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Review of Neural Network-Based Transient Stability Assessment

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Abstract. With the increasing share of renewable energy generation in recent years, the inherent uncertainty associated with renewables has posed unprecedented challenges to power systems. Consequently, the demand for fast and accurate transient stability assessment (TSA) methods has become more critical. Neural networks, a significant area of inquiry within artificial intelligence, have been utilized in TSA challenges. This work provides a thorough review and comparison of three prominent TSA methodologies: time-domain simulation, transient energy function techniques, and artificial intelligence-based approaches. Representative studies examining diverse artificial neural network topologies, input feature selection methodologies, and hybrid modeling techniques are presented. At present, TSA of power systems faces numerous challenges: Although artificial neural network (ANN)-based methods have high accuracy, they still have incorrect predictions and lack constraints of physical laws; traditional time-domain simulation methods are computationally time-consuming, and transient energy function methods are difficult to apply to complex systems; meanwhile, the industry lacks standardized datasets and evaluation benchmarks, hindering performance comparison among models. The future development directions include adopting deep learning methods to improve the accuracy and speed of real-time assessment and promoting physics-informed neural networks (PINNs) to integrate physical laws into training for enhancing prediction accuracy.

Keywords: Power system, Transient Stability Assessment, Neural Network, Convolutional Neural Network, Artificial Intelligence

1. Introduction

Transient stability has consistently been a significant issue in the domain of electrical engineering. Unexpected defects, such as short circuits, in the power system can compromise transient stability, resulting in extensive blackouts that significantly affect industrial productivity and public life. The growing integration of renewable energy sources, including wind and solar power, has rendered power system structures more complicated, complicating the evaluation of transient stability [1]. Conventional approaches for transient stability evaluation predominantly encompass the time-domain simulation method and the direct method, also referred to as the transient energy function method. Time-domain simulation is the predominant methodology among them. Time-domain simulations incur 5-30 min computational latency per contingency, precluding real-time application.

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The direct method, on the other hand, uses Lyapunov stability theory to determine system stability. While it offers fast evaluation, it is difficult to determine the transient energy function in complex power systems, which limits its applicability in large-scale systems [2].

The rapid development of neural network (NN) technologies offers new perspectives for solving transient stability problems in power systems. In practical applications, NN-based methods can be integrated with Wide Area Measurement Systems (WAMS) to perform rapid transient stability assessment using high-resolution, time-synchronized data provided by Phasor Measurement Unit (PMU). Transient instability is the core cause of cascading failures and large-scale power outages. In the context of the escalating proportion of photovoltaic (PV) and wind power generation, fluctuations in wind speed and solar irradiance significantly affect the output of PV and wind power systems. This intermittency has rendered the transient stability problem of power systems more complex and deserving of critical attention. This study focuses on leveraging neural network technology to enhance the real-time performance and accuracy of power system transient stability assessment while discussing its application challenges in complex power systems.

2. Traditional method of transient stability assessment

2.1. Time-domain simulation method

This is presently the predominant method for evaluating transient stability in power systems. The core premise is to formulate a collection of differential-algebraic equations (DAEs) that characterize the transient dynamics of the power system. By performing step-by-step numerical integration of these equations, the dynamic response of the system following a disturbance can be obtained, thereby determining its transient stability.

The differential-algebraic equation set can be expressed as:

$$\begin{cases} \dot{\mathrm{x}} = f(\mathrm{x}, \mathrm{y}) \\ 0 = g(\mathrm{x}, \mathrm{y}) \end{cases} \tag{1}$$

where $\mathrm{f}(\mathrm{x}, \mathrm{y})$ represents the system state function and $\mathrm{g}(\mathrm{x}, \mathrm{y})$ describes the power network constraints. The variable denotes state variables, such as generator rotor angles and speeds, while represents algebraic variables, including bus voltages and other system operation parameters.

The time-domain simulation begins with the power flow solution as the initial condition. When a disturbance occurs, numerical integration methods are applied to the DAEs to calculate the evolution of system variables over time. This process generates time series curves of system states such as rotor angles, speeds, and voltages. By analyzing these trajectories—particularly the differences in rotor angles between generators—one can determine whether the system remains transiently stable under the specified fault conditions.

Several well-established simulation tools support time-domain analysis, including BPA, PSS®E, SUROSTAGE, and PSASP. The main advantage of the time-domain simulation method lies in its ability to accurately represent detailed system models and provide comprehensive insights into variable dynamics during transient events. However, this method requires significant computational effort and longer simulation times, making it less suitable for real-time applications. The industry-recognized simulation duration is typically between 15 and 30 minutes [3].

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2.2. Direct method

The direct method, also known as the transient energy function method, is based on Lyapunov stability theory to assess the system's stability during transient processes. Lyapunov stability theory is a fundamental tool for analyzing the stability of nonlinear systems and plays a critical role in such analyses [4].

In this method, an energy function is constructed for the power system as follows:

$$V(\delta, \omega) = T + U$$

where represents the total kinetic energy of the generators in the system, and represents the potential energy, which refers to the electrical interaction energy caused by the rotor angle differences among generators.

The direct method assesses the transient stability of the system post-fault clearance by comparing the energy function's value at the clearing time with the critical energy threshold. Numerous established methodologies are available for ascertaining the critical energy, including the Potential Energy Boundary Surface (PEBS) method and the Controlling Unstable Equilibrium Point (UEP) method [5].

Unlike the time-domain simulation method, the direct method does not require step-by-step numerical integration, which significantly reduces computational effort and enables fast stability assessment. Lyapunov stability theory provides a sufficient condition for system stability, which means the stability conclusions obtained using this method are relatively conservative [6].

3. AI based methods of transient stability assessment

3.1. Introduction of AI based methods

Currently, AI-based transient stability assessment methods using ANN, support vector machine (SVM), and deep learning techniques (such as convolutional neural network (CNN) and long short-term memory network (LSTM)) have become popular research directions and have achieved a series of significant breakthroughs. As shown in table 1, compared with traditional methods, artificial intelligence methods have many differences.

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Table 1. Comparison of three transient stability assessment methods

	Time-domain simulation	Direct method	Artificial intelligence
Solution method	Solving differential equations of the system	Using transient energy function	Using artificial intelligence algorithm
Model request	Accurate model	Simplified model	Without modeling
Advantage	The results of the analysis are clear, intuitive, and reliable, free from the constraints of a power system model	The calculation speed is fast, enabling quantitative analysis of system stability	Without the need for modeling or solving complex equations, it demonstrates strong adaptability
Disadvantage	A high-fidelity model is required, resulting in significant computational time	The calculation results may be conservative and are difficult to apply to complex system	The relationship between input and output is difficult to understand, and training requires a large amount of high-quality data

3.2. ANN: structure

An ANN is a mathematical model that simulates the working mechanism of biological neurons in the human brain. It consists of an input layer, hidden layers, and an output layer, as shown in Figure 1, where the circles represent the neurons in the neural network. The input layer contains only one layer, and the number of neurons in this layer is equal to the number of input features.

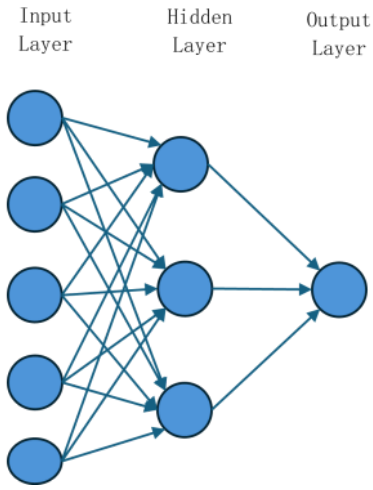

Figure 1. Structure of neural network

The hidden layer can have multiple layers. A deep neural network (DNN) refers to a neural network with a large number of hidden layers. The quantity of layers and the count of neurons within each concealed layer can be manually adjusted. The output layer generates the ultimate forecast result.

Each neuron in the neural network performs the following mathematical operation:

$$y = f\left(\sum_{i=1}^{N} w_i x_i + b_i\right) \tag{2}$$

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where is the output of the neuron, x_i is the input to the neuron, w_i is the weight associated with the input, b_i is the bias term, is the number of inputs to the neuron, and is the activation function of the neuron.

The neural network is trained by minimizing the loss function, which measures the difference between the predicted result and the true label. The goal of training is to reduce the loss function to a predefined acceptable value. The gradient descent algorithm, proposed in [7], is a classical method used to train the loss function. It can be expressed as:

$$\theta_{n+1} = \theta_n - \eta \nabla_{\theta_n} L \tag{3}$$

where represents the model parameters, is the learning rate used to adjust the step size during learning, and is the loss function of the neural network.

4. Application of ANN for transient stability

In recent years, the swift progression of artificial neural networks and deep learning technologies has led to their extensive application across various domains [8]. Neural networks have demonstrated strong performance in tasks such as prediction and pattern recognition across various domains [8]. Given their excellent capability in handling nonlinear classification problems, neural networks have now been widely adopted in TSA of power systems [8,9].

In neural network-based TSA, the selection of input features is paramount. For a certain power system under specified operating conditions, if the fault location, fault type, and fault duration are established, the transient stability outcome of the system is also deterministic, as observed by Zhang et al [10]. Therefore, the types of input features extracted for AI-based TSA should comprehensively reflect the fault scenario of the system.

Zhou et al. categorized the input features of the neural network into two types: operational information of the power system and disturbance information [11]. Different input layers were designed to feed these two types of information separately into the network. The results demonstrated that this method could effectively reduce the number of training samples required for the neural network and shorten the overall training time [11].

CNNs have already become mainstream in the field of image classification, as pointed out by Yang et al [12]. Yan et al. used data extracted during the time-domain simulation process, along with the final simulation results, to train a CNN. This approach allowed for early termination of the simulation while ensuring accuracy, thereby accelerating the evaluation process of the time-domain simulation method [13]. Gupta et al. transformed measured values of the power system into RGB color images, enabling the application of CNNs in transient stability assessment [14]. Zhu et al. converted PMU measurements into 2-D transient images and employed a hierarchical deep learning machine to train a convolutional neural network for transient stability assessment. This method demonstrated excellent performance in tests conducted on the power grid in southern China [15]. Since CNN models are prone to misclassification near the transient stability boundary, Liu et al. propose dividing the prediction results into three categories: stable, unstable, and uncertain (near the critical threshold). Cases predicted as uncertain are then re-evaluated using the time-domain simulation method to ensure the accuracy of the final assessment [16].

Moreover, Graph Neural Networks (GNNs) have garnered significant interest in the domain of transient stability assessment [17,18]. Yang et al. introduced an innovative GNN framework—Global Features-Exploiting Edge Features for Graph Convolutional Networks—which, in contrast to traditional GNNs, can aggregate node, edge, and global features of power systems [17]. Zhang et al.

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proposed a model utilizing a Graph Simplification-based Spatiotemporal Graph Convolutional Network (GS-STGCN). This model utilizes the GS module to improve computational efficiency by removing redundant feature information, while the STGCN layers extract spatial and temporal features from graph-structured data. Their findings demonstrate that this approach decreases training duration and enhances evaluation precision [18].

5. Discussion

Although most ANN-based TSA methods have already achieved classification accuracies exceeding 95%, incorrect predictions still occur [11,13,15]. Therefore, based on current results, it is difficult for ANN methods to completely replace the traditional time-domain simulation method. To ensure prediction accuracy, the approach proposed in the paper should be adopted—using ANN outputs as a preliminary judgment, and when the prediction lies near the critical stability boundary, applying time-domain simulation for further verification [16]. As a result, ANN methods show greater potential in real-time TSA, where they can effectively replace the more conservative transient energy function (TEF) method.

ANNs rely on large volumes of data and learn the mapping between fixed inputs and corresponding outputs. Consequently, unlike time-domain simulation and TEF methods, ANN-based approaches do not inherently adhere to known physical laws. To address this limitation, Liu et al. introduced the concept of physics-informed neural networks (PINNs), which incorporate known physical laws as constraints during the training process [16]. This significantly improves the prediction accuracy. However, research in this area is still limited and requires continued attention.

In addition, the TSA field currently lacks standardized datasets and evaluation benchmarks. Most studies train models using simulation data derived from the IEEE 39-bus system, making it difficult to compare performance across different models. Therefore, it is recommended to establish a unified data platform and evaluation standard for TSA research.

6. Conclusion

This study examines transient stability assessment in power systems and analyzes three predominant approaches: the time-domain simulation method, the transient energy function method, and artificial intelligence-based methods. The time-domain simulation method offers high accuracy, but its large computational burden and long simulation time make it unsuitable for real-time applications. The transient energy function method is computationally efficient; however, due to the difficulty in constructing energy functions for complex systems, it still faces significant limitations. In contrast, ANN-based methods, leveraging the powerful nonlinear modeling capability of ANNs, show great potential for real-time transient stability assessment. Furthermore, it is noted that the current research landscape lacks a unified benchmark dataset and evaluation framework, which hinders fair performance comparison among different models.

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