Research on the Application of Artificial Intelligence in Fault Diagnosis of Power Systems

Ruize Ji
Nanjing Normal University, Nanjing, China
2253863457@qq.com

Abstract. With the large-scale integration of new energy into power systems, the intermittency and volatility caused by the high penetration of renewable energy generation (such as wind power and photovoltaic power) require diagnostic systems to possess strong uncertainty-handling capabilities. Consequently, the complexity and uncertainty of power grid operation have increased significantly, posing unprecedented challenges to the safe, stable and economic operation of the power system. The traditional fault diagnosis and handling methods, which are based on fixed models and manual experience, can no longer adapt to the dynamic and complex operating characteristics of the new energy power grid, making it urgent to explore intelligent technical solutions. Traditional power grid fault diagnosis approaches rely mainly on expert experience and physical models. Model-based methods locate faults through state estimation and power flow calculation, whose accuracy heavily depends on model precision and parameter identification. However, under complex operating conditions such as high new energy penetration, grid topology changes, and frequent fluctuations in power supply and demand, establishing an accurate mathematical model that can cover all operating scenarios is extremely challenging—model mismatches often occur, leading to reduced fault diagnosis accuracy. Expert systems, on the other hand, integrate the operational experience of power grid engineers into rule bases, offering transparent reasoning processes that are easy to understand and verify. Yet, they suffer from inherent limitations: knowledge acquisition is time-consuming and labor-intensive, it is difficult to update rules in a timely manner with the iteration of grid technology, and they lack self-learning ability, making it impossible to adapt to new fault types and complex operating environments brought by new energy integration. When dealing with massive real-time data generated by the power grid (including new energy output data, load data, equipment monitoring data, and environmental data) and complex system environments, the following prominent problems frequently arise, which further restrict the efficiency and reliability of power grid operation and fault handling.

Keywords: Intelligent Fault Diagnosis, Renewable Energy Grid, Power System Operation.

1. Introduction

1.1. Large prediction errors in wind and photovoltaic output

Affected by weather, irradiance, wind speed, temperature and other uncontrollable natural factors, wind and solar energy exhibit strong randomness and volatility. Traditional forecasting methods (such as time series analysis and statistical regression) are difficult to capture the nonlinear and dynamic variation rules of new energy output, resulting in low forecasting accuracy and large errors. This not only makes it difficult for the power grid to formulate reasonable dispatch plans, but also brings great uncertainty to fault diagnosis—false alarms or missed alarms may occur when the actual output deviates significantly from the predicted value [3].

1.2. Insufficient accuracy in power load forecasting

User electricity consumption behavior is highly variable, affected by factors such as seasons, holidays, economic activities, and user habits. Traditional load forecasting models are often based on fixed historical data and simple correlation analysis, which cannot capture accurate load change patterns under the impact of new energy integration (such as the mutual influence between distributed photovoltaic power generation and user load). This leads to large forecasting deviations, which impair the scientificity of power grid planning, reduce the efficiency of economic dispatch, and even threaten the secure operation of the power grid when the actual load exceeds the predicted range.

1.3. Slow and inaccurate power grid fault diagnosis and location

With the continuous expansion of the power grid scale and the increasing complexity of topology, coupled with the randomness of new energy output and load fluctuations, the types of power grid faults have become more diverse and complex. Traditional experience-dependent fault diagnosis methods rely on manual judgment and simple logical reasoning, which cannot efficiently process massive real-time monitoring data. As a result, fault diagnosis and location are slow, and misdiagnosis or missed diagnosis often occurs, extending the fault handling time, increasing the scope of power outages, and causing huge economic losses and adverse social impacts [1], [2].

Driven by the rapid advances in machine learning and artificial intelligence technologies in recent years, we can effectively solve the above problems and realize intelligent fault diagnosis and efficient fault isolation of the power grid. First, for the problem of low data quality and large prediction errors, we can preprocess the collected massive real-time and historical data (including denoising, missing value filling, and abnormal data elimination) to automatically identify and filter data with quality defects, laying a solid foundation for subsequent diagnosis and forecasting. On this basis, machine learning algorithms (such as deep learning, random forest, and support vector machines) can autonomously learn the complex mapping relationships among fault causes, weather conditions, temperature, humidity, new energy output, and load changes from a large amount of historical fault data, thereby establishing high-precision intelligent diagnostic models for fault classification, location, and severity evaluation. These models can adapt to the dynamic changes of the power grid, continuously optimize their performance through self-learning with new data, and significantly improve the accuracy and speed of fault diagnosis [2], [3].

2. Artificial Intelligence-Based Fault Diagnosis Methods

Artificial intelligence-based fault diagnosis mainly depends on the effective extraction of fault-related features from multi-source power system data. In practical power grid operation, the available data may include voltage, current, relay protection signals, circuit breaker status, renewable energy output, load curves, weather conditions, and equipment monitoring records. Before model training, these data should be preprocessed through noise reduction, missing value imputation, abnormal data detection, and normalization. Such preprocessing can improve the consistency and reliability of input data and reduce the negative influence of measurement errors on diagnostic accuracy [2].

Machine learning models such as support vector machines, random forests, and artificial neural networks can be used to establish the mapping relationship between operating conditions and fault categories. Compared with rule-based expert systems, data-driven models have stronger adaptability because they can update their parameters with new historical samples. Deep learning methods further improve feature extraction ability by automatically learning nonlinear representations from massive monitoring data. Therefore, AI-based methods are suitable for fault detection, fault classification, fault location, and fault severity assessment in complex power systems with high penetration of renewable energy [2], [3].

3. Reinforcement Learning-Based Fault Isolation

Meanwhile, rapid determination of the optimal isolation path to minimize the number of outaged customers and reduce economic losses is critical during power grid faults, especially in urban power grids with high load density and complex user demands. This problem, which involves multi-objective optimization under complex constraints (such as grid topology constraints, equipment capacity constraints, and load priority constraints), can be effectively solved using the Q-learning algorithm—a classic reinforcement learning method. The Q-learning algorithm constructs a Q-value function to evaluate the long-term reward of taking a particular switching operation action under a specific power grid state (such as fault location, load distribution, and equipment status). Initially, the agent's estimation of the Q-function is random and inaccurate. Through repeatedly attempting different switching operation combinations, observing the fault isolation effect, and obtaining reward feedback (with the reward positively related to the reduction of outaged customers and the speed of isolation), the agent gradually revises its Q-value estimates, continuously optimizing its decision-making strategy [4].

After thousands of simulation iterations based on actual power grid data and various fault scenarios, the agent can fully learn efficient fault isolation strategies: prioritizing the operation of sectionalizing switches at the boundaries of faulty sections to achieve precise isolation of faulty areas with the fewest switching actions, thereby minimizing the scope of power outages and the number of affected customers. Compared with traditional manual isolation strategies, which rely on experience and are prone to subjective errors, the Q-learning-based intelligent isolation strategy is more efficient, accurate, and adaptive, capable of quickly responding to various complex fault scenarios and significantly shortening the fault recovery time [4].

From the perspective of fault isolation implementation, the reward function design directly affects the quality of the learned switching strategy. A reasonable reward mechanism should consider not only the number of restored loads, but also switching operation time, the importance level of affected users, equipment capacity limits, and the risk of secondary faults. By integrating these factors into the state-action evaluation process, reinforcement learning can generate an isolation sequence that balances safety, economy, and reliability. This makes the method suitable for distribution networks with frequent topology changes and high renewable-energy uncertainty [4].

4. Conclusion

This paper discusses the application of artificial intelligence in fault diagnosis and fault isolation of power systems with high penetration of renewable energy. The integration of wind power and photovoltaic generation increases the uncertainty of power grid operation, making traditional model-based and experience-based diagnosis methods insufficient for complex and dynamic fault scenarios. Artificial intelligence provides an effective data-driven approach by using machine learning and deep learning algorithms to process multi-source monitoring data, improve renewable energy and load forecasting, and enhance the accuracy and speed of fault classification and location.

Furthermore, reinforcement learning, especially Q-learning, can be applied to optimize fault isolation strategies by evaluating switching operations under different grid states. Compared with traditional manual isolation methods, the Q-learning-based strategy has better adaptability and can reduce outage areas, shorten recovery time, and improve the reliability of power supply. Future research should focus on multi-source data fusion, model interpretability, real-time deployment, and engineering validation under large-scale power grid scenarios. These directions will help promote the intelligent, efficient, and reliable operation of modern power systems.

References

[1] Li, Yihang, et al. "Research on the Application of Artificial Intelligence Technology in Power System Fault Diagnosis." Information and Computer, vol. 38, no. 4, 2026, pp. 88-90.

[2] Nasim, S. F., Aziz, S., Qaiser, A., Kulsoom, U., and Ahmed, S. "Fault Detection and Fault Diagnosis in Power System Using AI: A Review." Sir Syed University Research Journal of Engineering & Technology, vol. 14, no. 1, 2024, pp. 27-32. doi:10.33317/ssurj.598.

[3] Benitez, I. B., and Singh, J. G. "A Comprehensive Review of Machine Learning Applications in Forecasting Solar PV and Wind Turbine Power Output." Journal of Electrical Systems and Information Technology, vol. 12, article 54, 2025. doi:10.1186/s43067-025-00239-4.

[4] Srivastava, I., Bhat, S., Vardhan, B. V. S., and Bokde, N. D. "Fault Detection, Isolation and Service Restoration in Modern Power Distribution Systems: A Review." Energies, vol. 15, no. 19, article 7264, 2022. doi:10.3390/en15197264.