AI-Oriented Smart Power System Transient Stability: The Rationality, Applications, Challenges and Future Opportunities

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ABSTRACT

Nowadays, the power grid has become an active colossal resource generation and management system due to the wide use of renewable energy and dynamic workloads processed through intelligent information and communication technologies. Several new operations exist, such as power electrification, intelligent information integration on the physical layer, and complex interconnections in the smart grid. These procedures use data-driven deep learning, big data, and machine learning paradigms to efficiently analyze and control electric power system transient problems and resolve technical issues with robust accuracy and timeliness. Thus, artificial intelligence (AI) has become vital to address and resolving issues related to transient stability assessment (TSA) and control generation. In this paper, we provide a comprehensive review on the role of AI and its sub-procedures in addressing problems in TSA. The workflow of the article includes an AI-based intelligent power system structure along with power system TSA and AI-application rationality to transient situations. Outperforms other reviews, this paper discusses the AI-based TSA framework and design process along with intelligent applications and their analytics in power system transient problems. Moreover, we are not limited to AI, but we also combine the direction of big data that is highly compatible with AI, discusses future trends, opportunities, challenges, and open issues of AI-Big data based transient stability assessment in the smart power grid.

1. Introduction

With the progress of power system construction, super long distance, cross-regional, large capacity transmission, and the high proportion of electronic power have ushered in new risks. At the same time, high-power scarcity accidents and intricate chain faults improve the power system transient stability challenges further system analysis and control (1). There are theoretical constraints and technical bottlenecks to accurately grasp the transient status of a vast power grid to realize online security and stability analysis and management. As Figure 1 shows, with the booming development of electric power measurement and communication technology, and access to a large number of data such as external information (environment, meteorology, society, etc.), the power system has developed into a high-dimensional time-varying non-linear cyber power physical system (CPPS) with multi-source information interaction (2) (3). The complexity of the physical system and information system with multiple sources have raised stricter requirements for the accuracy and timeliness of transient stability analysis (4)(5).

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 modeling methods will be integrated into a model based on extra power electronic characteristics in the whole power system. Individual subsystems interact, resulting in a very strong nonlinearization. In addition, the significant investment in new energy will also bring volatility and instability to the system. The work angle stability of global power systems, including wind and flexible DC transmission lines, are studied in (6)(8). Understanding the system's characteristics through the system trajectory for complex nonlinear systems is most intuitive. But the system trajectory often cannot provide quantitative information on the system mechanism; on the other hand, the accurate model of the power electronic converter in the global system is impractical, so modeling is a crucial step in transient stability analysis. (7) states that voltage instability does not always occur alone. In the power electronic power system, the interaction between the power electronic converter and the power grid will be more complex, and the instability phenomenon is often intertwined. Therefore, it is necessary to study the mechanism of the transient instability of the electronic power system. Only by fully understanding the nature of the instability phenomenon can the system stability margin be calculated quantitatively, and then the system can be planned and controlled. The transient stability mentioned in this paper refers to the ability of the power electronic power system to achieve a new stable operation state or return to the original operation state after a large disturbed transient process.

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Abbreviation	Description
AI	Artificial Intelligence
TSA	Transient Stability Assessment
CPPS	Cyber Power Physical System
AC	Alternating Current
ML	Machine Learning
GPU	Graphics Processing Unit
WAMS	Wide Area Measurement System
UEP	Unstable Equilibrium Point
ANN	Artificial Neural Network
SVM	Support Vector Machine
CVM	Core Vector Machine
EL	Ensemble Learning
ELM	Extreme Learning Machine
DL	Deep Learning
RL	Reinforcement Learning
TL	Transfer Learning
VC	Vapnik-Chervonenkis
RF	Random Forest
NN	Neural Network
CNNs	Convolutional Neural Networks
DBN	Deep Belief Network
UHV	Ultra High Voltage
DC	Data Center
RUEP	Relevant Unstable Equilibrium Point
PEBS	Potential Energy Boundary Surface
EEAC	Extended Equal Area Criterion
CCT	Critical Clearing Time
PMU	Phasor Measurement Unit
EETC	Extended Equal Area Criterion

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

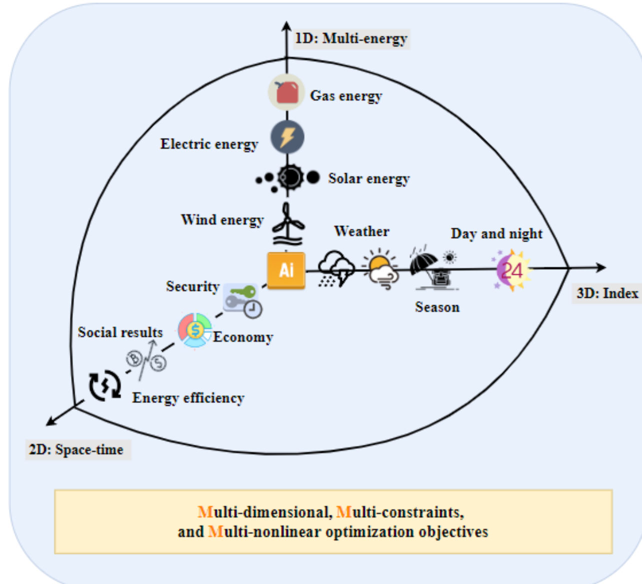


Figure 1: 3D-3M Power System Developing Diagram

analysis. Considering various transient problems also ensures the safe and stable operation of the whole power system (9) (82)(13).

The application of AI to the power system transient problem began in the late 1980s (54). 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 (12). Like things, the application of AI to the power system transient stability analysis and control has once again become a research hot spot 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 (14) (15) (16)(19).

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 (17). 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 (18). As long as the sample is rich and accurate, and the evaluation system is appropriately designed to obtain good evaluation accuracy,

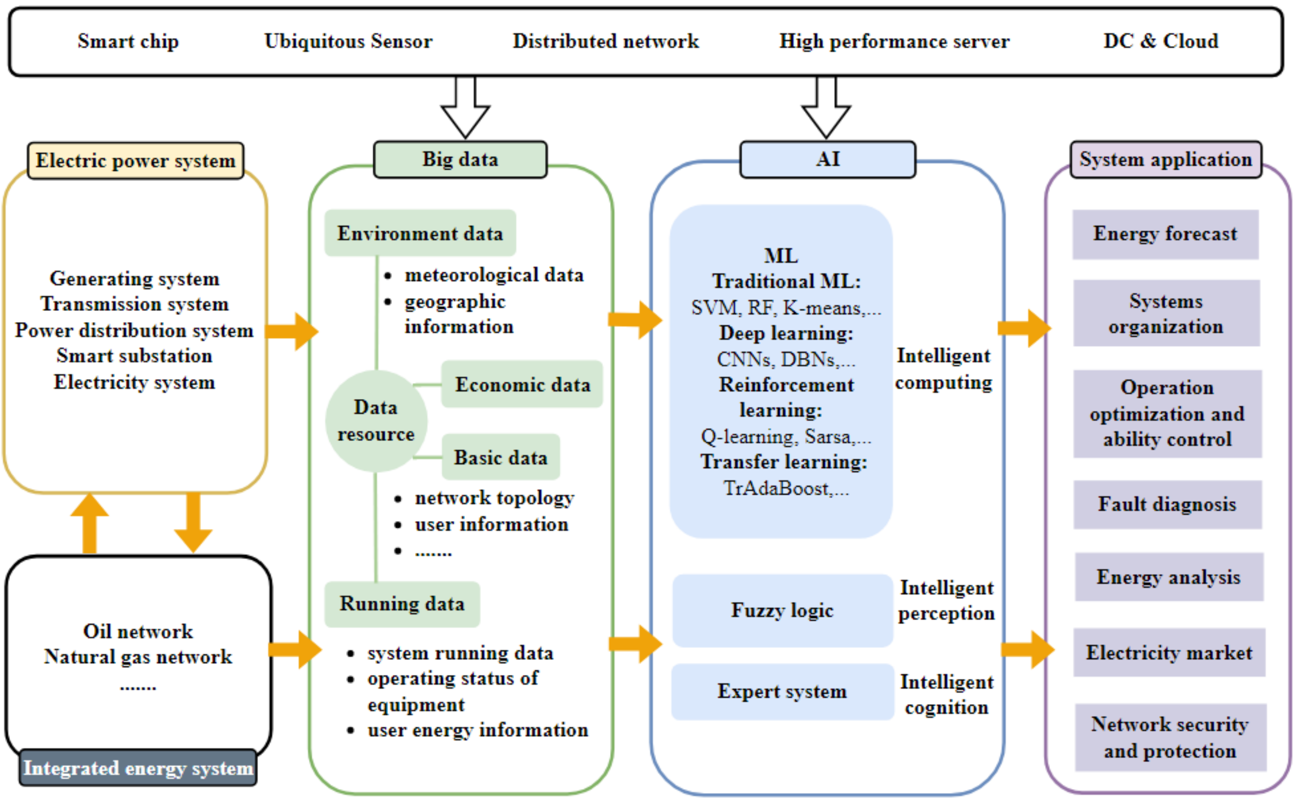


Figure 2: Smart Power System Structure

it also has advantages in the efficiency and interpretability of the evaluation.

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 complex, involving the electromagnetic and electromechanical transient processes (20)(25). The number of influencing factors is enormous, reaching hundreds in the test system of the IEEE39 node alone. Deep learning has superior advantages in solving complex problems with multiple factors and unknown mechanisms than traditional machine learning.
2. The transient problem time scale is from milliseconds to seconds, which requires completing the transient response characteristic data processing and calculating many components in a short time (21). In recent years, high-performance computing has developed rapidly, taking the peak performance of Graphics Processing Unit (GPU) floating-point computing as an example, which has grown from 10 billion times per second to trillions per second. A well-trained AI model for the transient stability prediction of a power system is usually able to achieve the forecast within 10ms, creating the conditions for the rapid analysis of the transient stability (22)(26).
3. The successful development of simulation technologies, software, and platforms for transient processes in power systems can provide samples of large data magnitude (23). Traditional machine learning studies the algorithm to improve performance, and it is challenging to continue to break through. AI algorithms based on big data can use massive data to improve the algorithm performance (24)(33).

This paper analyzes the changes in various research fields and the necessity of AI applications. Authors are reviewed from data acquisition, sample generation, and algorithm application, and the current deficiencies are analyzed. Based on the above inductive analysis, this paper puts forward the research idea of AI application to transient stability problems. Meanwhile, the authors also give the corresponding solutions to the current hot issues. Ultimately, the future development trends, opportunities, and challenges of TSA based on AI and big data are given. This paper not only introduces all the aspects of AI-TSA comprehensively but also analyzes the specific problems and provides possible solutions. In line with the trend of technology development, because of the inseparable relationship between big data and AI, the authors have further integrated the two technical parties, hoping to give scholars a reference. To show our contributions, we summarize the differences between our work and the existing reviews in Table 1, where the concerned topic stands for research points contained in the papers.

Table 1
The Comparisons of The Related Reviews In Power System

Papers	Year	Power System Type	The concerned topics
(27)	2012	AC power system	Provided a review of works related to application of ANN to TSA
(28)	2015	AC power system	Stability theories (Only transient analysis) Transient Power system modeling
(29)	2017	Power-electronized power system	Give out the comprehensive intelligent-based optimization techniques
(30)	2019	AC/DC power system	Optimization and control techniques that can be used to provide TSA
(31)	2019	Power-electronized power system	Power system evaluation method Probabilistic assessment method Key challenges(the stability evaluation AI methods in TSA)
(32)	2021	Power-electronized power system	From the aspects of data-driven power system, feature extraction and selection, model construction, Online learning and rule extraction are used for TSA
(34)	2021	AC and power-electronized power system	Summarize TSA prediction methods Response time evaluation
(35)	2022	Power-electronized power system	Provide a review of works related to application of ANN to TSA
(36)(56)	2022	Power-electronized power system	The state-of-the-art regarding the application of AI to TSA Focus on different machine, deep, and reinforcement learning techniques.
This paper	2022	Power-electronized power system	AI-based intelligent power system structure along with TSA The AI-based TSA framework and design process along with intelligent applications At application level, combine AI and big data to give the most potential future

2. Artificial Intelligence Technology

Since the first century BC, humans have been inquisitive about the feasibility of making some machine to simulate the human brain (37). In 1955, Dr. McCarthy proposed the new concept of "artificial intelligence" (38). And in 1956, McCarthy et al. organized a cross-generational conference named the "Dartmouth College Summer AI Research Program" (39)(57). Since then, machine learning, deep learning, and predictive analysis have entered a new era and have developed into the current standardized study.

Artificial intelligence makes the computer simulate human thinking logically. We divided advanced intelligence into three levels computational intelligence, perceptual intelligence, and cognitive intelligence, as Figure 3 shows :

- Computational intelligence aims to make the machine or computer have high-performance computing ability, to some extent even exceeding human computing ability to manipulate massive data; (40);
- Perceptual intelligence is mapping signals from the physical to the digital world through hardware devices. Then this digital information is further promoted to a cognitive level. In this process, human-computer interface interaction is crucial (41);
- Cognitive intelligence aims at making the machine own human rational mind power, make suitable decisions, and correct judgments (42)(97).

Computational intelligence is a relatively basic level of artificial intelligence. It refers to the fact that computers or machines rely on their own fast and massive computing power and massive storage capacity to complete some tasks that humans cannot. For example, Google's Alphago belongs to this type of intelligence. Above computational intelligence is perceptual intelligence, which refers to the intelligence that can find important information in a wide range of unstructured information centers. Such as finding essential elements. Above perceptual intelligence is cognitive intelligence. After perceptual intelligence finds critical data, it tries to find the connection between this information. It then does some corresponding important reasoning work,

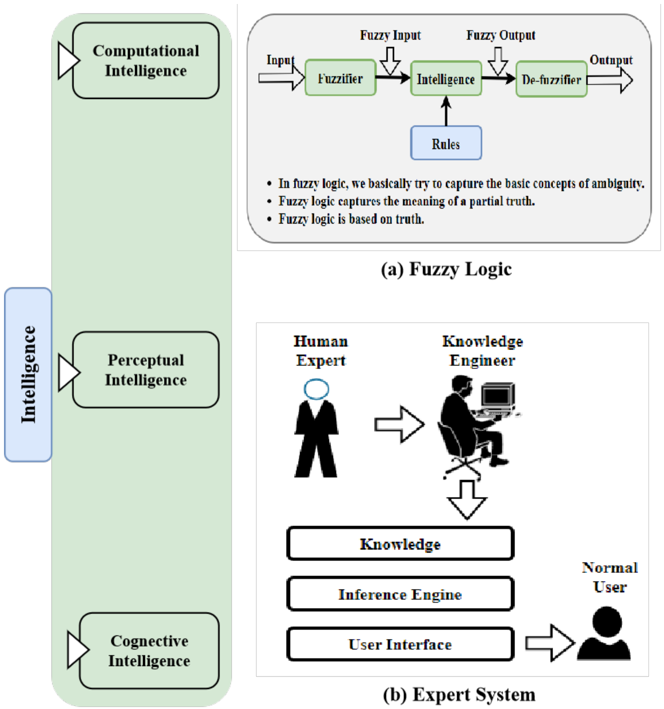


Figure 3: Advanced Intelligence Diagram

such as finding the occurrence, development, climax, process, the end. The integration of the three capabilities eventually allows machines to realize human-like wisdom to all-out to assist humans in working. To actualize hereinbefore requirements, the new breed of AI focuses on developing fuzzy logic, expert systems, machine learning, and other technologies (43).

1. Fuzzy logic: Regular logic blocks that computers can precise input, producing the output as true (True) or false (False) (50). Fuzzy logic mimics the indistinct concept of judgment, reasoning, and the thinking mode of the human brain. It should use a fuzzy set with fuzzy rules to reason, express transitional boundaries or qualitative knowledge and experience, implement the fuzzy comprehensive judgment, and cause to solve the rule-based fuzzy information problem that is hard to solve by usual methods. Therefore, fuzzy logic is closer to people's thinking logic (44).
   Fuzzy logic contains core elements such as fuzzy language variables, rules, reasoning, and control. Figure 3(a) gives a typical fuzzy logic structure diagram.
2. Expert system: The expert system is an essential component of early artificial intelligence (45)(98). It is a computer-intelligent program system that stores specialized knowledge and experience. It contains massive expert-level knowledge and experience in a specific field and effectively uses human expert knowledge to solve complex problems in this field. The expert system is a combination of early expert experience and computer technology. Figure 3(b) shows that the expression can be $Knowledge - base + Inference - engine$ (51).
   Expert systems have a very high interactive reliability. It is considered the highest level of human intelligence and expertise. The following are the essential features of the expert system: 1) The highest professional level: The expert system provides the highest professional knowledge. It provides efficiency, accuracy, and imaginative problem solutions. 2) Correct time response: the expert system interacts with users in a very reasonable period. The total time must be less than the time experts take to obtain the most accurate solution to the same problem. 3) Good reliability: the expert system must be reliable and can not make any mistakes. 4) Flexible: It must remain flexible because the expert system owns it. 5) Effective mechanism: The expert system must have an effective mechanism to manage the compilation of existing knowledge. 6) Ability to handle challenging decisions and problems: expert systems can handle challenging decision problems and provide solutions.
3. Machine learning: Machine learning is representative of modern artificial intelligence, using experience to improve the system's performance (46)(115). Here, "experience" usually exists in data, so machine learning is the technological path from data to intelligence. Machine learning is mainly divided into traditional, deep, reinforcement, and transfer learning.
   - Based on whether the data used is labeled, traditional machine learning (ML) is categorized as supervised learning, semi-supervised learning, and unsupervised learning (47);
   - Deep learning (DL) stems from the expansion of artificial neural networks. The multi-layer perceptron with multiple hidden layers is a typical deep learning structure (52). The previous several hidden layers can construct new features from the data in an unsupervised way automatically, and then extract the more abstract high-level category attributes layer by layer and find the deep feature representation of the data (47);
   - The main point of reinforcement learning (RL) is the repeated interaction between the learning system and the environment. If a particular behavior of the agent leads the environment to reward, the trend of the agent to produce this behavioral strategy will be strengthened (48);
   - Using the learned knowledge to solve problems in another new environment is one of the essential manifestations of advanced human intelligence. This is also the ability to transfer learning into artificial intelligence. It is, transfer learning can transfer the knowledge learned in one scene to another so that models and learning methods have more vital generalization ability (49)(119).

3. Power System Transient Stability Analysis

The transient stability mentioned in this paper means the ability of the electronic power system to achieve a new stable operation state or return to the original operation state after an extensive disturbed transient process.

After decades of development, the transient stability analysis theory and methods of the traditional alternating current (AC) power system has matured. Although there are significant differences between the power electronic power system and the conventional AC power system, these methods still have essential reference significance for the transient stability analysis of the electronic power system. Standard transient stability analysis methods include the time-domain simulation method, direct method, artificial intelligence method (58), and other methods, such as the inverse trajectory method and semi-tensor product method.

3.1. Time-domain simulation method

As one of the most critical approaches, the time-domain simulation method solves the system of differential-algebraic equations of the system to get the number of system states and generations to change the trajectory over time (59)(126). In the traditional AC power system, the time-domain simulation method determines the transient stability by the maximum work angle difference between the generators. As the most reliable evaluation method, the time-domain simulation can realize an arbitrarily complex system model and control strategy, often used as the standard for other transient stability analysis methods.

In addition, the above time-domain analysis method also has some disadvantages: first, the dynamic equation numerical integral is slow, and with the growth of the system state variable order, the time-domain simulation will significantly increase, and calculation speed cannot meet the needs of online monitoring and control (60); secondly, it does not provide the system stability information, unable to explore the mechanism of stability (61). Therefore, it is also essential to find the criterion of the transient instability of the power electronic power system to reduce the integration time of the time-domain simulation method.

3.2. Direct method

Besides the time-domain method, the direct method is also a typical transient energy function method. This method judges the power system's transient stability by comparing it with the maximum transient energy absorbed by the system (called the binding energy) (62). The transient energy function method can qualitatively determine the system stability, obtain the system stability margin, and analyze the system transient stability quantitatively. Calculating the binding energy in the traditional AC power system, the boundary calculation of the attractive domain, is the most challenging step of the direct method (63).

The traditional AC power system transient stability analysis has used the direct method. The applied direct approach to the electronic power system needs to solve two problems: constructing the appropriate energy function and how to estimate the attraction domain (64)(127). Compared with the traditional AC power system, the smart power system has the characteristics of topological time-change, fast transient process, strong non-linearity and high order of system state variables, which brings many challenges to TSA (65). Even without considering the fluctuation characteristics of new energy and various power electronic converters combined operation, the system model will become very complex.

At present, the more effective Lyapunov function is constructed with the concept of system energy. The main methods of solving unstable equilibrium points are the relevant unstable equilibrium point (RUEP) method, potential energy boundary surface (PEBS) method, extended equal area criterion (EEAC), etc.

The relevant Unstable Equilibrium Point (RUEP) method was introduced in 1978. This approach employs an approximate fault trajectory, accounting for fault location and transfer conductance effects for the first time. But the technique takes a long time and is difficult to calculate accurately.

The potential Energy Boundary Surface (PEBS) method initially emerged from an improvement of the enormous computational shortcomings of the RUEP method. Later, scholars perfected the theoretical basis and regarded PEBS as the stable boundary of the related gradient system. The technique is easier to compute and faster but has some errors in multiple oscillatory instability modes.

The boundary of the Stability Region-based Controlling Unstable Equilibrium Point (BCU) method was presented in 1994. This method finds the dominant unstable equilibrium point of the initial system by using the dimension reduction system. But this method still requires solving a nonlinear system of equations, so the computation is very slow.

Extended Equal-Area Criterion (EEAC) was proposed by scholars based on the equal-area criteria. The analysis premise of this method is that the system instability is the two-machine mode. The troubled system is then divided into critical, residual machine groups.

Later, a comprehensive method was proposed based on the RUEP, PEBS, and EEAC. Various ways are used to judge stability to improve the fault tolerance and reliability of the direct method.

3.3. AI method

Traditional TSA methods based on mathematical models are based on specific physical systems, with the help of solutions to mathematical equations. The advantages of artificial intelligence in solving TSA problems are (175; 54):

- Ensuring certain accuracy and efficiency;
- Not limited by complex mechanisms between many fields;
- Avoiding difficult problems through accurate models in practical engineering.

In the late 1980s, we began applying AI to TSA (55)(131). It is mainly traditional machine learning algorithms, such as NN and SVM, and then ELM to improve its performance. However, due to the algorithm's shortcomings and the hardware, it can be challenging to use it effectively. In recent years, the new generation of artificial intelligence represented by deep learning has been developed rapidly in electric power, which has become the focus of scholars' research. In the transient stability analysis of the power system, they mainly assume the functions of data pretreatment and post-processing (82). The power system is complex and large, and its operational data has infinite possibilities in time and space. Still, many data belong to similar samples, so the data needs to be pre-processed. When applying the AI algorithm for transient stability analysis, the mapping relationship between state parameters and stability indicators (such as critical resection time) is sought directly from the processed samples (67). The classifier model is trained offline through the data of the time-field simulation method. Then the new state parameters are obtained through Wide Area Measurement System (WAMS) to conduct the transient stability analysis of the system in the current state (68). This method is intuitive and fast.

Because the power electronic power system has the characteristics of a topological time-variable, a high order of state variables, and strong non-linearity (69), which causes difficulties in theoretical analysis, the artificial intelligence method will have unique advantages in the online transient stability analysis of the power electronic system. Of course, there are also shortcomings. We will analyze it specifically in the following sections.

3.4. Other methods

In addition to the above three methods, some other methods usually are applied in the transient stability analysis of the system, such as the inverse trajectory method and semi-tensor product method.

The inverse trajectory method thinks of an asymptotically stable region and the points set on the region boundary (70)(159), obtaining the inverse trajectories by inversely integrating these points to estimate the stable boundary with the set of the inverse trajectories. It is only possible to inversely integrate some points on the boundary. Moreover, to get high accuracy, the number of point sets on the boundary will grow exponentially with the order of the state variables. So this method is always used in low-order systems and needs to be more general.

The semi-tensor product method directly judges the stability of nonlinear systems through the semi-tensor product of multivariate polynomials (71). The most significant excellence of this method is that it does not construct the transient energy function of the system, basically realizes the automatic generation of the system stability judgment, and gives a suitable solution for the boundary of the attraction domain. But, the stable domain boundary approximation based on the semi-tensor product method is restricted by the system dimension, which is challenging to apply in large-scale power systems (72).

As Table 2 shows, We summarized all the above five methods in detail.

4. The Rationality of the Application of AI to Transient Problems

The traditional study of TSA problems begins from the physical mechanism, which mainly includes the numerical integration methods based on mathematical modeling and a direct analysis method of the energy transformation of the system (99). Using AI to study transient problems, data models are used to replace the complex power system model or energy function. As the following discussion, the current development state, the application of AI to the power system is mainly driven by three aspects.

1. Security Drive: Human security or power system operations and maintenance risks need to rely on AI technology to replace personnel or workflow.
2. Efficiency Drive: Traditional working methods and modes have low efficiency. So it isn't easy to adapt to the development needs, and they need to rely on AI technology to improve business efficiency.
3. Data Drive: A large amount of data has been generated and accumulated but is not effectively used. So we need to rely on AI technology to explore the value of data.

The theoretical basis of AI applied to the study of transient problems is that the causal data containing the physical mechanism usually also shows the external characteristics of the data correlation (100). To mine the data correlation in transient problems using AI is to reveal the physical properties of power system transient issues from the data perspective. New changes appear in information, mechanism, simulation, analysis, and control (101; 102; 125), as shown in Figure 4.

1. Depth Information. Under today's smart grid construction concept, electric power enterprises need to diversify power grid system transformation, combined with automation technology, artificial intelligence technology, big data technology, IoT technology, and sensor technology to external power physical information effective collection (104), analysis, fusion, use, then by the central processor issued directional control instructions, to complete the whole power system control. In this process, to realize the function module efficient cooperation, effective integration, and analysis of all kinds of data information, to advance the quality and efficiency of power system operation (105). At the same time, the whole power grid system to use the function should be compatible with each other to improve the integrity and comprehensiveness of the power grid system operation, realize the equipment coordination, cooperation, and mutual control form of work (106).
   In the existing power system information management mode, information technology, information generation, time, category, and structure size tends to diversify development trend (107). The related work needs to use vast amounts of data information as the primary support, realize the effective research on the transient problem of the power system, and give relevant research

Table 2
Comparison of transient stability analysis methods

<table>
<tr><th colspan="2">Methods</th><th>Information provided</th><th>Application</th><th>Challenges</th></tr>
<tr><td colspan="2">Time-domain simulation</td><td>System response time</td><td>Main methods in the industry;
Standards for other methods.</td><td>Model-solution methods require both simulation accuracy,speed and transient instability criterion to shorten calculation time (73; 74; 75; 76; 77)</td></tr>
<tr><td colspan="2">Direct method</td><td>Estimates of the domain of attraction</td><td>Reinforcement time domain;
Online transient stability analysis</td><td>Suitable Lyapunov functions and make the estimation of the domain of attraction (75; 78; 79; 80; 81; 82)</td></tr>
<tr><td rowspan="4">AI</td><td>ANN-based(83; 86)</td><td>Huge samples</td><td rowspan="4">For the pre-processing and post-processing of the data</td><td rowspan="4">Reduce the deviation of the analysis results from the actual stability index when the actual data is inconsistent with the preset data</td></tr>
<tr><td>SVM-based(85; 86)</td><td>Muti-scenes multi-parameters</td></tr>
<tr><td>EL-based (87; 88; 175)</td><td>Multi-learners</td></tr>
<tr><td>DL-based(90; 91; 92)</td><td>Mass data</td></tr>
<tr><td colspan="2">Inverse trajectory and Semi-tensor product</td><td>Estimates of domain of attraction</td><td>Low-order systems</td><td>Large-scale system extending (93; 94; 95; 96)</td></tr>
</table>

work sufficient data support (108). Meanwhile, with the increasing amount of data , people for the transient research and thinking methods have corresponding change and optimization, the causal logic to analyze and process data, but the related analysis work is challenging to adapt to today's high dimensional heterogeneous diversified information processing requirements, combined with the effective use of AI technology can also maximize the efficiency of data processing, fully realize the potential data mining and use, to maximize the value of multiple information.

2. Complicate Transient Stability Mechanism. In the current power system research, for example, in the existing power system that introduces new energy, UHV DC, and inverter loads, the transient problems we face often have very complex characteristics (109). Based on the sampled electronic components, if combined with the corresponding AI algorithm, the complete fitting analysis of the input and output information of the power electronic components can be realized. And on this basis, the long-term simulation processing can be realized by establishing the analysis model of the interweaving influence mechanism of the electronic system transient problem so that the related work can be stable and efficient. In recent years, the electricity market has further focused on the economic level. Therefore, power companies must comprehensively study the behavior of the current power market to determine the factors that affect the transient stability of the power system. In addition, researchers need to understand the complexity of the transient stability mechanism from sociology, physics, economics, and other perspectives to carry out relevant research work to establish a transparent artificial intelligence transient information system. Since the transient stability of the power system needs to combine a variety of mathematical analysis models and digital structure models, we not only need to carry out fragmented information analysis and control but also consider the actual operation of various equipment. In this way, the docking in the process of running data is completed, effective integration is carried out, the application quality is improved, and the efficiency of related stability analysis work is.

3. Refinement Power Grid Simulation. Due to the limited practical cases of the transient stability problems in the actual power grid, the need for more data highlights the importance of studying the transient problems in the power system through simulation. Two problems exist in the simulation (136). One is the complex links, and the other is that the existing hardware computing power and data throughput speed are difficult to process the huge simulation data volume of the large-scale power system. Because of the difficult problem of modeling the complex links of the actual power grid,

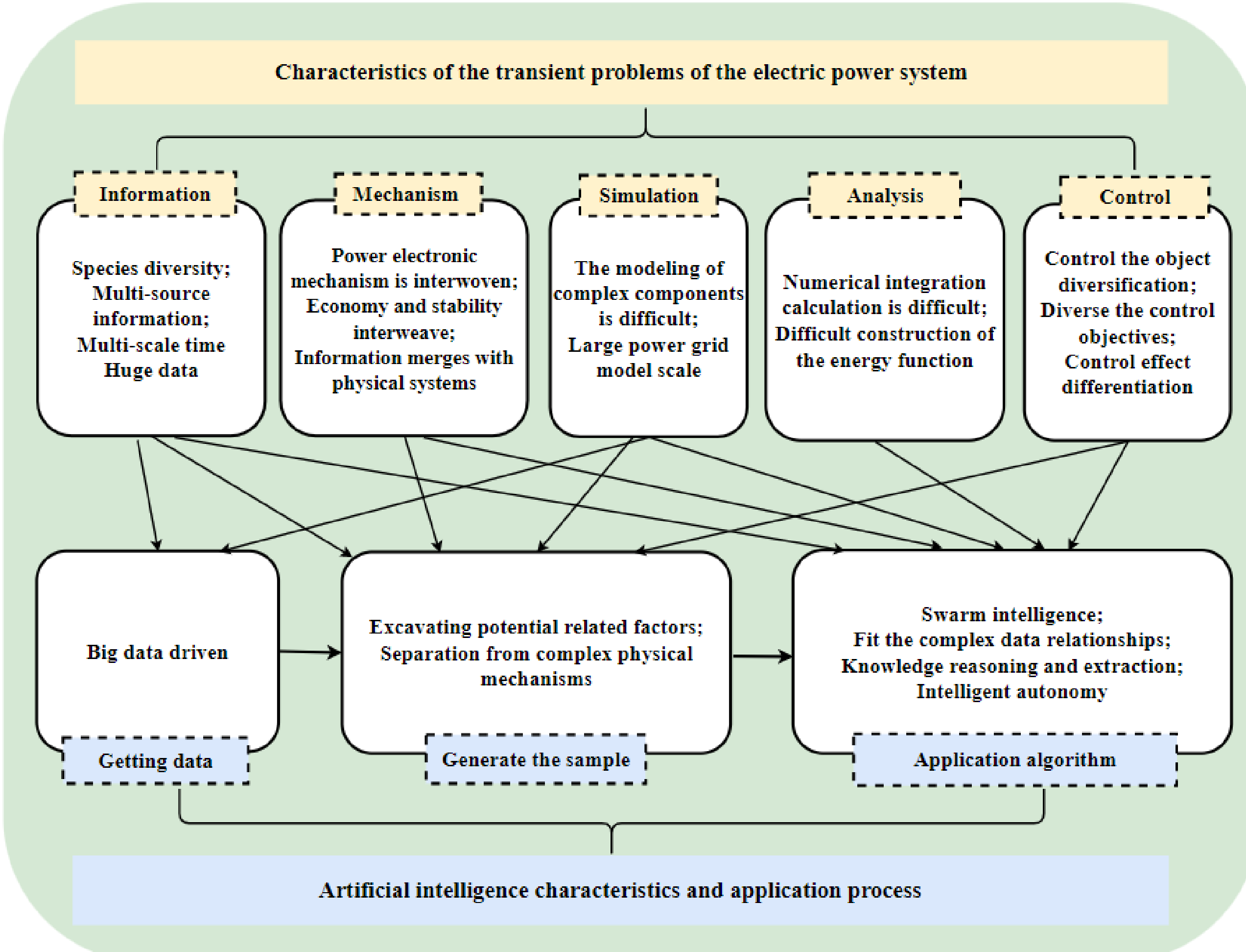


Figure 4: The Transient Problem Matches the Process of AI

we can explore the characteristics of AI separated from the physical mechanism and simplify the modeling problem by fitting the response characteristics of each link of the power system. For simulation computing problems caused by large scale, we can try to establish a simulation platform with self-learning ability through the introduction of AI algorithm to make the simulation program follow the rules, to improve the generalization of the overall fault set (112; 113; 114).

4. Limitations of the analytical methods. Generally speaking, electric power enterprises often combine the direct or the corresponding numerical integration method to analyze and discuss the current internal power system transient problems (116). The discrete characteristics of the power system have also been further improved with the support of diversified technologies. Therefore, combined with the traditional numerical integration method or the establishment of differential equations is often challenging to complete the practical analysis of the relevant transient stability. The direct method can usually only be applied to the transient first pendulum period and the whole transient interwoven environment. Only after fully guaranteeing the feasibility of analyzing the entire transient process can we fully use AI technology to diagnose and mine the existing power transient problems. Explore the mechanism of the analysis method effectively, with the help of extensive data knowledge and the related big data technology to conduct the deep mining of data information (117).

5. Diversification of Transient Control Problems. At the present stage, the transient problem control technology of the power system is faced with the expansion of the scope of the control object, the increase of the control target dimension, and the rise in the control challenges due to the unclear mechanism. The research on intelligent control in the power system is from the brilliant controlling perspective. We hope to give "knowledge" and "judgment" to the computer to realize the whole-process intelligence of prevention, emergency disposal, and recovery of transient problem control (118). Therefore, introducing AI into the control field of transient

problems, and taking advantage of AI in group intelligence, processing complex data relationships, and learning ability, can help to relieve the pressure of traditional control modes to cope with uncertain scene control.

Overall, the study of transient problems faces many technical difficulties, while AI can be separated from the constraints of physical causality through the complex. It is fitting for miscellaneous data relationships to implement data-driven problem analysis. Therefore, the application of data-driven AI technology to the transient stability problem of the power system has become a development trend of the combination of inside-out demand and inward-out drive.

5. The TSA Framework and Design Process Based on AI

In general, based on the sample non-mathematical model of the power system, TSA design includes the following steps: training sample generation, data pre-processing, candidate input characteristics and determining the results of the evaluation, key feature selection/extraction, intelligent stability evaluation technology selection, learning and assessment model establishment, result test, etc. (120), the feature selection has attracted wide attention in recent years, the specific role and requirements of each link are as follows:

1. Generation of the training samples. Theoretically, these samples are required to cover the entire sample space and obtain a reliable stability assessment through learning knowledge (121). Training samples can generally be generated from the history of the power grid or by numerical simulation.
2. Data pre-processing. The training samples were preprocessed to improve the efficiency of the subsequent evaluation process (122), such as excluding the unqualified samples and normalizing the characteristics of the different scales.
3. Selection of the candidate input and the evaluation output. Candidate input features must have a relatively complete representation of the system state, with sufficient information needed for stability assessment. The output of the stability evaluation results can generally choose the binary judgment of stability/instability or a continuous index that can reflect the stability level of the system (123).
4. Key feature selection/extraction. Most intelligent methods require reducing the input space dimension, eliminating redundant features, and improving prediction efficiency. Before, the process was almost completed by the subjective experience of experts, but now it tends to be realized through objective feature selection algorithms.
5. Establishment and learning of the stable evaluation model. Establishing the mapping relationship between input features and output through learning-functional intelligent technologies (124), including artificial neural networks, decision trees, knowledge mining, and reasoning, namely modeling and knowledge acquisition, is the core of intelligent stability evaluation design. Choosing a suitable algorithm model directly determines the reliability, interpretability, and generalizability of the stable evaluation results.
6. Results test. The intelligent stability assessment model must verify its effectiveness and adaptability through many test samples, widely distributed and independent of the training sample (125).

In practice, steps 1,2, and 6 are handled in the same way, and the differences are mainly concentrated in the three steps 3,4, and 5. A general TSA framework based on AI is shown in Figure 5.

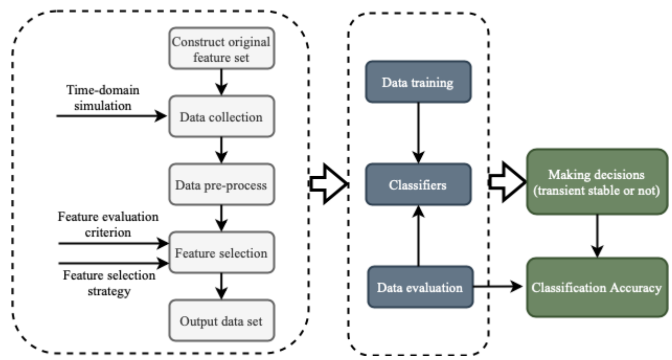


Figure 5: An Example of TSA Framework based AI

The authors think that "feature reduction" is significant to study here. Two important aspects must be considered: the evaluation criterion and the designed feature selection strategy. Now, much valuable research on TSA feature reduction has been done. We briefly review it as follows. In (128), sensitivity index and analysis were used to build an original feature set without redundant features. Then, the principal component analysis was used o reduce the dimensions of the input feature. In (129), correlation and principal component analysis were used for feature selection. Still, this method can only judge correlations between features and cannot reflect the interdependency between features and classes. The feature space obtained by principal component analysis cannot be as complete as the original one. In (130), a breadfirst searching technique based on the separability index was proposed to find an optimal feature set that considers the correlation between features and classes. But the redundancy still exists. According to the above, an optimal feature set must have no redundancy and be closely related to the classification.

6. Application of AI in Power System Transient Problem

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 (132). 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.

6.1. Data acquisition

Obtaining the state variable data related to the transient stability analysis of the power system is the primary problem of AI applications (133). The data's size, type, and quality greatly influence the research results. The data source of the existing research is mainly the simulation software simulation data, whose advantage is that it can customize various fault scenarios and data volume according to the study needs to provide a suitable training and test data set for the AI algorithm (134). The existing research simulation parameter setting methods can be divided into artificial determination and probabilistic model generation.

The first approach relies on researchers to set up typical power and load parameters, fault types, and network topology (135). The second type of method sets the simulation parameters based on the probabilistic model, which is usually generated based on the partial actual data of the component or the system to simulate the real power grid situation as much as possible (136).

Mass fault data can be generated through simulation calculation, but ensuring the consistency of simulation and accurate data can be challenging. The simulation results often need to be more consistent with the precise fault results for the actual power grid accident analysis. The research on the simulation platform and software can improve the performance and reliability of the simulation and provide technical support for the refinement of the temporary stability analysis model of the power system (137).

Currently, simulations obtain stability analysis data rather than actual failure data for stability analysis (138). This is due to the real failure of the power system, especially the very low probability of transient instability failure. Due to changes in the power system, the applicability of historical data reduces, and it is not easy to offer high-quality training data for AI algorithms (139). From this perspective, enhancing the similarity between simulation and actual fault data becomes a problem. It is feasible to solve the problem of establishing the mapping relationship between simulated and actual data, then correct the deviation of simulated data.

6.2. Sample generation

The original data of the power system includes each time data of each sampling point through the whole test system. So the spatial and temporal dimension of the data is relatively high. If all the data are included in the AI algorithm training, the training time, accuracy, and convergence are tough to control (140). The existing studies mainly process the original data from the aspects of data pre-processing, feature attribute selection, and dimension (141) to obtain the transient stable samples that can be used for the AI algorithm and improve the training efficiency of the algorithm and ensure the test accuracy.

Data pre-processing is to make the processing of raw data into standardized data to meet the research needs. Its processing methods vary according to the problem. In addition, the pre-processing data methods commonly used in AI applications include data cleaning, integration, and transformation (142). Data cleaning is to correct the error or missing data in the transient problem. The data integration will integrate the multi-source data related to the transient problem (143). The data transformation is to transform the transient simulation data or the actual data format into the form that the algorithm can use (144).

In essence, the feature attribute selection is mainly based on the known mechanism of the transient problem, which retains the factors closely related to the research problem while ignoring the factors with less influence. The feature selection of the existing studies is based on physical relevance. At the same time, the filtering, packaging, and embedding methods based on data analysis rules have yet to be widely used (145). Most existing studies focus on standard test systems, and the sample generation method can better adapt to them. However, the scale of the actual power grid is much larger than the test system, and the applicability of the existing methods remains to be verified. In addition, the feature attribute selection methods based on the physical mechanism are somewhat subjective and incomplete, which may affect the research results.

6.3. Algorithm application

Algorithm selection is the core content of the research. An appropriate algorithm and reasonable parameter configuration determine the speed and accuracy of the transient problem research. According to the type classification of AI algorithms, the existing research on transient problems is mainly the traditional machine learning classification, regression algorithms, and the newly developed deep learning-related algorithms (146). The following introduces 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. It analyzes the prospect of frontier deep learning technology for transient stability.

6.3.1. ANN-based TSA method

The artificial neural network has strong plasticity, which can transform the network structure and activation function according to the research needs. Therefore, it is widely used in the strong non-linearity condition of the power system to establish the accurate mapping relationship of many influencing factors and the system state in the transient stability problem (147). Studies have shown that ANN has advantages in data fitting ability, but there are also the following problems: first, ANN needs a large number of samples for training; second, the computing scale of ANN training increases exponentially with the number of network nodes

6.3.2. *SVM-based TSA method*

Based on the Vapnik-Chervonenkis (VC) Dimension and the minimum structural risk principle in the statistical theory, the SVM enables an accurate classification in a small sample space (149). The study shows that the SVM can judge the transient stability after the system suffers symmetry and MIS failure. When the system's stability is affected by improper parameter selection, SVM can reduce the probability of misjudgment or omission. Even if the transient samples in the power system are updated in real-time, the incremental sample training can be stably improved with SVM, thus improving the training efficiency and timeliness of the prediction model.

6.3.3. *EL-based TSA method*

Ensemble learning combines multiple learners into more robust generalization algorithm models by combining strategies, sacrificing computational complexity for algorithm performance (150). The weighted ensemble algorithm based on cross-entropy achieves accurate prediction in a small sample space; the ensemble learning model is constructed to adapt to the system operating conditions and line topology and realize the online dynamic security evaluation. The integrated learning algorithm solves the accuracy fluctuation problem of a single algorithm prediction model and dramatically improves the reliability of transient problems (151).

6.3.4. *DL-based TSA method*

With the rapid development of AI technology in recent years, deep learning has shown strong data mining capabilities, and its application to transient problems has also been practical. Compared with traditional machine learning methods, deep learning can use massive samples to improve the accuracy of the algorithm and mine deep complex associations in data (152). Advanced technologies such as the two-stage deep learning training framework of "pre-training and fine-tuning parameters" and the quantification technology of system emergency control strategies after large disturbance failure not only improve the accuracy of transient stability assessment problems under a small number of samples and irrelevant features but also provide more intelligent regulation strategies.

In addition to the above algorithms, other AI algorithms used for transient stability include expert systems, limit learning machines, Bayesian models and decision trees, etc,(153). In addition, many new technologies in deep learning, such as generative adversarial networks, reinforcement learning, and tensor computing units, are emerging and have the potential for application in transient problems in power systems. The network can realize a zero-sum game between generating and discriminant models and realize iterative training between the simulation data generation model and stability evaluation model; reinforcement learning is based on the existing environment to minimize the loss by emergency control. The tensor computing unit is a special chip designed by Google for the deep learning framework TensorFlow, which significantly improves the computing speed of the deep learning model rate (154). The huge scale of tens of thousands of nodes and lines in the power system puts forward strict requirements on the training and prediction time of the transient stability evaluation model. The tensor computing unit can provide floating-point computing millions of times per second and accelerate the training of the deep learning model.

Currently, the limitations of applying AI algorithms to transient problems are as follows:

1. The high dimensional characteristics of the power system lead to the long time-consuming algorithm training (155);
2. The generalization performance of a single prediction model is challenging to cope with the complex and changeable power system operation scenarios (156);
3. The AI algorithm, divorced from the power system physics, is a "black-box" model for researchers. It is weakly interpretable, and it is difficult to analyze the physical nature of transient problems (157).

For a more precise understanding, as shown in Table 3, we present the standard algorithms under different AI models and the application scenarios.

7. Specific Application Analysis of AI in Transient Problems

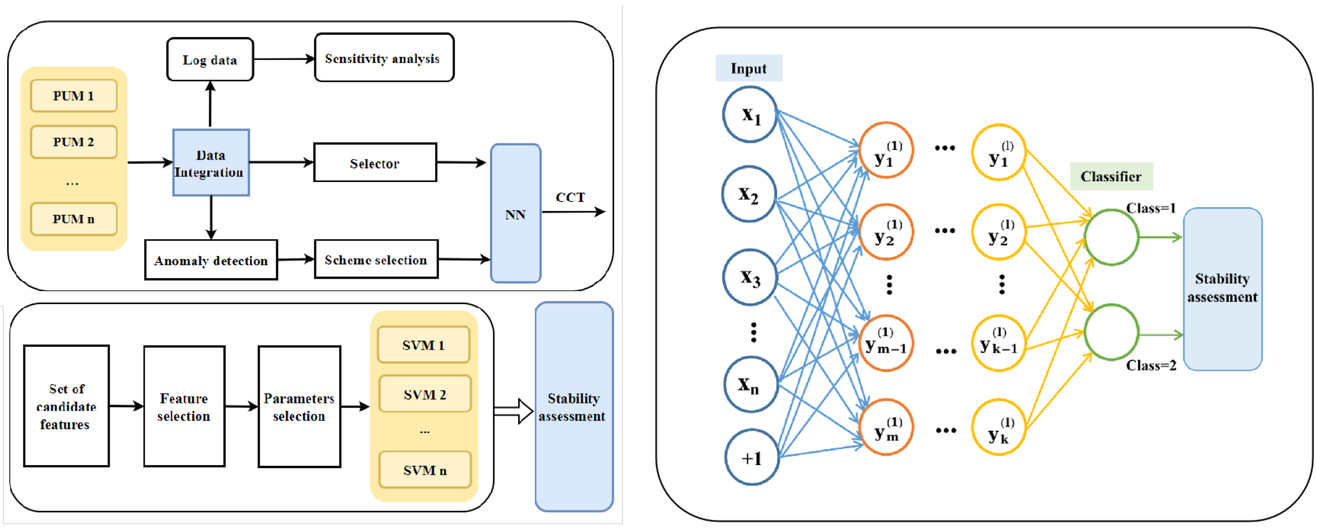
The above analyzes the application status of AI in the transient stability of the power system and summarizes the three problems existing in data acquisition, sample generation, and algorithm application. Given some issues living in the existing research, this paper puts forward the following research ideas to discuss the application of AI in the transient problem of electric power systems.

7.1. AI-based data scarcity time-changing problem

Influenced by the network topology, component state, and fault type, the transient process scenes of the power system are diverse, and the data is scarce in a single scene. The stable condition and small disturbance scenes are primarily present, while the large disturbance scenes are few. Therefore, it is urgent to fully excavate the correlation of data sets under different scenarios, realize the mining and migration of common knowledge, and achieve the breadth of knowledge inheritance.

Data accumulation during the power system operation can provide data supplement for the original law mining. Due to the time limit of the online application, the knowledge update should be realized without resuming the large-scale calculation to realize the online depth growth of the knowledge model.

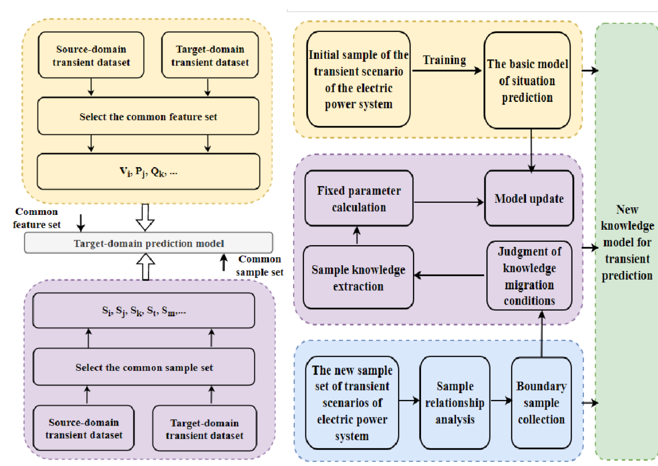
Breadth-inheritance: The initial state of a power system forms many new scenarios in the grid topology, generator configuration, and external power grid (158). When the target domain appears, the transient stability prediction model of the power system may fail due to the lack of data. Therefore, the breadth inheritance of the model can be sought



(b) ANN-based and SVM-based TSA Model

(b) DL-based TSA Model

Figure 6: AI algorithms-based TSA Model



(a) Thinking of Breadth-inheritance

(b) Thinking of Deep-inheritance

Figure 7: Thinking of Breadth-inheritance and Deep-inheritance

from the perspectives of the feature set and sample set. As shown in Figure 7(a), considering the transfer of knowledge based on standard features before and after the mining scene changes, that is, using the standard feature set in the source field and target field to improve the applicability of the source field prediction model in the target field; considering the operation scene of the power system, there are still some samples in the source field and target field that follow the same data rules.

The generic sample set is trained as the predictive model to expand the sample set in the target domain and improve the prediction accuracy.

Deep-inheritance: To effectively manage the new sample data continuously generated in the power system's operation and strengthen the power system's transient stability analysis based on AI, the latest data needs to be classified and learned in time (178). If the way of relearning all the data is adopted, it will take a lot of time and may even cause the learning speed to lag behind the data update speed. That is, the transient stability prediction model of the power system urgently needs the ability to update, correct, and strengthen knowledge quickly. As shown in Figure 7(b), improving the knowledge-learning efficiency of the transient stability prediction model of the power system mainly includes two aspects: on the one hand, analyzing the inclusion relationship between the new sample and the initial sample set, the samples containing the latest information are retained, and the redundant new samples are eliminated to form the boundary sample set; on the other hand, the parameters or structure of the original algorithm model are modified by using the boundary sample set.

7.2. AI-based features extraction subjectivity and incomplete problem

Feature extraction based on physical causality can only be conducted for features with a precise mechanism while ignoring some factors that have an unknown agent or indirectly affect the transient problem (179). This paper proposes a solution based on deep learning for this problem.

Compared with general machine learning algorithms, which require the artificial design of efficient feature sets, deep learning can automatically handle all features (180). Therefore, more complex combined features eliminate the possible omission of feature extraction algorithms and subjective factors. Figure 8 shows the process of deep learning for feature extraction and modeling the power system's transient stability problem. The framework consists of two layers of deep learning models, one for feature extraction and the other for advanced modeling of critical regions.

Existing modeling methods are usually based on the unified simplified modeling standards of the whole network.

Table 3
Comparison of AI-based TSA methods

Method	Algorithm	Usage
ANN	Long short-term memory (160)	To equilibrate the trade-off between the response time and accuracy, a temporal self-adaptive method is raised.
	Convolutional neural network (161)	It could analyze whether the power system is stable or not and predict the unstable pattern in the unstable state.
	Spatial-temporal graph convolutional network (162)	It integrates the information from network topology and evaluates the temporal information using 1-D convolution.
	Recurrent graph convolution network (163)	It forms the RGCN by aggregating the GCN and the LSTM units.
SVM	SVM (164; 165)	It can make early predictions based on post-failure measurements of the generator voltage, speed, or rotor angle.
	Aggressive SVM and conservation SVM (166; 167)	A strategy combining two SVMs and a grey region is proposed to address the problems of false dismissals and alarms.
	Core vector machine(168)	A TSA model which is based on a core vector machine is developed.
	Multi-layer SVM (169)	It uses a genetic algorithm based on the TSA model of the MLSVM to identify a subset of valued features with a different number of features.
EL	Stacked autoencoder and a voting ensemble (175)	The ross-entropy is used to evaluate the underlying learner fit performance and sets the weight coefficients in the integrator.
	Bayesian multiple kernel learning (171)	Using post-disturbance PMU data to predict stability margins and given emergency.
	Mahalanobis kernel(172)	Utilizing the data under different network topologies effectively improves the estimation accuracy and reduces the need for training samples.
	Adaptive ensemble decision tree(173)	A transient stable method based on DT learning is proposed, considering changes in operating conditions and topology.
DL	Deep belief network (174)	Unsupervised learning with unlabeled samples was used to initialize the data, and then fine-tuned using supervised learning with labeled samples.
	Stacked autoencoder(175)	A stacked autoencoder-based method for TSA feature reduction is proposed.
	CNN-LSTM (176; 177)	For small signal and transient stability, a unified DL prediction model is raised.

They need to distinguish modeling according to the importance of each region and equipment, resulting in reduced accuracy and even errors in model results. Therefore, it is necessary to fine-model the relevant parts of key features extracted by deep learning (181). Characteristic extraction and dimension reduction are realized through the convolutional neural network in the deep learning framework. In the convolutional neural network algorithm, the weight-sharing technology can recognize the aggregation of input parameters, combined with the construction of different convolution kernels with other parameters, to realize the extraction and abstraction of critical features (182). Based on the correlation between the input features, the compression and dimension reduction of the feature parameters of the

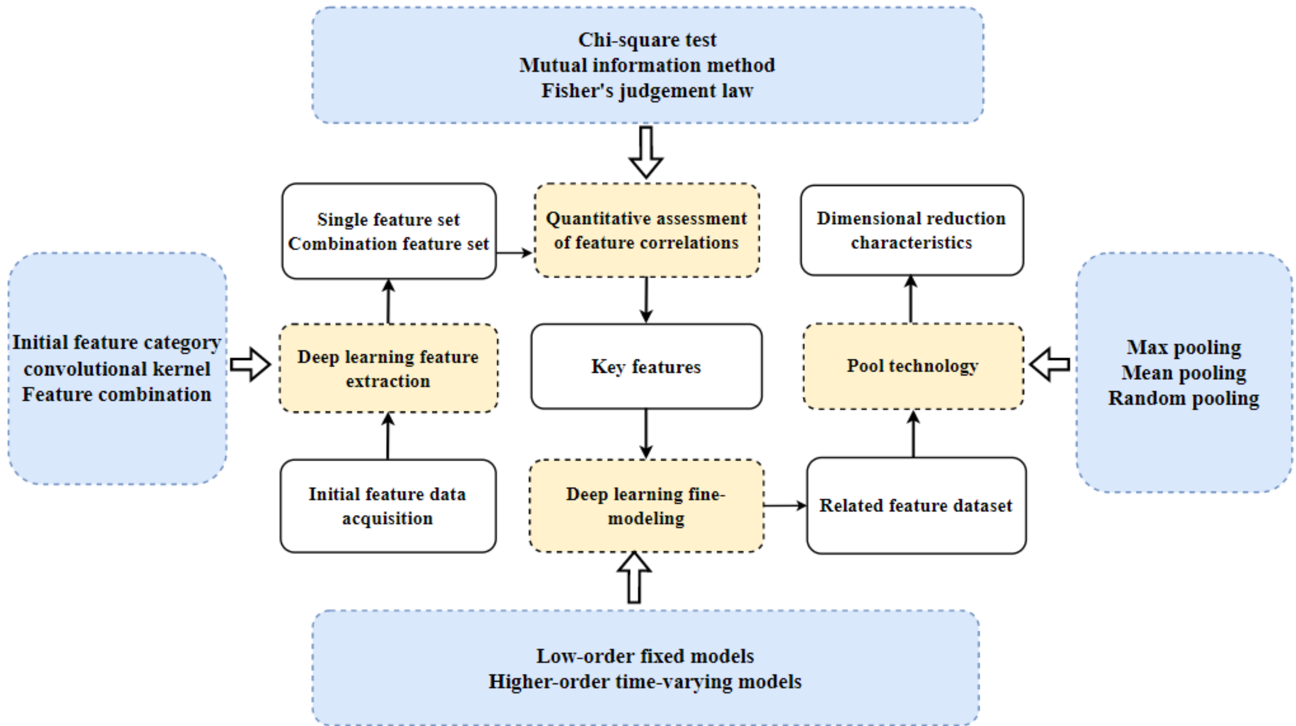


Figure 8: Deep Learning Modeling Process of Transient Stability Power System

refined model can be further realized by designing proper pooling functions.

7.3. AI-based transient prediction models interpretability problems

To make full use of the known physical causal knowledge of the power system, improve the model interpretability and reduce the over-fitting of AI to the data, the research team at home and abroad put forward the method of the physical model and data-driven fusion and carried out preliminary exploration and research.

On the one hand, the physical analysis method can provide high entropy information for data analysis methods and improve the efficiency of data model analysis. The search space can reduce the calculation complexity when solving the data model parameters. The high entropy input feature makes the goal of building the data model and improving the rationality of data model. Data-driven methods can compensate for the loss of laws caused by model simplification in physical analysis methods (183).

The core of physical data fusion modeling lies in the fusion mode of the two. According to the difference between target and data sets predicted by transient problems, different physics, and data-driven method fusion modes should be studied:

1) Embedding physical knowledge into the data model to improve the computing efficiency of the data model;
2) The low accuracy problem is caused by the excessive simplification of the physical model, and the data-driven method with a rich sample basis can be used to fit the error rule and correct it; The physical model is challenging to model because the mechanism is unknown, and the physical mechanism is mined through the data-driven method to assist in the establishment of the physical model or the correction of the model parameters;
3) Weighting the prediction results of the physical model and the data model is used to improve the stability of the prediction results.

8. Future Challenges and Trends

The power system has remarkable characteristics, including many nodes, complex electrical connections, and AC and DC interconnection across different regions. It puts higher requirements for prevention and control before failure. As Table 4 shows, artificial intelligence has different degrees of requirements for designing, controlling, and maintaining power systems. The existing technology can no longer well meet the future development trend. In this section, we will discuss the future trends and challenges in 2 directions: AI orientation and AI-Big data orientation.

8.1. 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 classification model applying the machine learning algorithm has weak adaptability to the system network frame structure. The retraining caused by the network frame change leads to a long time cost, a long rapidity, and a weak generalization ability. The NN (Neural Network)-based TSA method causes misclassification due to the limitations of the algorithm itself or the insufficient boundary sample density; the accuracy of a single SVM classification is not high, and there are often "overlapping regions" between different types of sample data, resulting in the misjudgment. Missing results are treated as the same situation.

Challenge 2: Deep learning has been applied in transient stability evaluation in recent years. Compared with traditional machine learning algorithms, its advantages are also relatively obvious. However, some difficulties, such as DBN's structure and parameter optimization problems, and noise's anti-interference ability and misjudgment problems should be studied more. At the same time, there is also weak adaptability to the system network structure.

Challenge 3: The WAMS measurement data has spatial and temporal characteristics, which can provide a large amount of state information about the system, which plays a crucial role in realizing the quantitative assessment of transient stability. However, the construction of transient stability could be better and sometimes cannot meet the strict concept of margin.

Challenge 4: Using big data technology from the perspective of data mining, judging the transient stability is relatively poor, and the evaluation index system is not perfect.

The 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 transient stability assessment of power systems. Possible future research includes the following points.

Trend 1: Improve the real-time performance of the classification models. Existing machine learning-based TSA methods all train the data samples offline and then classify or predict the steady state. Although some literature gives the online evaluation method of transient stability by combining WAMS response, the real-time performance could be higher due to its offline training. Future studies should focus on implementing online training to meet real-time requirements better. (The meaning of online training is that at the end of each data entry, the model will enter the renewal stage, using the model of the previous time node and the real-time data of the current time node for evaluation.)

Trend 2: To improve the comprehensive application research of deep learning in transient stability evaluation. Compared with traditional machine learning algorithms, deep learning has certain advantages in key feature quantity extraction and model adaptability, but there are still some problems to be studied urgently. It is suggested to quantitatively analyze the influence of the system network structure change on the model and the interference degree of the noise on the training process and the results in the future, strengthen the study of the miscalculation problem, and finally analyze and verify its practicability in the existing system.

Trend 3: Enhanced model robustness to insufficient data. Some bad data will still exist in the sample obtained by the dimension reduction of the original data set, and some key data may be lost in the process. On the one hand, the model can analyze the existing system's possible missing data and insufficient data. On the other hand, the training model should be used to test the quality of the data.

Trend 4: According to the research, most existing TSA methods are not applied to practical operation. To analyze and verify its practicability and reliability, it is necessary to establish the identification model of the power grid fault form and construct the intelligent power grid fault identification and stability evaluation framework. The characteristics of different TSA methods should be accurate simulation analysis of other TSA methods based on multi-source real-time measurement data, offline simulation data, and dynamic simulation experimental data further to promote the TSA method's application in practical systems.

8.2. AI & Big data-orientation opportunities and challenges

As the importance of data gradually gets attention, big data technology to solve problems related to the power field is also gradually increasing. In big data technology, to a certain extent, the operation can be separated from the actual physical model and mine the internal correlation. The operation characteristics of the power grid from the massive PMU data so that the operators can correct the dire state of the power grid in time to reduce the probability of the power grid failure. In the future, TSA will mainly focus on the following directions using big data technology.

Challenge 1: Massive data integration and storage. Traditional data assessment always deals with data from a single domain. Therefore, finding a suitable fusion method for multi-source datasets with different patterns, formats, and representations is necessary. Although some systems seem feasible in terms of big data storage, they still need to be adjusted and modified to accommodate big data.

Challenge 2: Real-time data processing technology. The reaction time must be in milliseconds for some emergency applications. However, the proposed system can offer high-speed computing, network congestion, and flexible algorithms. Combining massive data still needs to be completed on time. A database in memory may be a feasible measure.

Challenge 3: Compression of data. This technique is essential in wide-area surveillance systems. It can meet high-fidelity requirements through its characteristics. Moreover, unique compression methods are needed to detect transient interference (184).

Challenge 4: Big data visualization technology. Visualized figures can show apparent differences in granularity and frequency and voltage. However, effectively discovering and representing correlations in multi-source data is a considerable challenge. Other challenges include visualization algorithms, information extraction, representation, and image synthesis techniques.

Challenge 5: Data security and privacy. Because of the increase in the number of smart meters for home energy consumption, more personal information has emerged. Since data is shared between different entities, private data leakage can be a disaster and cause cascading problems.

Trend 1: Deep generation learning based on data enhancement is a promising technique that can be used to solve complex data analysis problems. But machine learning algorithms have high learning efficiency but are restricted by computational complexity, so they cannot effectively analyze large-scale data sets. The following study is recommended for this problem: (1) Use parallelized and improved machine learning algorithms. That is, through the big data distributed platform, the parallel machine learning algorithm is rewritten to realize parallel computing. (2) Compared with SVM, the running time and space of a core vector machine (CVM) are less affected by the data scale and are more effective than big data technology. However, there are very few studies on the application of CVM in stability evaluation. Therefore, it is suggested that the future combines big data technology to study further the adaptability of CVM to solve the TSA problem and to quantitatively analyze its computational efficiency in the context of big data.

Trend 2: To deal with mas data, a standardized information model should be proposed to describe interoperability among various big data analytic platforms, architecture, and operational integration. Besides, cloud computing service vendors are necessary.

Trend 3: Existing big data applications are all based on a single data type. However, future applications should leverage multiple big data sources, which can help to assess critical infrastructure dependencies. Therefore, data centers should be created and easily accessible to improve the resilience of critical infrastructure. Future grid applications will leverage these heterogeneous large data sets, which can reveal vital hidden information.

9. Conclusions

Power electronization, physical information integration, and complex interconnection of large power grids have become the development trend of the new generation of power systems. The characteristics of transient problems also change regarding information, mechanism, simulation, analysis, and control. AI can be used to break away from physical mechanisms and fit complex data relations to realize data-driven problem analysis. Therefore, the application of data-driven AI technology to the transient stability problem of the power system has become a development trend of combining inside-out demand and inside-out drive.

This paper proposes the following research ideas for the application of AI in the transient stability problem of electric power systems:

1) Deal with the problem of small data quantity and substantial time variation of the actual system through data inheritance thought;
2) Use deep learning algorithms to mine potential relevant feature values to solve the possible subjective and incomplete problems in feature engineering based on physical mechanisms;
3) Integrate a physical data model to analyze transient problems, which helps to improve the interpretability of research results.

The application of AI technology in the transient stability problem of power systems is expected to make breakthroughs in the following two levels: in the application algorithm level, advanced algorithms represented by deep learning have the potential for broader application; in the research direction, it can expand to the level of online prediction of stable situation and proper stability control strategy of a stable situation. And if artificial intelligence and big data are effectively combined, it will bring more significant performance improvement to the transient stability of the power system.

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