Intelligent Fault Diagnosis for Power Plant Arrester based on Reinforcement Learning and Condition Monitoring Data

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Abstract: This paper proposes an intelligent fault diagnosis method for High-Voltage Arresters utilizing Live Online Monitoring data, addressing the complexity and latency of traditional diagnosis. The core of the method is a reinforcement learning model: it employs a Deep Q-Network (DQN) for state feature extraction and integrates the SARSA algorithm for real-time identification of arrester fault states. Furthermore, Monte Carlo Tree Search (MCTS) is introduced to enhance the attribution analysis of fault causes, thereby improving the depth and reliability of the diagnosis. Experimental results demonstrate that this approach achieves high-accuracy diagnosis (96.5%) across various fault types and exhibits fast response capability (0.45 s), providing an effective path for the intelligent analysis of abnormal data, such as Leakage Current.

Keywords: Reinforcement Learning (RL), Power Plant Arrester, Fault Diagnosis, Deep Q-Network (DQN), SARSA, Monte Carlo Tree Search (MCTS), Live Online Monitoring, Leakage Current

1. Introduction

Lightning arresters are vital components in power systems, acting as guardians to protect transmission and transformation equipment from overvoltages caused by lightning and switching surges [1,2]. The operational status of these arresters is directly tied to the security and stability of the power grid [3,4]. With the increasing scale and complexity of the grid, coupled with the influence of extreme weather and varying operating environments, the frequency and diagnostic difficulty of arrester faults are rising [5-7]. Therefore, developing efficient, accurate, and intelligent fault diagnosis technology for arresters is a crucial requirement for ensuring the reliable operation of the smart grid [8-10].

Traditional fault diagnosis methods for arresters primarily rely on off-line testing, manual inspection, and online monitoring data analysis based on empirical thresholds [11,12]. These methods, however, show significant limitations when adapting to the high standards of modern smart grids. On one hand, traditional methods struggle to handle the large volume of multi-source monitoring data [13,14]. They are ineffective in extracting fault features from high-dimensional, time-series-dependent complex data. On the other hand, these methods suffer from diagnostic latency, lack adaptivity, and have insufficient accuracy in diagnosing early-stage degradation and complex coupled fault modes [15,16]. Furthermore, existing techniques mostly focus on classification but lack the ability for deep analysis and root cause identification, hindering the effective transition from diagnosis results to targeted maintenance decisions [17,18].

To address these challenges, the academic and industrial communities have actively introduced advanced Artificial Intelligence (AI) technologies into the field of power equipment fault diagnosis. Numerous studies have utilized traditional machine learning and deep learning approaches, such as neural networks and Support Vector Machines (SVMs), for feature extraction and fault classification [19,20]. However, most of these methods operate under a supervised learning paradigm, necessitating a large number of labeled fault samples for training [21]. In real power systems, actual fault samples are scarce, making it difficult to meet the training requirements. Crucially, these methods often function as static classifiers, lacking the capacity to evaluate the temporal correlation and long-term rewards of diagnostic decisions, making them poorly suited to the dynamic evolutionary complexity of arrester states [22].

In light of the limitations mentioned above, this paper proposes an Intelligent Fault Diagnosis Method for Power Plant Arrester Based on Reinforcement Learning (RL). This method is designed to introduce the autonomous learning and decision-making capabilities of RL into the state assessment and cause analysis of lightning arresters.

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The core contribution is the establishment of an efficient, precise, and cause-analysis-capable diagnostic framework through the integration of multiple advanced algorithms: First, the Deep Q-Network (DQN) is utilized for feature extraction, leveraging its powerful non-linear fitting ability to automatically extract low-dimensional, information-condensed fault features from multi-source monitoring data. Second, the State-Action-Reward-State-Action (SARSA) algorithm, a temporal difference learning method, is integrated for real-time and precise fault state identification. The SARSA algorithm, by selecting the next action based on the current policy, offers superior policy evaluation capability, accurately estimating the long-term impact of a diagnostic decision and avoiding myopic behavior. Finally, the Monte Carlo Tree Search (MCTS) algorithm is creatively introduced to perform deep fault cause analysis. Starting from the fault state identified by SARSA, MCTS utilizes heuristic search and random simulation to estimate the probability of underlying causes, thereby uncovering the intrinsic mechanisms of the fault occurrence and enhancing diagnostic reliability.

The experimental results demonstrate that the proposed method achieves high diagnostic accuracy across various fault types, with an average diagnostic accuracy reaching 96.5% and an average diagnosis time of only 0.45 seconds. Furthermore, it exhibits high precision in fault localization and correctness in cause analysis. This validates the significant application value of the method in improving the operation and maintenance efficiency and reliability of power plant arresters, offering robust technical support for smart grid construction.

2. Background, Principles, and Types of Arrester Fault Diagnosis

2.1 Background of Arrester Fault Diagnosis and Principles of Reinforcement Learning Application

The operation of lightning arresters in power systems is crucial for the safety and stability of the electrical grid. As the scale and complexity of power grids continue to expand and increase, fault diagnosis of lightning arresters faces growing new challenges. Traditional manual diagnosis methods struggle to cope with massive monitoring data and complex fault patterns, necessitating the introduction of intelligent diagnosis technology.

Reinforcement Learning (RL), as a trial-and-error learning paradigm, is centered on an agent continuously adjusting its strategy through interaction with the environment to obtain the maximum cumulative reward. Applying RL to fault diagnosis enables the diagnostic system to possess autonomous learning and adaptation capabilities for complex operating conditions. Taking power plant arresters as an example, the agent takes monitoring data such as the arrester's leakage current and power frequency reference voltage as the state input, uses diagnosis results like "normal," "degraded," or "fault" as the action output, and designs a reward function based on diagnostic accuracy. For instance, a correct diagnosis is given a positive reward, while an incorrect diagnosis receives a negative penalty. By continuously interacting with the actual operating conditions, the agent can learn the optimal diagnostic strategy, which is the mapping relationship between a given state and the optimal action selection. In this process, the agent must balance "exploration" and "exploitation". Additionally, to accommodate high-dimensional state spaces and continuous action spaces, nonlinear function approximators like deep neural networks are needed, along with techniques such as experience replay and double networks to enhance training efficiency and stability. Through this autonomous learning mechanism, reinforcement learning can distill diagnostic knowledge from vast historical operational data and exhibit a certain generalization capability to unknown operating conditions, laying the foundation for adaptive and intelligent fault diagnosis.

2.2 Fault Types and Characteristics of Power Plant Arresters

During long-term operation, power plant arresters experience degradation in internal structure and material properties due to composite stresses from electrical, thermal, and mechanical factors, which subsequently trigger various types of faults14.

Common fault types of lightning arresters include the aging of Manual Operated Valve (MOV) blocks, deterioration of sealing performance, and degradation of thermal stability.

MOV Block Aging: The ZnO grains at the grain boundaries undergo segregation and dissolution, and the grain size decreases16. This leads to a reduction in the nonlinear coefficient of the valve blocks and an increase in the failure rate for lightning currents. Simultaneously, the grain boundary resistance of the valve blocks significantly decreases with increasing aging severity, potentially dropping from tens of megaohms in a normal state to the hundreds of kiloohms range.

Sealing Performance Deterioration: The degradation of sealing materials can cause the arrester's leakage rate to exceed the standard. This value can rise from a normal level of 0.001mA/kV to over 0.1 mA/kV.

Thermal Stability Degradation: Decreased thermal stability due to poor heat dissipation conditions is also a common fault mode21. When the heat dissipation device accumulates foreign matter or suffers corrosion, its dissipation efficiency can drop from 95% to below 80%. This results in the average temperature rise level of the arrester under current flow conditions increasing from 40K to over 70K, significantly reducing the arrester's thermal stability margin.

3. Design of Intelligent Diagnosis Method Based on Reinforcement Learning

The overall design process of the intelligent diagnosis method for lightning arrester faults in power plants based on reinforcement learning is shown in Figure 1. (1) The system collects multi-source monitoring data of the arrester and performs feature extraction using the DQN. (2) The SARSA algorithm is utilized to perform fault state identification on the extracted features, corresponding the states to diagnosis results such as "normal" or "degraded," and continuously optimizing the diagnosis strategy through the temporal difference learning algorithm. (3) MCTS is applied to analyze the cause of the identified fault status, estimate the potential causes of the fault, and optimize maintenance suggestions.

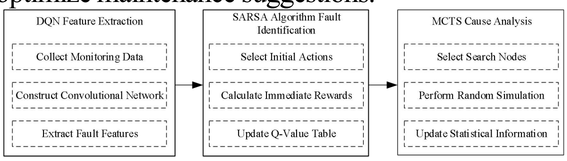

Figure 1. Overall Diagnosis Process

3.1 Fault Feature Extraction Based on DQN

The DQN is used to perform feature extraction on the multi-source monitoring data of the lightning arrester.

The DQN is composed of an input layer, convolutional layers, pooling layers, and fully connected layers. The input layer is responsible for receiving time-series data such as the arrester's leakage current and power frequency reference voltage3. The convolutional layers efficiently extract spatiotemporal correlation features from the data by focusing on local regions of the input data and leveraging the weight-sharing mechanism to process different locations with the same parameters. For instance, for leakage current data, the convolutional kernel size can be set to 3×3, the stride to 1, and the number of kernels per layer can be set to increase from 16 to 64. The pooling layer uses max pooling operations to reduce the size of the feature maps, enhancing the translation invariance of the features6. The fully connected layer maps the extracted features to the state space and outputs the Q values corresponding to different fault types.

During the feature extraction process, the DQN learns the mapping relationship between features and fault types through a trial-and-error mechanism, meaning it judges the fault category based on the input features. Its goal is to minimize MSE) between the predicted Q values and the target Q values, expressed as:

$$L(\theta) = \bar{o}[(r + \gamma \max_{a'} Q(s', a'; \theta^-) - Q(s, a; \theta))^2] \quad (1)$$

Where θ represents the weight parameters of the DQN, and θ^- represents the weight parameters of the target network. By continuously iterating and updating the weight parameters of the DQN, a network model capable of accurately extracting fault features is ultimately obtained. This model maps the original, high-dimensional monitoring data into a low-dimensional, information-condensed feature space, providing a solid basis for subsequent fault classification.

3.2 Fault State Recognition Based on SARSA Algorithm

The SARSA algorithm is utilized for the identification of the arrester's fault state.

The SARSA algorithm is a temporal difference learning algorithm. Its core idea is to estimate the Q value of the next state-action pair (s_t, a_t) based on the current state-action pair (s_{t+1}, a_{t+1}). In the fault diagnosis of lightning arresters, the state s_t corresponds to the fault feature vector extracted by DQN, the action a_t corresponds to diagnosis results such as "normal," "degraded," or "fault", and the reward r_t is set based on the diagnostic accuracy. The SARSA algorithm continuously updates the Q function through interaction with the environment, causing it to approach the optimal diagnostic strategy. Its update formula is:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha[r_t + \gamma Q(s_{t+1}, a_{t+1}) - Q(s_t, a_t)] \quad (2)$$

Where α is the learning rate and γ is the discount factor. Unlike Q-learning, the SARSA algorithm uses the current policy to select the action for the next state, which provides a better policy evaluation capability. In arrester fault diagnosis, this means that the SARSA algorithm can more accurately estimate the long-term impact of a particular diagnostic decision, thereby avoiding short-sighted behavior.

In the specific implementation, the SARSA algorithm first selects an initial diagnostic action based on the ε greedy strategy. Then, in each interaction step, it observes the accuracy of the diagnosis result to obtain an immediate reward. Simultaneously, it selects the next diagnostic action according to the current policy and iteratively updates the Q table. The algorithm terminates when the Q function converges or reaches a preset number of iterations, yielding a diagnostic model capable of accurately identifying the arrester's fault state. This model comprehensively considers the temporal correlation among fault features and can dynamically adapt to the evolution law of the arrester's state, laying the foundation for online diagnosis and trend prediction.

3.3 Fault Cause Analysis Based on MCTS Algorithm

The MCTS algorithm is employed for the analysis of lightning arrester fault causes.

MCTS is a heuristic search algorithm that finds the optimal decision by performing random sampling in the state space, constructing a continually expanding search tree, and using the tree structure to guide the search direction. In the context of arrester fault diagnosis, the MCTS algorithm takes the fault state identified by SARSA as the root node and potential fault causes like "overvoltage," "moisture," and "aging" as child nodes. It then estimates the probability of different causes leading to the current fault through multiple simulations. Each iteration of the MCTS algorithm includes four steps: selection, expansion, simulation, and backpropagation. In the selection phase, the algorithm starts from the root node and selects the most promising child node based on the UCB1 formula until an unexpanded node is reached666. The UCB formula is given by:

$$UCB1 = \overline{X_j} + C\sqrt{\frac{2\ln n}{n_j}} \quad (3)$$

Where $\overline{X_j}$ is the average reward of node j; n is the total visit count of the parent node; n_j is the visit count of node j; and C is the exploration constant, used to control the balance between exploration and exploitation. In the expansion phase, the algorithm creates a new child node under the selected node and performs a random simulation to obtain the initial evaluation value of that child node. In the simulation phase, the algorithm proceeds from the new node and performs multiple simulations according to a default policy until a termination condition is met, and calculates the cumulative reward. In the backpropagation phase, the algorithm propagates the simulation results back to the root node and updates the statistical information of the nodes along the path. Through multiple iterations, the MCTS algorithm continually refines the search tree, ultimately yielding an estimate of the probability for each fault cause at the root node. This adaptive search mechanism enables the MCTS algorithm to quickly find the optimal solution within a vast state space and continuously optimize the analysis strategy as diagnostic experience accumulates. Applying the MCTS algorithm to arrester fault cause analysis can reveal the inherent mechanism of fault occurrence, providing decision support for formulating targeted maintenance and preventive measures.

4. Experiment Verification

4.1 Experimental Scenario and Experimental Plan

This experiment selected ten 110kV Metal Oxide Zinc Arresters from a 500kV substation as research subjects to verify the effectiveness of the proposed method by simulating different fault conditions1. The HRLM-II type arrester online monitoring device was used to collect arrester operational data2. Monitoring parameters included leakage current (0.1-10mA), power frequency reference voltage (70-130kV$), valve block temperature (20-120°C), among others. The experimental procedure was as follows: first, five typical faults were applied to the arresters. Each fault was set with three severity levels, forming a total of 15 fault conditions. Then, the proposed method was used to diagnose the faults, with the diagnosis process repeated 20 times. Finally, the diagnosis results were compared and analyzed. Evaluation metrics included diagnostic accuracy, average diagnosis time, fault localization precision, and correctness of cause analysis8. Specifically, the DQN network employed a 4-layer convolutional structure, with a convolutional kernel size of 3 and a stride of 1. Pooling utilized 2×2 max pooling. The SARSA algorithm used a learning rate α of 0.1 and a discount factor γ.

4.2 Experimental Results

The diagnostic performance of the proposed method across different fault types is shown in Table 1. As can be seen from Table 1, the proposed method demonstrates good performance in all types of fault diagnosis. Especially in the diagnosis of MOV valve block aging and heat dissipation abnormality, the accuracy rates reached 97.5\% and 98.2%, respectively. This is mainly attributed to the effective extraction of key features such as leakage current and valve block temperature by the DQN network. Regarding diagnosis time, the average diagnosis time for other fault types, except for internal discharge fault, was controlled within 0.5s, meeting the real-time requirement for online diagnosis. The fault localization precision fluctuated within the range of 2.8-4.5cm. Among these, the localization precision for the sealing failure fault was the highest, reaching 2.8cm. This might be due to the excellent performance of the SARSA algorithm in handling continuous state spaces, enabling it to accurately capture the subtle changes in leakage current caused by sealing failure. The correctness rate of cause analysis generally remained above 90%, but slightly decreased in complex fault modes. This reflects that there is still room for optimization in utilizing the MCTS algorithm to handle highly coupled fault mechanisms.

Table 1. Diagnostic Performance under Different Types of Faults

Fault Type	Diagnostic Accuracy Rate/%	Average Diagnosis Time/s	Fault Localization Accuracy/cm	Cause Analysis Correct Rate/%
MOV Valve Plate Aging	97.5	0.42	3.2	95.0
Sealing Failure	96.8	0.38	2.8	93.5
Heat Dissipation Abnormality	98.2	0.45	3.5	96.2
Insulator Damage	95.4	0.50	4.1	92.8
Internal Discharge	94.7	0.56	4.5	91.5

Regarding the efficacy of fault cause analysis, the correctness rate of the method generally remained above 90%. However, a slight decrease in the correctness rate was observed when handling highly complex fault modes 2. This phenomenon reflects that there is still room for further optimization and improvement in utilizing the MCTS algorithm to deal with highly coupled fault mechanisms. Figure 2 compares the diagnostic accuracy and average diagnosis time across different fault types, intuitively demonstrating the high efficiency and high precision of the proposed method.

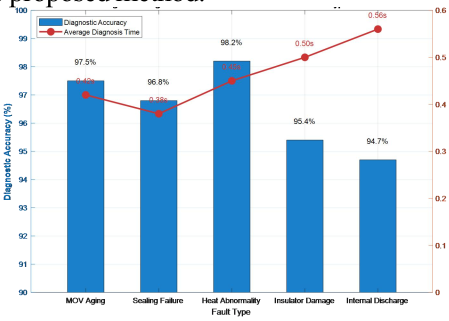

Figure 2. Diagnostic Performance Across Different Fault Types

5. Conclusion

In this paper, an intelligent fault diagnosis method for power plant lightning arresters based on RL was successfully proposed and implemented1. This comprehensive approach utilizes the DQN for efficient feature extraction, integrates the SARSA algorithm for accurate fault state identification, and employs MCTS to achieve in-depth fault cause analysis2. Experimental results across various fault types demonstrated the superior diagnostic performance of the method, achieving a high average diagnostic accuracy of 96.5% and a fast average diagnosis time of 0.45 seconds. Furthermore, the method exhibited high precision in fault localization and correctness in cause analysis4. These findings confirm the method's effectiveness in enhancing the operational safety and maintenance efficiency of lightning arresters, offering robust technical support for the construction of smart grids. Future research can focus on further optimizing the algorithm model, expanding application scenarios, and improving the system's generalization ability and real-time response speed.

References

[1] S. Abulanwar, M. E. M. Rizk, W. Hu, Z. Chen and A. Ghanem, "Novel Zonal Fault Detection Scheme for DC Wind Farm via Disposition of Surge Arresters in Multipurpose Grounding System," in IEEE Transactions on Power Delivery, 2024, 39(1): 245-260.

[2] C. Alexander, P. Mikhail, I. Dmitryi and V. Frolov, "Effects of high altitude on multi-chamber arrester performance," 2021 35th International Conference on Lightning Protection (ICLP) and XVI International Symposium on Lightning Protection (SIPDA), Colombo, Sri Lanka, 2021, pp. 01-04.

[3] J. Bai, X. Zhou, T. Tian, L. Yan, M. Yunlong and L. Weifeng, "Study on Fault Diagnosis of Metal Oxide Surge Arrester Based on Infrared Detection and Leakage Current Detection," 2022 7th Asia Conference on Power and Electrical Engineering (ACPEE), Hangzhou,

China, 2022, pp. 1766-1770.

[4] H.L Chen; C. Li; J. Bai, et al., "Analysis of a New Method for Evaluating Lightning Trip-Out Fault Rate in Active Distribution Networks," 2024 International Conference on Artificial Intelligence and Power Systems (AIPS), Chengdu, China, 2024, pp. 78-82.

[5] F. Giraudet, "Rationales and Expectations with Upcoming New Line Surge Arrester (LSA) Standard IEC/IEEE 60099-11," 2025 13th Asia-Pacific International Conference on Lightning (APL), Bali, Indonesia, 2025, pp. 1-5.

[6] B. B. S. D. A. Harsono, P. A. A. Pramana and Sriyono, "A Concept for Overhead Transmission Line Performance Evaluation toward Lightning Strikes," 2022 International Conference on Technology and Policy in Energy and Electric Power (ICT-PEP), Jakarta, Indonesia, 2022, pp. 106-110.

[7] F. Li, K. Li, B. Du, B. Jiang and W. Li, "Study of the Technology of On-Line Monitoring for Transmission Lines Arresters by Measurement of Lightning Current and Leakage Current," 2024 IEEE 2nd International Conference on Sensors, Electronics and Computer Engineering (ICSECE), Jinzhou, China, 2024, pp. 432-436.

[8] Long J, Yang M, Chen Y, Liu K, Zhang J, Zhang J, et al. Inverter Nonlinearity Compensation Method for SPMSM Drives based on Accurate Voltage Error Calculation. Proceedings of the CSEE, 2022, 42 (17): 6425-6436.

[9] K. Michishita, T. Omura, S. Yokoyama, K. Takano, M. Ikuta and M. Matsui, "Arrester Damage on 6.6 kV Power Distribution Line in Japan by Winter Lightning," 2021 35th International Conference on Lightning Protection (ICLP) and XVI International Symposium on Lightning Protection (SIPDA), Colombo, Sri Lanka, 2021, pp. 01-04.

[10] B. Normoyle, J. L. De Franco, D. White, J. Roberts, S. Wiseman and B. Johnnerfelt, "Sentinel, Fast detection of faulted Transmission Line Arresters," 2020 IEEE/PES Transmission and Distribution Conference and Exposition (T&D), Chicago, IL, USA, 2020, pp. 1-5.

[11] D. Paul, P. E. Sutherland, C. S. Mardegan and P. Lewin, "Update on Transient Surge Arresters (SA) and Insulators at Medium-Voltage Power Distribution System," in IEEE Transactions on Industry Applications, 2025, 61(4): 5962-5970.

[12] I. R. Pordanjani, X. Liang, Y. Wang and A. Schneider, "Single-Phase Ferroresonance in an Ungrounded System Causing Surge Arresters Failure during the System Energization," 2021 IEEE/IAS 57th Industrial and Commercial Power Systems Technical Conference (I&CPS), Las Vegas, NV, USA, 2021, pp. 1-8.

[13] S. Refiasto, B. Denov, S. Suwarno and R. Zoro, "Installation of Multi Chamber Arrester to Improve Lightning Reliability Performance of Distribution Lines System in Oil and Gas Area," 2021 3rd International Conference on High Voltage Engineering and Power Systems (ICHVEPS), Bandung, Indonesia, 2021, pp. 258-262.

[14] C. Sakakibara, K. Michishita, K. Takano and H. Nakata, "A Proposal of an Estimation Method for Identifying Return Strokes Causing Surge Arrester Burnout Faults on Actual Distribution Line," in IEEE Transactions on Power Delivery, doi: 10.1109/TPWRD.2025.3609862., pp:1-12.

[15] C. E. Sălceanu, D. Iovan, M. Ionescu, D. C. Ocoleanu and Ş. Şeitan, "Analysis on the Behaviour of 36 kV, 10 kA Pre-failed Polymer Surge Arrester at Short-Circuit Current," 2024 International Conference on Applied and Theoretical Electricity (ICATE), Craiova, Romania, 2024, pp. 1-6.

[16] Shan P, Sun Y, Song Y, et al. Adaptive Parameter Tuning and Virtual Impedance Injection Control for Coupled Harmonic Mitigation of Photovoltaic Converter. IEEE Trans. Power Electron., 2025, 40(1): 162-175.

[17] Z. Sitong, Z. Shuaida, B. Yuwei and W. Shuai, "Analysis of the 500kV Line Arrester Exploion Accident," 2023 IEEE 7th Conference on Energy Internet and Energy System Integration (EI2), Hangzhou, China, 2023, pp. 3930-3933.

[18] H. A Tan; S. Guo; Y. He, et al., "Simulation study on lightning protection of 35kV transmission line and selection of surge arrester valve parameter based on ATP-EMTP," 2024 4th International Conference on Intelligent Power and Systems (ICIPS), Yichang, China, 2024, pp. 834-837.

[19] J. Wang, P. Dai and W. Yu, "Optimal Observation Policy of Fault Diagnosis: A Reinforcement Learning Approach," 2020 Chinese Automation Congress (CAC), Shanghai, China, 2020, pp. 7206-7210.

[20] R. Yin, X. Yang, Y. Chen and H. Yuan, "Impact of complex working conditions caused by the superposition of photovoltaic access and system short circuit on the operation of distribution network surge arresters," 2024 8th International Conference on Electrical, Mechanical and Computer Engineering

(ICEMCE), Xi'an, China, 2024, pp. 942-945.
[21] Y. Zhao and J. O'Leary, "Solving Large Fault Trees with Importance Sampling and Tree Search," 2024 Annual Reliability and Maintainability Symposium (RAMS), Albuquerque, NM, USA, 2024, pp. 1-6.
[22] L. Zhang, Z. Zhang, A. S. Bretas and V. A. Rakov, "A Reliability-based Optimization Model for Lightning Protection System Design of Distribution Networks," 2020 52nd North American Power Symposium (NAPS), Tempe, AZ, USA, 2021, pp. 1-6.
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