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Intelligent acceptance systems for distribution automation terminals: an overview of edge computing technologies and applications

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Abstract

The investigation into intelligent acceptance systems for distribution automation terminals has spanned over a decade, furnishing indispensable assistance to the power industry. The integration of cutting-edge edge computing technologies into these systems has presented efficacious, low-latency, and energy-efficient remedies. This paper provides a comprehensive review and synthesis of research achievements in the field of intelligent acceptance systems for distribution automation terminals over the past few years. Firstly, this paper introduces the definition, composition, functions, and significance of distribution automation terminals, analyzes the advantages of employing edge computing in this domain, and elaborates on the design and implementation of intelligent acceptance systems based on edge computing technology. Additionally, this paper examines the technical challenges, security, and privacy issues associated with the application of edge computing in intelligent acceptance systems and proposes practical solutions. Finally, this paper summarizes the contributions and significance of this paper and provides an outlook on future research directions. It is evident from the review that the integration of edge computing has effectively alleviated these challenges, but new issues await resolution.

Keywords Distribution automation terminals, Intelligent acceptance systems, Edge computing

Introduction

With the continuous development and modernization of the power industry, the intelligent acceptance system for distribution automation terminals plays a critical role in ensuring the reliability and security of power supply [1]. The intelligent acceptance system for distribution automation terminals is a system that utilizes advanced technologies and algorithms to automate the inspection, testing, and evaluation of distribution terminal equipment. Traditional acceptance of distribution terminals is typically performed manually, relying on human intervention for the coordination and acceptance between field terminals and distribution control centers [2]. Field personnel manually simulate analog quantities and switch positions according to signal definitions, communicate with dispatch center personnel via telephone on a per-signal basis, and rely on dispatch center personnel to observe system responses and analyze and judge the acceptability of each signal change.

Therefore, traditional manual methods suffer from issues such as lengthy coordination times, a lack of standardization in the acceptance testing process, a lack of rigor and precision in acceptance management, significant burdens on main station personnel during peak periods, and limited accuracy. To overcome the limitations of traditional manual methods, the introduction of

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an intelligent acceptance system for distribution automation terminals is crucial. This system automates various testing and inspection tasks, enhancing efficiency and accuracy. It can rapidly identify potential issues and defects, providing timely feedback. Automation reduces manual intervention, cutting labor costs, and ensuring consistent acceptance processes. By automating multiple testing and inspection tasks, the intelligent acceptance system for distribution automation terminals significantly shortens the acceptance duration, promptly identifies potential issues and defects, and provides timely feedback. Furthermore, it enhances accuracy by employing advanced algorithms and sensors to precisely evaluate equipment performance, minimizing human influence. Consequently, the intelligent acceptance system significantly enhances the quality and reliability of distribution terminal equipment.

The intelligent acceptance system of distribution automation terminals faces challenges like delays [3], network loads [4], data security [5], and system robustness [6]. Researchers and engineers are increasingly adopting edge computing technology to address these challenges. The intelligent acceptance system of distribution automation terminals typically involves processing and analyzing a large amount of data, and moving computational tasks from traditional centralized servers to mobile edge nodes near the terminal devices can significantly reduce data transmission delays. This enables real-time data processing and decision-making, thereby improving the efficiency and responsiveness of the acceptance process.

Traditional intelligent acceptance systems usually require transmitting a large amount of data to remote servers for processing and analysis. This can increase the network transmission load and potentially impact the performance of other network services. By introducing mobile edge computing, the intelligent acceptance system of distribution automation terminals can perform data processing and analysis locally, thereby alleviating the network load and enhancing the overall system's reliability and stability [7]. The intelligent acceptance system of distribution automation terminals involves a vast amount of sensitive data, such as power equipment status and power quality. Storing and processing data at the edge nodes can reduce the risks associated with data transmission, minimizing the possibilities of data tampering or leakage. Edge computing offers a more secure and controllable data processing environment, contributing to safeguarding data security and privacy. This system often operates in complex environments with unstable network conditions. By conducting data processing and decision-making at the edge nodes, the system can better cope with network interruptions or unstable connections, ensuring the normal operation of the system. This distributed edge computing architecture provides higher system robustness and reliability.

Edge computing technology shifts computational and data processing tasks from centralized servers to edge nodes near terminal devices [8]. This distributed architecture offers low-latency data processing, reduces network load, and improves system reliability [9]. Leveraging edge computing technology, the intelligent acceptance system of distribution automation terminals can better address challenges related to large data volumes, real-time requirements, and security [10–13]. These advantages make mobile edge computing an ideal choice for achieving efficient, reliable, and secure intelligent acceptance systems. These intelligent grid solutions provide reliability in power distribution and transmission for developing countries, such as maintaining large-scale power infrastructure without excessive costs [14]. However, there is currently a relatively limited amount of literature that provides a comprehensive overview of edge computing technologies applied to intelligent acceptance systems for distribution automation terminals. Although the application of edge computing technology in the power industry is continuously growing, the research on its specific use in intelligent acceptance systems for distribution automation terminals is still in its early stages. Existing research primarily focuses on the infrastructure, control strategies, data acquisition, and processing of distribution automation systems, and the potential of edge computing technology in intelligent acceptance systems has not been fully explored and investigated. Therefore, the aim of this paper is to address this research gap and provide a comprehensive review of the latest advancements and applications of edge computing technology in intelligent acceptance systems for distribution automation terminals, along with the challenges and prospects that lie ahead.

The contributions of this paper are as follows: Firstly, it fills the research gap in the literature regarding the use of edge computing technology in intelligent acceptance systems for distribution automation terminals. By providing a comprehensive review of the latest advancements and applications, it offers a profound understanding and insights into this field. Secondly, from various perspectives and through concrete case studies and performance evaluations, it reveals the practical potential of edge computing technology in intelligent acceptance systems. These insights shed light on its real-world applications and benefits. Thirdly, the paper addresses the technical challenges, security, and privacy issues faced by edge computing technology in intelligent acceptance systems. It also explores possible solutions and future research directions, offering valuable guidance for both academia and the industry. Lastly, the in-depth review of the latest developments in edge computing technology for intelligent acceptance systems in distribution automation terminals holds practical significance for professionals and researchers in the power industry. It provides valuable technological references and guidance for the intelligent upgrading and development of power systems.

The remainder of this paper is structured and organized as follows. In Overview of Distribution Automation Terminals (DAT) section, we provide a comprehensive introduction to distribution automation terminals. Edge computing for DAT's intelligent acceptance system section elaborates on the application of edge computing technology in intelligent acceptance systems for distribution automation terminals. Our focus on the design and implementation of intelligent acceptance systems based on edge computing technology is presented in Design and implementation of edge computing-based intelligent acceptance system section. In Challenges and Limitations of Edge Computing in DAT's Intelligent Acceptance System section, we analyze the technical challenges, security, and privacy issues faced by edge computing technology in intelligent acceptance systems, and propose possible solutions and future research directions. Finally, we conclude the paper and provide an outlook on future research directions.

Overview of distribution automation terminals (DAT)

In this section, we provide an overview of distribution automation terminals, a critical component in power distribution systems. We define distribution automation terminals and highlight its functions, emphasizing its importance in ensuring efficient and reliable power distribution.

Definition

An automatic process refers to a task that is executed in an automated fashion, leading to enhanced operational efficiency. The notion of distribution automation was initially introduced in the 1970s [15]. The Institute of Electrical and Electronics Engineers (IEEE) has provided a definition for Distribution Automation Systems (DAS) as systems that empower electric utilities to remotely monitor, coordinate, and operate distribution components in real time. [16].With the rapid economic development, there is an increasing demand from users for power supply quality and reliability. Distribution automation systems utilize modern computer, communication, and network technologies to achieve automation in medium-voltage distribution networks, effectively improving power supply quality and production management efficiency. Distribution automation terminals transmit information to the substation or master station of the distribution automation system, while receiving control commands from the substation or master station to remotely operate distribution switches, thereby enabling real-time monitoring, fault detection, fault isolation, and network reconfiguration of the distribution network. In recent years, distribution automation has gained significant attention from national power grids and research and production units.

The distribution automation system consists of three parts: the master station, communication network, and terminal devices [17]. Distribution automation terminals are mainly used for monitoring and controlling ring main units, reclosers, pole-mounted sectional switches, distribution transformers, and other components in medium-voltage distribution networks. They communicate with the distribution automation master station to provide the necessary data for distribution operation, control, and management. The performance and reliability of these terminals directly influence the effectiveness of the entire system [18].

Types

Terminal units are grouped into three types: distribution terminal unit (DTU), feeder terminal unit (FTU), and transformer terminal unit (TTU). They are utilized to oversee operational data linked to feeders, distribution switching stations, and distribution transformers, correspondingly [19].

The first type is the monitoring terminal for switchgear, public, and user distribution substations, commonly referred to as the DTU terminal. Its basic structure is similar to that of traditional remote data terminals, mainly sharing structural similarities, without the need for additional protective devices. This approach saves space and maximizes the utilization of limited resources. Unlike traditional remote data terminals, the DTU terminal features editable logic control functionality, allowing for remote unit monitoring and operation independently of the master station. Additionally, fault detection functionality is added to the traditional terminal technology, enabling the issuance of commands and automatic isolation of the area with faults when the main unit experiences a failure, ensuring power stability [20]. The DTU terminal typically does not have a backup power supply, which simplifies its structure. Furthermore, due to its protective functionality, there is no need to design operational control loops, greatly improving the structural flexibility of the terminal equipment, making it easier to maintain and manage. The schematic representation of the decentralized distributed DTU structure is shown in the Fig. 1.

The second type is the monitoring terminal for sectionalizing switches along distribution feeders, known as

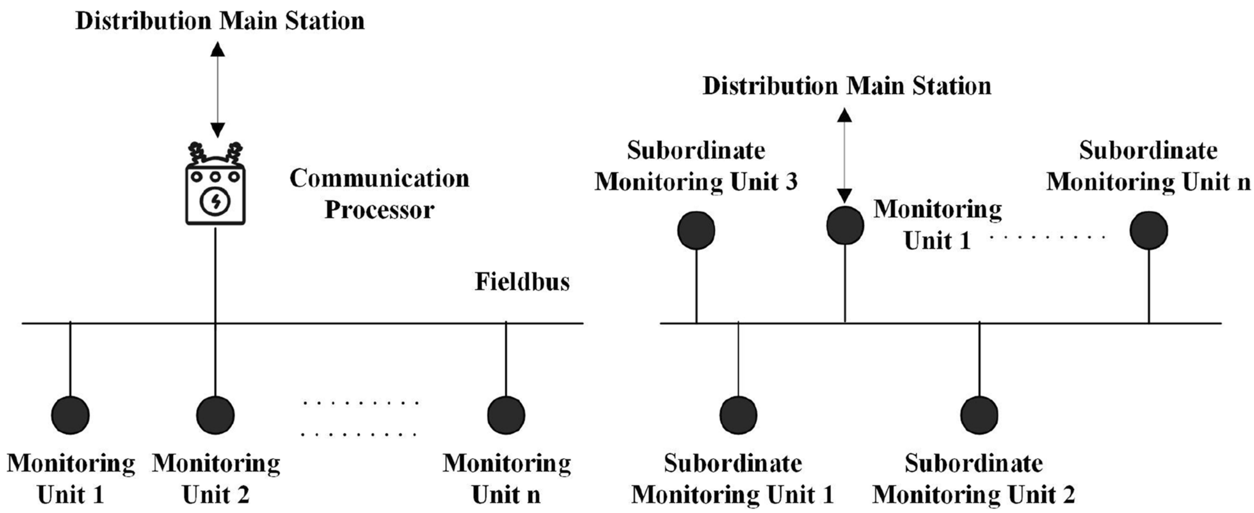

Fig. 1 The structure of a decentralized distributed Terminal Unit (DTU)

the feeder terminal unit (FTU) [21]. The feeder terminal unit is classified into two types: one type is suspended on outdoor overhead line poles, known as pole-mounted feeder terminal switches. These devices are typically made from corrosion-resistant materials and are housed in rainproof, moisture-proof, and dust-proof enclosures due to the harsh outdoor environment they operate in. The other type is used in ring main units, and their structure and the number of feeder terminals used may differ depending on the specific environmental conditions. Additionally, the installation methods vary between the two cases. If the outdoor ring main unit has conditions suitable for installing feeder terminal units within the unit, there is no need for specialized enclosures. Conversely, protective enclosures with the required functionality are used. However, if space constraints exist within the ring main unit for accommodating the monitoring and control equipment, there is no need to use specialized enclosures, which saves space. The configuration of the pole-mounted feeder terminal unit is shown in the Fig. 2.

The third type is the monitoring terminal for distribution transformers, commonly known as the transformer terminal unit (TTU). The TTU is an effective device used in the substation automation system to monitor the operational status of transformers. It is a crucial component of the substation automation system, installed as a remote terminal at the bottom of the system to monitor

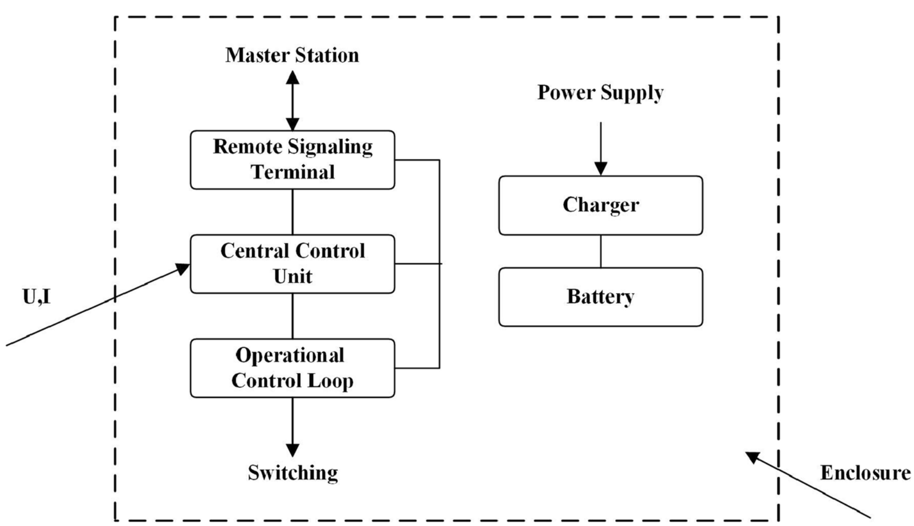

Fig. 2 The composition of a pole-mounted Feeder Terminal Unit (FTU)

real-time operating parameters of distribution transformers [22]. Its primary function is to record and detect the load conditions of distribution transformers. The TTU can promptly upload the collected data and report the condition of the distribution system based on the actual situation. The structure of the transformer terminal unit is relatively simple and compact, without the need for a battery backup. If the TTU is installed outdoors, a protective enclosure made of corrosion-resistant materials is required. The basic structure of the TTU is depicted in the Fig. 3.

Components

The distribution automation terminal primarily consists of five components: the central monitoring unit, the human-machine interface module, the operation control loop, the communication terminal, and the power module [23], as depicted in Fig. 4.

Distribution automation terminals are centered around the central monitoring unit, which performs critical functions including the acquisition of analog and digital input signals, fault detection, calculation of vital operational parameters like voltage, current, and active power, generation of control signals, and facilitating remote communication. These distribution automation terminals currently employ a platform-based and modular design for their output and communication interfaces. This design offers scalability and configurability, enabling tailoring to specific requirements.

The communication terminal, also known as a communication adapter, establishes a connection between the monitoring unit and the distribution network automation

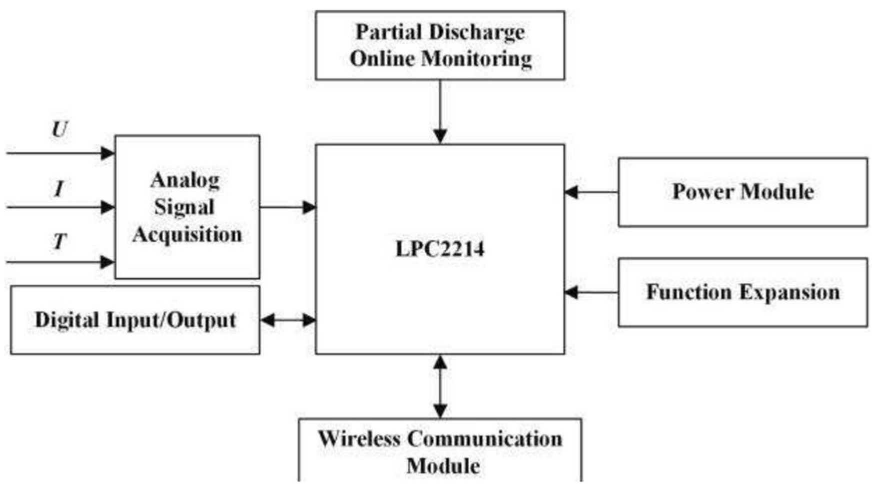

Fig. 3 Basic structure diagram of transformer terminal unit (TTU)

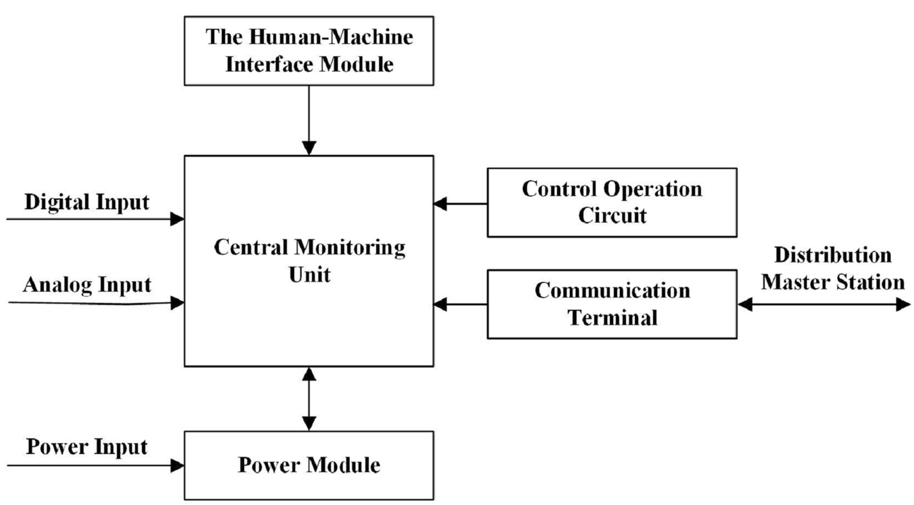

Fig. 4 The basic components of a distribution automation terminal

communication medium. It can be connected via the monitoring unit's Ethernet interface or RS232 serial interface. Different types of communication terminals are available, including fiber optic terminals, wireless terminals, modems (for analog channels), and carrier terminals, depending on the communication equipment channel type. The operation control circuit can be utilized in FTU (Feeder Terminal Unit) and requires manual control buttons. This device aids operators in understanding the switch status through circuit displays based on the switch positions.

The power module supplies various DC power sources required by the distribution terminal circuit. For DTU (Distribution Terminal Unit), the external power source is typically obtained from the AC 220 V utility power within the switchgear. In the event of a utility power failure, an uninterruptible power supply (UPS) is utilized as a backup power source. For TTU (Transformer Terminal Unit), the power input is derived from the low-voltage side output of the distribution transformer. In the case of FTU, since there is generally no dedicated AC 220 V power supply along the distribution lines, voltage transformers are commonly used to provide voltage measurement signals and power the FTU simultaneously. The FTU power supply should be equipped with a storage battery to ensure uninterrupted power supply to the terminal's circuit during line power outages and to provide power for switch operations.

Functions

The functional requirements of distribution automation terminals vary depending on the monitoring objects and application scenarios. Therefore, in practical engineering, it is necessary to make choices regarding the following functions based on specific application requirements [24]. The primary functions of the distribution automation terminal are illustrated in Fig. 5.

The Supervisory Control and Data Acquisition (SCADA) function represents the "three remotes" (telemetry, telecontrol, and telecommunication) of the traditional Remote Terminal Unit. The distribution terminal should be able to measure electrical quantities reflecting the system's imbalance under normal operating conditions, such as voltage, current, active power, reactive power, apparent power, and power factor. It should also be capable of accessing direct current input to monitor the voltage and supply current of the backup battery. Telecommunication mainly involves accessing signals from auxiliary contacts of distribution switches, energy storage unit's normal operation signal, and so on. Telecontrol includes outputs for closing and tripping distribution switches, as well as switch status outputs [25–27].

Importance

In recent years, distribution automation terminals have become increasingly important in distribution automation systems. Their significance can be summarized as follows:

Firstly, distribution automation terminals continuously monitor the state, parameters, and performance of the power grid through built-in sensors and measurement devices. They collect a vast amount of data, including key indicators such as voltage, current, power, and frequency. Secondly, distribution automation terminals are equipped with built-in protection devices that can promptly detect faults, short circuits, overloads, and other abnormal

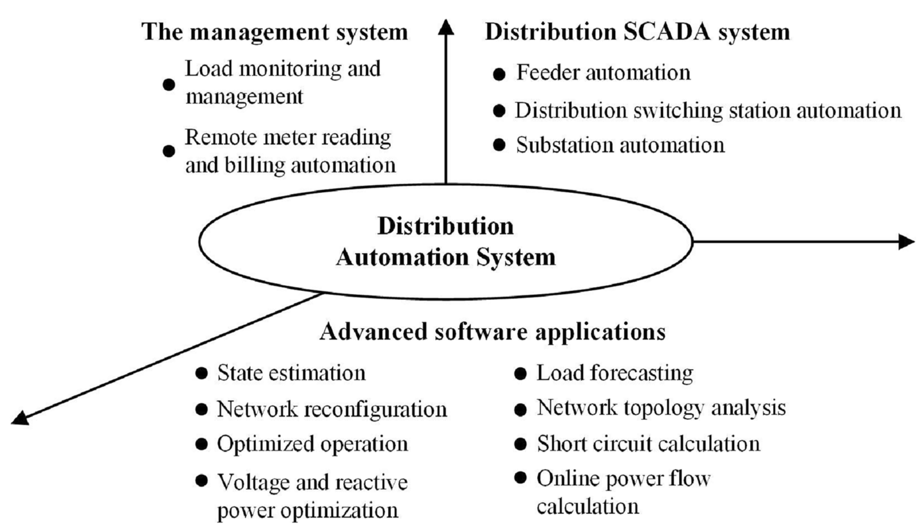

Fig. 5 The new functional structure diagram of the distribution automation system

conditions within the power system [28]. The fault detection and protection functions of distribution automation terminals are critical components for achieving reliable power supply. Additionally, distribution automation terminals possess remote control and operation capabilities, allowing them to communicate with the higher-level control center or other terminal devices for remote control and operation of grid equipment. This flexibility in remote control enables operators to respond quickly to changes in the power system's requirements, carry out load adjustments, switch lines, optimize equipment, and achieve efficient operation and optimized management of the power system [29]. Lastly, through the intelligent features of distribution automation terminals, the power system can integrate distributed energy resources, optimize power load management, and engage with the electricity market. The automation capabilities of distribution automation terminals reduce manual intervention, enhance the system's level of automation and operational efficiency, and extend the lifespan of existing distribution system infrastructure.

The overview of distribution automation terminal presented in this section sheds light on its significance in modern power distribution systems. Understanding the definition, functions, and types of distribution automation terminals provides a foundation for exploring the application of edge computing in distribution automation terminals' intelligent acceptance system, as discussed in the subsequent sections.

Edge computing for DAT's intelligent acceptance system

In this section, we delve into the concept of edge computing and its advantages in the context of distribution automation terminals' intelligent acceptance system. By combining the power of edge computing with the functionalities of distribution automation terminals, we aim to enhance the system's efficiency, responsiveness, and decision-making capabilities.

Edge computing

In recent years, driven by advancements in technologies like the Internet of Things (IoT), cloud computing, and big data, data volume has surged. Traditional cloud computing models necessitate uploading extensive data to cloud servers. However, due to the gap between cloud servers and terminal devices, challenges like transmission speed, energy use, latency, network interference, and data security become hard to circumvent. Despite the powerful computing capability of cloud computing, which can address the challenges of extensive calculations and device battery consumption, the advancement of smart terminals, new network applications, and evolving user demands for seamless experiences have raised requirements for data transmission speed, low latency, and service quality. Consequently, cloud computing struggles to meet the needs of many technologies and scenarios [30–32]. To address the issues of latency and energy consumption caused by the distance between cloud data centers and terminal devices, scholars have proposed shifting cloud functionality to the network edge. Mobile Edge Computing (MEC) is a novel network architecture and computing paradigm that offers information technology services and computational abilities at the edge of mobile networks, in close proximity to terminal mobile devices [33–36].

In 2014, the concept of MEC was defined as "a new platform that provides IT service environment and cloud computing capabilities at the edge of mobile networks." by ETSI (European Telecommunications Standards Institute). In 2016, ETSI expanded MEC to Multi-Access Edge Computing, encompassing multiple access paths extending beyond mobile communication networks to other access networks such as Wi-Fi and wired connections [37]. MEC does not replace cloud computing but rather serves as its extension [38]. Unlike cloud computing, MEC offloads the computational tasks of terminal devices to edge servers closer to the devices. These edge servers can provide computing and content caching functionalities. Edge servers, distributed at the network edge and sometimes referred to as computing or edge nodes, relieve the computational load on terminal devices, curbing interactions with central cloud data centers and notably diminishing message exchange wait times. With a defined storage and computing capacity, these edge servers, positioned closer to terminal devices, enable computation-intensive or latency-sensitive mobile devices to shift their computing tasks for execution at the edge [39, 40].

Figure 6 depicts the fundamental three-layer architecture of MEC. It consists of a three-layer structure: the cloud layer, the edge layer, and the terminal layer. In MEC, mobile terminal devices cannot communicate directly with servers; they need to communicate with MEC servers through base stations or wireless access points in the terminal layer. MEC servers are deployed in the edge layer, closer to the terminal devices, and can provide computing and caching services, thus mitigating the latency and energy consumption issues caused by having all terminal device tasks request services from a remote cloud.

Intelligent acceptance system

The intelligent acceptance system is a key technology in distribution automation terminals, used to ensure the correct installation, configuration, and proper

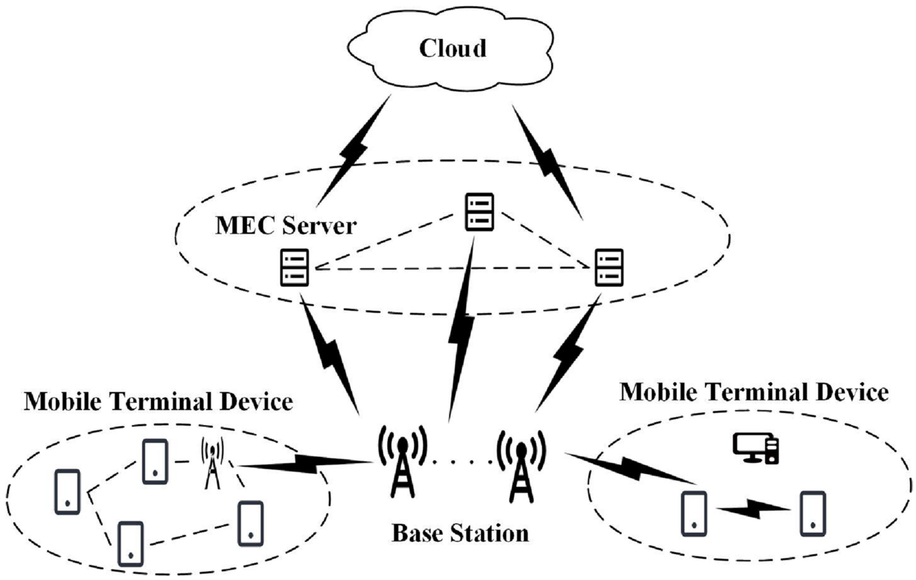

Fig. 6 The basic three-layer architecture of MEC

functioning of distribution automation terminals. This system utilizes advanced sensors, communication, and data analysis technologies to comprehensively monitor and assess distribution automation equipment, providing an automated acceptance process. The main aspects of the intelligent acceptance system are as follows:

1. Equipment installation and configuration: The intelligent acceptance system can be used for the installation and configuration of distribution automation equipment. It verifies the correct connection and configuration of the equipment, ensuring its proper functioning. Through automated testing and diagnostics, the intelligent acceptance system can quickly detect and rectify issues in installation and configuration, reducing human errors.
2. Function validation and performance assessment: The intelligent acceptance system can validate the functionality and assess the performance of distribution automation equipment. It can perform various tests and operations, such as sending control commands and detecting device responses. Through real-time data collection and analysis, the intelligent acceptance system can evaluate the performance indicators of the equipment, ensuring compliance with design and specification requirements.
3. Fault diagnosis and early warning: The intelligent acceptance system can conduct fault diagnosis and early warning. It monitors the operational status and parameters of the equipment and identifies potential faults and abnormal conditions by comparing them with pre-defined normal operation modes and behavioral rules. Through timely alerts and alarms, the intelligent acceptance system assists operation and maintenance personnel in quickly identifying and resolving problems, minimizing the impact of faults on the power system.
4. Data analysis and optimization: The intelligent acceptance system can perform data analysis and optimization. It can collect and analyze real-time data, identify potential issues and bottlenecks in the power system using algorithms and models, and provide corresponding optimization recommendations. The data analysis capabilities of the intelligent acceptance system can enhance the efficiency, reliability, and security of the power system.
5. Operation and maintenance management and remote monitoring: The intelligent acceptance system can be integrated with higher-level control centers or other management systems to enable remote operation, monitoring, and management of equipment. Through remote access and control, the intelligent acceptance system enhances the efficiency of maintenance personnel, allowing them to promptly address issues and conduct remote maintenance.

In practical application scenarios, the intelligent acceptance system verifies the correct connection of all cables, ensures sensor calibration accuracy, and checks if communication interfaces are configured according to specifications. If any inconsistencies are detected, the system generates an automated report, highlighting the specific issues. After the installation of remote control devices in a distribution substation, the intelligent acceptance system tests their functionality by sending control commands to open and close circuit breakers. It then monitors the equipment's response, including response times and sequence of operations. By evaluating these parameters against design specifications, it ensures that circuit breakers perform as expected in real-world situations, such as breaker operations. A utility company employs the intelligent acceptance system to manage and monitor a network of telemetry equipment distributed across various substations. Through a centralized control center, operators can remotely access and control equipment at different substations. For instance, they can remotely close circuit breakers to restore power after temporary faults without dispatching on-site personnel. This reduces downtime and enhances the overall operational efficiency [41].

In summary, the intelligent acceptance system plays a significant role in distribution automation. Through automated testing, diagnostics, and data analysis, it provides comprehensive equipment acceptance and performance assessment, supporting equipment installation, configuration, and fault handling. Applying the intelligent acceptance system can bolster the power system's reliability, efficiency, and security, offering vital support to distribution automation systems' operation and management.

Application of edge computing in intelligent acceptance system

In recent times, edge computing has assumed a pivotal role in the intelligent acceptance system of distribution automation terminals (DAT). This section will delve into the utilization of edge computing within the intelligent acceptance system of DAT.

Firstly, edge computing provides real-time data processing capabilities to the intelligent acceptance system. As early as 2017, Nastic et al. [42] proposed a real-time data processing platform applied in the context of the Internet of Things (IoT). By performing local data processing on edge devices, the system can rapidly analyze data and make timely decisions. Secondly, edge computing enables secure local data storage and caching for the intelligent acceptance system. For instance, paper [31] proposed a blockchain-based data security storage method in an edge computing scenario. Utilizing this capability, the power system can securely store and cache relevant data on edge devices, reducing the demand for data transmission to the cloud. This facilitates quick access to historical data, real-time analysis, and comparisons, thereby enhancing the efficiency and flexibility of the acceptance system. Furthermore, edge computing empowers the intelligent acceptance system with offline operation and autonomy, allowing the system to operate independently even when disconnected from the cloud [10]. Lastly, edge computing delivers edge analysis and machine learning capabilities to the intelligent acceptance system. Sophisticated analysis and machine learning algorithms can be deployed on edge devices for real-time data analysis [11], anomaly detection [12], and fault prediction [13].

Edge computing holds significant application value in the intelligent acceptance system of distribution automation terminals. It offers capabilities such as real-time data processing, local data storage and caching, offline operation and autonomy, edge analysis and machine learning, and bandwidth optimization. These applications bring higher efficiency, flexibility, and reliability to the intelligent acceptance system, providing robust support for the acceptance work of distribution automation terminals.

Limitations of traditional intelligent acceptance system

Although the intelligent acceptance system played a pivotal role in distribution automation terminals, the limitations of traditional intelligent acceptance systems have restricted their widespread adoption and application in several aspects.

One problem with traditional intelligent acceptance systems is data processing latency. Relying on cloud-based data processing and analysis leads to elongated data transmission and cloud processing durations, thereby constraining the system's responsiveness [43]. This latency can be further increased in scenarios that require large-scale data processing and complex algorithm execution. Such delays may prevent acceptance personnel from timely accessing critical real-time data and analysis results, adversely affecting the accurate assessment and decision-making regarding the status of power equipment [44].

Traditional intelligent acceptance systems typically rely on cloud resources for data storage, computation, and analysis [45, 46]. Handling large amounts of data transmission and storage requires high bandwidth and large-capacity cloud resources, which increases costs and introduces complex network management. For real-time acceptance requirements, the time delay in cloud processing may not meet the system's demands, thereby affecting the accuracy and efficiency of acceptance. Furthermore, traditional intelligent acceptance systems that depend on cloud resources face challenges in ensuring data privacy and security requirements, especially considering the sensitive nature of the multidimensional data in power systems.

Traditional intelligent acceptance systems have high bandwidth requirements. In large-scale distribution automation terminals, a tremendous amount of data is generated, particularly when it involves high-frequency sampling and sensor data. Traditional systems need to transmit this data to the cloud for processing and storage, which places high demands on network bandwidth [47]. However, in network environments with limited bandwidth, such as remote areas or mobile network environments, this high bandwidth requirement may result in data transmission delays and instability.

Undoubtedly, traditional intelligent acceptance systems have various limitations, and these limitations are also the advantages offered by intelligent acceptance systems that employ edge computing technology.

Benefits of using edge computing

Based on edge computing, intelligent acceptance systems have the following advantages compared to traditional intelligent acceptance systems:

Improved acceptance efficiency: Edge computing technology significantly enhances the efficiency of intelligent acceptance systems. By performing real-time data processing and analysis on edge devices, the system reduces the time delay of transmitting data to the cloud for processing [48]. This enables acceptance personnel to promptly access critical real-time data and analysis results, facilitating quick assessment of the status of power equipment and accurate decision-making.

Reduced dependence on the cloud: Edge computing-based intelligent acceptance systems decrease reliance on cloud resources. By processing and analyzing data locally on the devices, the system reduces the need for data transmission and computation with the cloud. This not only lowers communication latency with the cloud but also reduces dependence on cloud resources [49]. By enabling local computation and decision-making at the edge, intelligent acceptance systems enhance system independence and reliability while reducing requirements for network connectivity to the cloud and associated costs.

Optimized bandwidth usage: Edge computing technology optimizes the bandwidth usage of intelligent acceptance systems. By performing real-time data processing and analysis on edge devices, the system can filter and aggregate data locally, transmitting only relevant information or insightful results to the cloud. This bandwidth optimization reduces data transmission volume and lowers the demand for network bandwidth, thereby improving system performance and scalability. By effectively utilizing limited network resources, intelligent acceptance systems can operate more efficiently and reduce operational costs.

Challenges and limitations of using edge computing

Despite the advantages of edge computing technology in the intelligent acceptance system of distribution automation terminals (DAT), its application also faces several challenges and limitations, including:

Limited computing resources: Edge devices often feature restricted processing power, memory, and storage capacity when compared to cloud servers. This limitation could curtail the extent and intricacy of data processing and analysis attainable on edge devices. Therefore, it is essential to optimize algorithms and develop efficient resource management techniques to allocate available resources properly, ensuring the effective utilization of limited computing resources. Allocating computing and network resources amid diverse or fluctuating circumstances poses a demanding endeavor [50]. To tackle this obstacle, numerous scholars have put forth assorted approaches. For instance, a Joint Communication and Computation (JCC) resource allocation method has been recommended. This method aims to fulfill resource requisites on Mobile Edge Computing (MEC) servers, aligning with user specifications, given that the necessary resources are accessible on MEC servers [51].

Network resource reliability: Edge computing relies on network connections to transfer data between edge devices and central systems. However, in certain deployment environments, network connections may be unstable, intermittent, or subject to delays. Due to limited edge computing server resources, congestion may occur when there is a large number of requests and an increase in data traffic. The primary reason for congestion is the limitation of server resources. This is an important issue in edge computing networks that can be addressed through the following methods: (1) Traffic buffering: When network capacity is at maximum and resources are in use, data packets are stored and queued until the buffer capacity is reached [52]; (2) Intelligent resource allocation: In this technique, limited resources are used to support incoming requests one by one [53].

Data security and privacy: Edge computing involves data processing and storage on edge devices, which elevates the significance of data security and privacy protection. Edge devices are susceptible to physical security risks and the potential for data leakage [54]. Using different encryption techniques can reduce such risks, but it may increase processing time and decrease application performance [55].

System management and maintenance: As the intelligent acceptance system of distribution automation terminals involves the collaborative work of multiple edge devices and central systems, system management and maintenance can become complex. Ensuring the stable operation of edge devices, software updates, and troubleshooting are challenging tasks.

These challenges and limitations need to be addressed through appropriate technical solutions and effective system design to overcome them, ensuring the effective application and optimal performance of edge computing in the intelligent acceptance system of distribution automation terminals.

The exploration of edge computing for DAT's intelligent acceptance system highlights its potential to revolutionize traditional methods and enable real-time data processing and analysis. The advantages of edge computing in this domain set the stage for discussing the design and implementation of an intelligent acceptance system powered by edge computing in the next section.

Design and implementation of edge computing-based intelligent acceptance system

In this section, we introduce the architecture and components of an edge computing-based intelligent acceptance system for distribution automation terminals. We discuss the selection of edge devices and sensors, data collection, processing, and the application of machine learning algorithms to optimize the acceptance process.

Architecture and components

The edge computing-based intelligent acceptance system for distribution automation consists of three layers: cloud, edge, and device. Each layer performs specific functions, working together to ensure the system's efficient and stable operation, as shown in Fig. 7.

Cloud layer

The cloud layer serves as the core management and data processing center of the intelligent acceptance system. It is responsible for the following functions:

Data Storage and Management: The cloud layer handles the storage and management of large-scale data, including acceptance data, historical data, and system configuration information. By utilizing high-performance databases and storage systems, the cloud layer efficiently stores and retrieves data, providing support for subsequent data analysis and decision-making [56].

Data Analysis and Algorithms: The cloud layer utilizes powerful computing capabilities and machine learning algorithms to analyze and process collected data. It can execute complex data analysis and mining algorithms, achieving intelligent identification and prediction of power equipment status, performance indicators, and abnormal situations [57].

Decision Support and Optimization: Based on data analysis results, the cloud layer provides decision support and optimization suggestions. The system can generate detailed acceptance reports, fault diagnosis reports, and equipment performance evaluation reports, assisting operations personnel in making accurate decisions [58].

Edge layer

The edge layer serves as an intermediary between the cloud layer and the device layer, encompassing the following functionalities:

Data Preprocessing and Filtering: The edge layer preprocesses and filters raw data from the device layer to minimize data transmission volume and alleviate cloud processing loads. It can perform simple data cleaning, denoising, and sampling operations, enhancing data quality and availability [59].

Real-time Data Analysis and Decision-making: The edge layer has a certain computing and analytical capability, allowing real-time analysis and decision-making on preprocessed data. It can execute rapid data analysis algorithms and rule engines to achieve real-time monitoring, fault detection, and warning functions for power equipment.

Data Caching and Buffering: The edge layer can locally cache a portion of data to provide fast data access and response capabilities. It can intelligently manage data caching and buffering based on system requirements and

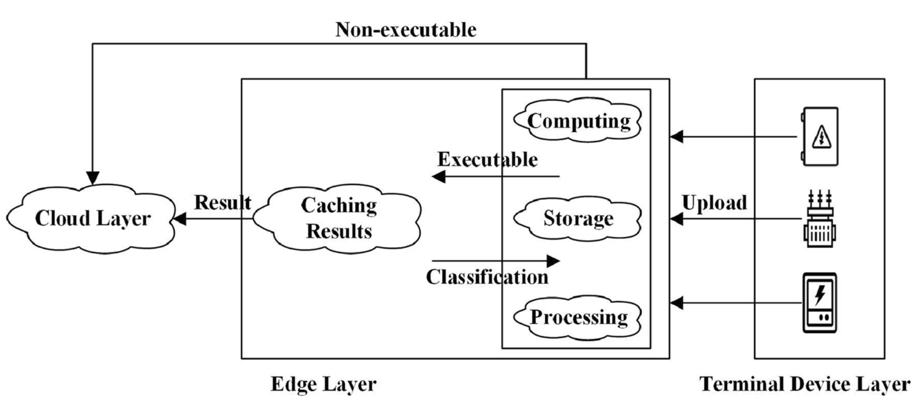

Fig. 7 Intelligent Acceptation System

resource constraints, reducing frequent access and transmission to the cloud layer [60].

Device layer

The device layer comprises the actual equipment of distribution automation terminals, including sensors, measurement instruments, and controllers. It possesses the following functions:

Data Collection and Transmission: The device layer is responsible for real-time data collection from power equipment, including parameters such as current, voltage, power, and temperature. It transmits the data to the edge layer or cloud layer for processing and analysis through sensors and measurement instruments [61].

Control and Execution: The device layer executes control operations on power equipment based on system instructions and control strategies. It can achieve automated switch control, protection actions, and fault handling functions, ensuring the safe operation and fault recovery capability of the power system.

Device Status Monitoring and Maintenance: The device layer can monitor the real-time status and operational parameters of power equipment, detecting the health status and fault conditions of the equipment. Through self-checking and self-diagnostic functions, it provides real-time feedback and anomaly reports on equipment status, assisting maintenance personnel in equipment maintenance and fault troubleshooting.

Selection of edge devices and sensors

Before selecting edge devices and sensors, a thorough analysis and definition of the intelligent acceptance system's requirements are necessary. This includes functional requirements, data collection needs, computing capability requirements, communication requirements, as well as reliability and security requirements. By clarifying the system's needs, it can better guide the selection of edge devices and sensors.

Selection of edge devices

The selection of edge devices should be evaluated based on the system requirements and available resources, considering the following factors:

Computing Capability: Edge devices should have sufficient computing power to handle real-time data processing, analysis, and decision-making tasks. Depending on the system's complexity and data volume, appropriate hardware and software components such as processors, memory, and operating systems need to be chosen. High-performance edge devices can better meet the demands for complex algorithms and real-time data processing [62].

Network Connectivity: Due to the rapid growth of IoT devices, IoT faces several communication-related challenges in edge computing networks. One key issue in these networks is how to effectively choose IoT edge computing devices when multiple edge nodes are available to transmit information. Edge devices should support stable network connections to facilitate data exchange and communication with the cloud layer and other edge devices. When selecting edge devices, factors such as network interfaces, transmission rates, and protocol compatibility need to be considered. A higher network connectivity performance ensures timely data transmission and communication reliability. To overcome this problem, Shafig et al. [63] introduced a novel framework called SoftSystem that utilizes the soft set technique to suggest relevant IIoT devices.

Reliability and Stability: Edge devices should have high reliability and stability to operate continuously in uninterrupted operating environments. Choosing high-quality and low-failure-rate edge devices ensures system stability and reliability. Additionally, the temperature range and environmental adaptability of edge devices need to be considered to cope with various harsh working conditions.

Manageability: Select edge devices that are easy to manage and maintain for system configuration, monitoring, and troubleshooting. Edge devices should have features such as remote management, software update support, and fault diagnosis capabilities, facilitating remote management and maintenance operations. This improves system manageability and maintenance efficiency.

Selection of sensors

The selection of sensors is a critical step based on data collection needs and the system's monitoring objectives [64]. The following factors need to be considered:

Measurement Parameters: Select appropriate types of sensors based on the power equipment parameters that need to be measured by the system. For example, current sensors, voltage sensors, temperature sensors, etc. Depending on different monitoring objectives, choose sensors with corresponding measurement parameters to meet the monitoring requirements for power equipment status.

Accuracy and Sensitivity: Choose sensors with sufficient accuracy and sensitivity to ensure data quality and accuracy. The resolution, error range, and sensitivity of sensors directly impact the accuracy and reliability of data collection.

Data Acquisition Rate: Depending on the system's real-time requirements, select sensors that can provide fast data acquisition. Consider factors such as the sensor's sampling rate and response time to ensure the sensor meets the system's requirements for real-time data.

Reliability and Durability: Choose sensors with high reliability and durability, capable of operating for an extended period in harsh environments. Consider factors such as the sensor's protection level, anti-interference capability, and lifespan to ensure stable operation of the sensor under various working conditions.

By comprehensively considering the characteristics of edge devices and sensors and the system's requirements, the most suitable combination can be selected to achieve accurate monitoring and data collection of power equipment in the intelligent acceptance system. Furthermore, considering system scalability and cost-effectiveness, standardized devices and sensors can be considered to achieve better interoperability and maintainability.

Data collection and processing

Data acquisition is a crucial step in the intelligent acceptance system, used to obtain real-time data from distribution automation terminal devices. Edge computing provides the intelligent acceptance system with real-time data processing capabilities, enabling data acquisition to take place at the edge devices. Edge devices can be equipped with various types of sensors, such as current sensors, voltage sensors, temperature sensors, etc., to collect different parameters from power equipment.

Edge computing has distinct advantages in data collection and processing. Firstly, it pushes data processing closer to the data source, reducing data transmission latency [48]. This means that data can be processed closer to where it is generated, resulting in faster response times. Secondly, edge devices can perform real-time data processing and analysis tasks, extracting valuable information according to system requirements, without the need to send all data to central servers for processing [49]. This distributed data processing approach enhances system efficiency.

As the volume of power data continues to grow, advanced data acquisition and processing methods are crucial for the intelligent acceptance system. MEC is an architectural technology that offers a computing paradigm and IoT services from centralized servers to distributed network edges. In the context of MEC, the management of data streams is handled by proximate edge nodes. This approach leads to a significant augmentation in computational capacity and a reduction in data transmission latency [65]. To illustrate, Zhou and colleagues [66] leveraged deep learning techniques to validate the accuracy of sensor data. They established a MEC-driven framework for local data processing, ensuring consistent computation and adaptable data conveyance.

Machine learning algorithms

Deep learning has gained significant attention in recent years, thanks to its exceptional capabilities [67]. These algorithms are known for their robustness, generality, scalability, and adaptive learning, all of which have played a pivotal role in advancing modern sustainable power systems [4, 68].

Numerous studies have demonstrated the outstanding performance of deep learning algorithms in the power system. For instance, in [69], researchers proved the effectiveness of deep learning algorithms in tackling complex power system problems. By learning patterns and features from large-scale datasets, deep learning can extract valuable information, including power load forecasting, power equipment fault diagnosis, and power system security assessment, among others. The application of deep learning algorithms in these tasks has yielded remarkable results, playing a vital role in enhancing power system operational efficiency and reducing the risk of faults.

Machine learning algorithms are playing an increasingly vital role in various fields, particularly in IoT domain [70]. Machine learning algorithms can also be applied to fault diagnosis in intelligent acceptance systems. Faults in distribution systems can lead to power outages, and issues such as short circuits, overloads, and human errors can result in significant losses. Fault detection is an analytical process that enables the rapid identification of the root cause of a problem based on power operation data and configuration data when subsequent issues arise. This facilitates the prompt resolution and restoration of normal power system operation. In [71], a method combining wavelet transform and DNN (Deep Neural Network) is proposed to provide fault types, fault phases, and fault locations in microgrid systems. Compared to traditional methods, the proposed approach demonstrates more accurate prediction results. In [72], an adaptive Convolutional Neural Network (CNN) approach for fault diagnosis is proposed, aiming to locate faults in distribution networks. This method boasts advantages such as short computation time and high accuracy/speed in fault selection. Additionally, in [73], the authors introduce a CNN algorithm for obtaining fault types and locations within distribution systems. Simulation results demonstrate the precise performance of CNN in comparison to other techniques like Support Vector Machine (SVM). Additionally, in [74], a method for fault recognition in the voltage sampling module of distribution terminals is introduced. This method employs a combination of Generative Adversarial Network (GAN) and CNN. The GAN model is employed to generate patterns and learn from developed samples, subsequently enhancing the CNN's fault detection accuracy significantly.

Integration with existing DAT infrastructure

The existing distribution automation infrastructure is a critical component in the power system, comprising a series of components and functional modules designed to achieve monitoring, control, and management of the distribution system [75, 76]. The distribution automation infrastructure includes various vital equipment and systems, such as intelligent electronic devices [77], monitoring devices [78], data acquisition systems [79], and communication networks [80].

In modern power systems, various distribution automation infrastructures play crucial roles. With the increasing power demand, integration of renewable energy, and challenges in grid security, the distribution system becomes more complex. The combination of edge computing with distribution automation infrastructure provides the power system with more intelligent, automated, and sustainable operation and management capabilities. This integration not only enhances system efficiency and reliability but also provides essential support for the development and sustainable growth of the power system.

Integrating edge computing technology with the existing distribution automation infrastructure can further enhance system intelligence and performance. In modern power systems, deploying edge devices such as edge servers or edge nodes at the edge of the distribution network allows real-time data collection and processing, tightly integrated with sensors and monitoring devices. Furthermore, harnessing the computational capabilities of edge devices allows for the offloading of certain data processing and analysis tasks from the cloud to these edge devices [81, 82]. This reduces data transmission latency to the cloud, achieving real-time data processing and decision-making, thereby enhancing system response speed and efficiency. The distribution system can conduct data filtering and preprocessing on edge devices, reducing data transmission to the cloud. Additionally, edge devices can have storage space for data storage and caching, reducing reliance on cloud storage resources and improving data access speed and efficiency.

Implementation details and challenges

To combine edge computing with distribution automation terminals and integrate it into the intelligent acceptance system, a comprehensive system architecture must be designed, incorporating edge computing as part of the distribution automation terminal infrastructure. This architecture should clearly define the data flow and communication methods between edge devices and cloud systems, ensuring secure and reliable data transmission. Additionally, the deployment locations and quantities of edge devices should be planned based on the distribution system's requirements and topology. Furthermore, to seamlessly integrate edge devices with existing sensors and monitoring equipment for real-time data collection and transmission, sensor networks and communication technologies can be utilized to facilitate efficient and security data exchange and communication between edge devices and various nodes within the distribution system [83]. This enables real-time monitoring and data acquisition of power equipment status. An effective collaborative mechanism between edge devices and cloud systems should be established, allowing edge devices to transmit processed data to the cloud for further analysis and decision-making, while the cloud system can send instructions and configuration parameters to edge devices. This collaborative effort between edge and cloud allows for advanced data processing and system control. Lastly, when integrating edge computing technologies, security and privacy preservation are key considerations. To ensure data security and prevent unauthorized access as well as data leakage, it is crucial to implement suitable encryption and authentication mechanisms. An effective solution, for example, is to adopt the data security framework proposed by Chadwick et al. [84].

Integrating edge computing technology with existing distribution automation terminal infrastructure involves work in system architecture design, data collection and transmission, introducing edge computing capabilities, data storage and caching, edge-cloud collaboration, as well as security and privacy protection. Such integration can enhance the intelligence level of distribution automation systems and improve system reliability, real-time performance, and overall efficiency.

The design and implementation of the edge computing-based intelligent acceptance system for distribution automation terminals demonstrate its potential to enhance system efficiency and decision-making capabilities. The integration of edge computing with the existing distribution automation terminal infrastructure and the provided case studies contribute significantly to the advancement of intelligent acceptance systems in power distribution.

Challenges and limitations of edge computing in DAT's intelligent acceptance system

This section addresses the challenges and limitations that edge computing may encounter when applied to distribution automation terminals' intelligent acceptance system. We discuss technical constraints, reliability issues, power consumption, and security and privacy concerns that warrant attention for successful implementation.

Technical challenges and limitations

Latency and bandwidth constraints

When applying edge computing to intelligent acceptance systems, there are still challenges and limitations that need to be addressed. One of these challenges is data processing latency and bandwidth. Due to the relatively limited computational and storage capabilities of edge devices, edge computing nodes may not be able to process and analyze large amounts of data as quickly as the cloud [85]. This results in data processing latency issues, affecting the real-time capability and responsiveness of the system. Another related limitation is bandwidth constraints. Edge devices typically communicate with the cloud or other edge nodes through limited network bandwidth. When a large amount of data needs to be transferred between edge devices and the cloud, bandwidth constraints can become a bottleneck, causing data transfer speeds to slow down [86]. This can lead to increased data processing latency, potentially affecting real-time capabilities and system performance. Such constraints and limitations can have adverse effects on the reliability and performance of intelligent acceptance systems, particularly with regard to real-time data processing and analysis, which are essential components of these systems. Therefore, the presence of processing latency and bandwidth constraints may prevent acceptance personnel from obtaining real-time data and accurate analysis results in a timely manner.

Reliability and availability issues

The extensive use of distribution automation terminals not only enhances the operational management level of distribution networks but also improves power supply quality. However, practical applications often encounter issues such as low online rates, frequent crashes, and data security concerns, seriously affecting the normal operation of distribution automation systems. Addressing these issues has become a top priority for power supply enterprises [87].

When applying edge computing to intelligent acceptance systems, reliability and availability are other important aspects that need to be considered and addressed [88]. Reliability refers to the stability and dependability of the system when facing faults, errors, or exceptional situations. Since edge computing involves multiple distributed nodes and devices, communication and coordination between nodes may encounter instability and errors. This may lead to issues such as data transmission loss, processing errors, or system crashes, thereby affecting the reliability of the intelligent acceptance system. Availability refers to the system's ability to continuously provide services. Edge computing nodes may be affected by factors such as power failures, network interruptions, or device malfunctions, causing nodes to function improperly or fail to provide the required services. This can result in the unavailability of the intelligent acceptance system, preventing acceptance personnel from accessing data and making timely decisions.

Power consumption and heat dissipation

During urbanization in developing nations, power consumption demand has surged alongside a substantial increase in the count of IoT devices across manufacturing and usage sectors [89]. The proliferation of IoT devices and escalating data processing needs intensify the energy demands on the power system. Edge devices' computation and communication actions can lead to elevated energy consumption, a concern that escalates as the system expands. Moreover, during intensive computing, edge devices may generate a considerable amount of heat, necessitating effective heat dissipation measures to maintain stable device operation. Energy consumption issues can potentially impact the long-term sustainability and operational costs of intelligent acceptance systems [90]. High energy consumption implies more frequent power supply or larger battery capacity requirements, significantly increasing the operational costs of the system. Additionally, higher energy consumption can have adverse effects on the environment, which is a critical concern that could potentially be addressed by providing sustainable and renewable energy sources [91]. The heat dissipation issue arises from the intensive computing of edge devices. During extensive data processing and the execution of intricate algorithms, edge devices have the potential to generate considerable heat. Prolonged exposure to elevated temperatures can result in device overheating, consequently diminishing the system's performance and reliability [92]. Therefore, effective heat dissipation measures are crucial factors in ensuring the proper functioning of the devices.

These challenges and limitations necessitate a series of mitigation measures when applying edge computing to intelligent acceptance systems. Firstly, exploring optimized data processing algorithms, offloading certain tasks to the cloud for processing, or employing higher-performance edge devices can alleviate data processing latency and address bandwidth limitations. Secondly, ensuring system reliability and availability is of paramount importance, achievable through measures such as device redundancy and backup configurations, fault detection, and automatic switchover. Additionally, regarding power consumption and heat dissipation concerns, consideration can be given to the use of more energy-efficient hardware devices and the adoption of renewable energy sources to mitigate the environmental impact of energy consumption.

Security and privacy concerns

Data confidentiality and integrity

Intelligent acceptance systems handle substantial volumes of sensitive data, encompassing power equipment status, monitoring data, and analysis outcomes. Thus, safeguarding data privacy and integrity becomes pivotal to uphold user rights and sustain system credibility [93]. Data privacy refers to the assurance that sensitive data is not accessible, acquired, or tampered with by unauthorized individuals or entities during processing and transmission. Edge computing involves multiple distributed nodes and devices, and data transmission and processing between different nodes may face security threats and risks, such as data leaks, theft, or tampering. Thus, to protect data privacy, it's essential to employ measures like data encryption, access control, and identity authentication [94]. Data integrity refers to the assurance that data is not accidentally or maliciously altered, damaged, or lost during transmission and processing. In the edge computing environment, data transmission and processing involving multiple nodes and devices may encounter situations such as transmission errors, packet loss, or node failures, which can affect data integrity. Therefore, measures such as data verification, error detection, and fault tolerance mechanisms need to be implemented to ensure data integrity.

Data confidentiality and integrity are crucial security aspects within intelligent acceptance systems. In the context of edge computing, these aspects encounter specific challenges, including complex management and resource constraints. Nonetheless, these challenges can be surmounted by implementing suitable technologies and strategies, thereby ensuring data security and bolstering system reliability [95]. As technology continues to evolve, we can anticipate witnessing further innovative solutions in intelligent acceptance systems that address these challenges while concurrently satisfying data privacy and integrity requisites.

Authentication and access control

Identity authentication and access control play a critical role in intelligent acceptance systems to ensure that only authorized users or devices can access and operate system resources and data. Appropriate identity authentication and access control mechanisms can prevent unauthorized access and potential malicious activities, thereby safeguarding system security and data integrity [96]. However, when edge computing is applied to intelligent acceptance systems, although identity authentication and access control are important measures to ensure data security and system trustworthiness, edge computing also brings some challenges and limitations. Firstly, the distributed nature of the edge computing environment increases the complexity of identity authentication and access control. Due to the diversity of edge devices and nodes, there exist different identity authentication mechanisms and access control policies. Therefore, how to unify the management and coordination of identity authentication and access control mechanisms distributed across edge nodes becomes a challenge. Secondly, resource limitations of edge nodes may impact the implementation of identity authentication and access control. Edge devices often possess constrained computing power and storage capacity, potentially limiting the use of intricate identity authentication and access control algorithms. In the edge computing environment, lightweight authentication and authorization schemes need to be designed to achieve efficient identity authentication and access control in resource-constrained environments.

Compliance with regulations and standards

Intelligent acceptance systems handle sensitive data and operational information of power equipment, thus requiring adherence to relevant regulations and legal standards to ensure data security, privacy, and legality. Compliance requirements encompass a wide range of areas, including data protection, privacy preservation, and network security. Depending on the regulations and standards of different regions and industries, intelligent acceptance systems may need to comply with a series of regulations and legal requirements. To adhere to these legal regulations, it's crucial to adopt suitable security measures, encompassing data encryption, access control, and identity authentication. This ensures the preservation of data confidentiality, integrity, and availability.

In the edge computing environment, implementing compliance and legality requirements poses certain challenges. Firstly, the distribution and heterogeneity of edge nodes increase the complexity of management. Given the number and diversity of edge nodes, it is essential to ensure that all nodes comply with legal requirements, including security configurations, access control, and log recording, among others. Secondly, the changing and updating of legal regulations also present challenges for the edge environment. As relevant regulations and standards evolve and update, intelligent acceptance systems need to promptly adjust and update their security measures to meet the latest requirements. Regular compliance assessments and reviews are essential to maintain consistent adherence to regulatory and legal mandates in the system.

Potential solutions and future research directions

Edge-cloud collaboration

Edge computing is an architecture that performs distributed processing and storage at the data source, offering numerous advantages in data processing and computation [97]. Solutions that include edge computing can typically reduce communication latency, improve network scalability, and enhance information accessibility, thus enabling more agile and efficient business development. Edge nodes are deployed at the edge side, and various terminal devices access the platform through the edge side, placing higher demands on edge-side resources. The edge-cloud computing architecture consists of numerous edge servers and terminals that require unified management through the edge cloud to support edge applications.

Edge-cloud synergy is a potential solution to address the challenges faced by edge computing in intelligent acceptance systems. By enabling coordinated work between edge devices and cloud resources, their respective strengths can be fully utilized. As an example, edge devices can handle real-time data processing and analysis tasks, while cloud resources can offer enhanced computing capabilities and expanded storage capacity [31, 98]. Through optimizing data flow and task allocation to achieve collaboration between the edge and the cloud, the performance and efficiency of intelligent acceptance systems can be improved.

To enhance intelligent acceptance systems, optimizing their performance is crucial. Achieving this involves close collaboration between edge computing and cloud computing to cater to varying application scenarios. This synergy entails resource coordination, application management, data integration, and intelligent operations. Resource synergy combines edge nodes' computing, storage, network, virtualization, and other infrastructure resources to facilitate network services. Application management synergy refers to the deployment and runtime environment of network applications provided by edge nodes, managing and scheduling multiple application lifecycles on the nodes. Data synergy involves edge nodes taking charge of data collection at the edge, performing initial data processing and analysis based on predefined models, and subsequently uploading the results to the cloud. Intelligent synergy encompasses the execution of inference using intelligent models on edge nodes. This enables distributed intelligence to be achieved [99].

In the context of the power industry, edge-cloud synergy technology, as shown in Fig. 8, conducts decision-making on edge-side data through value mining, data computation, and data application from bottom to top, uploading it to the cloud center. The cloud center controls the edge-side data with instructions, enabling

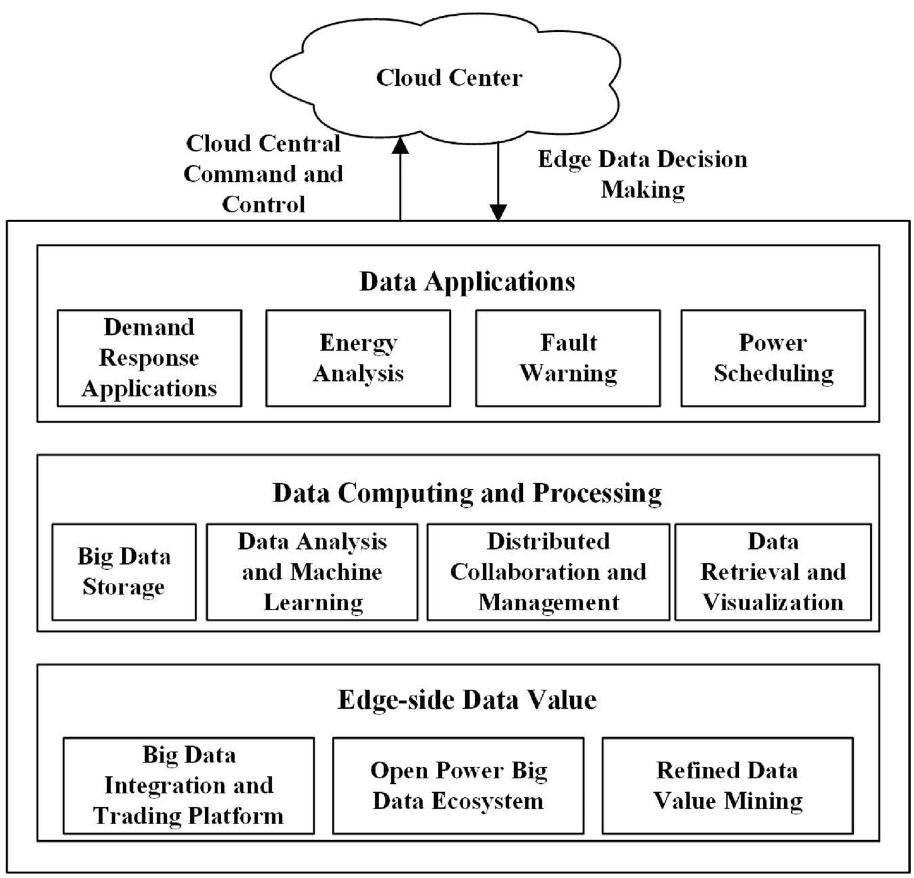

Fig. 8 Technical architecture of edge-cloud collaboration

collaborative bidirectional interaction between user edge-side data and the power grid cloud center.

Demand response business is an essential service that facilitates the interaction between the power supply side and the user side. It involves user-side participation in response to pricing or incentives, leading to changes in consumption patterns. This participation plays a crucial role in reducing peak loads on the power grid and ensuring safe and stable operations. The adjustment of electricity prices or incentive mechanisms by the power supply side relies on relevant data from supply-demand interactions. Therefore, the application of edge-cloud synergy technology holds significant significance for optimizing demand-side resources. Electricity analysis primarily involves the analysis of various aspects of electricity consumption, faults, repair efficiency, peak power consumption, among others, encompassing scenarios associated with multiple data analyses. Fault warning focuses on predicting equipment failures, power consumption loads, and potential electricity usage conditions. Electricity scheduling assesses the power grid's safety and operational status based on data or monitoring information provided by various information collection devices, combined with power grid operational parameters, and subsequently makes adjustments to the system. The data application of edge-cloud synergy encompasses various aspects of data analysis, prediction, and control for equipment and systems.

Hybrid edge-cloud architecture

When developing energy-saving solutions, various approaches can be taken to store and process energy footprints. Cloud computing platforms are the most widely used paradigms for this purpose [100, 101]. Despite the slight delays in implementing real-time energy efficiency applications, cloud computing technology is garnering increasing attention [102, 103]. Meanwhile, edge computing has emerged as a more favorable solution to address the challenges encountered in cloud computing, particularly as an alternative or supplementary method for processing energy data at the Internet of Things (IoT) edge to mitigate latency issues [104, 105]. Nevertheless, edge computing still demands additional electrical power for independent utilization in order to fulfill the high computational requirements of AI-based energy-saving solutions. Consequently, the hybrid edge-cloud architecture is presently considered the most optimal trend for implementing intelligent acceptance systems in distribution automation [106, 107]. Figure 9 illustrates the hybrid edge-cloud architecture.

Additionally, in recent years, the analysis, detection, and visualization of abnormal energy consumption and behavior in distribution automation systems have received increasing attention. This is because such research is crucial in developing efficient energy-saving systems [108]. For example, in [109], supervised and unsupervised anomaly detection methods were introduced, while in [110], an energy anomaly detection approach based on using micro-moments and deep learning models was proposed and compared with various traditional machine learning models. Although these technologies can achieve high accuracy in anomaly detection, their main challenge lies in the computational resources required for implementation and operation. Consequently, researchers have explored various architectures, including cloud-based, edge-based, and edge-cloud hybrid solutions [110].

Although most energy-saving solutions in distribution automation smart acceptance systems currently utilize cloud computing for data collection, preprocessing, and analysis of energy data, edge computing has garnered increasing interest. Nevertheless, edge computing still requires more electrical power for individual use to meet the high computational demands of AI-based energy-saving solutions. At the same time, the hybrid edge-cloud architecture emerges as a promising approach in current energy-efficient systems implementation. It provides flexible control over energy usage in distribution automation smart acceptance systems, minimizes cloud hosting costs, and enhances privacy protection. For instance, in [111], authors propose a novel energy-efficient system based on a hybrid edge-cloud computing architecture. In the edge-cloud collaboration, high concurrency in offloading deep learning tasks can overload edge servers and lead to unacceptable latency. Optimal offloading decisions are challenging in dynamic, heterogeneous edge-cloud environments. To tackle these concerns, Xu et al. [112] introduced GPOV (Game theory-based Partitioning and Offloading with CNN, a dynamic offloading approach that fuses game theory and CNN. The CNN partitioning allows for more efficient resource utilization and reduces latency through parallelism.

Blockchain-based security and privacy protection

In recent times, blockchain distributed technology has surfaced as a remedy for fortifying the architecture of enterprise systems and hierarchical network operations. This technology introduces attributes like integrity, transparency, privacy, and security [113]. Through the creation and implementation of distributed applications (DApps), accessing information becomes more convenient, and blockchain-backed APIs amplify the effectiveness and dependability of designing distributed information systems [114–116]. In the context of smart grids and distribution environments, blockchain can be utilized to protect intelligent acceptance systems, encrypt

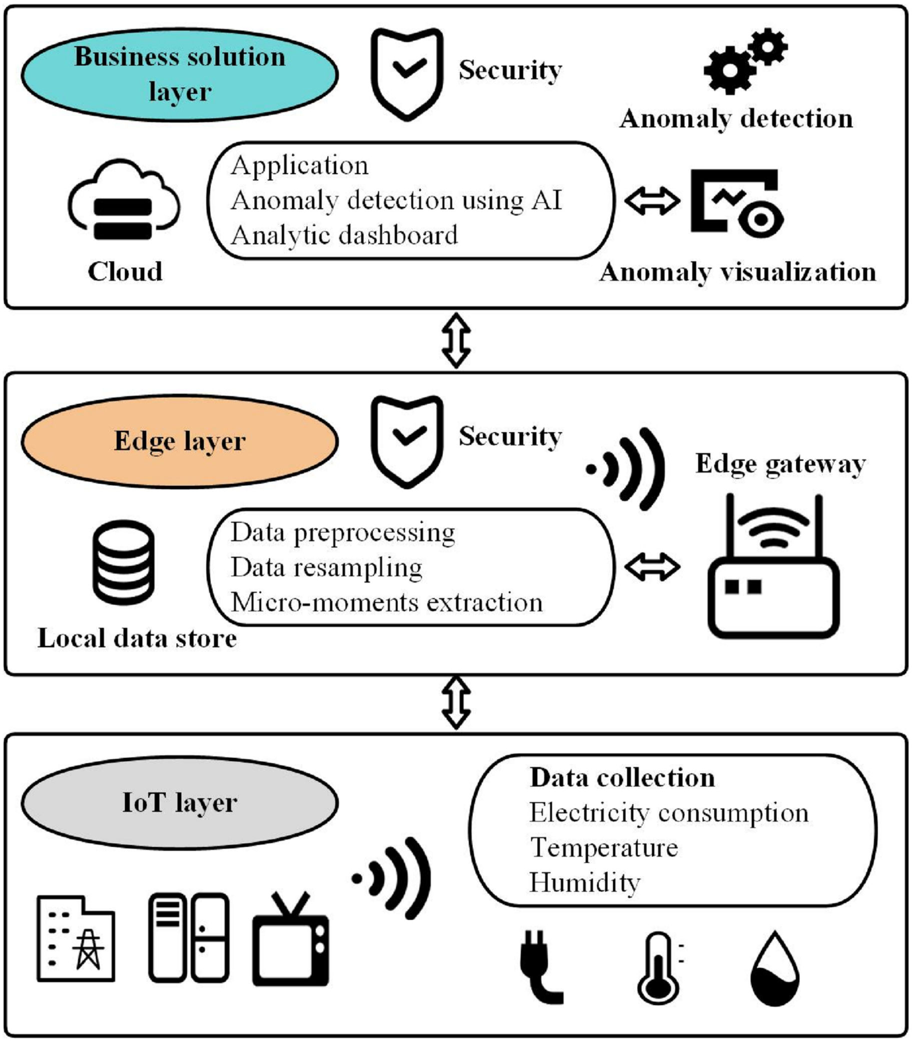

Fig. 9 Hybrid edge-cloud architecture

information, and record node execution details and events. The storage based on blockchain relies entirely on its immutability, preserving the ledger for transparent information investigations [117]. Furthermore, blockchain, which supports a distributed ledger environment, provides a chronologically ordered structure to record transaction execution events and distribution fluctuations in the smart grid nodes. To facilitate execution and delivery, two different channels are deployed in alliance public/private networks. However, the independent execution of distribution tasks within the smart grid is accomplished using chaincode scripts, orchestrating various operations through DApps for scheduling, control, management, and organization. This decentralized distributed technology bolsters the security and privacy of the ledger, allowing the creation of a transparent ecosystem that resists tampering and forgery [118].

The assessment of challenges and limitations in the application of edge computing to DAT's intelligent acceptance system calls for proactive measures to mitigate latency, enhance reliability, and address security and privacy concerns. The potential solutions and future research directions proposed in this section offer promising avenues for overcoming these obstacles.

Conclusion and future work

This paper presents a comprehensive review of the latest advancements and applications of edge computing technologies in intelligent acceptance systems for distribution automation terminals. Initially, we introduce the definition and functions of distribution automation terminals, emphasizing their significance in power system operation and management. Subsequently, we delve into the definition and advantages of edge computing, providing examples and explanations of its applications in intelligent acceptance systems, particularly highlighting its advantages in data analysis and decision support. Furthermore, we focus on the design and implementation of intelligent acceptance systems based on edge computing technologies, including system architecture, device and sensor selection, data acquisition and processing, and the application of machine learning algorithms. When discussing technical challenges, security, and privacy issues, we identify the challenges faced by edge computing in intelligent acceptance systems and propose potential solutions. In particular, we emphasize the importance of edge-cloud collaboration, hybrid edge-cloud architectures, innovative edge devices and sensors, advanced machine learning algorithms, and blockchain-based security and privacy protection in future research.

Intelligent acceptance systems have extensive application prospects and significant development potential, especially in the field of distribution automation and power. In the future, they will evolve in several key directions:

Firstly, intelligent acceptance systems will collaborate more with other intelligent systems, such as smart distribution grids and energy management systems. This collaboration will enable broader data sharing and cooperative control, thereby enhancing the overall efficiency and reliability of the power system. Secondly, with the continuous advancement of artificial intelligence and machine learning technologies, intelligent acceptance systems will become more intelligent. They will have the capability to conduct in-depth data analysis, automatically identify potential issues, and provide more intelligent fault detection and diagnostics, ultimately reducing maintenance time and costs. Sustainability and energy efficiency are critical topics in the future. Intelligent acceptance systems will adopt more energy-efficient hardware and green energy sources to reduce energy consumption and minimize their environmental impact. The application of blockchain technology will ensure data security and integrity, particularly in data sharing and exchange. This will help establish trustworthy data records and auditing mechanisms. Finally, as the level of system intelligence increases, network security and data privacy protection will become crucial focus areas. Future systems will employ stronger security measures to defend against potential threats. These directions will collectively drive the widespread application and continuous development of intelligent acceptance systems in the field of power and beyond.

In the development of intelligent acceptance systems, edge computing technologies will continue to play a pivotal role. To propel further advancements in this field, several key research directions merit exploration:

Enhancing the Performance and Efficiency of Edge Computing: With the continuous increase in data volume and complexity, improving the performance and efficiency of edge computing is a critical concern. Researchers can explore novel edge device and sensor technologies and optimize edge computing algorithms and models to enhance system responsiveness and processing capabilities.

Strengthening Edge-Cloud Collaboration: Edge-cloud collaboration is crucial to enhancing the performance and reliability of intelligent acceptance systems. Future research can explore improved collaboration mechanisms and data transfer schemes to facilitate efficient cooperation and data sharing between edge devices and the cloud.

Enhancing Security and Privacy Protection: Intelligent acceptance systems involve vast amounts of sensitive data, making security and privacy paramount. Researchers can further explore security solutions based on blockchain and encryption technologies to ensure data confidentiality and integrity.

Developing Autonomous Decision-Making Capabilities for Intelligent Acceptance Systems: Future research can explore the application of autonomous decision-making technologies such as reinforcement learning in intelligent acceptance systems, enabling the system to learn from experience, optimize acceptance strategies, and adapt automatically to different devices and environments.

Leveraging Emerging Technologies: With continuous technological advancements, intelligent acceptance systems can leverage emerging technologies like the IoT, big data analysis, and AI to further enhance their performance and functionality.

The application of edge computing technologies in intelligent acceptance systems holds tremendous potential. By improving the performance of edge computing, enhancing security protection, strengthening edge-cloud collaboration, and advancing autonomous decision-making capabilities, we are poised to achieve more precise, efficient, and reliable intelligent acceptance systems, providing robust technical support for the acceptance work of distribution automation terminals.

Authors' contributions

Mingzhen Liang conceived the paper, designed its structure, and drafted the initial manuscript. Mingzeng Zhu collected reference materials and organized the literature review. Hefeng Li and Ying Lu supervised and guided the paper's completion, overseeing content validation and proofreading to ensure accuracy. Min Pang was responsible for preparing the final manuscript and overall coordination of the work. All authors discussed the results and contributed to the preparation of the final manuscript. All authors reviewed the manuscript.

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Availability of data and materials
The data that support the findings of this study are available from the corresponding author upon reasonable request.

Declarations

Ethics approval and consent to participate
The research has consent for Ethical Approval.

Competing interests
The authors declare no competing interests.

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