Opportunities and Challenges in AI Based Modern Power System

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Abstract:
Nowadays, the power grid has transformed into a dynamic and extensive resource generation and management system. This transformation is primarily driven by the widespread adoption of renewable energy sources and the utilization of intelligent information and communication technologies to handle dynamic workloads. The smart grid encompasses various innovative operations, including power electrification, intelligent information integration at the physical layer, and intricate interconnections. These operations leverage data-driven deep learning, big data, and machine learning paradigms to effectively analyze and control transient issues within the electric power system. Artificial intelligence (AI) has emerged as a crucial tool in addressing and resolving challenges associated with transient stability assessment (TSA) and power generation control. In this research paper, we present a comprehensive review that explores the role of AI and its sub-procedures in tackling TSA problems. The article outlines an AI-based intelligent power system structure, along with the rationality of applying AI to transient situations in power system TSA. Distinguishing itself from other reviews, this paper delves into the AI-based TSA framework and design process, highlighting intelligent applications and their analytical capabilities in addressing power system transient problems. Furthermore, our analysis extends beyond AI alone, as we also explore the integration of big data, which aligns seamlessly with AI. The paper discusses future trends, opportunities, challenges, and open issues pertaining to AI-Big data based transient stability assessment in the smart power grid.

Keywords: Artificial intelligence, power system

1. Introduction

As power system construction advances, super-long-distance, cross-region, large-capacity transmission, and the high share of electronic power create new risks. High-power shortage accidents and complex chain faults also increase the complexity of power system transient stability analysis and control. There are theoretical limitations and technical barriers to accurately understand the transient state of a large-scale power grid for online security, stability analysis and management.

As Figure 1 illustrates, with the rapid growth of electric power measurement, communication technology, and large-scale access to external information (e.g., environment, weather, social etc.), the power system has evolved into a large-scale, high-dimensional, time-varying, non-linear CPP (cyber power physical system) with multiple-source information interactions. The complexity of physical systems and information systems with multiple sources has increased the need for more accurate and timely transient stability analysis. The electric power system is a time-varying nonlinear system. A transient stability analysis is a transient stability analysis of a specific non-autonomous nonlinear system.

Because the multi-time scale control interaction causes high state variable order and strong nonlinearity of the system, the scholars should model the system and simplify the model according to these characteristics, and then establish the theories and methods corresponding to the model analysis work continue. Different modelling methods will be integrated into a model based on extra power electronic characteristics in the whole power system. Different Version: The Interaction between individual subsystems leads to a strong nonlinearization. Moreover, the introduction of new energy sources requires a significant investment, which in turn brings volatility and instability to the system. The stability of global power systems, including wind and flexible DC transmission lines, is analysed in point . To understand the characteristics of complex nonlinear systems, studying the system trajectory is the most intuitive approach. However, the system trajectory alone may not provide quantitative information about the system mechanism. Additionally, creating an accurate model of the power electronic converter in the global system is impractical, making modelling a crucial step in transient stability analysis. voltage instability is not always an isolated occurrence. In power electronic power systems, the interaction between the power electronic converter and the power grid is more complex, often resulting in intertwined instability phenomena. Therefore, it is essential to study the mechanism of transient instability in electronic power systems. Only by fully understanding the nature of instability phenomena can the system's stability margin be quantitatively calculated, enabling effective planning and control of the system. The term "transient stability" in this paper refers to the power electronic power system's ability to achieve a new stable operating state or return to the original operating state after a significant disturbed transient process.

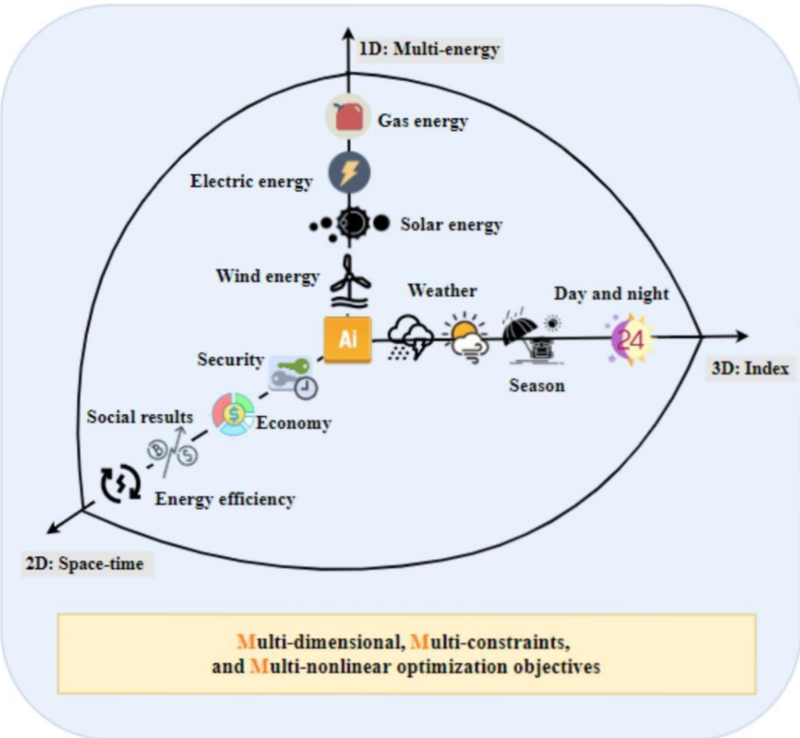

Figure 1: 3D-3M Power System Developing Diagram

Based on the above description, it is easy to find the traditional method's difficulty in solving the transient problem. Therefore, the introduction of AI to meet the current transient stability research requirements has become a hot research direction in this digital era. Artificial intelligence system has a significant use effect on the transient problem of the smart power system, combined with the information, digital, intelligent operation mechanism, and operation mode, to realize the practical analysis. Considering various transient problems also ensures the safe and stable operation of the whole power system. The application of AI to the power system transient problem began in the late 1980s. During this time, the researchers have made valuable explorations in the research framework, data processing, and algorithm design. However, due to hardware performance constraints and algorithm efficiency limitations, AI still needs a large-scale practical application in this field. But, with the progress of science and technology, in recent years, AI has opened a new round of rapid development characterized by deep learning, high- performance computing, and big data. Like things, the application of AI to the power system transient stability analysis and control has once again become a research hotspot in this big context.

Figure 2 shows the relationship between the electric power system, the big data, and the artificial intelligence and the system application. In the past, dispatchers with long-term experience often judge the safety level and stable weak links of the power grid according to the operation mode and power current level. It is the starting point of power grid security and stability evaluation based on artificial intelligence technology. Its basic idea is to rely on the analogy and learning of a large number of training samples to form the knowledge of power grid stability evaluation and conduct the online discrimination of power grid security level. It generally does not need to establish a detailed mathematical model of the power system, the heavy training sample acquisition, and the learning process is completed offline. The online stability evaluation speed is extremely fast. As long as the sample is rich and accurate, and the evaluation system is appropriately designed to obtain good evaluation accuracy, it also has advantages in the efficiency and interpretability of the Evaluation.

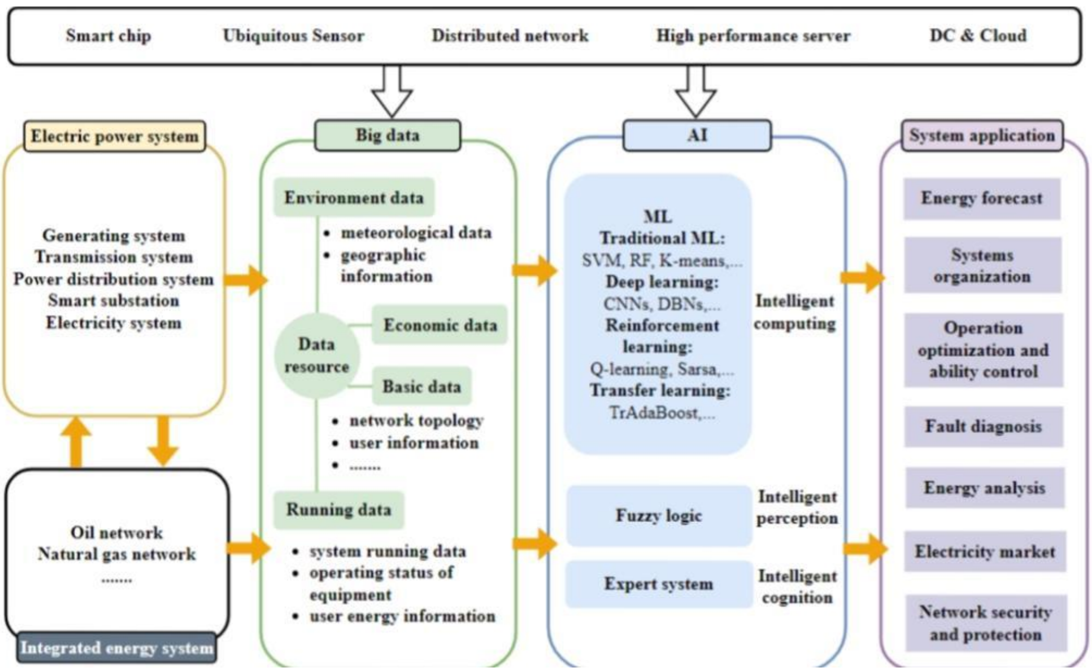

Figure 2: Smart Power System Structure

The characteristics of the new generation of AI and the power system transient problem are closely fit, mainly reflected in the following:

1. The power system transient process mechanism is intricate, encompassing both electromagnetic and electromechanical transient processes. The number of factors that influence this mechanism is vast, with the IEEE39 node test system alone having hundreds of factors. Deep learning offers distinct advantages over traditional machine learning in solving complex problems with multiple factors and unknown mechanisms.
2. The transient problem time scale ranges from milliseconds to seconds, necessitating the efficient processing of transient response characteristic data and the calculation of numerous components within a short timeframe. In recent years, high-performance computing has made significant advancements, exemplified by the exponential growth in the peak performance of Graphics Processing Unit (GPU) floating-point computing from 10 billion to trillions per second. A well-trained AI model for transient stability prediction in a power system can typically achieve forecasts within 10ms, facilitating rapid analysis of transient stability.
3. The successful advancement of simulation technologies, software, and platforms for transient processes in power systems can yield vast amounts of data. Conventional machine learning focuses on enhancing algorithms to boost performance, which poses a significant challenge. AI algorithms leveraging big data have the potential to enhance algorithm performance by utilizing extensive datasets

2. Intelligence Technology:

Since ancient times, humans have been curious about the possibility of creating a machine that can imitate the human brain. In 1955, Dr. McCarthy introduced the concept of “artificial intelligence,” and a year later, McCarthy and his colleagues organized the “Dartmouth College Summer AI Research Program.” This event marked a significant milestone in the field of artificial intelligence. Since then, machine learning, deep learning, and predictive analysis have advanced and become standardized studies.

Artificial intelligence enables computers to logically simulate human thinking. We can categorize advanced intelligence into three levels: computational intelligence, perceptual intelligence, and cognitive intelligence, as depicted in Figure 3:

a. Computational intelligence focuses on equipping machines or computers with high-performance computing capabilities. In some cases, these capabilities even surpass human computing abilities, allowing for the manipulation of vast amounts of data.
b. Perceptual intelligence involves the conversion of signals from the physical world into digital information through hardware devices. This digital information is then elevated to a cognitive level. The interaction between humans and computers through interfaces plays a crucial role in this process.
c. Cognitive intelligence aims to imbue machines with human-like rational thinking abilities, enabling them to make appropriate decisions and accurate judgments.

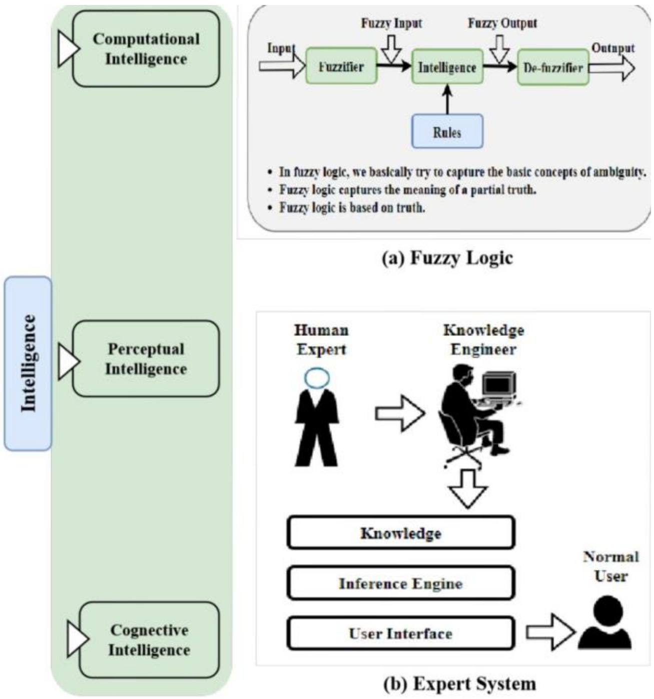

Figure 3: Advanced Intelligence Diagram

In order to meet the aforementioned requirements, the latest generation of AI is focused on the development of fuzzy logic, expert systems, machine learning, and other advanced technologies.

1. Fuzzy logic, which involves the use of regular logic blocks, allows computers to process imprecise input and generate output as either true or false. Fuzzy logic aims to replicate the ambiguous nature of human judgment, reasoning, and thinking. It utilizes fuzzy sets and fuzzy rules to handle transitional boundaries, qualitative knowledge, and experiences. By employing fuzzy comprehensive judgment, it enables the resolution of complex problems that cannot be easily solved using traditional methods. Therefore, fuzzy logic closely resembles human thinking patterns.
   Fuzzy logic comprises key elements such as fuzzy language variables, rules, reasoning, and control. Refer to Figure 3(a) for a typical structure diagram of fuzzy logic.
2. Expert systems, an integral part of early artificial intelligence, are computer-based intelligent programs designed to store specialized knowledge and experience . They contain vast amounts of expert-level knowledge in specific fields and effectively utilize human expertise to solve complex problems within those fields. Expert systems combine early expert experience with computer technology. Figure 3(b) illustrates an expression that can be understood as “Knowledge-based inference engine".
3. Machine learning, a prominent aspect of contemporary artificial intelligence, leverages experience to enhance the performance of systems. Typically, this “experience” is derived from data, making machine learning the conduit through which data transforms into intelligence. The field of machine learning encompasses various branches, including traditional, deep, reinforcement, and transfer learning.

3. Application of AI in Power System

The application of AI in the transient stability problem of power systems includes determining the transient stability after failure, predicting the situation of critical parameters such as system frequency, power angle,

and voltage after failure, and including the quantification of emergency control Measures after transient failure. The research objectives of the above three transient problems are different, but The research conducted using AI technology includes data acquisition, sample generation, and algorithm application.
The main challenge in AI applications for transient stability analysis of the power system is obtaining the state variable data. The size, type, and quality of the data have a significant impact on the research outcomes. Currently, the data used in research primarily comes from simulation software, which allows customization of fault scenarios and data volume based on the study requirements . This approach provides a suitable training and test dataset for the AI algorithm. The existing methods for setting simulation parameters in research can be categorized into artificial determination and probabilistic model generation.

3.1. Data acquisition

The main challenge in AI applications for transient stability analysis of the power system is obtaining the state variable data. The size, type, and quality of the data have a significant impact on the research outcomes. Currently, the data used in research primarily comes from simulation software, which allows customization of fault scenarios and data volume based on the study requirements. This approach provides a suitable training and test dataset for the AI algorithm. The existing methods for setting simulation parameters in research can be categorized into artificial determination and probabilistic model generation. At present, stability analysis simulations primarily yield data related to stability analysis rather than actual failure data. This is mainly because the occurrence of power system failures, particularly transient instability failures, is extremely rare. As the power system undergoes changes, the usefulness of historical data diminishes, making it challenging to provide high-quality training data for AI algorithms. Consequently, bridging the gap between simulated and actual fault data becomes a significant concern. One potential solution is to establish a Mapping relationship between simulated and actual data, allowing for the correction of any deviations in the simulated data.

3.2. Sample generation

The initial information of the power system consists of the data from each sampling point throughout the entire testing system. As a result, the data possesses a high spatial and temporal dimension. If all the data is utilized in the training of the AI algorithm, managing the training time, accuracy, and convergence becomes challenging. Previous research primarily focuses on handling the original data by means of data pre-processing, selecting feature attributes, and adjusting dimensions to acquire transient stable samples suitable for the AI algorithm. This approach enhances the training efficiency of the algorithm and guarantees the accuracy of the testing process.

3.3. Algorithm application

The research primarily focuses on algorithm selection, which plays a crucial role in determining the speed and accuracy of transient problem research. The appropriate algorithm and parameter configuration are key factors in this process. The existing research on transient problems mainly revolves around traditional machine learning classification, regression algorithms, and newly developed deep learning-related algorithms. In this context, the application of AI algorithms such as artificial neural networks (ANN), support vector machine (SVM), ensemble learning (EL), and deep learning (DL) in transient problems is discussed. Furthermore, the potential of frontier deep learning technology for transient stability is analyzed. (Version 1)

4. Future Challenges and Trends

The power system possesses notable features, such as numerous nodes, intricate electrical links, and interconnection of AC and DC in various areas. This necessitates more stringent measures for preventing and managing failures. According to Table 4, artificial intelligence imposes varying levels of demands on the design, control, and upkeep of power systems. Current technology is inadequate to adequately address future trends. This section will delve into the forthcoming trends and obstacles in two aspects: AI focus and AI-Big data focus.

Version 1: The power system exhibits remarkable characteristics, with numerous nodes, complex electrical connections, and interconnection of AC and DC across different regions. This necessitates stricter measures for preventing and managing failures. As indicated in Table 4, artificial intelligence imposes different levels of demands on the design, control, and maintenance of power systems. Existing technology is no longer sufficient to meet future development trends. This section will explore future trends and challenges in two directions: AI orientation and AI-Big data orientation.

4.1. AI-orientation challenges and trends

Artificial intelligence plays a vital application role in the power system. Here are some of the following tricky challenges to address.

Table 4
The requirements of AI for Power System

Requirements	Design	Control	Maintenance
Computation	High	Medium	Medium
Algorithm Speed	Low	High	Medium
Accuracy	Medium	High	High
Dataset	Low	Low	High
Interpretability	Low	High	High

Challenge 1: The machine learning algorithm used in the classification model lacks adaptability to the system network frame structure. When the network frame changes, retraining is required, resulting in a significant time and speed cost, as well as a weak ability to generalize. The Neural Network (NN)-based TSA method often leads to misclassification due to limitations in the algorithm itself or insufficient boundary sample density. Additionally, the accuracy of a single SVM classification is not high, and there are overlapping regions between different types of sample data, leading to misjudgments. In some cases, missing results are treated as the same situation.

Challenge 2: In recent years, deep learning has been applied to transient stability evaluation, offering advantages over traditional machine learning algorithms. However, there are still some difficulties that need further study, such as the structure and parameter optimization problems of DBN, as well as the anti-interference ability and misjudgment problems caused by noise. Furthermore, deep learning also exhibits weak adaptability to the system network structure.

Challenge 3: WAMS measurement data possesses spatial and temporal characteristics, providing a wealth of state information about the system. This data plays a crucial role in achieving quantitative assessment of transient stability. However, the construction of transient stability could be improved, as it sometimes fails to meet the strict concept of margin.

Challenge 4: The use of big data technology for transient stability assessment, particularly from a data mining perspective, is relatively inadequate. The evaluation index system is not yet perfect. To address this, continuous improvement of traditional algorithms, the application of new algorithms, and the rapid development of artificial intelligence and big data technology will bring new research ideas to the assessment of transient stability in power systems. Possible future research directions include the following points.

Trend 1: Enhance the real-time performance of classification models by focusing on implementing online training for better meeting real-time requirements. Online training involves the model entering the renewal stage at the end of each data entry, using the previous time node's model and the real-time data of the current time node for evaluation.

Trend 2: Improve the comprehensive application research of deep learning in transient stability evaluation by quantitatively analyzing the influence of system network structure changes on the model, the interference degree of noise on the training process and results, and strengthening the study of miscalculation problems.

Trend 3: Strengthen model robustness to insufficient data by analyzing possible missing data and insufficient data in the existing system, as well as testing the data quality using the training model.

Trend 4: Most existing TSA methods are not applied to practical operation according to research findings.

4.2. AI & Big data-orientation opportunities and challenges

As the recognition of data's significance continues to grow, the utilization of big data technology to address power-related issues is also increasing. Within big data technology, there is the ability to separate the operation from the physical model to uncover internal correlations. By analyzing the extensive PMU data, operators can identify and rectify potential issues within the power grid, reducing the likelihood of grid failures. Moving forward, TSA will primarily focus on the following areas using big data technology.

Challenge 1: Integration and storage of massive data. Traditional data assessment typically involves analyzing data from a single domain. Therefore, it is crucial to find a suitable method to merge multi-source datasets with varying patterns, formats, and representations.

Challenge 2: Real-time data processing technology requires a reaction time in milliseconds for emergency applications. The proposed system offers high-speed computing, network congestion management, and flexible algorithms. Timely completion of combining massive data remains a challenge, with the use of a database in memory being a potential solution.

Challenge 3: Data compression is crucial in wide-area surveillance systems to meet high-fidelity requirements. Unique compression methods are necessary to detect transient interference effectively.

Challenge 4: Big data visualization technology enables the display of differences in granularity, frequency, and voltage. However, discovering and representing correlations in multi-source data poses a significant challenge. Other obstacles include visualization algorithms, information extraction, representation, and image synthesis techniques.

Challenge 5: Data security and privacy are paramount due to the rise in smart meters for home energy consumption, leading to an increase in personal information exposure. Sharing data among different entities can result in private data leaks, potentially causing cascading issues.

Trend 1: Deep learning generation enhanced by data shows promise in solving complex data analysis issues. While machine learning algorithms are highly efficient, they are limited by computational complexity, hindering effective analysis of large-scale data sets. To address this, it is recommended to: (1) Utilize parallelized and enhanced machine learning algorithms by rewriting them for parallel computing on big data distributed platforms. (2) Core Vector Machine (CVM) is more efficient than SVM in terms of running time and space, especially with large data sets. However, there is a lack of research on CVM's stability evaluation. Future studies should combine big data technology to explore CVM's adaptability in solving TSA problems and quantitatively analyze its computational efficiency within the realm of big data.
Trend 2: A standardized information model is essential to manage massive data and ensure interoperability among various big data analytic platforms, architectures, and operational integration. Additionally, cloud computing service providers are crucial for this purpose.
Trend 3: Current big data applications rely on a single data type, but future applications should utilize multiple big data sources to evaluate critical infrastructure dependencies. Establishing easily accessible data centers can enhance the resilience of critical infrastructure. Future grid applications will harness diverse large data sets to uncover valuable hidden insights.

5. Conclusions

The evolution towards power electronization, integration of physical information, and complex interconnection of large power grids is shaping the development trajectory of the new generation of power systems. The nature of transient issues is also evolving in terms of information, mechanisms, simulations, analyses, and controls. Artificial Intelligence (AI) can be leveraged to move beyond physical mechanisms and adapt complex data relationships to facilitate data-driven problem analysis. Consequently, the utilization of data-driven AI technology in addressing the transient stability problem of power systems is emerging as a trend that combines internal demand and internal drive.

This study puts forth the following research concepts for employing AI in tackling the transient stability problem in electric power systems:

1. Address the challenge of limited data volume and significant temporal variations in the actual system through the concept of data inheritance;
2. Utilize deep learning algorithms to uncover potential relevant feature values to resolve potential subjective and incomplete issues in feature engineering based on physical mechanisms;
3. Incorporate a physical data model to analyze transient issues, thereby enhancing the interpretability of research findings.

The integration of AI technology in addressing the transient stability problem in power systems is anticipated to achieve breakthroughs at two levels: at the algorithm application level, advanced algorithms such as deep learning hold promise for broader application; in terms of research direction, it can extend to the realm of online prediction of stable conditions and the development of appropriate stability control strategies for stable conditions. Furthermore, the effective combination of artificial intelligence and big data is poised to deliver substantial performance enhancements to the transient stability of power systems.

References

1. Wang X, Blaabjerg F. Harmonic stability in power electronic-based power systems: Concept, modeling, and analysis[J]. IEEE Transac-tions on Smart Grid, 2018, 10(3): 2858-2870.
2. Zamani N, Askari J, Kamali M, et al. Distributed adaptive consensus tracking control for non-linear multi-agent systems with time-varying delays[J]. IET Control Theory & Applications, 2020, 14(20): 3382-3394.
3. Yohanandhan R V, Elavarasan R M, Manoharan P, et al. Cyberphysical power system (cpps): A review on modeling, simulation, and analysis with cyber security applications[J]. IEEE Access, 2020, 8: 151019-151064.
4. Wagan, S.A., Koo, J., Siddiqui, I.F., Qureshi, N.M.F., Attique, M. and Shin, D.R., 2022. A Fuzzy-Based Duo-Secure Multi-Modal Framework for IoMT Anomaly Detection. Journal of King Saud University-Computer and Information Sciences.
5. Mazumder S K, Kulkarni A, Sahoo S, et al. A Review of Current Research Trends in Power-Electronic Innovations in Cyber–Physical Systems[J]. IEEE Journal of Emerging and Selected Topics in Power Electronics, 2021, 9(5): 5146-5163.
6. Preece R, Milanović J V. Probabilistic risk assessment of rotor angle instability using fuzzy inference systems[J]. IEEE Transactions on Power Systems, 2014, 30(4): 1747-1757.
7. Gao B, Morison G K, Kundur P. Voltage stability evaluation using modal analysis[J]. IEEE transactions on power systems, 1992, 7(4): 1529-1542.
8. Guo, W., Koo, J., Siddiqui, I.F., Qureshi, N.M.F. and Shin, D.R., 2022. QoS-Aware Energy-Efficient MicroBase Station Deployment for 5G-Enabled HetNets. Journal of King Saud University-Computer and Information Sciences.
9. Advanced solutions in power systems: HVDC, FACTS, and Artificial Intelligence[M]. John Wiley & Sons, 2016.
10. Wang H, Li Z. A Review of Power System Transient Stability Analysis and Assessment[C]//2019 Prognostics and System Health Management Conference (PHM-Qingdao). IEEE, 2019: 1-6.