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A Review of Research on the Application of Artificial Intelligence Technology in Electrical Automation

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Abstract. With the continuous integration of a new generation of information technology and the energy industry, artificial intelligence (AI) is increasingly used in data processing, learning and analysis, and decision-making support, and has gradually become an important technology to promote the development of automation and intelligence in the power industry. In a complex operating environment, traditional power automation systems are easily limited by control accuracy, fault identification and scheduling efficiency, making it difficult to adapt to the development needs of new energy integration into the grid, intelligent manufacturing and smart grid construction. This article introduces the main AI technologies such as machine learning, deep learning, reinforcement learning and expert systems, and discusses the development status of artificial intelligence in the field of electricity and the issues it faces, including data security, model interpretability and industry standardisation, in combination with specific applications such as power system regulation, equipment fault diagnosis, power grid scheduling, industrial control and new energy operation and maintenance. In addition, this article also discusses the application prospects of emerging technologies such as edge intelligence, digital twins and multimodal large models. Existing research shows that artificial intelligence can improve the reliability and control accuracy of power systems to a certain extent, and improve the efficiency of operation and maintenance, bringing new possibilities for the intelligent development of the power industry.

Keywords: Artificial intelligence, Electrical automation, Power system, Fault diagnosis, Intelligent dispatching

1. Introduction

As an important guarantee for the operation of the national economy, the role of electrical engineering and automation is not only to support the production, transmission and distribution of electricity, but also extends to the terminal utilisation of electricity, and almost covers many application scenarios, including industrial manufacturing. The large-scale grid connection of new energy and the increasingly complex industrial production process, coupled with the continuous changes in the operation mode of the power grid, have brought considerable pressure to traditional electrical automation systems, and the challenges in control and operation are becoming increasingly prominent. In the past, in the field of electrical automation, PID control, PLC and SCADA systems

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were the mainstream configurations, but the operation logic of these technologies was relatively fixed, and was basically supported by preset algorithms. When encountering complex situations, experienced personnel were often needed to intervene and handle them. In the case of new energy fluctuations, multivariable strong coupling, and dynamic adjustment of power grid topology, the shortcomings of traditional systems are exposed: slow control responses, insufficient fault identification accuracy, and low energy scheduling efficiency [1].

The development of big data, cloud computing and edge computing has provided more favourable technical conditions for the upgrading of electrical automation systems. Artificial intelligence can extract features from massive power operation data and identify potential patterns, which allows the power system to shift from passive response to proactive early warning and from fixed control to dynamic optimisation. This helps address technical challenges in operation control and collaborative management under complex conditions [2]. At present, artificial intelligence has been applied to many business areas, such as load prediction, fault detection, scheduling decision-making, and energy storage operation and maintenance.

2. Mainstream artificial intelligence technologies in the field of electrical automation

2.1. Characteristics of traditional machine learning and its applications

Traditional machine learning builds mathematical models through algorithms to achieve tasks such as classification, regression and clustering. Compared with deep learning, traditional machine learning usually has the characteristics of lower training cost and faster response, and is suitable for some field application scenarios in the electrical industry. Li Zheng et al. pointed out in the review that traditional machine learning and deep learning have different applicable boundaries. Traditional machine learning has a computational cost advantage in structured data processing and field terminal deployment [3]. Support vector machine (SVM) is suitable for processing small sample and high-dimensional data, and can be used for electrical equipment fault classification and transmission line fault location, decision tree and random forest are suitable for structured electrical data and can be used for load forecasting and equipment status assessment, clustering algorithms such as K-means and DBSCAN can be used for power grid abnormal operating condition identification and equipment status monitoring. Since the computational resource requirements are relatively low, some traditional machine learning models can be deployed on PLC and smart terminals, and are suitable for industrial scenarios with high real-time requirements [4].

2.2. Characteristics of deep learning and its applications

Deep learning relies on a multi-layer neural network architecture, which can automatically extract features from high-dimensional data, reduce the dependence on manual feature engineering, and is suitable for time series data, image and acoustic signal processing in electrical systems. Long short-term memory network (LSTM) and gated recurrent unit (GRU) are suitable for time series data and can be used for power load and new energy output prediction, convolutional neural network (CNN) is suitable for image, vibration and partial discharge signals and can be used for electrical equipment defect detection and fault diagnosis [5], Transformer and graph neural network (GNN) can handle complex spatiotemporal and power grid topology relationships and are suitable for tasks such as distribution network status assessment and power flow calculation [6].

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2.3. Reinforcement learning and application characteristics

Reinforcement learning relies on a trial-and-error mechanism to operate. The agent continuously interacts with the external environment to iteratively optimize decision-making strategies, which is especially suitable for dynamic optimization control scenarios of electrical systems [7]. In grid dispatching, microgrid load management, motor regulation and other work, reinforcement learning does not need to build a high-precision system mathematical model. It can solve the optimal operation scheme under multiple constraints, taking into account the system's economic efficiency, safety and stability. Mainstream algorithms such as deep Q network (DQN) and near-end policy optimization (PPO) are mostly used for unit combination optimization, energy storage charging and discharging regulation, reactive power compensation and voltage stability control. They can effectively smooth out the fluctuations in new energy output and the random load changes of the power grid, and adapt to the scenario of dynamic adjustment of power operation conditions [8].

2.4. Expert systems and fuzzy logic control

Expert systems utilize domain knowledge through knowledge bases and logical reasoning modules, and are suitable for electrical fault diagnosis and operation and maintenance decision-making with clear rules [9]. Fuzzy logic control is used to handle uncertainties in the operation process and can realize control tasks such as motor speed regulation and voltage regulation without the need for precise mathematical models. In practical applications, the two types of technologies can be combined with machine learning for substation fault alarms, equipment status judgment and other scenarios to improve decision-making ability under complex working conditions [10].

2.5. Comprehensive comparison and analysis of various AI technologies and their suitable scenarios

Having clarified the differences in characteristics among various artificial intelligence technologies, and considering the actual application scenarios in the electrical automation industry, the following analysis focuses on application scenarios, core business needs, and optimal adaptation technologies, as shown in Table 1. By combining the operational characteristics and actual requirements of different business scenarios such as power production, equipment operation and maintenance, and industrial control, the applicability and advantages of various artificial intelligence technologies are compared, providing a reference for on-site technology selection and implementation.

Table 1. Comparison of the applicability of different AI technologies to typical electrical automation scenarios

Typical Electrical Automation Scenario	Core Business Requirements	Best-Fit Technology	Second-Best-Fit Technology	Core Technical Advantages
Electrical Equipment Fault Diagnosis and Maintenance	Fault identification, condition assessment, and anomaly warning	Traditional Machine Learning	Deep Learning	Suitable for structured equipment data with relatively low computational costs

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Table 1. (continued)

Real-Time Power System Operation and Control	Rapid response, dynamic adjustment, and operational stability	Reinforcement Learning	Deep Learning	Suitable for dynamic decision-making and real-time optimisation
Intelligent Power Grid Dispatching	Multi-objective optimisation, safety constraints, and energy coordination	Reinforcement Learning	Deep Learning	Capable of handling complex constraints and dynamic operating environments
Industrial Electrical Automation Production Line Control	Parameter optimisation, equipment coordination, and real-time control	Reinforcement Learning	Deep Learning	Suitable for complex nonlinear processes and multi-source data processing
New Energy and Energy Storage System Management	Power output forecasting, power balancing, and charge/discharge optimisation	Deep Learning / Reinforcement Learning	Traditional Machine Learning	Suitable for predictive analysis and dynamic strategy optimisation, respectively

3. Typical application scenarios of artificial intelligence in electrical automation

3.1. Power system operation and intelligent control

Power systems are characterized by multivariables, strong coupling, and nonlinearity. Artificial intelligence can be used for load forecasting, operation control, and parameter optimization. LSTM-based load forecasting models can integrate data such as meteorology, holidays, and electricity consumption patterns to improve load forecasting capabilities and provide auxiliary decision-making basis for power grid dispatch [11]. Reinforcement learning can be used for unit operating parameter optimization and microgrid energy management to adjust operating strategies under complex constraints. Neural networks can also be used in scenarios such as high-voltage direct current transmission to compensate for changes in equipment operating parameters and improve the adaptability of system control [11].

3.2. Electrical equipment fault diagnosis and predictive maintenance

The safe and stable operation of electrical equipment is the foundation for ensuring the reliability of power supply. Traditional periodic maintenance has problems such as large investment in operation and maintenance resources and limited ability to identify hidden faults. Artificial intelligence can use equipment operation data to carry out status identification and fault early warning, and promote the transformation of operation and maintenance mode from post-fault maintenance to predictive maintenance [3, 9]. In transformer fault diagnosis, CNN, SVM and other models can combine oil chromatography, partial discharge and temperature monitoring data to identify insulation and structural abnormalities, for motor equipment, deep learning models can use vibration, current and

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temperature data to perform status identification and fault diagnosis. In the operation and maintenance of transmission lines, machine vision and sensing technology can be used for line inspection and defect identification [5], and infrared thermal imaging, ultrasonic and other technologies can also assist in the status detection of substation equipment [3].

3.3. Smart power grid dispatch and resource optimization

Smart grids are an important carrier for energy transformation. Artificial intelligence can be used for integrated coordinated scheduling and operation optimization of power generation, grid, load and storage. Reinforcement learning can optimize scheduling strategies under multiple constraints, comprehensively consider power generation costs, new energy consumption and grid operation safety, and provide auxiliary decision-making for power system operation [7]. Virtual power plants can use artificial intelligence to coordinate distributed photovoltaic, wind power, energy storage and adjustable loads to achieve distributed energy cluster optimization [12]. The distribution network intelligent system can improve the reliability of distribution network operation by analyzing line operation data to achieve fault location, isolation and power supply restoration [9]. On the electricity consumption side, artificial intelligence can optimize the operation strategies of air conditioning, lighting and production equipment according to the electricity consumption patterns of industrial and commercial and residential users to achieve load management and energy-saving operation [11].

3.4. Industrial electrical automation intelligent upgrade

In industrial settings, artificial intelligence can be combined with devices such as PLCs, distributed control systems, and frequency converters to enhance the control and coordination capabilities of the production process. Its applications mainly include four aspects: control optimization, production line collaboration, vision applications, and edge deployment. Control optimization: Deep learning can be combined with intelligent PID to dynamically adjust control parameters according to the operating status, thereby improving the control performance in time-varying production processes [13]. Production line collaboration: Multi-agent systems (MAS) can realize collaborative decision-making among production equipment, used for production planning and material scheduling optimization [14]. Vision applications: CNN-based machine vision can be used for target recognition, positioning, and assembly of industrial robots, improving the automation level of complex production processes [15]. Edge deployment: Edge artificial intelligence can be combined with field control devices such as PLCs to realize process parameter optimization and equipment status monitoring, meeting the real-time requirements of industrial sites [16].

3.5. Intelligent management and control of new energy and energy storage systems

Wind and solar power generation are intermittent and random, and their output fluctuations increase the difficulty of large-scale grid-connected operation and regulation. Artificial intelligence can combine data such as meteorology, wind speed, and solar irradiance to predict renewable energy output, providing support for grid dispatch and renewable energy consumption. Energy storage systems can use deep reinforcement learning to integrate information such as electricity prices, renewable energy output, and real-time load to dynamically optimize charging and discharging strategies. In microgrids, artificial intelligence can also coordinate the operation of solar, wind, energy storage, and other power sources, improving energy management capabilities during islanded and grid-connected operation.

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4. Existing problems of artificial intelligence in electrical automation applications

4.1. Data quality and data security issues

Electrical data sources are complex and the formats are inconsistent, which can easily lead to signal interference and data loss. Some old equipment lacks data acquisition modules, making it difficult to meet the training needs of AI models. The operation data of the power grid is closely related to energy security, while industrial electrical data is closely linked to enterprise business operations and is therefore highly sensitive. During data transmission, storage and model training, there is always a risk of data leakage and cyberattacks. Although federated learning, differential privacy and other technologies can provide security support, the high costs of implementation and the lack of industry standards still restrict the large-scale application of these technologies in the power and industrial control sectors [17].

4.2. Model interpretability and operational reliability issues

The black-box characteristics of deep learning models make it difficult to trace the decision-making process, which creates obstacles to verification and accountability in scenarios such as power grid scheduling and relay protection. At the same time, the generalisability of the model is affected by topological changes and fluctuations in equipment conditions. The prediction and control performance may decline, and its reliability under extreme conditions also needs to be tested. Taking extreme ice and snow disasters as an example, after the distribution grid topology changes, the recognition rate of existing fault diagnosis models may decrease, exposing their insufficient adaptability to complex operating conditions.

4.3. Lack of a unified industry technical standard system

The standards, testing requirements and access systems for AI in the electrical industry are not mature enough at present. Across different manufacturers, compatibility problems between algorithms and device interfaces are relatively prominent, which hinders data interoperability and model reuse. In addition, there is still room for improvement in the safety, accident accountability and risk management mechanisms of AI-based control systems.

4.4. Hardware compatibility difficulties and a shortage of multi-skilled personnel

In industrial settings, some older electrical equipment has limited computing capacity, which makes it difficult to run even lightweight AI models without hardware modifications. Upgrading this equipment can require substantial investment and lengthy installation work. The cost of application is also affected by the need to purchase and maintain high-performance computing equipment. Another challenge is the shortage of professionals who have expertise in both electrical engineering and AI. As a result, some companies may struggle to handle model training, deployment and maintenance on their own, which adds further difficulties to the implementation of these technologies.

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5. The development trend of integrating AI and electrical automation

5.1. Large-scale application of edge intelligence and cloud-edge collaborative architecture

Edge intelligence pushes some data processing, feature extraction and model inference to field devices such as substation terminals, PLCs and smart sensors, reducing the pressure of original data transmission and response latency, the cloud is responsible for model training, global optimization and long-term data analysis, forming a cloud-edge collaborative computing architecture [16]. With the development of lightweight technologies such as model pruning, quantization and knowledge distillation, AI models will be more adaptable to the limited computing power in industrial sites, and can be combined with local data processing to reduce the risk of sensitive data transmission. This architecture is expected to be further applied to scenarios such as power distribution networks, industrial production lines and distributed new energy, providing support for real-time control and intelligent operation and maintenance of electrical systems.

5.2. Deep integration of AI and digital twins

Digital twins establish virtual models of electrical equipment, power grids and industrial production lines to map the operating status of physical systems. Traditional digital twins have certain limitations in parameter updates and dynamic operating condition adaptation. AI can use real-time operating data to dynamically adjust model parameters and improve the ability of digital twins to depict complex operating states. After the integration of AI and digital twins, simulation analysis can be used to analyze scenarios such as equipment failure, line anomalies and new energy output fluctuations to assist in verifying control strategies and fault handling schemes. At the same time, online status assessment and fault trend prediction can be carried out in combination with multi-source monitoring data to support predictive operation and maintenance of equipment. In the fields of power grid dispatching and industrial automation, digital twins can also be used for operation simulation, parameter optimization and production process debugging to promote further collaboration between monitoring, simulation and control [18].

5.3. Multimodal large-scale models empower intelligent applications across all scenarios

Traditional power AI models are mostly trained and deployed for a single task, and it is difficult to share data and models between different businesses. Multimodal large models can simultaneously process heterogeneous information such as time series data, equipment images, acoustic signals, operation and maintenance texts and power grid topology, providing a new technical path for cross-modal data analysis and multi-business collaboration. Multimodal large models for the power industry can be adapted to tasks such as fault diagnosis, equipment operation and maintenance, and power grid dispatch through pre-training and fine-tuning. For example, they can assist in analyzing inspection information, identifying equipment anomalies and generating operation and maintenance suggestions, and provide support for source-grid-load-storage collaborative decision-making. Lightweight industry models are also expected to lower the threshold for SMEs to use AI technology, but they still need further verification and standardization in terms of data quality, model reliability and security [2].

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5.4. Explainable AI and data security management technology upgrades

The decision-making process of deep learning models is difficult to explain intuitively. In safety-critical scenarios such as power grid dispatch, relay protection and equipment fault diagnosis, insufficient interpretability will increase the risk of model verification, auditing and operation. Therefore, explainable artificial intelligence (XAI) and causal analysis will become important technical directions to improve the transparency and verifiability of models. XAI can show the basis of model decision-making through feature importance analysis, attention visualization and other methods to help operation and maintenance personnel understand and verify the diagnostic results, causal analysis can further explore the causal relationship between data and provide support for model analysis under complex working conditions. In terms of data security, privacy computing technologies such as federated learning and differential privacy can reduce the direct sharing of raw data and improve the security of power grid and industrial data [14]. At the same time, the industry will further improve the security testing, anomaly monitoring and risk protection mechanisms of AI systems and promote the standardized application of AI in safety-critical scenarios.

5.5. Improvement of industry standards and construction of a multi-skilled talent training system

With the further application of artificial intelligence in the field of electrical automation, the standardization needs of data interfaces, model evaluation, fault diagnosis and system safety will become more prominent. Establishing unified data acquisition specifications, equipment communication interfaces, model evaluation indicators and safety protection requirements will help improve software and hardware compatibility and model reuse capabilities, and reduce the cost of repeated construction. In terms of talent training, the industry needs to strengthen the cross-integration of electrical professional knowledge and artificial intelligence technology, and cultivate compound talents who have the ability of electrical systems, automatic control and AI applications. Universities can strengthen the training of relevant talents through curriculum system optimization, school-enterprise cooperation and engineering practice, while enterprises can improve the digital capabilities of existing technical personnel through job training, and provide talent support for the engineering application of artificial intelligence technology [15].

6. Conclusion

Artificial intelligence provides a new pathway for the intelligent development of electrical automation. Technologies such as machine learning, deep learning, and reinforcement learning have been applied in power system control, fault diagnosis, grid dispatching, industrial control, and energy management, supporting intelligent decision-making under complex conditions. However, AI adoption remains constrained by data security, limited model interpretability, incomplete standards, and a shortage of interdisciplinary talent. With advances in edge intelligence, digital twins, multimodal models, and explainable AI, AI-driven electrical automation is expected to achieve further intelligent and collaborative development.

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