The scenario of the mirror world for health management has been implemented in various applications, including power electronic converters, battery packs, offshore wind turbines, and large generators [156,157].

To address the potential impact of low-probability, high-impact events such as earthquakes and tornadoes, the power systems have adopted the concept of resilience. Resilience refers to power systems' ability to anticipate, withstand, and recover from external shocks, returning to their pre-shock state in a timely manner and better preparing for future disaster events. The implementation of the mirror world can enhance the resilience of the power systems by minimizing the degree, speed, and duration of degradation caused by external shocks, aiding operators in comprehending various types of attacks, creating mitigation strategies that can be applied before, during, and after attacks, and achieving resilience of the power systems from diverse levels of system anomalies [152]. Nowocin [158] utilized a virtual power system to evaluate the resilience performance of microgrid controllers.

4.4. VIRTUAL WORLD

The scenario of the virtual world in the meta-power involves a unidirectional flow of information from the real power systems to the virtual power systems. The main focus of this scenario is to analyze future power systems at a systemic level, and it offers a platform for users to access virtual power plants from any location and at any time, transcending the constraints of time and space. The virtual power systems, modeled after real power systems, can offer a low-risk and cost-effective simulation platform for designers, maintenance crews, and trainees. The scenario of the virtual world in the meta-power encompasses power system design, future energy planning, and maintenance training.

By facilitating the analysis of efficiency, reliability, and safety of equipment and systems, the scenario of the virtual world in the meta-power can enhance the design performance of modern power systems at both equipment and system levels while also providing a means to optimize the design of real power systems. At the equipment level, the scenario of the virtual world can aid designers in simulating operating conditions under different failure modes during the design phase. This approach enables the optimization of power equipment design and reduces the failure rate of equipment put into operation in the future. The virtual grid model can be designed and subsequently simulated at the system level to evaluate the power systems' operating conditions under various working conditions. This process can identify and eliminate potential operating risks [159].

The generation capacity and technology of real power systems are continuously evolving due to the rising demand for electricity and the development of new energy strategies. The development of energy strategies has always been a crucial topic in both the academic and industrial sectors. The development of energy strategies is a strategic decision that is closely tied to the economic benefits of power companies. Thus, decisions related to the development of energy strategies must be made with a focus on accurate long-term forecasting of demand growth, technology trends, and regulatory rules. The virtual power systems serve as effective testing platforms for predicting the responses of the power systems under varying time frames and operating scenarios. Through analysis of the short-term and long-term impacts of various incentive mechanisms, demand response strategies, electricity price schemes, renewable energy access schemes, and electric vehicle penetration strategies, the virtual power systems facilitate the simulation and evaluation of future energy strategies.

The scenario of the virtual world in the meta-power offers an inexpensive and safe training and maintenance practice environment for interns and maintenance crews. Training interns is crucial to enhancing their practical skills and plays a vital role in ensuring the safety of the power systems [160]. By creating a virtual power plant environment using VR devices, interns can experience a greater sense of immersion and practical operation [161].

5. CHALLENGES AND PERSPECTIVES OF META-POWER

The meta-power aims to enhance the flexibility, reliability, and economy of real power systems by leveraging four primary modules: virtual power systems, virtual-reality interaction, intelligent analysis, and HMI. The primary challenges that the meta-power encounters pertain to virtual power system modeling, virtual power system updating, intelligent inference systems, extended reality, computing power, security, and privacy.

5.1. VIRTUAL POWER SYSTEM MODELING

Acquiring relevant and accurate data from various sources, such as sensors, devices, and systems, can be complex. Integrating data from disparate sources and formats into a coherent and consistent model is a significant challenge. Data quality, consistency, and compatibility issues need to be addressed to ensure the reliability and effectiveness of virtual power systems. Developing appropriate models to simulate the behavior of real power systems can be challenging. Calibration of the model to match real-world observations and performance requires careful validation.

5.2. VIRTUAL POWER SYSTEM UPDATING

Updating the virtual power systems represents two significant challenges. The update of virtual power systems can be divided into two aspects: convergence rate and update rate. In the future, guaranteeing the synchronization accuracy between the real and virtual power systems represents a challenging obstacle that must be overcome. Moreover, determining the optimal update rate of the virtual power system is another issue that requires careful consideration. While a higher update rate allows for more precise and timely analysis of the power system, it also places a substantial load on communication networks and computing resources. The article puts forth two potential solutions to the update challenges of the virtual power systems: (1) creating a hardware-in-the-loop test bed to validate the accuracy of the update algorithm; and (2) forming an expert committee to establish standards for the virtual power systems. Furthermore, as the fundamental component of the meta-power, the virtual power systems are also vulnerable to malicious attacks, highlighting the need for encryption technology that can safeguard both the real and virtual power systems, representing a future research direction.

5.3. INTELLIGENT INFERENCE SYSTEMS

Although deep learning-based inference systems have great predictive performance, the inference systems not only need accurate inference results but also need to bring interpretability to the industry. Recently, researchers have recognized the problem of weak interpretability of deep learning models and developed two major ways to interpret deep learning models: Rule-based surrogate models with decision tree retraining, and physics-informed deep learning that can train the deep learning model guided by physical laws. A decision tree-based surrogate model trains a decision tree that can explain the features learned by the deep learning model, while physics-informed deep learning mainly utilizes the physical laws to guide the training of deep learning, and thus the trained model conforms to the basic physical law and has a certain physical interpretation.

5.4. EXTENDED REALITY

The main research challenge for the HMI module in the meta-power lies in the development and integration of extended reality devices and holographic projection devices. The main issue with virtual reality devices is communication, which involves transmitting information from the real power systems to the virtual power systems and user-operated digital human operation instructions. This challenge becomes more significant when multiple users are involved, as it can lead to communication delays. The main challenges of augmented reality technology in the HMI module in the meta-power are tracking accuracy and effective field of view, which can impact the convenience and immersion of the operators during the inspection process. MR devices, being an integration of virtual reality and augmented reality devices, pose challenges that need to be overcome for their further development, including communication, tracking accuracy, and effective field of view. Currently, holographic projection can integrate real and virtual environments of power stations and enable the information visualization of power systems in any location. However, holographic projection faces several challenges, including low resolution, small display size, poor mobility, and high costs. Overcoming these weaknesses would provide holographic projection with an opportunity for widespread application in real power systems and further promote the development of meta-power.

5.5. COMPUTING POWER

Computing power plays a fundamental role in the development of meta-power, as it is essential for the proper functioning of various software and hardware components within the meta-power architecture. In the increasing digitalization, computing power serves as an extension of human capabilities, facilitating the digital transformation and advancement of power systems. According to predictions, achieving the metaverse would necessitate computing power at least 106 times greater than the current capacity.

5.6. SECURITY AND PRIVACY

With the advent of the meta-power, the function of linking reality and virtuality in the meta-power will lead to a substantial increase in the online time of consumers. To gain a deeper understanding of consumers' thinking and behavior, the meta-power developer will inevitably collect more personal privacy information about users and even continuously monitor users' behavior patterns. In order to prevent the theft of information and misuse of data, strict supervision of data must run through the entire life cycle of data, including storage and management. Moreover, dealing with meta-power big data requires an efficient and lightweight security and privacy scheme.

6. CONCLUSION

Meta-power is a new generation of digitalized power systems that integrates multiple technologies, offering strong interactivity and hyper-spatiotemporality beyond the original characteristics of smart grids. The meta-power necessitates the support of diverse advanced technologies, particularly advanced HMI and DT technologies. Advanced HMI technology based on extended reality devices and holographic projection can contribute to achieving strong interactivity in the meta-power, improve the ubiquitous information visualization of power systems, and ensure the convenience and immersion of the operators. DT technology can replicate past power systems, perform real-time analysis and control of current power systems, and predict and evaluate future power systems, thereby achieving hyper-spatiotemporal operation of meta-power. In the future, the meta-power is expected to have more applications to enhance the operational flexibility of power systems with a high power electronics ratio, high renewable energy ratio, and high electric vehicle ratio. This will accelerate the realization of the goal of carbon neutrality by improving the efficiency of energy usage and reducing greenhouse gas emissions.

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CONFLICTS OF INTEREST

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