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A Review of Intelligent Verification System for Distribution Automation Terminal based on Artificial Intelligence Algorithms

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Abstract
Artificial intelligence (AI) plays a key role in the distribution automation system (DAS). By using artificial intelligence technology, it is possible to intelligently verify and monitor distribution automation terminals, improve their safety and reliability, and reduce power system operating and maintenance costs. At present, researchers are exploring a variety of application methods and algorithms of the distribution automation terminal intelligent acceptance system based on artificial intelligence, such as machine learning, deep learning and expert systems, and have made significant progress. This paper comprehensively reviews the existing research on the application of artificial intelligence technology in distribution automation systems, including fault detection, network reconfiguration, load forecasting, and network security. It undertakes a thorough examination and summarization of the major research achievements in the field of distribution automation systems over the past few years, while also analyzing the challenges that this field confronts. Moreover, this study elaborates extensively on the diverse applications of AI technology within distribution automation systems, providing a detailed comparative analysis of various algorithms and methodologies from multiple classification perspectives. The primary aim of this endeavor is to furnish valuable insights for researchers and practitioners in this domain, thereby fostering the advancement and innovation of distribution automation systems.

Keywords Distribution automation, Intelligent Acceptance, Artificial Intelligence, Machine learning, Research Progress

Introduction

With the rapid advancement of technology, Artificial Intelligence is increasingly permeating various domains, bringing about significant transformations and opportunities to contemporary society. Within the domain of electrical power systems, the application of AI is becoming increasingly notable, offering new possibilities for the intelligent upgrade and optimization of these systems [2]. The DAS embodies an intelligent strategy, facilitating utility companies to remotely oversee, harmonize, and manage distribution components in real-time. The key goals of the DAS encompass enhancing voltage regulation, precise load prediction, bolstering system dependability and security, meticulous data planning and execution, along with optimizing fault detection and system reconfiguration. Automating the various functions of the distribution grid serves as an effective approach to alleviate the burden on operational personnel [3]. Distribution automation has been a focal point of research for an extended period. Achieving automation in distribution operations involves deploying data collection devices,

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remote control apparatuses, and by providing information processing and decision-support functionalities [4]. Installing remotely controllable devices on the network aids in reducing switch-over times and the labor cost requirements of manual operations. Reduced manual interventions aid in minimizing potential human errors, and the incorporation of data collection devices enables thorough network monitoring. Within this context, the intelligent acceptance system for DAS terminals, as a crucial component within the power system, holds key significance in ensuring the safe and reliable operation of the electric power system [5]. The application of artificial intelligence in power systems makes energy management more intelligent, efficient and sustainable. The adoption of these technologies can help reduce energy waste, improve the reliability of power systems, and promote the wider application of renewable energy, thus bringing positive changes to the energy industry and environmental sustainability. The key goals of distribution automation systems are to improve voltage regulation, accurate load prediction, and enhance system reliability and safety.

Artificial Intelligence algorithms, such as deep learning and machine learning, serve as examples of cutting-edge technologies that have been extensively applied to address complex problems in electric power systems. Over the past two decades, machine learning has emerged in the power sector, capable of learning from vast historical data and making swift decisions without human intervention. Machine learning encompasses diverse algorithms that have proven successful in various fields, including but not limited to classification, regression, prediction and more [6]. Deep learning is a subset of machine learning that employs cascaded layers to automatically extract multiple features from raw data. The evolution of deep learning techniques has been swift, finding applications in numerous domains. Categorizations of deep learning algorithms include supervised, semi-supervised, and unsupervised approaches, alongside another classification known as reinforcement learning or deep reinforcement learning [7]. Figure 1 summarizes the AI technologies and related models available for use in the Distribution Automation System.

Distribution automation integrates computer technology, data transmission, control techniques, modern equipment, and management to enhance power supply reliability, elevate energy quality, provide superior user services, cut operational costs, and ease the workload of operational staff [8]. The intelligent acceptance system for distribution automation terminals aims to utilize artificial intelligence technologies to intelligently verify and monitor the distribution automation terminals. This enhances the safety and reliability of the distribution system while reducing operational and maintenance costs [9].

Traditional acceptance methods for distribution automation terminals often rely on manual operations and offline testing, resulting in low efficiency and an inability to meet the needs for rapid response. However, with the introduction of artificial intelligence algorithms, distribution automation terminals can achieve autonomous learning, intelligent judgment, and real-time monitoring, significantly elevating the system's automation level and efficiency. Modern distribution automation systems play an essential role in enhancing the efficiency, reliability, and safety of distribution networks. They can achieve rapid response and precise control, enhancing the resilience and interference resistance of the power system, catering to the demands for automation, intelligence, and sustainable development of the power system [10].

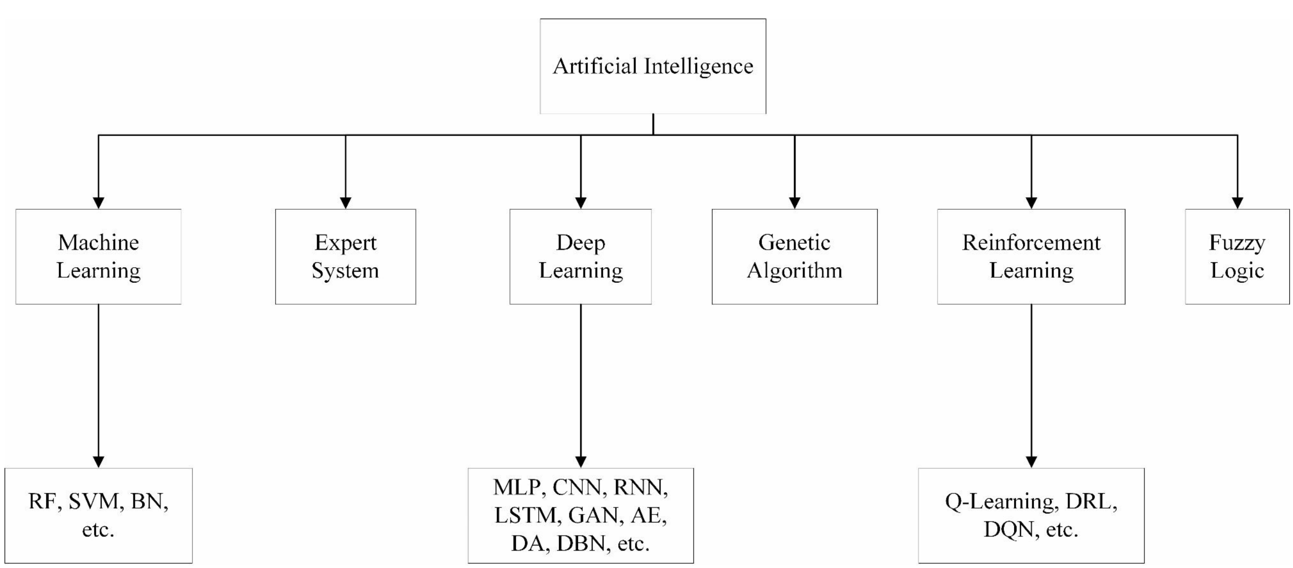

Fig. 1 Classification of AI methods available in DAS

Currently, researchers are actively exploring application methods and algorithms for the intelligent acceptance system of distribution automation terminals based on artificial intelligence. AI algorithms such as machine learning and expert systems have made significant progress in this area. By analyzing and learning from vast historical data, distribution automation terminals can achieve functions like fault detection, network restructuring, load forecasting, network security, and voltage control, providing robust support for power system stability [11].

This paper provides a research overview and application developments of the intelligent acceptance system for distribution automation terminals based on artificial intelligence algorithms. The second section briefly introduces the traditional distribution automation system. The third section presents the main methods of artificial intelligence. The fourth section details the research progress of the distribution automation system based on artificial intelligence algorithms, which is further divided into sub-sections concerning fault detection, network restructuring, load forecasting, network security, and voltage control. The fifth section describes the challenges and limitations of AI technology in distribution automation systems. The sixth section concludes the paper.

Overview of distribution automation system

There are three stages in the evolution of distribution automation: The initial stage entails distribution automation based on the coordinated operation of automated switching devices. The second stage introduces distribution automation systems built upon communication networks, feeder terminal units, and backend computer networks. With the advancement of computer technology, the third stage of distribution automation emerged, which integrates automatic control capabilities onto the foundation of the second stage distribution automation system [12].

Traditional distribution system

The large quantity, wide distribution, and diverse types of distribution automation terminals pose challenges for the commissioning and acceptance process, which currently relies on manual efforts given the existing technological conditions. On-site personnel engage in manual simulation of analog signals and switch positioning according to signal definitions. They establish communication via telephone with dispatch center personnel, conducting a step-by-step assessment of signal changes through observation of system responses. The primary drawbacks of this approach include dependence on meticulous pre-arrangements for mutual commissioning, resulting in coordination difficulties at the dispatch center. The acceptance testing process lacks standardization, and acceptance management exhibits shortcomings in terms of precision and rigor. Furthermore, during peak periods, frequent occurrences of telephone queues and traffic congestion exacerbate the situation [9].

Modern distribution automation systems

Modern distribution automation systems are integrated systems designed to enhance the operational efficiency and safety of power systems. Leveraging advanced communication and computing technologies, these systems enable the monitoring, control, protection, and management of distribution networks. Modern distribution automation systems typically encompass the following components and functions:

1) Monitoring and Measurement: Real-time monitoring and measurement of distribution networks are accomplished through intelligent sensors, monitoring devices, and data acquisition units.
2) Remote Communication and Control: Modern communication technologies such as wireless communication, fiber optics, and the internet facilitate remote communication and control between distribution equipment.
3) Automated Protection and Switching Control: Distribution automation systems can automatically detect faults and anomalies, taking appropriate actions based on preset protection strategies.
4) Fault Diagnosis and Maintenance: The system is capable of fault diagnosis and anomaly detection, offering assessments of equipment health.

In general, modern distribution automation systems improve the efficiency, reliability and sustainability of power distribution by introducing advanced technologies and intelligent functions. These improvements are important for meeting growing electricity demand, improving energy efficiency and promoting the use of renewable energy.

Figure 2 illustrates the structural segmentation of distribution grid operation into two distinct categories. On the one hand, decision support systems utilize measurements to visualize grid conditions, enabling operators to take manual control actions. These systems are termed decision support systems, functioning in a human-in-the-loop or open-loop control mode, as they are not fully automatic. Notably, this category encompasses state estimation, fault diagnosis systems, and stability assessment methods.

Intelligent acceptance system for distribution automation terminals

The final criterion for the commissioning of distribution automation terminals is graphical acceptance, which

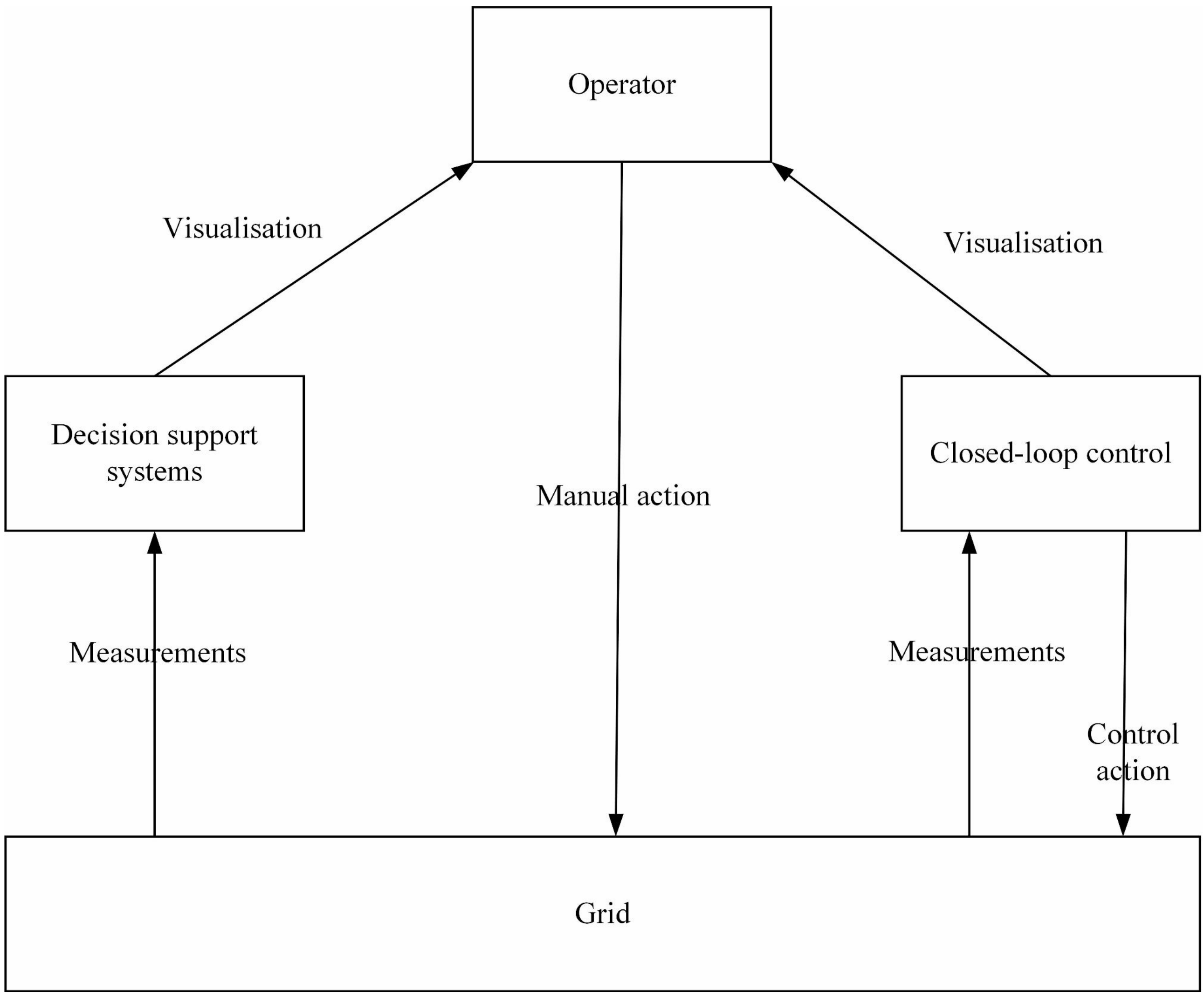

Fig. 2 Acceptance principle

involves cross-referencing the on-site data with the SCADA graphics at the central station. Whether during the commissioning phase or in later operational stages, the testing main station provides a model-data verification function. Even in the event of changes, it ensures the standardization and accuracy of the entire process of automation terminal integration [1]. Additionally, the system boasts the following advantages: ease of maintenance, reduction of external risks and communication-related failure probabilities. The central station does not require continuous tracking by automation personnel; on-site personnel independently complete the commissioning tests. The system is accessible from anywhere, enabling multiple sites to simultaneously initiate acceptance tasks and carry out automated acceptance.

Terminal personnel use the system to realize power distribution automation, send tests through intelligent acceptance handhelds and obtain test result data, the main station commercial library calls system data for acceptance tests, the test module has a complete debugging plan, the communication module interacts with the test module and communicates with the Master station communication. The acceptance test module is used to verify whether the distribution automation terminal works normally according to specifications and requirements. The master control module is the terminal for acceptance testing. Figure 3 shows the acceptance principle of the system.

In the past few years, numerous AI algorithms have been widely applied in distribution automation systems, playing a crucial role in enhancing system performance and optimizing power distribution. However, to effectively harness the advantages brought by these algorithms, a familiarity with key artificial intelligence algorithms is essential. Therefore, in the upcoming section, we will delve into a detailed analysis of some

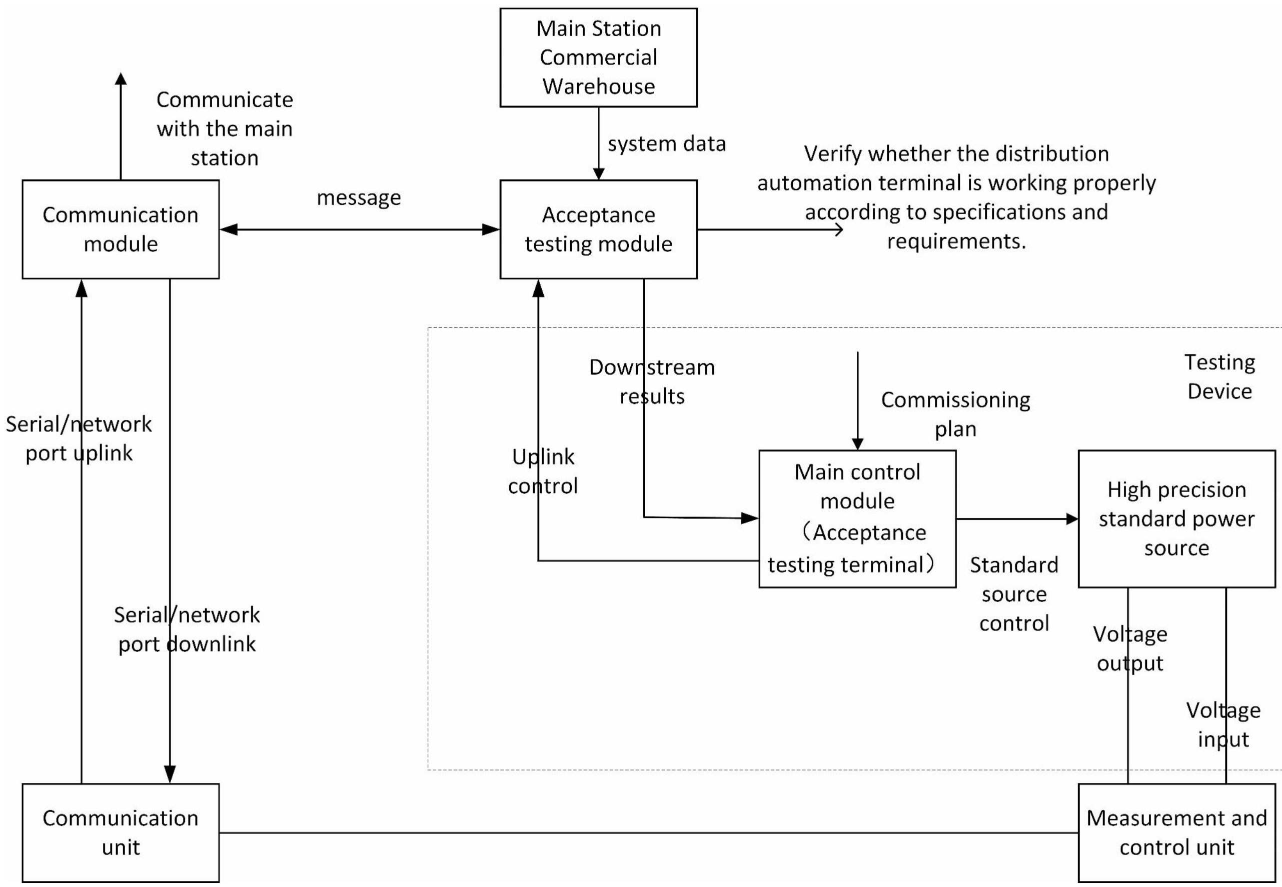

Fig. 3 Acceptance principle

frequently encountered algorithms in distribution automation systems. This analysis will encompass their fundamental principles, application domains, as well as potential advantages and limitations. This effort will contribute to a comprehensive understanding of how artificial intelligence algorithms can be applied to distribution automation systems, driving progress and innovation in this field.

Artificial intelligence methods

AI represents an emerging domain in technological research encompassing the investigation, advancement, theory, methods, techniques, and applications aimed at replicating, extending, and amplifying human intelligence. Machine learning, on the other hand, is the science of enabling computers to mimic human-like learning and behavior through exposure to data and observations, facilitating autonomous enhancement of their learning process. Deep learning is a branch of machine learning that aims to use multi-layer computational models with complex structures or multiple nonlinear transformations to achieve high-level abstractions of data. Deep learning methods have been widely employed across diverse fields including image processing, speech recognition, and natural language processing, and have achieved significant breakthroughs [13]. In addition, using edge computing technology, the intelligent acceptance system of distribution automation terminals can better meet the challenges related to large data volume, real-time requirements and security. These advantages make mobile edge computing an ideal choice for achieving efficient, reliable and secure intelligent acceptance systems. Although many technologies such as edge computing technology and Internet of Things technology have been used in research in the field of distribution automation, this article focuses on artificial intelligence technology [14–17].

Algorithms based on machine learning

As depicted in Fig. 1, this paper frequently employs several ML algorithms such as Support Vector Machines, Bayesian Networks, Random Forest, and more [18].

SVM is a frequently employed machine learning technique for tackling binary classification tasks. It achieves this by finding a separating hyperplane within the sample space to differentiate between samples of different classes while maximizing the minimum distance between points from each class to the hyperplane. Various studies [19, 20], [21, 22] have employed this method and combined methods thereof.

Bayesian Networks are probabilistic graphical models utilized to represent dependencies between variables and perform probabilistic inference. These networks are built on the principles of Bayesian theorem and graph theory, serving as tools to model and analyze complex uncertainty problems. Numerous references such as [23, 24] have employed this method and combinations thereof.

Algorithms based on deep learning

Similarly, numerous deep learning algorithms such as Autoencoders, Convolutional Neural Networks, Multi-Layer Perceptron, and Deep Belief Networks have been employed [25, 26].

ANN is a computational model that draws inspiration from the structure of biological neural systems, designed to simulate and solve a variety of problems. ANNs find widespread applications in fields like pattern recognition, image and speech processing, natural language processing, prediction, and classification. References such as [27, 28] have employed this method and combinations thereof.

Autoencoders (AE) are unsupervised learning models initially proposed by Rumelhart et al. Literature references like [29, 30] have employed this method and combinations thereof.

Deep learning models can automatically learn higher-level feature representations from raw data, while traditional machine learning usually requires manual design of features. This makes deep learning more effective when processing complex, large-scale data. A series of efficient optimization algorithms and deep learning frameworks have emerged in the field of deep learning, making model training easier and more efficient.

Algorithms based on reinforcement learning

Based on reinforcement learning, algorithms like Q-learning, Deep Reinforcement Learning, and Deep Q Networks are also frequently utilized.

RL is a subset of machine learning that centers on enabling intelligent agents to learn optimal decision-making through interactions with their environment, aimed at accumulating maximum rewards. The core idea of reinforcement learning is learning through trial and error, where the agent learns the optimal strategy by observing the environment's states and reward signals during interactions. References like [31, 32] have employed this method and combinations thereof.

Other algorithms based on artificial intelligence

In addition, several other AI-based algorithms such as Expert Systems, Fuzzy Logic, and Genetic Algorithms are also mentioned.

Expert Systems (ES) are computer software systems that can solve complex problems in a specific domain, mimicking the problem-solving abilities of human experts. They effectively apply the accumulated experience and expertise of experts to tackle problems that typically require expert knowledge. Expert systems involve storing expert knowledge in a knowledge base through specific knowledge acquisition methods. They then use an inference engine combined with human-computer interaction to operate. Subsequently, valuable expert systems have been developed by experts worldwide [33, 34] .

Heuristic algorithms are problem-specific analysis and step-design approaches that aim to improve computational performance. Commonly used heuristic algorithms include Simulated Annealing (SA), Genetic Algorithms (GA), and Ant Colony Optimization (ACO) [35, 36] .

This section provides an overview of commonly used artificial intelligence algorithms to lay the groundwork for understanding the subsequent section's applications of artificial intelligence. Additionally, the usage of literature in distribution automation system contexts will be thoroughly reviewed and summarized in the upcoming content. This will facilitate a better understanding of how artificial intelligence is practically applied in distribution automation systems and reveal research trends and cutting-edge issues in related fields.

Optimization and control of distribution automation system driven by intelligence

The significance of AI technology in the field of distribution automation cannot be understated. Faced with common challenges in power systems, artificial intelligence technology not only offers effective solutions but also has predictive capabilities, thereby reducing future risks. In numerous areas such as fault detection, network reconfiguration, load forecasting, and network security, artificial intelligence technology has been adeptly applied and achieved significant accomplishments [37]. These applications not only help power systems save costs but also yield notable economic benefits, rendering power systems safer and more reliable. Simultaneously, this demonstrates the substantial potential of artificial intelligence technology in driving progress and innovation within the distribution automation domain.

Fault detection and recovery

In distribution systems, faults often result in power outages, leading to substantial losses. These faults can stem from causes like short circuits, overloads, and human errors. Consequently, fault detection and classification stand as crucial functionalities that distribution automation systems need to possess. This not only enhances the reliability of distribution systems but also improves their operational efficiency and power supply quality.

Specifically, fault detection involves analyzing historical data to identify and locate faults within the power system, enabling timely repairs and restoration, thereby minimizing the impact of power outages on power supply and users [38].

The studies below provide a comprehensive overview of artificial intelligence methods in fault detection, as presented in Table 1.

In the study [10], researchers employed Genetic Algorithms (GA) to find optimal switching processes to achieve rapid power restoration in the event of transmission line faults, thereby significantly improving power system operation.

Table 1 Sub-problems of Fault Detection

Sub-Problem	Description	Type of method	Status
Line trip fault prediction	Diagnose and predict faults through changes in current before they occur.	SAE + DLNN LSTM + SVM PCA + SVM + SSAE	[39] [19] [20]
Power distribution during faults	When a fault occurs in a distribution line, the system can exchange electricity in a larger area faster than before.	GA	[10]
Fault diagnosis	Improving the accuracy of Electrical fault diagnosis.	ES + FL BN BN + MLP Petri WT + ANN	[34] [23] [24] [40] [41]
Automatic recovery after power outage	Automatically restore power when an emergency occurs in the system.	ES	[33]
Fault detection and classification	Detect faults in the power system and classify them for processing	RNN, LSTM, GRU, FFNN, ANN GAN + CNN RS + KCV WT + DNN CWT + CNN GAN + CNN Petri + Kalman filter WT + MRA + ANN	[38] [42] [43, 44] [45] [46] [47, 48] [49] [50]
Detect transformer faults	Identify faults in the transformer.	CSAE + DBN + BP DBSAE + DGA	[51] [52]
Cable fault diagnosis	Identify faults in the cable.	DBN	[53]
Single-phase grounding fault diagnosis	When a grounding fault occurs in a small current system, it is necessary to quickly diagnose it to shorten the time of operation with faults.	ACNN	[27]
Fault cause analysis and rapid restoration of power supply	Analyze the cause of the malfunction and restore power supply.	CNN	[54]
Fault assessment	Evaluate unlearned faults.	Transfer learning	[55]

Predicting line tripping faults is a sub-problem within fault detection. In reference [19], authors combined a Long Short Term Memory (LSTM) network with a hybrid algorithm of Stacked Sparse Autoencoders to predict line tripping faults in both transmission and distribution, using LSTM networks to train and extract temporal features from data. Moreover, to enhance the accuracy of power system fault diagnosis, Yixing Wang et al. [20] introduced an approach based on Stacked Sparse Auto Encoder (SSAE), SVM, and Principal Component Analysis (PCA) networks. Simulation experiments demonstrated the effectiveness and practicality of this method. Furthermore, Wang et al. [39] proposed a method using trained SAE to initialize and train DLNN for diagnosing and predicting faults based on current variations before the fault occurrence.

In the realm of fault diagnosis, Sragdhara Bhattacharya [41] proposed a method using Electromagnetic Transients Program software and ANN to classify and locate various types of faults in non-radiating power system networks. Experimental results demonstrated the method's capability to rapidly and accurately identify faults and determine their locations. References [33] and [34] introduced new schemes for automatic restoration after power outages. One proposed method is based on ES, an advanced software application that has the potential to help engineers diagnose anomalies. It offers protective measures for unexpected process conditions and employs Fuzzy Logic (FL) to address the imprecision inherent in process trend representation for fault diagnosis. Furthermore, [23] proposed three simplified Bayesian Network-based (BN) models for estimating fault segments in transmission systems. These models handle uncertain or incomplete power system diagnostic data and knowledge, demonstrating flexibility. Similarly, in reference [24], Bayesian Networks and Multi-Layer Perceptron (MLP) artificial neural networks were used for pattern recognition and non-linear regression in fault detection. Lastly, in [40], a simplified method for the Transmission Power Transfer Structure (TPTS) was presented. This approach employed a finite-capacity Petri net to formally describe the simplified structure. In contrast to previous fault diagnosis research, this method not only detects and recovers faults but also utilizes graphical tools from Petri nets to showcase the entire process of fault diagnosis.

In tandem with diagnosis, classification operations are often necessary. Mnyanghwalo et al. [38] studied DL methods for fault detection in secondary distribution networks, including GRU, RNN, and LSTM. Real-time measurements from datasets spanning 2014 to 2020 showed that the RNN method achieved an accuracy of 94%, while Gated Recurrent Unit (GRU) and LSTM methods achieved an accuracy of 50%. Additionally, S. Chan et al. [42] introduced a hybrid algorithm, CANN, combining GAN and CNN for fault detection. The algorithm's accuracy exceeded 85% in both single-phase and three-phase tests. References [43] and [44] proposed Rough Set (RS) technology-based solutions that provide information and system alert levels to operators, enabling more informed decisions and enhancing intelligent grid security and system management. James J.Q. Yu et al. [45] proposes a microgrid fault detection scheme based on wavelet transform(WT) and DNN. By preprocessing relay protection samples, extracting statistical features, and using deep neural network for fault information analysis, fast and accurate fault type and location detection can be achieved, showing superior performance in different systems, achieving higher predictive accuracy compared to traditional methods. Furthermore, reference [46] introduced a fault selection method for resonant grounded distribution networks using Continuous Wavelet Transform (CWT) and CNN. The trained CNN performed feature extraction and fault feeder detection simultaneously, demonstrating more accurate performance compared to other techniques like SVM. Reference [47] proposed a fault recognition method for distribution terminal voltage sampling modules using GAN and CNN. By utilizing a GAN model to generate samples and training CNN, this approach significantly improved fault detection accuracy. Similarly, reference [48] presented a specific fault category discrimination method for distribution terminal measured electrical data, combining GAN and CNN. Finally, reference [50] introduced a power system fault detection and classification approach that combines WT, Multi-Resolution Analysis (MRA), and Adaptive Resonance Theory Neural Networks (ARTANN). This algorithm demonstrated high accuracy, robustness to various faults, and resistance to changes in electrical parameters.

In the context of transformer fault detection, reference [51] suggests the use of a deep belief SAE method. Reference [52], on the other hand, employs a Deep Basic Sparse Autoencoder (DBSAE) method based on DGA data. This method achieves an average correct rate of 95.4% for transformer fault diagnosis, showing good discrimination accuracy. Experimental results indicate that compared to KNN, SVM, and Back Propagation (BPNN), this method outperforms them in terms of performance.

For underground cable fault recognition in distribution systems, methods based on the DBN algorithm are widely employed [53]. Compared to traditional shallow neural networks, this approach achieves a recognition rate of 97.8%, while BP network recognition rate is 86.6%, and ACCLN recognition rate is 94.1%. This underscores the evident advantages of the DBN-based cable fault recognition method. Similarly, in reference [49], a hybrid Petri net modeling method combined with fault tree analysis and Kalman Filtering is utilized for fault prediction and handling. Results show that this approach is practical and meets the demands of state-based fault prediction and handling in power systems. Furthermore, Jiefeng Liang et al. [27] propose an adaptive CNN-based fault diagnosis method for fault localization in distribution networks. This method provides short computation time and achieves high precision and speed in fault line selection. Similarly, reference [54] employs CNN for similar purposes. In reference [55], authors introduce a novel transfer learning technique to assess multiple untrained faults. By comparing it with a dynamic security assessment model, the effectiveness of this method is verified, with transfer learning achieving a 97.27% accuracy rate in fault assessment.

Network reconstruction and recovery

Distribution Network Reconfiguration (DNR) is an optimization decision-making process aimed at enhancing the performance of distribution systems by altering the operational states of remotely controlled switches. DNR holds immense potential in several crucial aspects of power grid operation enhancement. It can be employed to minimize power losses or system costs, ameliorate voltage distribution, enhance load balancing, or improve system reliability. The DNR problem constitutes a mixed-integer nonlinear conundrum, the intricacy of which is influenced not only by the uncertainty in active and reactive power but also by the physical parameters of the system [56]. Consequently, for a more effective utilization of DNR techniques in optimizing power grid operations, an in-depth exploration of these challenges is imperative.

The ensuing studies provide a comprehensive overview of artificial intelligence approaches in network reconfiguration, as depicted in Table 2.

For the loss minimization issue, RL methods were employed by [31] and [32] to propose a batch-constrained algorithm using RL method, and Yuanqi Gao et al. [31] proposed a data-driven batch constraint RL algorithm. By learning the network reconstruction control strategy in the historical operation data set, it does not need Power network interaction, and performed well in multiple distribution network experiments. At the same time, they use the offline RL method based on historical operation data, in the absence of network parameter information, the optimal network configuration can be realized online through Markov decision process modeling. The algorithm aims at Minimize operating costs [32]. Additionally, John G. Vlachogiannis et al. [57] introduced a GA-based tabular Q-learning approach for network reconfiguration in distribution grids with the goal of minimizing power losses. References [58] and [59] presented a GA-based method for distribution network

Table 2 Sub-problems of Network Reconstruction and Recovery

Sub-Problem	Description	Type of method	Status
Loss minimization	In reconfiguration of networks, it is beneficial to select the configuration that provides the minimum distribution losses.	RL RL + Q-Learning GA Minimum Spanning Tree	[31] [32] ˋ [57] [58, 59] [60]
Planning and Control	Increase generation capacity and optimize transmission and distribution system design.	ANN + GA DRO + DNN	[5] [61]
Voltage limit violation	Maintaining the voltages within specified limits in all parts of the distribution network is essential.	HR + ES	[3]
Protection device coordination	Coordination between protection devices in the network should be done properly in order to avoid adverse effects.	Multiagent Systems + Q-Learning	[62]
Load balance of equipment	Realize the load balance of equipment such as transformers and feeders, and avoid the situation that some equipment is overloaded and other equipment is lightly loaded.	LSTM + GRU Q-Learning RL + Q-Learning HR	[63] [64] [56] [35]
Real time implementation	Real time operation of restoration assistance system will be beneficial.	HS Multiagent Systems GAM	[65] [66] [36]
Cost control	Reduce power losses and switching costs in distribution networks.	LSTM + ADR Quantum PSO HSA	[67] [68] [69]

loss-minimizing reconfiguration. On the other hand, Mustafa Mosbah et al. [60] proposed an algorithm based on the minimum spanning tree, aiming to minimize the total power loss by using the Kruskal algorithm on the premise of satisfying the power system constraints, and proves its effectiveness in optimizing quality, which provides a useful reference for practical applications.

K. Manjunatha Sharm et al. [5] introduced a network reconfiguration approach based on ANN and developed a software package named DISTFLOW. Genetic algorithms (GA) were utilized to determine the optimal compensation levels. In another study, [61] presented a method for obtaining optimal configurations for worst-case scenarios of three-phase unbalanced DNR problems based on a distributed robust model's probability distribution and a fuzzy set of loads. This method takes into account the characteristics of stochastic optimization and combines the characteristics of robust optimization to obtain the optimal configuration scheme with robustness.

Regarding the issue of equipment load balancing, a novel hybrid approach was proposed in [63], combining LSTM and GRU models with real-time multi-stage scheduling for load management of controllable loads like Plug-in Electric Vehicles (PEVs). This approach not only applies to network applications involving loads and market operations but also enhances the efficiency of distribution networks. Sanjoy Das et al. [64] introduced a algorithm based on Q-learning for ship power system reconfiguration, achieving the shortest operating time by determining the optimal switch sequence. Similarly, [56] introduced a Q-learning framework for distribution network restoration, aiming to optimize switch states and reduce power losses. This framework employs a tabular Q-learning algorithm for controlling network reconfiguration to minimize power losses. J.S. Wu et al. [35] introduced a candidate feeder system search method based on the main search path, incorporating a weighted evaluation function and heuristic rules (HR). System optimization through efficient switching operations and load balancing provides a feasible solution for partially automated power distribution systems.

Xingquan Ji et al. [67] presented a real-time autonomous dynamic reconfiguration (ADR) method based on DL algorithms to reduce switching costs in distribution networks. This method can achieve reconfiguration solutions within milliseconds and exhibits high robustness. Dayong Ye et al. [62] proposed a hybrid multi-agent and Q-learning algorithm framework for rapid recovery under catastrophic power grid disturbances, combining the advantages of centralized and decentralized architectures to achieve accurate decision-making and rapid response in cascading fault detection. Avoids single points of failure and demonstrates effectiveness. This approach enables swift recovery from catastrophic disturbances in the power grid system, including generator losses, ensuring accurate decisions and rapid responses to avert single-point failures in the network. A heuristic rule-based expert system was introduced in [3], leveraging optimal priority tree search techniques to address issues of main transformer or feeder overloads and violations of feeder constraints in automated distribution systems. A heuristic search (HS) approach for distribution network fault restoration was presented in [65], aimed at determining the fault location, isolating the faulty area, and devising appropriate recovery plans thereafter. [66] proposes a power system restoration method based on Q-learning, multi-agent systems, and battery algorithms, which comprehensively consider power constraints and find system switch configurations to maximize system performance after load-picking failures and keep constraints intact during real-time adjustments sex. Yang HuPing et al. [36] determined the optimal timing of DNR using a gradual approach. Additionally, metaheuristic methods such as Quantum PSO [68] can be employed to address this problem. A method was proposed in [69] for determining annual feeder reconfiguration plans that consider time-varying variables such as switch costs and load distribution. This approach utilizes collaborative harmony search algorithm (HAS) and graph theory to independently determine optimal configurations for each day of the year, resulting in effective configuration plans.

Load forecasting

In many fields, predictive technology has been used to help avoid unnecessary losses [70–72]. Power load forecasting is a technology that predicts power demand for a period of time in the future by analyzing past power consumption data and other factors. This is crucial for the management and planning of power systems. It can help power companies and operators better arrange the use of power generation equipment, optimize energy distribution, and ensure stable operation of the power system and efficient use of resources [6]. The high penetration of distributed energy resources into existing grids increases uncertainties in the operation and planning of smart grids. Therefore, accurate load prediction at different levels is highly beneficial for enhancing the economic efficiency and energy conservation of distribution automation systems. This is particularly important for achieving optimized grid operations while ensuring stable and reliable power supply [12].

Table 3 Sub-problems of Load Forecasting

Sub-Problem	Description	Type of method	Status
Load Forecasting	Predicts power demand for a period of time in the future by analyzing past power consumption data and other factors.	SVM	[73]
		SVRM	[22]
		WT	[74]
		ANN + PSO	[28]
		PSO + SVM	[75]
		DBN	[76]
		DRNN-GRU	[77]
		Empirical Mode	[78, 79]
		Decomposition	[80]
		CNN	[81]
		SDA	[82, 83]
		LSTM	[84]
		LSTM-RNN	[85]
		PDRNN	
STLF	Ultra short-term load forecasting generally outputs load changes in the next few minutes to several hours.	DFN	[86]
		FFDNN + RDNN	[87]
		CNN + K-Means	[88]
		DNN	[89]
		DBN	[90]
		COSMOS	[91]
MTLF	Medium term load forecasting predicts the load values for the coming weeks and months.	SVM	[21]

Below, I provide a detailed overview of artificial intelligence methods used in load forecasting, as depicted in Table 3.

Load forecasting is influenced by various factors, including those that can alter the consumption patterns of loads. According to the time frame of the forecast, the first is short-term load forecasting (STLF), which predicts load changes in the next few hours, medium-term load forecasting (MTLF) covers the next few days to a week, and long-term load forecasting (LTLF). Load trends over weeks or even months [92].

SVM is a machine learning method utilized for load forecasting, as discussed in references [21] and [73]. Furthermore, hybrid approaches are also often present and applied, which involves combining two different methods [22] [74]. In comparison to individual methods, hybrid approaches exhibit greater potential in addressing load forecasting challenges. Qi Wu et al. [22] introduces a Gaussian loss function to reduce the impact of noise on regression estimation. Reference [74] employed a wavelet neural network as the fundamental unit for air conditioning load prediction, and an Improved Differential Evolution Algorithm (IDEA) for optimizing the parameters of the wavelet neural network. Concerning hybrid methods, two types have been reported: one involves a blend of traditional and artificial intelligence methods, while the other combines two artificial intelligence methods [28] [75]. Reference [28] proposed an electricity consumption prediction method for equipment maintenance based on ANN and PSO algorithm. A. Selakov et al. [75] proposed a hybrid model for electric load forecasting that combines particle swarm optimization (PSO) and SVM, and the results proved the feasibility of the method. The combination of these two artificial intelligence methods presents an intriguing approach, as it leverages the strengths of artificial intelligence methods, as compared to either a single method or a blend of traditional and artificial intelligence approaches. In reference [76], a method based on DBN and Composite Parameter Copula model was introduced for hourly load forecasting, validated through experiments with load data from urban areas in Texas. The effectiveness of the model was confirmed through

MAPE and RSME experiments. Using consumption data to construct a load dataset, the DRNN-GRU model for both STLF and MTLF was proposed [77]. Experimental data demonstrate the superiority of the model in adapting to time dependence, high prediction accuracy, and limited input variables, and it also shows effectiveness in data filling. Jatin Bedi et al. [78] introduces the importance of electricity in the economy and society, proposes a method based on empirical pattern decomposition and deep learning for estimating electricity demand, and verifies its effectiveness on urban electricity consumption data. Ultimately, the predicted results from all IMFs are combined to obtain a composite output for power demand. Reference [79] presented a method for load demand prediction using the Empirical Mode Decomposition method, which involved an Australian energy DBN consisting of two Restricted Boltzmann Machines (RBM). In reference [80], the use of CNN for residential load forecasting was suggested, and the proposed model was combined with CNN to reduce MAE. The paper also compared the CNN approach with other techniques. A Stacked Denoising Autoencoder (SDA) model for power load prediction was proposed in reference [81]. The output data of the SDA model was used as input for the SVR model during the training process. In reference [82], two methods based on LSTM were introduced for hourly and minute-level load demand forecasting. The results showed that the standard LSTM method struggled with accurate prediction, while the sequence-to-sequence (S2S) approach based on LSTM achieved more accurate predictions. Weicong Kong et al. [84] proposed a framework based on LSTM recurrent neural network to solve the short-term forecasting problem of single energy user's power load with high volatility and uncertainty, and performed well in actual data tests. In reference [85], a Pooling-based Deep Recursive Neural Network (PDRNN) was proposed, where a batch of user load distribution data was fed into an input pool. A hybrid ensemble prediction model based on LSTM was presented in reference [83]. The predictive performance of this model surpassed several state-of-the-art time series forecasting models, exhibiting higher accuracy and robustness for peak demand prediction.

Particularly, significant achievements have been made in STLF. In reference [91], the Combined Short-term Energy Management and Forecasting System (COSMOS) was employed to combine short-term load forecasting models, achieving more accurate predictions of building electricity consumption. STLF uses various techniques, including traditional time series analysis and modern deep learning methods, to effectively deal with load fluctuations, thereby providing reliable power load forecasts and helping power system planning and operations to be more efficient [6]. MTLF and LTLF can be used for power plant planning and represent the dynamic characteristics of power systems [12]. Several artificial intelligence algorithms have been utilized for load forecasting based on small datasets [92]. Zhifeng Guo et al. [86] used a deep feedforward network for short-term power load forecasting for the first time, which performed better than the popular machine learning model. Combining the comprehensive analysis of power consumption patterns and temperature characteristics, they proposed a probability density forecasting method, which was proved by case studies. Effectiveness in Electric Load Forecasting. The results of this method were compared with machine learning tools like Random Forest and Gradient Boosting. Other studies have applied different types of deep learning to various STLF problems. In reference [87], the application of feedforward DNN and recursive DNN models was investigated using STLF data for comparison. Reference [88] suggested using the K-means algorithm to synthesize CNN suitable for STLF, enhancing scalability by clustering large datasets into appropriate subsets and utilizing them for CNN training. Experimental results confirmed the effectiveness of this approach. Reference [89] combined DNN and CNN for STLF in northern Chinese cities. The CNN method learned deep features from historical datasets, while RNN based on LSTM modeled changes in historical load data, predicting loads through dense layers. This flexible and effective approach could be applied to other prediction problems. In reference [90], a method using DBN was introduced, composed of a Macedonian STLF multilayer RBM, employing unsupervised training and supervised backpropagation for parameter fine-tuning.

Network Security

The core objective of network security is to safeguard network infrastructure from the threats of network attacks. Attacks on the power system infrastructure pose challenges to the security of intelligent power systems [76]. Adversaries can manipulate measurement data without detection, thereby affecting the normal operation of the system. Therefore, early detection and response to such attacks are crucial for ensuring the secure operation of the power system. This necessitates not only the enhancement of protective technologies and measures but also the elevation of security awareness and risk response capabilities within the system [93].

The following studies offer a detailed overview of artificial intelligence methods in network security, as presented in Table 4.

To counter network attacks, various detection-based machine learning algorithms exist. In [100], a B-PDA framework based on artificial intelligence and blockchain-supported technology is proposed for solving security issues in smart grids. This framework ensures

Table 4 Sub-problems of Network Security

Sub-Problem	Description	Type of method	Status
Attack detecting	Replay attacks in attack detection exploit the system to accept previous communications without adequate security measures, which can lead to security breaches.	CNN CDBN	[94, 95] [96]
Security threat detection	Check and report potential vulnerabilities in the system.	Stacked Deep Polynomial Network	[97]
Malicious traffic detection	Detect malicious traffic in IoT networks and provide security as a service.	DBN	[98, 99]
Interval state estimation	Maximize the variation range of system variables.	SAE	[29]
Safety hazard prediction	Predict potential safety hazards that may arise in the system.	B-PDA SAE	[100] [101]
Electricity theft detection	Fraudulent electricity consumption reduces power supply quality, increases power generation load, leads to legitimate consumers paying excessive electricity bills, and affects the overall economy.	CNN + LSTM CNN Text CNN LSTM-UNet-Adaboost	[102] [103–105] [106] [107]
Identify non-technical power losses	Power loss is inherent in power transmission and distribution, but it will lead to lower power conversion efficiency.	CNN、LSTM、SAE	[30]
False data injection	FDI is an attack on Data integrity, which poses a serious threat to the SCADA system.	CDBN MLP AAE GAN	[108] [109] [110] [111]

the integrity and privacy of the entire transaction execution. In [94], the use of CNN algorithms for detecting replay attacks is presented. The model is compared with other machine learning and deep learning models, demonstrating high detection accuracy. The application of deep learning has found broad application in the security field. In [96], a Conditional DBN based on a distributed DL algorithm is proposed for detecting electricity theft behavior. Experimental results showcase high detection accuracy, confirming the method's effectiveness. In [97], a Stacked Deep Polynomial Network is employed for intrusion detection, effectively categorizing datasets into normal and attack data, yielding strong intrusion detection performance. In [98] and [99], the application of DBN in network attack detection is explored. Experimental outcomes reveal DBN's robust performance in attack detection. In [29], an approach based on SAE is presented for detecting data manipulation in power systems. Similarly, for predicting and detecting power system security vulnerabilities, employing SAE models is recommended [101]. This model boasts simple implementation and shorter training time, achieving an average prediction accuracy of 95.78% in a real Chinese system. In [95], a CNN algorithm based on DL is proposed for network intrusion detection in SCADA systems. Experimental results demonstrate high accuracy in detecting attacks in actual SCADA systems, reaching a detection accuracy of 99.84%.

For the issue of electricity theft detection, a system utilizing a CNN and LSTM structure is proposed in [102]. CNNs can perform data extraction functions and can classify the results. To protect smart grids, [103] suggests employing a CNN model for electricity theft detection. The wide branch learns and memorizes global knowledge, while the DCNN branch classifies non-periodic and periodic power data. Similarly, in [104], an integrated CNN model for electricity theft detection is introduced. Compared to other methods like DCNN, Random Forests, and SVM, this model exhibits superior performance. Considering the characteristics of power data structures as time series data, Florian Thams et al. [105] proposes a two-dimensional CNN for electricity theft detection. A unique ANN approach called Text CNN is presented for electricity theft detection in [106]. Zeeshan Aslam et al. [107] proposed a new model, the combined ETD model consists of LSTM, UNet and Adaboost, called LSTM-UNet-Adaboost. overcomes the shortcomings of the limited capacity of traditional methods. This method leverages deep learning techniques and ensemble learning to enhance the performance of electricity theft detection, yielding a 39.6% increase in accuracy compared to SVM.

To address the issue of false data injection attacks, Rajendra Rana Bhat et al. [30] propose a new solution that combines techniques such as LSTM, CNN and SAE. These methods are researched for attacks in SCADA systems, providing a certain level of protection. In [108], the adoption of CDBN algorithm is proposed to identify false data injection attacks in smart grids. Experimental results demonstrate effective detection of FDI attacks with high accuracy (over 93%), surpassing ANN and SVM methods. In [109], MLP method is employed to detect two different types of attacks based on false data injection. Meanwhile, [110] proposes a data-driven algorithm based on autoencoders and generative adversarial networks to detect unobservable false data injection attacks in smart grids, effectively improving security and accuracy. Saeed Ahmadian et al. [111] proposed a new network security method using GAN algorithm. This method targets attackers seeking to conceal identity and gain profits from attacking the power grid. Experimental results demonstrate the model's effective detection of FDI attacks with high accuracy.

Table 5 Sub-problems of Voltage Control

Sub-Problem	Description	Type of method	Status
Detection and prediction of voltage limit violations	It is necessary to identify high or low voltage limit violation in the distribution network. Unexpected low voltage problems can arise due to many reasons such as emergency restoration, change of weather patterns or unexpected events.	CMDP DRL	[113] [114]
Voltage stability	When there is a problem with the voltage, it may cause the system to lose stability.	NFC CFPSS ANN Cuckoo Search optimization Q-learning	[115] [116] [117] [118] [119]
CLF problem	By adjusting power system control variables to meet physical and operational constraints.	Q-learning	[112]
ORPD problem	Optimizing reactive power can improve voltage stability and reduce energy loss.	Q-learning	[120]
Voltage deviation issue	Find a strategy to minimize the voltage deviation of the entire system by mapping the measurement of voltage amplitude and topology information to the variation of LTC tap ratio.	LSPI DQN EDLPC ANN	[121] [122] [123] [124]
VVO problem	This process aims to optimize the distribution of reactive power so that the power system can operate in the most efficient manner subject to various physical and operational constraints.	DRL Grid Mind	[125–127] [128]

Voltage control

Voltage Var Control (VVC) is one of the important applications of power distribution system automation, with its primary aim being the reduction of network losses and enhancement of voltage distribution. Through effective VVC strategies, it is possible to achieve energy-efficient operation of the power system while ensuring the quality of power supply [112]. Therefore, this technology is of key significance in realizing optimal management of power systems.

The following studies provide a comprehensive overview of artificial intelligence methods in voltage control, as illustrated in Table 5.

Mina Jafari et al. [112] proposed a reinforcement learning method for network constraints to set control variables, applying the Q-learning algorithm to constrained reactive power control. The results show the superiority and flexibility of the Q-learning algorithm. For the VVC problem, a constrained MDP method is formulated [113]. In [114], Deep Deterministic Policy Gradient (DDPG) is introduced to modify voltage distribution and alleviate constraints on photovoltaic (PV) generation.

In order to solve the voltage stability problem, Sabo et al. [115] designed a nonlinear robust neuro-fuzzy controller (NFC) damping controller to replace the traditional power system stabilizer (PSS), and successfully improved the stability and performance of the power system. NFC combines fuzzy control and artificial neural networks, integrating expert knowledge into fuzzy logic, eliminating the need for plant models and the learning capacity of artificial neural networks. Similar approaches are employed by Douidi et al. [116], employing a cascade controller consisting of multiple PD fuzzy control blocks, and utilizing Particle Swarm Optimization for parameter tuning. Masrob et al. [117] propose a simple artificial neural network for real-time tuning of controller parameters to achieve responsive control behavior. Chitara et al. [118] propose a hyper-heuristic approach, employing the Cuckoo Search optimization algorithm. Notably, all implemented algorithms have computation times exceeding 15 min. Applying metaheuristic algorithm PSS aligns with logical expectations as the problem can be easily formulated as a quality factor. Zhu and Jin [119] adopt different methods. In this context, the reinforcement learning framework is applied to the optimization problem of PSS. The Q-learning algorithm is applied to the PSS as an additional control.

In [120], a multi-agent Q-learning VVC framework is proposed to computational burden on central controllers. The method is based on a fully distributed multi-agent framework. In [121], a Least Squares Policy

Iteration (LSPI) algorithm is Used in power distribution systems to minimize voltage deviations by adjusting tap positions of on-load tap-changers, effectively reducing voltage deviations. The algorithm is introduced as a batch RL method, with considerations for scalability. In [122], a voltage regulation scheme combining data-driven and physics-based optimization is proposed to effectively deal with the voltage fluctuation challenges in modern distribution networks through smart inverters and deep reinforcement learning algorithms. An Emotional DL programming controller (EDLPC) is proposed for voltage control in power systems [123], comparative results with DNN and Q-learning algorithms attest to the effectiveness of this approach. Additionally, ANN is utilized for online estimating the optimal parameters of traditional PSS [124].

Jiajun Duan et al. [125] using a multi-agent deep reinforcement learning method, a model-free voltage and reactive power optimization algorithm is developed, which achieves the dual goals of voltage regulation and power loss reduction in unbalanced power distribution systems through intelligent agents, and has achieved significant superiority. Yuanqi Gao et al. [126] proposed a voltage and reactive power control algorithm based on consensus multi-agent deep reinforcement learning, which is used to improve the performance of the active distribution network management system, and solve the operation time of voltage regulators, on-load tap-changers and capacitors It exhibits superior performance, communication efficiency and resilience in table problems. Wang et al. [127] propose a voltage control multi-agent framework based on deep reinforcement learning. Duan et al. [128] also present an autonomous voltage control method based on the 'Grid Mind' framework, through data-driven model-free control agents, the safe operation and voltage control of the power grid are realized.

While the application of artificial intelligence technology in distribution automation is becoming increasingly widespread, we still face certain challenges and limitations. The following content provides a brief overview of frequently mentioned issues. These challenges are not only the current focus of research but also reveal critical factors that shape future directions. By comprehending and addressing these challenges, we can harness artificial intelligence technology more profoundly, facilitating progress and innovation in the field of distribution automation.

Challenges and limitations of distribution automation systems

In the course of advancing the development and application of distribution automation systems, we inevitably encounter a plethora of challenges and limitations. From the perspectives of data quality and reliability, algorithm precision and interpretability, security and privacy protection, as well as resource and cost constraints, these issues collectively constitute critical topics that necessitate careful consideration and resolution as we strive to implement intelligent acceptance systems for distribution automation. By surmounting these challenges and constraints, we can enhance the continuous improvement and innovation of distribution automation systems, making valuable and positive contributions to the future development of the energy sector [129–131].

Data quality and reliability

The quality and reliability of data directly influence the accuracy and performance of a system, holding significant implications for ensuring the safety and reliability of distribution systems. Issues within the data collection process constitute among the primary considerations for data quality and reliability [19] [39]. Factors such as sensor errors, insufficient sampling frequency, and interference during transmission can lead to distortion and inaccuracy in the data. Therefore, ensuring the accuracy and stability of data acquisition equipment, as well as reasonable sampling frequency, is the key to ensuring data quality and reliability [132]. During data transmission, errors, data loss, or transmission delays may occur, impacting data integrity and accuracy, thereby diminishing system reliability. Thus, effective data transmission mechanisms and error correction measures, such as employing redundant data, error correction, and data validation techniques, are necessary to enhance data reliability and accuracy [133]. In addition, data integrity is also a key factor in ensuring data quality and reliability. Problems such as missing data, outliers, and inconsistencies may mislead the intelligent verification and monitoring of the system, thereby reducing system reliability and performance. Therefore, measures need to be taken to monitor and improve data integrity [134, 135].

Algorithm accuracy and interpretability

Algorithm accuracy is a key metric for evaluating the effectiveness of artificial intelligence algorithms. Within the framework of intelligent acceptance systems for distribution automation, we aim to precisely validate and monitor the status and performance of distribution terminals using algorithms. The accuracy of an algorithm is influenced by various factors, such as the quality of training data, feature selection, and model choice. These factors can lead to decreased algorithm accuracy, thus impacting system reliability and performance [63]. Interpretability pertains to the capacity of artificial intelligence algorithms to explain and present their decision-making processes and outcomes. Researchers need to seek methods to enhance algorithm interpretability, such as designing and developing interpretable models. This allows users and system operators to comprehend and trust the decision-making process and outcomes of the algorithm [136]. At times, improving algorithm accuracy may come at the cost of sacrificing a certain level of interpretability, as more complex algorithms can be difficult to explain. Therefore, researchers need to comprehensively consider performance requirements, system needs, and user expectations for algorithm selection, finding the optimal balance between accuracy and interpretability for distribution automation intelligent acceptance systems [48] [73].

Security and privacy protection

Security involves safeguarding the intelligent acceptance system for distribution automation terminals from external threats and attacks. As automation and connectivity advance, distribution automation systems become more vulnerable to network attacks and malicious activities. These attacks could lead to severe consequences such as system paralysis, data tampering, and information leakage [99]. Consequently, ensuring the security of distribution automation terminal intelligent acceptance systems is paramount. Privacy protection entails preventing the abuse or leakage of private and sensitive information related to distribution automation terminal data [108]. The system involves a substantial amount of power data and user information, encompassing sensitive details like users' electricity consumption behavior and load information. Without proper protection, this data could pose risks to user privacy and information leakage. Thus, researchers must employ privacy protection measures like data anonymization, differential privacy preservation, and access permission management to effectively safeguard the privacy of distribution automation terminal data [105]. Strengthening security and privacy protection can sometimes increase system complexity and costs, impacting system performance to some extent. Consequently, researchers need to holistically consider the relationship between security, privacy protection, and system performance, seeking suitable solutions [137].

Resource and cost constraints

Resource limitations refer to the potential inadequacy or constraints on resources within the intelligent acceptance system for distribution automation. These resources encompass computing power, storage capacity, communication resources, and more. When applying artificial intelligence algorithms, these resource limitations can impact algorithm execution speed, data processing capabilities, and system scalability [138]. Hence, in designing and implementing the system, careful consideration of resource allocation and optimization is necessary to meet system requirements and ensure efficient resource utilization [49]. Cost constraints are a significant factor to be reckoned with in the context of distribution automation intelligent acceptance systems. The application of artificial intelligence technology often incurs substantial costs in research and development, implementation, and maintenance. This includes costs associated with algorithm development and optimization, data collection and processing, system integration and deployment, among other aspects [139]. Moreover, hardware and software expenses, human resources, and training costs also need to be taken into account. When applying artificial intelligence technology, a comprehensive consideration of system performance, feasibility, and cost-effectiveness is crucial to make sure that the application of the technology remains within an acceptable cost range [140, 141] .

In summary, addressing the challenges and limitations in the field of distribution automation systems is to ensure a reliable, efficient and sustainable power supply to meet the needs of modern society and the economy and to prepare for future energy demands. This also helps make the power system more resilient, allowing it to cope with changing demand and environmental conditions.

Conclusion

This paper presents a thorough examination of how artificial intelligence algorithms are utilized in the field of intelligent acceptance systems for distribution automation terminals. By employing artificial intelligence techniques, intelligent validation and monitoring of distribution automation terminals can be achieved, enhancing system security and reliability while reducing operational and maintenance costs of the power system. Through researchers' endeavors, methods and algorithms based on artificial intelligence for intelligent acceptance systems of distribution automation terminals have been continuously developed and explored, such as machine learning, deep learning, and expert systems. These studies have made significant progress and demonstrated the immense potential of artificial intelligence technology in distribution automation terminal intelligent acceptance systems.

The paper primarily reviews the existing research on artificial intelligence technology in distribution automation systems, encompassing areas like fault detection, network reconfiguration, load forecasting, and network security. Concurrently, it discusses the challenges and limitations that artificial intelligence still faces in distribution automation terminal intelligent acceptance systems. Among these challenges, data quality and reliability, algorithm precision and interpretability, security and privacy preservation, as well as resource and cost constraints stand out as the most crucial. Addressing these challenges necessitates bolstering fundamental research and technological innovation to elevate the application level and effectiveness of artificial intelligence in distribution automation terminal intelligent acceptance systems.

In conclusion, this paper offers a comprehensive and thorough perspective, elucidating the significant role and current applications of artificial intelligence algorithms in distribution automation terminal intelligent acceptance systems. It serves as a pivotal reference for researchers and professionals engaged in power system intelligence and automation, while also providing insights for the future development and enhancement of distribution automation terminal intelligent acceptance systems. Moving forward, sustained research and innovation are imperative to confront the encountered challenges and propel the widespread application of artificial intelligence in the field of distribution automation.

Authors' contributions
Hongwei Li conceived the paper, designed its structure, and drafted the initial manuscript. Qiyuan Xu collected reference materials and organized the literature review. Qilin Wang supervised and guided the paper's completion, overseeing content validation and proofreading to ensure accuracy. Bin Tang was responsible for preparing the final manuscript and overall coordination of the work. All authors reviewed the manuscript.

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

Declarations

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