iEnergy

REVIEW

https://doi.org/10.23919/IEN.2024.0027

Artificial intelligence techniques for stability analysis in modern power systems

Jiashu Fang[1] and Chongru Liu[2]

ABSTRACT

Effective stability analysis is essential for the secure operation of modern power systems. As smart grids evolve with increased interconnection, renewable energy integration, and electrification, the large-scale deployment of ultra-high voltage AC/DC networks introduces various operational modes and potential fault points, posing significant challenges to maintaining stability. Traditional analysis and control methods fall short under these conditions. In contrast, emerging artificial intelligence (AI) techniques, combined with real-time data collection, provide powerful tools for enhancing stability analysis in smart grids. This paper comprehensively explores AI techniques in stability analysis, discussing the necessity and rationale for integrating AI into stability analysis through the lenses of knowledge fusion, discovery, and adaptation. It provides a thorough review of current studies on AI applications in stability analysis, addresses key challenges, and outlines future prospects for AI integration, highlighting its potential to improve analytical capabilities in complex power systems.

KEYWORDS

Smart grids, artificial intelligence, deep learning, stability analysis.

Power systems form a strategic foundation for national economic and social development, representing one of the largest, most widespread, and complex man-made systems in modern society. Their secure and stable operation is critical to sustaining economic growth and social stability[1–3]. The increasing integration of power electronics, coupled with rapid advancements in technologies such as ultra-high voltage AC/DC interconnection and renewable energy integration, has heightened the complexity of power systems, expanding the range of their operational states[4]. These developments impose stricter requirements on the system's security and stability[5,6].

Since the early 21st century, large-scale blackouts caused by natural disasters, human error, or malicious attacks have become more frequent worldwide[7–9]. For example, in 2018, a cascading failure due to the overload protection of a circuit breaker in Brazil resulted in the disconnection of a regional grid from the main network, triggering a large-scale blackout[8]. This incident led to a loss of 18 GW of load, or 22.5% of Brazil's national grid, affecting one-quarter of its population. Such events underscore that system instability is a major contributor to widespread blackouts, posing significant risks to societal safety, economic activities, and public well-being. Ensuring power system stability has thus become a crucial challenge for safe operation[10].

Traditional stability analysis methods in power systems primarily rely on stability mechanism-based modeling and analysis[11–14]. By simulating grid components and their dynamic behaviors, these methods provide a detailed understanding of the mechanisms underlying system stability, aiding in the optimization of grid operations and control strategies. However, as operational modes diversify and potential fault points increase, the complexity and time-varying nature of system dynamics complicate these traditional approaches.

In recent years, the rapid advancement of measurement and communication technologies within power grids has significantly improved data collection capabilities[15]. Supervisory control and data acquisition (SCADA) systems now gather extensive historical measurement data, with provincial grid dispatch centers recording terabytes of data annually. Meanwhile, phasor measurement units (PMUs) and wide area measurement systems (WAMSs) provide real-time power system information at high sampling rates[16,17]. In addition to traditional measurement devices, the global deployment of various smart meters and wireless sensor networks (WSNs) has expanded[18,19]. These technologies contribute both to offline training data and real-time situational awareness, forming a robust data foundation for artificial intelligence (AI)-driven stability analysis in power systems.

On the other hand, artificial intelligence methods, particularly deep learning (DL)[20], become a focal point in power system stability analysis research[19]. DL-based stability assessments utilize large-scale electrical datasets and exploit the enhanced feature extraction capabilities of neural networks. By bypassing the complexities of physical modeling, deep learning facilitates stability analysis in highly complex systems[21].

The advancement of these technologies establishes a solid foundation for integrating AI into power systems. AI enhances accuracy, efficiency, and operational effectiveness while reducing human intervention. This paper offers a detailed review of recent advancements and future directions in AI-driven stability analysis.

The remainder of this paper is structured as follows: Section 1 provides an overview of AI, exploring its necessity and rationale in stability analysis through three stages: knowledge fusion, discovery, and adaptation. The following sections introduce the three stages of AI integration with stability knowledge: fusion, discovery, and adaptation. These stages sequentially achieve the characterization of stability features, the establishment and the evolution of AI models. Section 2 provides a comprehensive review of the fun-

[1]School of Mechanical and Electrical Engineering, University of Electronic Science and Technology of China, Chengdu 610054, China; [2]State Key Laboratory of Alternate Electrical Power System with Renewable Energy Sources, North China Electric Power University, Beijing 102206, China
Address correspondence to Chongru Liu, chongru.liu@ncepu.edu.cn

damental principles and application characteristics of AI. Sections 3 and 4 elaborate on the three stages of AI integration, addressing the rationale for applying AI, the current state of its application, and the role AI plays in the establishment and evolution of stability analysis models. Section 5 explores the key challenges and future directions for AI in this domain. Finally, Section 6 concludes the paper.

1 Fundamental principles and application characteristics of AI

In recent years, AI approaches have emerged as a dominant methodology in scientific research, facilitating the transition from traditional paradigms of theoretical, experimental, and computational science to "data-intensive science"[22]. The organization of AI, machine learning (ML) and DL is illustrated in Figure 1.

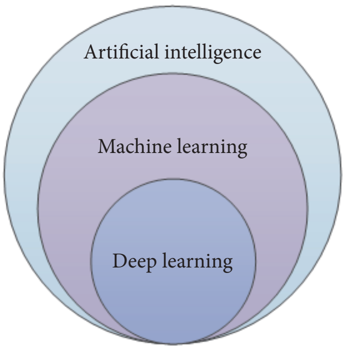

Figure 1 Organization of artificial intelligence, machine learning and deep learning concepts.

AI aims to enable computers to think, learn, and make decisions in a manner that closely mimics human cognitive processes. By harnessing a range of advanced technologies, such as ML, DL, and expert systems, AI systems can efficiently process and analyze vast datasets. This capability allows them to autonomously learn from data, adapt to new information, and optimize algorithms to perform complex tasks that would otherwise be challenging or impractical for human operators to handle[23].

ML refers to the ability of computers to automatically detect patterns and relationships within data through the application of algorithms, making predictions or decisions based on new, unseen data without explicit programming[24,25].

DL, a subfield of ML, represents a significant advancement in the evolution of AI, often referred to as the third wave of AI[20]. By utilizing multilayer neural networks and large-scale training datasets, DL exhibits powerful representation and learning capabilities. DL has achieved remarkable success in various fields, including computer vision[26], speech recognition[27], image classification[28], and natural language processing[29].

2 Knowledge fusion and stability feature characterization

2.1 Necessity and rationality

From the perspective of knowledge fusion and stability feature characterization, as the scale of AC-DC interconnections expands and the capacity for renewable energy integration sharply increases, the dual high characteristics of the power system—namely, high proportions of renewable energy and power electronic devices—are becoming increasingly significant. In such dual high systems, different devices operate on varying time scales. Consequently, establishing a unified characterization method for stability knowledge within multi-source heterogeneous data becomes difficult.

AI is suitable for establishing a unified representation method for multi-source heterogeneous data through feature engineering. This data-driven characterization process includes the construction, reduction, and selection of stability features, aiding in the identification of key information that characterizes the states of power grids[30]. Additionally, interpretable methods delineate the key parameters influencing instability dynamics, allowing modifications to the parameter space defining the stability boundary. Consequently, the AI approach facilitates the adaptive representation of high-dimensional parameter spaces in lower-dimensional forms, enabling the integration of multi-source heterogeneous grid dynamics with varying time scales, even without specific device parameters.

Data fusion and knowledge fusion are complementary and interdependent in stability analysis. Data fusion involves integrating information from multiple, often heterogeneous sources to create a more comprehensive and accurate representation of the system. In power systems, this typically includes combining electrical measurements (e.g., voltage, current, frequency) from sensors such as PMUs, SCADA systems, and weather stations to provide a unified view of system states. Knowledge fusion, on the other hand, integrates domain-specific knowledge—such as physical laws and operator expertise—with computational models, including machine learning algorithms and system simulations. This approach integrates both empirical insights and data-driven models into a unified framework. For example, incorporating expert knowledge or features derived from physical principles as model inputs, or adapting the model based on specific electrical tasks (such as the supervised mapping of sample data and instability moments in Ref. [31] within an unsupervised data generation framework), exemplifies knowledge fusion. By incorporating stability knowledge, AI models can more effectively capture the dynamic behaviors inherent in real-world power systems.

2.2 Construction of stability knowledge

The representation of stability knowledge seeks to capture the complex dynamic behavior of the power grid effectively. The key aspects of stability information include load variability, generator output fluctuations, rotor angles, angular velocities, accelerations, kinetic energy, and system topology[32,33]. For instance, Zhou et al.[32] analyzed the dynamic trajectories of all generators, incorporating rotor angles, rotational speeds, and relative electromagnetic power. Moreover, statistical knowledge is also employed to achieve knowledge fusion. For instance, Guo et al.[34] integrated fault probability distributions. In Ref. [35], trajectory clustering features based on post-fault rotor angles were used to represent the transient responses in power systems. Similarly, Frimpong et al.[36] constructed input features based on the maximum frequency deviations of each generator, employing the Euclidean norm of these deviations at various time points. A significant advantage of knowledge fusion based on statistical features is that the feature dimensions remain independent of the power grid's size.

Unlike traditional temporal or frequency domain approaches, Zhang et al.[37] introduced a distinct method for feature representation. This approach uses symbolic strings to describe trajectories for (fault-on + 2) sequences, enabling the abstraction of sequential evolution trends in transient trajectories through spectral word extraction. The frequency histogram is then converted into 2-D image data for input into the assessment model. As shown in Figure

2(a), different electrical trajectories from generators are represented statistically by various histograms, with all frequency values mapped to a specific colormap. By systematically integrating the pixel vectors from multiple generators, a unified 2-D image is created, depicting system-wide transients, as demonstrated in Figure 2(b). The resulting 2-D image features relatively sparse pixel patches, reflecting the brief durations of the (fault-on + 2) trajectories, which limit the spectral evolution to a narrow range[37].

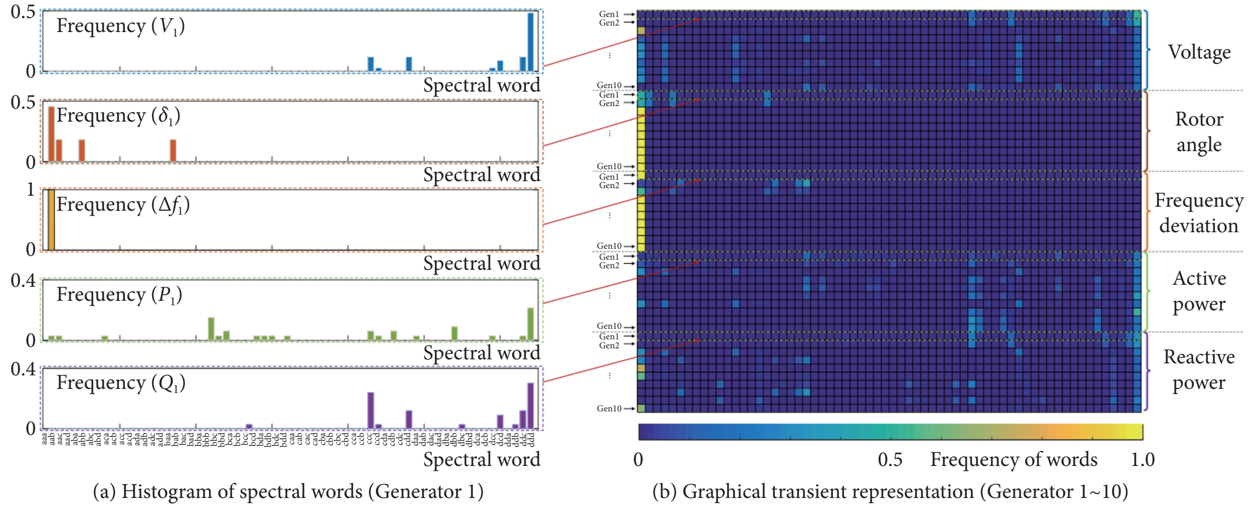

Figure 2 A 2-D graphical representation of transient trajectories. Reprinted with permission from Ref. [37], © 2020, IEEE.

Moreover, as presented in Ref. [38], each sample in the database comprises input data including voltage magnitude time series V, active power injection time series P, reactive power injection time series Q, and topology W. The topology matrix W is specifically formed from a node admittance matrix, reflecting the electrical coupling between power transmission lines, which is essential for understanding short-term voltage stability (SVS) dynamics. As shown in Figure 3, this method first applies a time series shapelet transform to convert the post-fault time series into a set of flattened features. Following this, a graph convolutional network (GCN) is utilized to merge these features with the topology data. By effectively capturing the spatial and temporal aspects of SVS dynamics, this approach enhances the accuracy of assessments, while integrating topological information increases its robustness to changes in system topology[38].

2.3 Source of stability knowledge

AI-driven stability analysis models learn from vast amounts of data, sourced from three main components: historical information, time-domain simulations, and generation techniques. The extensive deployment of WAMS has enabled the direct utilization of large-scale electrical data for model training[39]. However, historical records of power system operations present certain challenges, particularly the lack of instability samples[40]. Therefore, in the absence of sufficient original and simulated data, data generation techniques have been developed to enhance stability knowledge.

2.4 Supplement of stability knowledge

To enhance stability knowledge, various generation techniques are employed, including interpolation methods based on existing data and generative models that leverage the statistical distribution of the original dataset.

Interpolation methods, such as the synthetic minority oversampling technique (SMOTE)[41] and adaptive synthetic sampling (ADASYN)[40] , are employed to oversample electrical samples. For example, a hybrid approach combining k-means clustering with

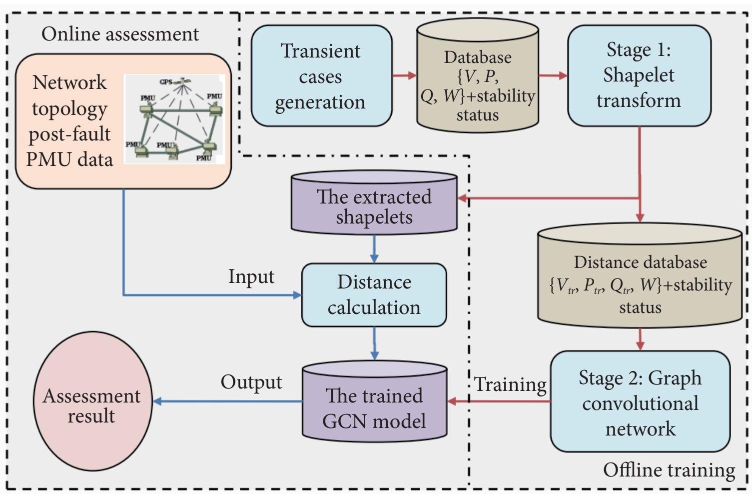

Figure 3 An illustration of the fusion and extraction of multimodal stability knowledge. Reprinted with permission from Ref. [38], © 2023, IEEE.

SMOTE has been proposed to increase the representation of instability samples[41]. However, these interpolation-based techniques often struggle to capture the inherent nonlinearity of power systems, which may lead to overfitting in data-driven models [42].

Generative models, particularly those employing generative adversarial networks (GANs)[43–47], have gained widespread adoption. For example, Yan et al.[44] proposed a GAN search algorithm that automatically identifies the optimal GAN architecture for more efficiently learning underlying data distributions. Similarly, Yan et al.[45] introduced a semantic-guided contrastive network to enhance GAN adaptability in handling previously unseen scenarios. The self-attention GAN (SAGAN)[43] incorporates an attention mechanism to model long-range dependencie, while Ouyang et al.[46] modifies the wasserstein GAN (WGAN)[48] to accelerate training and improve performance. Additionally, Shao et al.[49] integrated attention mechanisms and spectral normalization to enhance training stability. Moreover, Ren and Xu[50] leveraged GANs to learn the complex distribution of pre-fault data, significantly improving the model's ability to detect instability samples. Liu et al.[51] utilized an auxiliary classifier GAN (ACGAN) to learn the boundary distribution of small sample sets, generating diverse samples through supervised learning attributes. In another study, Li et al.[52] applied deep convolutional GANs (DCGAN) to generate additional instability samples and employed CNN to capture the nonlinear relationship between disturbance features and stability categories. Additionally, Zhu and Hill[53] proposed a recurrent generative adversarial network to address challenges related to small sample sizes and class imbalances in historical datasets. Gan et al.[54] presented a transformer-based data augmentation techniques for transient simulation of power systems, integrating swap noise and random masking mechanisms.

When using GANs to generate unstable samples, a straightforward approach is to directly use observed unstable samples as input data for model training[31]. Another effective strategy is to employ conditional generative adversarial networks (CGANs), where the model is conditioned on the instability status (stable or unstable) of the samples[55]. This allows the CGAN to specifically generate unstable samples while ensuring their diversity and representativeness of real-world instability scenarios.

Given that samples near the stability boundary have the greatest impact on classification performance, the GAN model can be adapted to generate samples distributed around this boundary. One approach to achieve this is by incorporating a supervised model, as demonstrated in Ref. [31], into an unsupervised GAN structure. This supervised mapping models the relationship between the generated samples and their proximity to the stability boundary. By integrating this mapping into the GAN's loss function, the model can prioritize generating samples near the boundary. Alternatively, this relationship can be treated as a conditioning factor within a CGAN, where the model is conditioned on the distance between generated samples and the stability boundary, ensuring that the generated samples are more relevant for stability analysis[52].

As shown in Figure 4, a cross-modal generative adversarial network (cGAN) model is introduced, featuring two spatial-temporal transformer models. This setup is designed to optimize the use of multi-modal data and enhance scenario data quality. In this framework, the generation of scenarios is treated as a probability approximation problem. A structure for cross-modal scenario generation processes various observational data. Theoretically, this method enables the creation of an unlimited number of uncertain scenarios through repeated random noise sampling. Furthermore, a technique for cross-modal data fusion combines graph data from GPS with time-series power output data using the spatio-temporal transformer. As shown in Figure 4, the generator receives graph data, Gaussian noise samples, and real scenarios as inputs, resulting in the output of generated scenarios[56].

3 Knowledge discovery and model establishment

3.1 Necessity and rationality

From the perspective of knowledge discovery and model establishment, the interaction among various types of power electronic devices in modern power systems, along with the strong nonlinear dynamics between devices and networks, as well as the randomness and volatility of renewable energy output, lead to the transient response characterized by strong coupling and uncertainty. Additionally, the mutual influence of transient responses at electromechanical and electromagnetic time scales complicates the establishment of a mathematical model for power system transient responses.

AI methods serve as powerful tools for data analysis and mining, enabling the efficient modeling high-dimensional representations of actual power systems based on extensive data. Moreover, a significant advantage of training AI models is the elimination of the need to solve complex differential-algebraic equations, allowing stability results to be derived through a single forward algebraic calculation. This capability is crucial for meeting the real-time demands of online assessments.

3.2 Knowledge discovery through different algorithmic approaches

In the domain of power systems, various assessment tasks exist, including fault location[57], fault diagnosis[58,59], and fault cause identification[60]. For different tasks in stability analysis, machine learning modeling methods can be categorized into three primary types: supervised learning, unsupervised learning, and reinforcement learning, as illustrated in Figure 5. Although tasks such as angle, voltage, and frequency stability have distinct inputs and outputs, they often share a common AI framework. The core objective across these tasks is to extract and learn patterns from system dynamics. For instance, in stability determination, despite variations in data and outputs, the supervised learning process —encompassing data preparation, model selection, and training—remains fundamentally consistent.

(1) Supervised Learning: Supervised learning utilizes labeled training data to develop models that define the relationship between input features and corresponding target outputs. This method is widely applied in classification and regression tasks. Classification models are used to determine system stability[61,62] and identify unstable units[63,64]. For instance, Shi et al.[62] proposed a three-class classification algorithm that distinguishes between two instability modes: aperiodic instability and oscillatory instability. On the other hand, regression models are often employed to predict stability margins[65–68]. For example, the adaptive neuro-fuzzy inference system (ANFIS)[67] and extreme learning machine (ELM)[68] have been utilized to evaluate online critical clearing times, accounting for variations in load levels and fault locations across buses and transmission lines.

As illustrated in Figure 6, two supervised models were trained in Ref. [69] to achieve transient stability assessment (TSA) and critical generator identification (CGI). A database was prepared

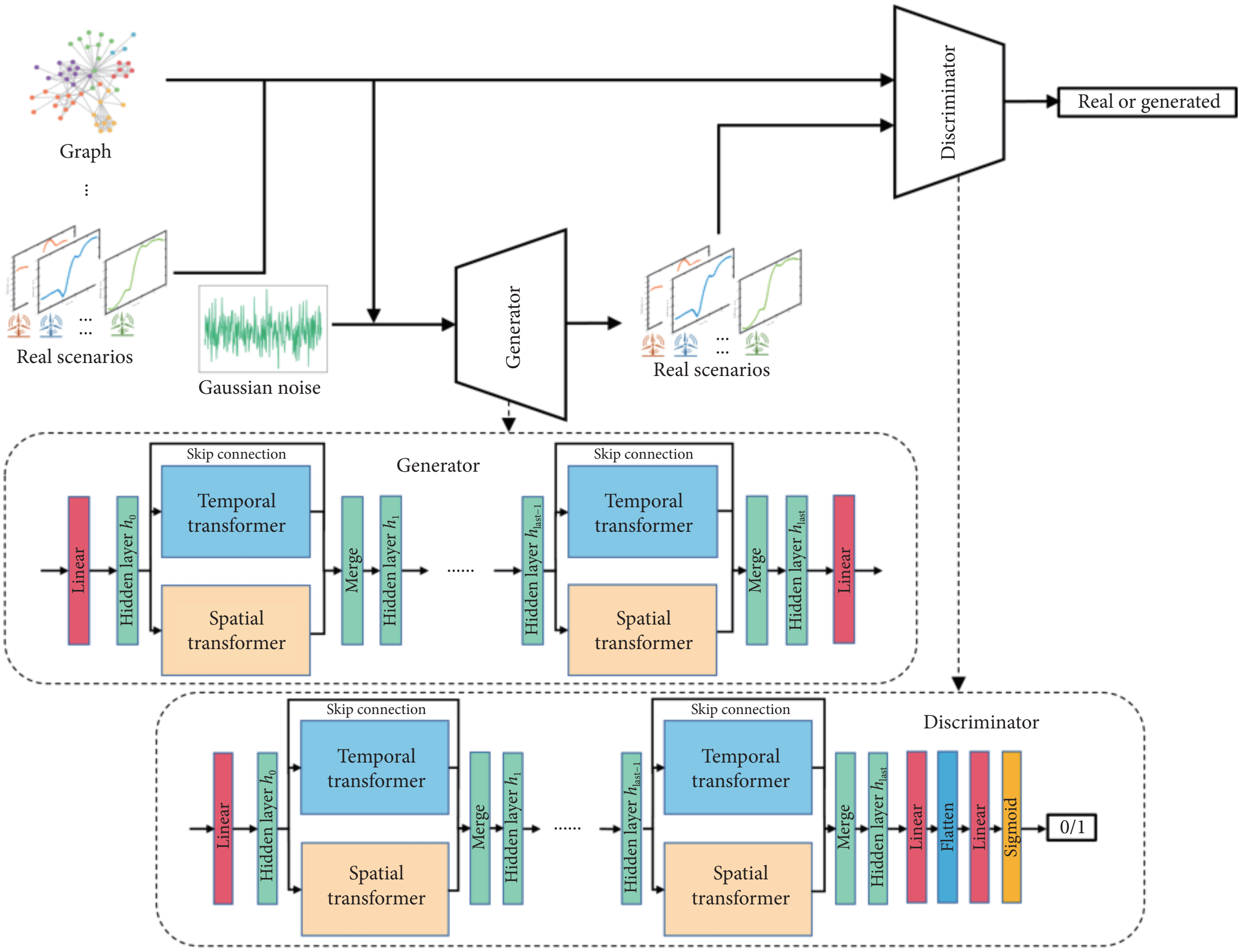

Figure 4 **An illustration of the cGAN architecture for data generation. Reprinted with permission from Ref. [56], © 2024, IEEE.**

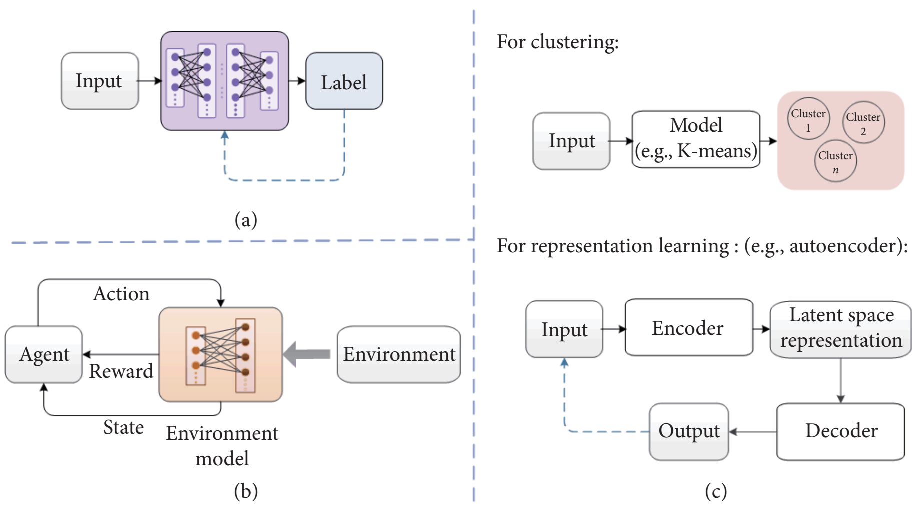

Figure 5 **Machine learning paradigms in power systems: (a)** Supervised learning, **(b)** reinforcement learning, and **(c)** unsupervised learning.

for both TSA and CGI model development, and during the sample preparation phase, each sample needed to be labeled according to the specific task. The internal parameters of the two supervised classification models are not shared and are trained independently. In the online phase, once the output of the TSA model meets a certain threshold, real-time PMU data is sent to the second model for critical generator assessment. It is important to note that the labeling process for samples can be time-consuming and may not always be entirely accurate. Therefore, existing approaches have leveraged semi-supervised models, such as deep belief networks (DBN), to reduce the reliance on labeled samples in intelligent algorithms.

(2) Unsupervised learning: Unsupervised learning focuses on analyzing and clustering unlabeled training data to uncover

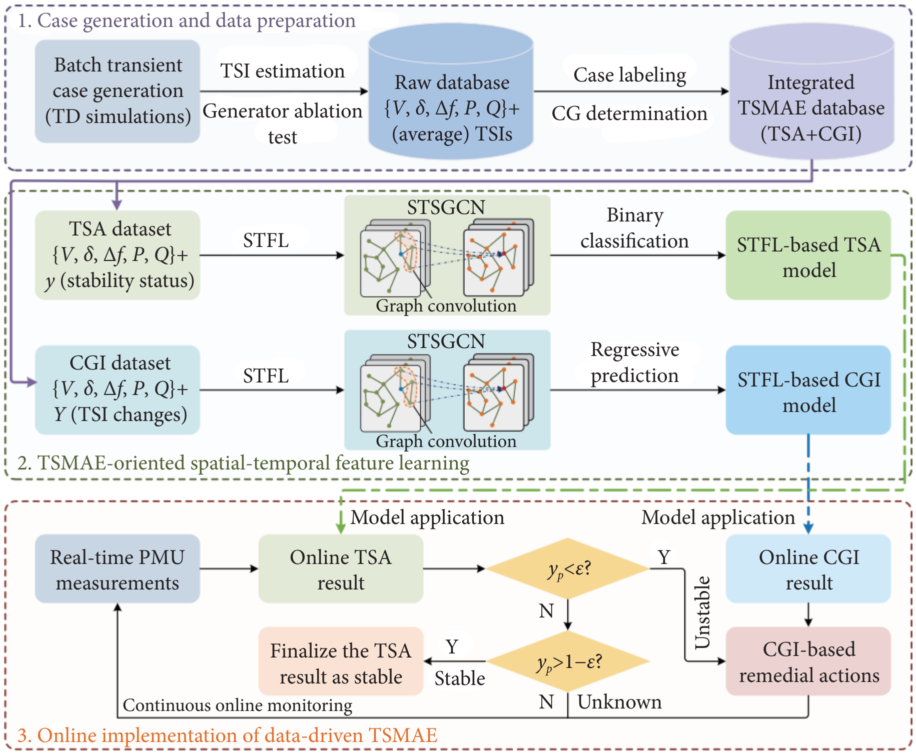

Figure 6 An example of the supervised model training and application process. Reprinted with permission from Ref. [69], © 2024, IEEE.

underlying structures and patterns. Common algorithms in this domain include clustering techniques such as K-means[41] and hierarchical clustering[70], as well as dimensionality reduction methods like principal component analysis (PCA) and factor analysis[71]. Notably, generative algorithms , including variational autoencoders (VAE)[72], generative adversarial networks (GANs)[50] and denoising diffusion probabilistic models[73,74], are extensively employed in power systems. These methods leverage historical data to generate synthetic electrical samples tailored to specific requirements, thereby addressing sample distribution imbalances commonly encountered in power system data.

Figure 7 presents a deep autoencoder (DAE) designed for scenario clustering. To achieve simultaneous feature representation and cluster assignment, a Kullback–Leibler divergence (KLD)-based clustering module is incorporated between the convolutional neural networks (CNN) encoder and decoder. This arrangement enables the encoder and decoder to collaboratively extract comprehensive feature representations from large data matrices of cases in an unsupervised manner. The integration of the KLD-based clustering module establishes a pathway for effective cluster assignment[75].

Figure 8 illustrates a two-stage clustering algorithm proposed in Ref. [76]. The training dataset encompasses operating scenarios characterized by considerable variability, primarily due to topological changes and fluctuations in generation and load. To systematically categorize these complex scenarios into coherent clusters, a two-step methodology is employed. In the initial stage, clustering is performed on the topological features, followed by a second stage focusing on clustering additional relevant features. This comprehensive approach yields multiple clustered datasets, with each dataset comprising operating scenarios that exhibit similar distributional characteristics, thereby facilitating more effective analysis and interpretation[76].

(3) Reinforcement learning: Reinforcement learning (RL) is a dynamic machine learning approach that emphasizes learning optimal behavioral strategies through continuous interaction with an environment[77]. Unlike supervised and unsupervised learning, where models are trained on fixed datasets, RL is typically framed as a Markov decision process. In this framework, an agent explores and learns from the consequences of its actions. The

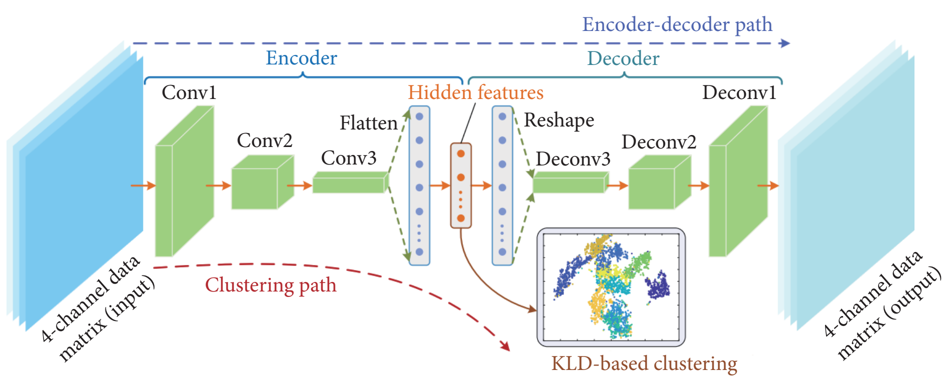

Figure 7 The DAE-based case clustering method. Reprinted with permission from Ref. [75], © 2024, IEEE.

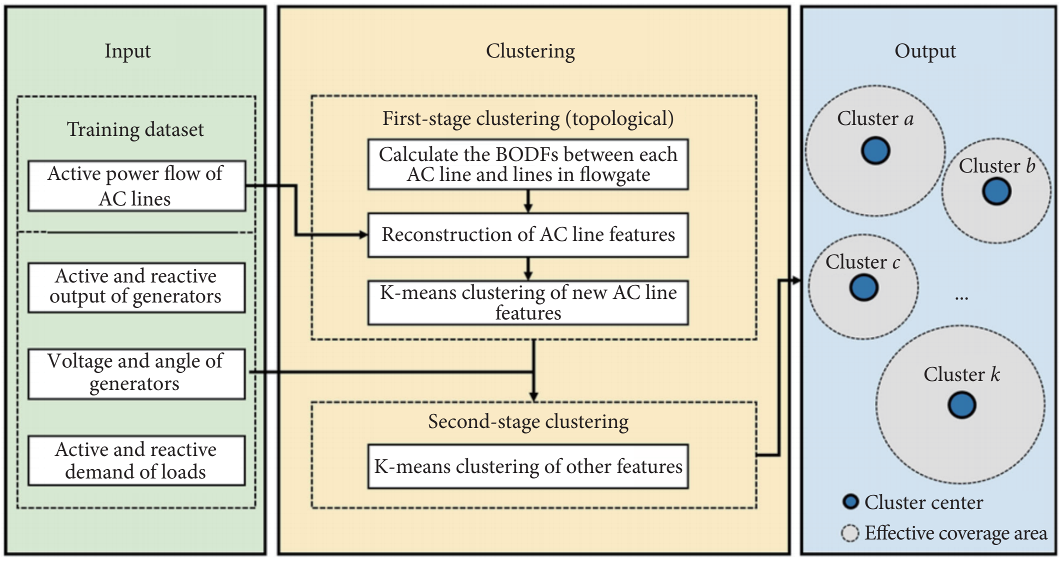

Figure 8 **Process of a two-stage scenario clustering. Reprinted with permission from Ref. [76], © 2022, IEEE.**

agent observes the current state of the environment, selects actions based on its policy, and receives feedback in the form of rewards or penalties. This feedback mechanism allows the agent to iteratively improve its strategy, ultimately converging on a policy that maximizes cumulative rewards within a given context.

Figure 9 introduces a multi-agent reinforcement learning (MARL) method known as shapley Q-value deep deterministic policy gradient (SQDDPG). In this approach, the shapley Q-value is adapted for credit assignment, functioning as a payoff distribution mechanism in RL. The method utilizes the traditional deep deterministic policy gradient (DDPG) algorithm to facilitate the learning of decentralized policies and centralized critics, thereby ensuring privacy preservation during MARL policy updates. Overall, the SQDDPG method effectively integrates the shapley Q-value with the DDPG algorithm to accurately assess each agent's contribution to the system's resilience while accommodating continuous state and action spaces. The coordination challenge is framed as a decentralized partially observable Markov decision process (Dec-POMDP), enabling the representation of diverse system dynamics and uncertainties[78].

As illustrated in Figure 10, this study presents an innovative multi-task RL approach designed for concurrent learning of multiple tasks. In contrast to traditional methods that indiscriminately share parameters across tasks, the proposed framework employs a selective feature extraction mechanism for each transmission interface task, utilizing an attribution-based methodology. A multi-task attribution map (MAM) is developed to explicitly delineate the influence of various power system nodes on each respective task.

In detail, as outlined in Ref. [79], the approach initiates with a graph convolutional network that captures node features pertinent to the operational state of the power system. Concurrently, task representations are derived through a common task encoder, facilitating the identification of inter-task relationships. Each task representation functions as a query to compute node-level attention weights, culminating in the creation of a task-adaptive attribution map. This map enables the model to selectively integrate relevant node features, thereby yielding a compact representation of the state. Ultimately, a dueling deep Q network is employed to formulate the reinforcement learning policy, enhancing the efficacy of the multi-task learning process[79].

3.3 Knowledge discovery for extracting critical information

The key to model establishment lies in extracting the most relevant and valuable stability knowledge from the power system. By mapping complex raw information to a lower-dimensional space, this process significantly improves calculation efficiency, alleviates the sparsity problem, and enables the effective fusion of heterogeneous information.

AI-based stability analysis identifies key characteristics by analyzing observable electrical data, such as current and voltage from PMU measurements. In characteristics selection, statistical methods, like Relief-based approaches, assess feature importance by comparing values between similar and dissimilar samples, assigning higher weights to discriminative features[80]. Deep neural networks, using backpropagation and gradient-based attention mechanisms, automatically identify important features by quantifying output sensitivity to specific inputs[64].

Moreover, feature selection can also be approached from a power system modeling perspective. For instance, Xie et al.[81] identified stability through the equivalent one-machine virtual power-angle characteristics of generator pairs based on rotor acceleration equations. Zheng et al.[82] investigated the spatiotemporal distribution of node voltage magnitudes and phases in the network, as well as power transmission characteristics, and introduced a transmission capability index to characterize transient power angle stability. Additionally, Wang et al.[83] detected transient angle instability by examining generator speed trajectories, while Ma et al.[84] used the extended phase plane, combining angular velocity and acceleration for a more comprehensive TSA analysis.

Physical-based feature selection relies on fundamental system principles like rotor dynamics and power flow equations, offering clear interpretability. However, it requires detailed system models and accurate parameters, which can be challenging in complex systems. In contrast, AI-based techniques excel in handling large-scale, heterogeneous data, accommodating diverse scenarios and incomplete information, but their performance depends heavily on data quality, risking overfitting and reduced generalizability. From the perspective of AI-based extraction methods, it can be categorized into feature engineering-based and gradient optimization-based techniques.

(1) Feature engineering-based knowledge discovery: This approach focuses on extracting relevant features to enhance model

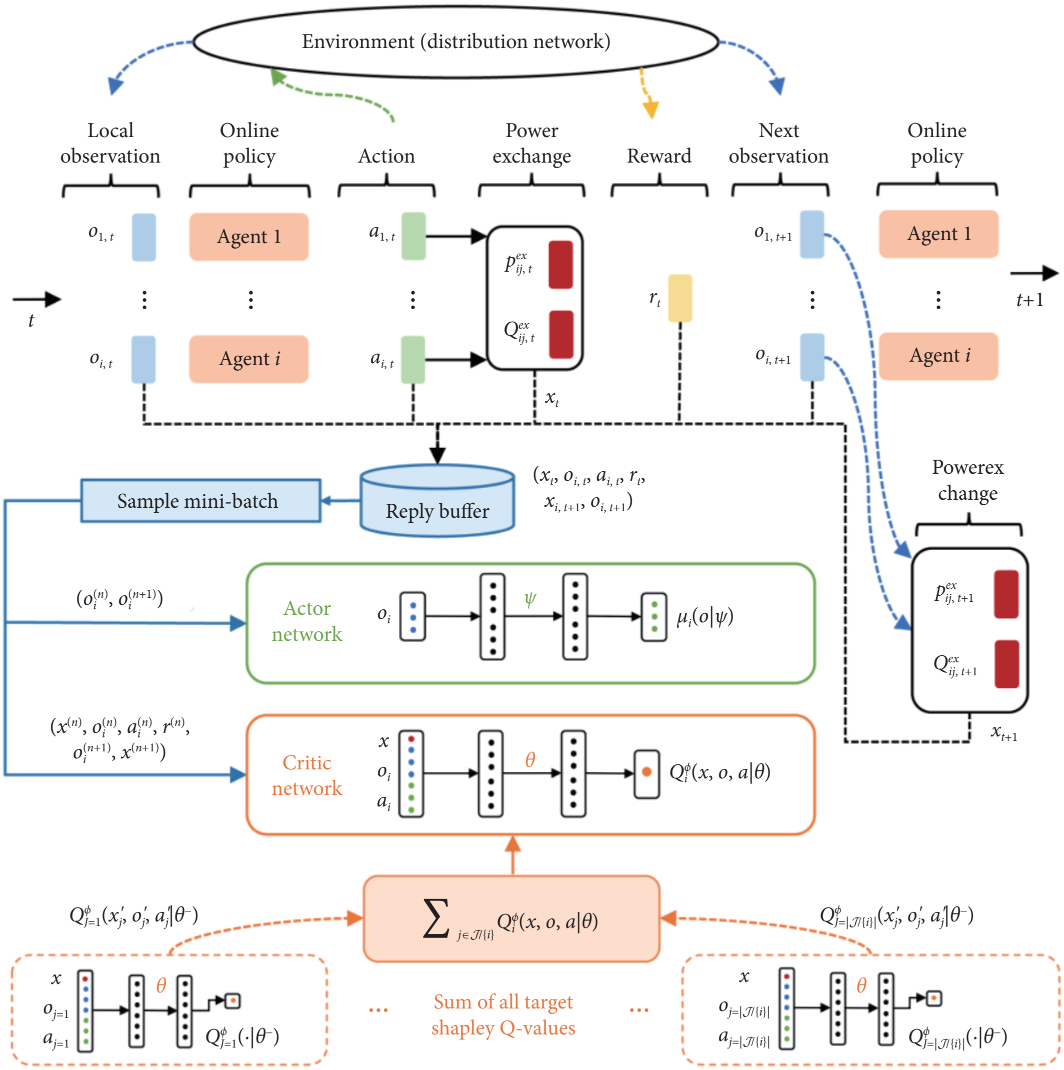

Figure 9 An example of multi-agent RL method. Reprinted with permission from Ref. [78], © 2024, IEEE.

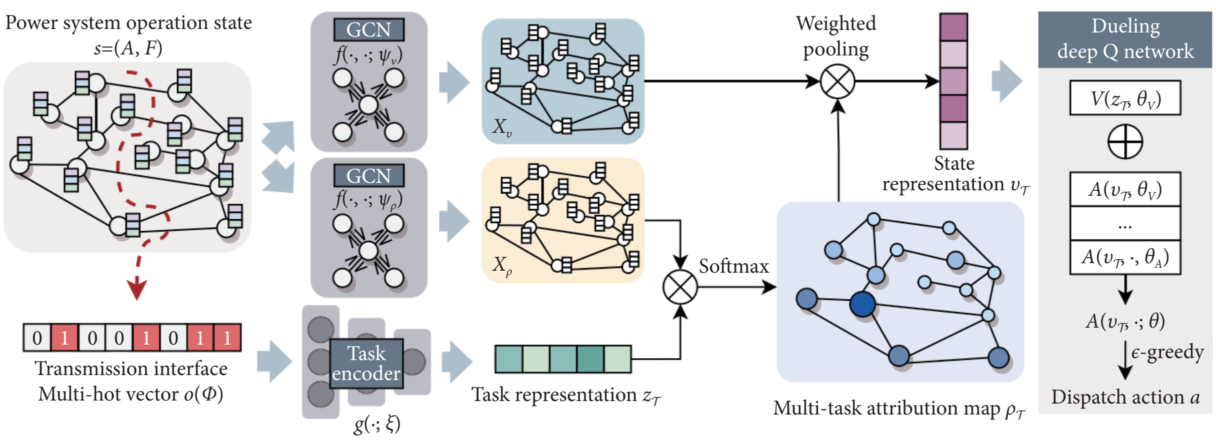

Figure 10 An example of a deep RL structure method employing task-adaptive attention weights. Reprinted with permission from Ref. [79], © 2024, IEEE.

performance and interpretability. Techniques such as PCA are utilized to extract key features, simplifying algorithmic complexity[85]. In Ref. [80], a Relief-based approach was introduced to evaluate the importance of time-series features, leading to the establishment of an optimal PMU clustering model for selecting the most critical feature subset. Zhang et al.[86] proposed a feature selection algorithm that combines random forests with recursive feature elimination. In Ref. [72], feature selection was based on the correlation between time and frequency features, effectively extracting key feature subsets close to the decision boundary.

(2) Gradient optimization-based knowledge discovery: Deep learning algorithms inherently combine representation and learning, enabling the discovery of grid knowledge through gradient changes during model backpropagation. For example, Sun et al.[87]

employed a deep autoencoder to transform raw state variables, such as power flow, into a lower-dimensional space, establishing a framework for efficient transient stability feature extraction. Wu et al.[88] utilized gradients obtained through backpropagation to extract higher-order features. Furthermore, Tan et al.[89] integrated a convolutional structure into the last hidden layer of a stacked autoencoder (SAE) framework, enhancing the extraction of stability knowledge. As illustrated in Figure 11, a typical end-to-end structure incorporates interpretability based on an attention mechanism.

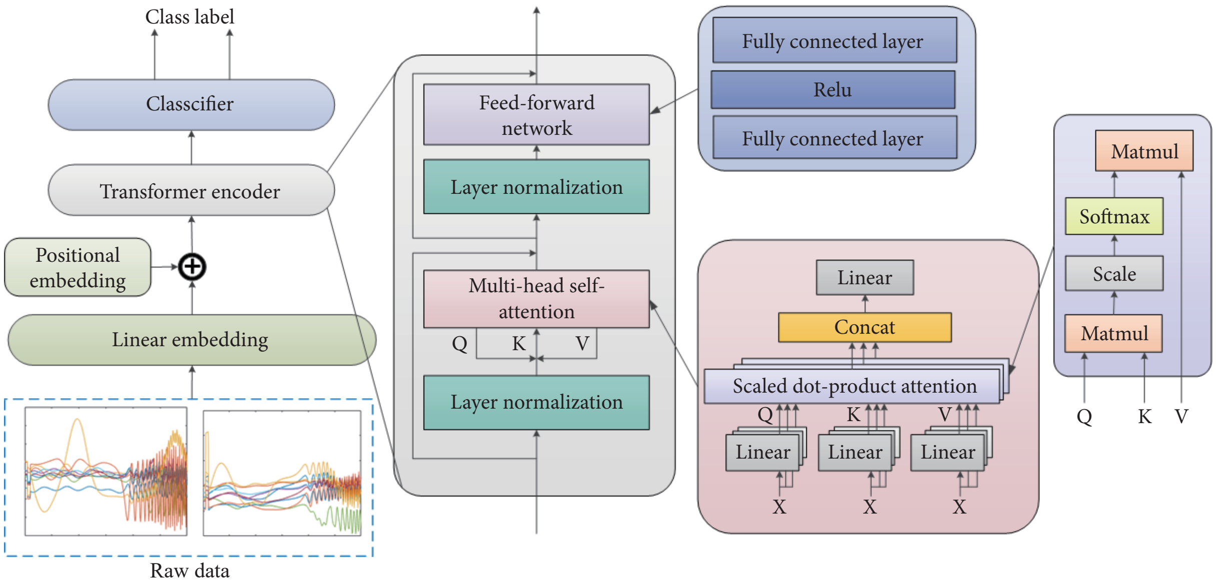

Figure 11 Model structure for gradient optimization-based knowledge discovery. Reproduced with permission from Ref. [64], © 2023 Elsevier Ltd. All rights reserved.

3.3.1 Temporal information extraction

The relationship between time expression and time series, encompassing both absolute and relative time series, is utilized to extract temporal knowledge from power grid signals. Temporal features capture the dynamic behavior of power systems, often structured as an $n \times T$ feature map, where n represents the selected key variables (e.g., voltage, current, or power) and T denotes the chosen time steps. In TSA, the time scale T is defined in various ways. One approach focuses solely on data after fault clearance ($T \geqslant 1$), reflecting the system's deceleration area at that point[64,90]; Another approach extends the time scale by incorporating fault-on information, including transient fault-on trajectories and two adjacent sampling points from the pre- and post-fault stages, i.e., fault-on +2 trajectories, enabling faster online stability assessment[37].

As demonstrated in Ref. [91], shapelets are subsequences that capture unique characteristics of time series data. Figure 12 illustrates a time series extraction algorithm that extracts shapelets, which serve as distinctive features of electrical variable sequences. Figure 12(a) shows the closest match between a shapelet and the temporal sequences. Figure 12(c) presents the distance calculation from the sequence to the shapelet, which can be transformed into a sequence projection in two-dimensional space, referred to as shapelet transform[91].

With the development of AI, as illustrated in Figure 13, various DL-based temporal information extraction algorithms are built to maintain the temporal correlation through distinct structural approaches. Long short-term memory (LSTM), CNNs, and attention modules each possess unique approaches to retaining temporal information. LSTM networks are specifically designed to capture long-range dependencies in sequential data through their internal memory cell structure, which allows them to store and selectively

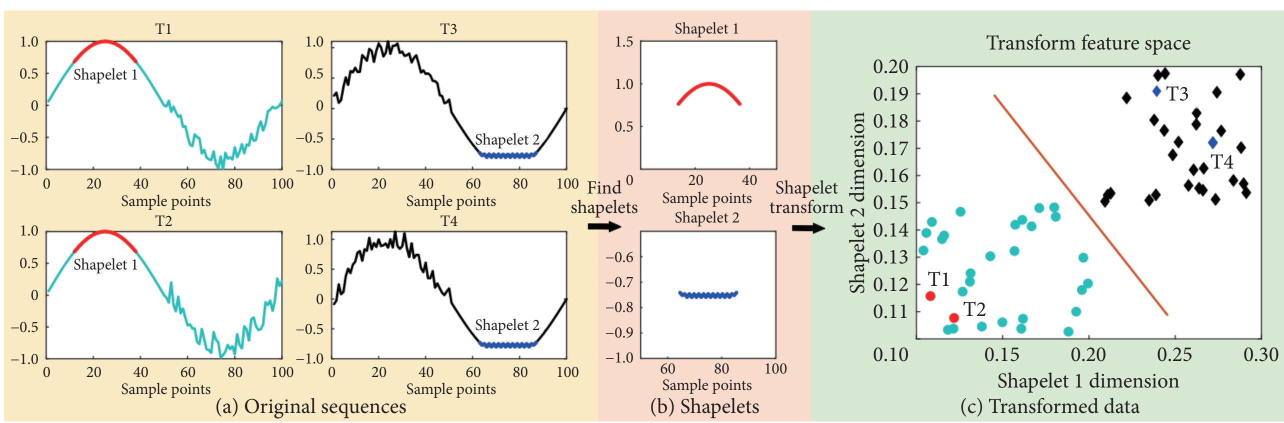

Figure 12 A shapelet-based method for extracting temporal sequences. Reprinted with permission from Ref. [91], © 2024, IEEE.

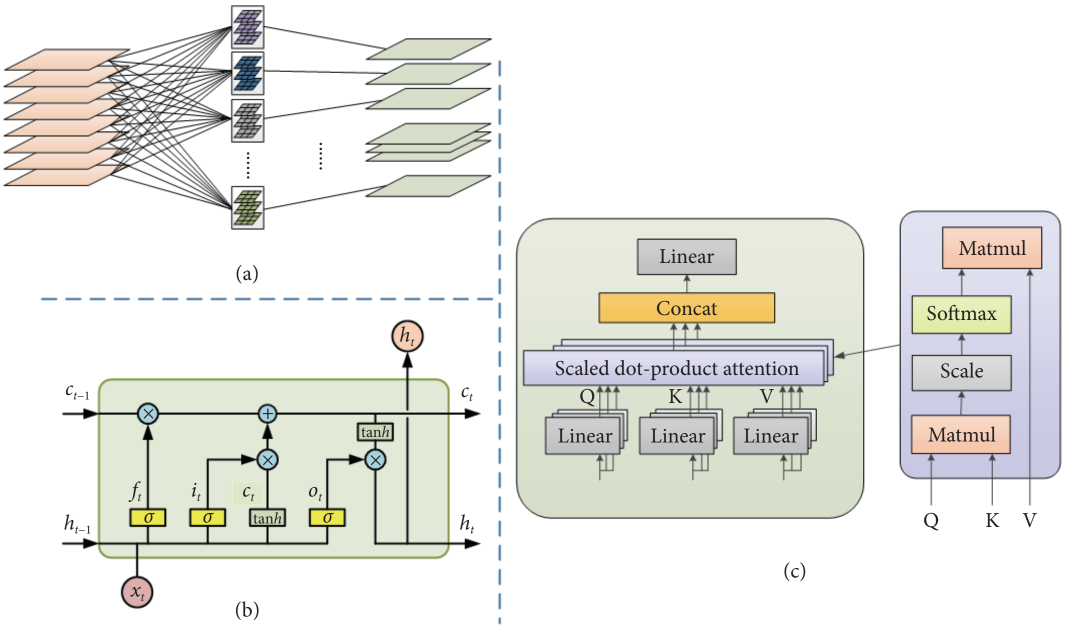

Figure 13 Schematic diagrams of typical DL algorithms for temporal knowledge. (a) CNN, **(b)** LSTM, and **(c)** self-attention module.

retrieve relevant information across time steps. CNNs, while primarily known for their spatial feature extraction capabilities, can also preserve temporal information by utilizing convolutions along time series data, enabling the identification of local patterns over time through their hierarchical layer structure. On the other hand, attention mechanisms enhance temporal information retention by dynamically weighting the importance of different time steps in the input sequence, allowing the model to focus on relevant parts of the data while ignoring less significant elements. Together, these techniques provide complementary strengths in handling sequential data, improving the overall performance of models in tasks requiring an understanding of temporal dynamics.

For instance, Gupta et al.[92] introduced a CNN-based continuous monitoring system that uses a sliding window to monitor voltage curves, continuously updating stability predictions. Similarly, Fang et al.[64] developed an online monitoring system for TSA that utilizes the self-attention mechanism in the transformer architecture, enhancing the model's capacity to capture time-series information through its global receptive field, with temporal knowledge preserved via position embedding. Given the time correlation of dynamic information in power systems, recurrent neural networks (RNNs) are frequently employed to restore spatiotemporal data. James et al.[93] and Tan et al.[80] directly input post-fault time-series data into long short-term memory (LSTM) networks, achieving high accuracy in predicting transient stability. Additionally, Yu et al.[94] proposed a gated recurrent units (GRUs)-based framework for delay-aware synchrophasor recovery and prediction, addressing the impact of missing state variables due to communication latency. LSTMs, as demonstrated in Ref. [95], also exhibit high performance in predicting missing data in power grids.

3.3.2 Spatial information extraction

Power grid data exhibits distinct spatial characteristics, and the topology of power systems often changes during operation, necessitating models capable of adapting to these evolving conditions. Graph neural networks (GNNs) have emerged as a promising solution for such dynamic environments, as they can effectively capture both node features and topological information. For instance, Gu et al.[96] developed a GNN-based model that integrates bus characteristics with the topological connections within the power network. Recent studies have also explored the application of CNNs to graph-structured data. In works such as Refs. [97] and [98], both spatial and spectral graph convolutional layers were incorporated, enhancing the learning of stability knowledge by leveraging the spatial relationships inherent in power grid topology. However, the reliance on detailed topological information increases complexity and computational demands, requiring extensive preprocessing of the grid's structure to establish effective AI models. Pei et al.[99] proposed a multi-task learning scheme for the joint optimization of control policies in distribution system voltage regulation, considering topology changes. In this approach, the system topology is incorporated as an additional state within the reinforcement learning framework.

Figure 14 illustrates a grid structure represented through an adjacency matrix-based graph, which showcases system-wide voltage values from various bus trajectories at three distinct time points (t = 0, 0.25, and 0.5 s). Each graph corresponds to these moments, using different colors to represent voltage levels at the respective buses, thereby depicting the voltage distribution across the grid. By feeding this graph data into a GCN, the model learns spatial features associated with voltage distributions throughout the network. This method effectively accounts for the non-Euclidean characteristics of the power grid and captures the temporal dynamics during voltage stability scenarios[100].

3.3.3 Stability region extraction

The transient stability region encompasses the entire set of operating points within the power injection space that ensure transient stability before a disturbance occurs. The relationship between the system's operating point and the boundary of stability regions offers critical insights into stability margins (SMs)[101]. For example, transient SM can be efficiently estimated using polynomial-based nonlinear transformations and kernel ridge regression[102]. Similarly, a multi-step Lasso regression approach for estimating SMs is presented in Ref. [103]. However, these methods are event-specific, limiting their adaptability to new transient events. In contrast, a hybrid data-driven approach proposed in Ref. [104] allows for fast approximation of the practical dynamic security region

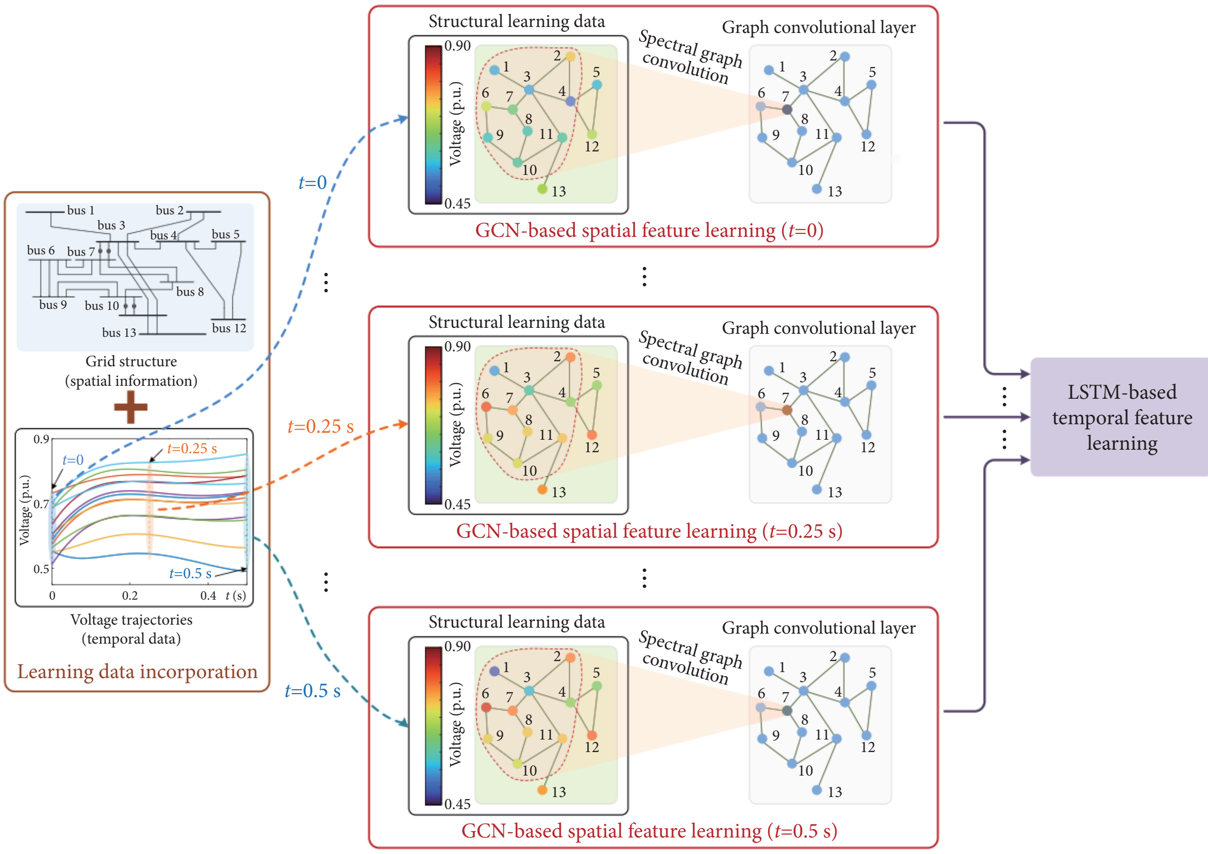

Figure 14 An illustration of spatial-temporal feature learning using GCN and LSTM. Reprinted with permission from Ref. [100], © 2024, IEEE.

(PDSR) boundary using a hyperplane expression. This approach first applies the relief algorithm to analyze operating point data in the high-dimensional nodal injection space, identifying key generators whose active output significantly impacts transient angle stability. Next, the orthogonal point selection method is used to determine the equivalent search space and critical points.

Research in Ref. [105] demonstrates that the gradient-building process of AI models focuses on information pertaining to the stability boundary. Consequently, constructing a dataset that accurately represents this boundary is essential for improving the model's capacity to learn stability knowledge. Searching for the boundary characteristics of the stability region is crucial for its construction. For instance, Fang et al.[31] proposed a GAN-based model to generate instability samples, where a CNN-based supervised model guides the GAN in producing samples close to the boundary. The iterative binary sampling (BS) method described in Ref. [106] increased the density of samples near the stability boundary. In Ref. [107], a sampling strategy based on decision trees was developed, utilizing importance sampling algorithms to identify high-information regions within the multi-dimensional operational parameter space. Similarly, Thams et al.[108] effectively reducing the search space and simulation time through parallelizable algorithms.

3.4 Knowledge discovery from interpretability perspective

Interpretability is a critical aspect of knowledge discovery, as it allows for the identification of features that are most relevant to stability tasks. One of the primary ways to ensure the credibility of AI results is through the application of explainable AI techniques. These methods enhance the transparency of AI models, enabling stakeholders to understand the rationale behind the model's predictions. In the context of power system stability analysis, this means providing clear and actionable explanations for how key input features, such as voltage levels, frequency, and fault conditions, influence the model's output. Interpretability in AI models generally stems from two main approaches: model-agnostic interpretability and model-based interpretability.

Model-agnostic interpretability is independent of the specific architecture of AI models. For instance, Wu et al.[88] proposed a local linear interpreter (LLI) to examine the relationship between grid features and output results. Additionally, Lan et al.[109] introduced the shapley additive explanations (SHAP) algorithm, which quantifies the impact of features on predictions, thereby enhancing interpretability in the imbalance-XGBoost algorithm. Furthermore, Tan et al.[110] developed the gradient SHAP algorithm to offer both global and local explanations for probabilistic models.

Figure 15 presents a first-order sensitivity analysis of control variables aimed at assessing post hoc interpretability. This type of interpretability, referred to as result-based interpretability, assesses the model's interpretability regarding its internal mechanisms after training is complete. It maintains the model's structure and is inherently model-agnostic. The analysis accounts for changes in steady states occurring before and after disturbances. As shown in Figure 15, the sensitivity of the model objective is evaluated concerning the active power outputs from the five most significant generators. The findings from this interpretability analysis can inform practical operations and control strategies within power systems, thereby enhancing the utility of the proposed AI model[76].

In contrast, model-based interpretability focuses on analyzing the internal parameters of the model. For example, Zeiler and Fergus[111] employed deconvolution techniques to visualize the functions of intermediate feature layers and the operation of the classifier. Similarly, Simonyan et al.[112] and Sundararajan et al.[113] utilized input layer gradients to indicate the importance of input

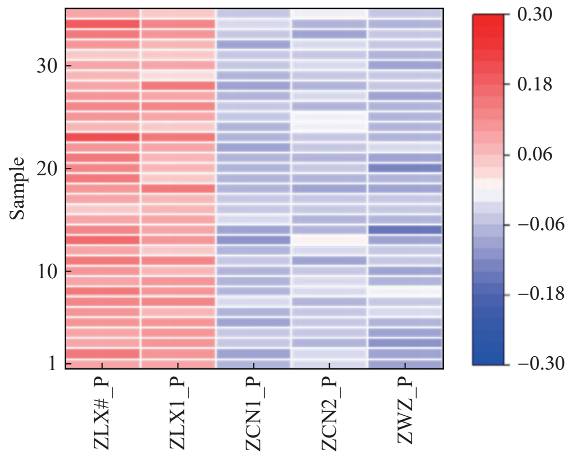

Figure 15 An example demonstrating the interpretability derived from first-order sensitivity analysis. Reprinted with permission from Ref. [76], © 2022, IEEE.

features, thereby providing interpretability from the perspective of input dimensions. Moreover, Zhou et al.[114] applied class activation mapping (CAM) to create a general local deep representation, revealing the implicit focus of CNN through activation mappings. Additionally, Fang et al.[115] visualized the attention of different nodes using an attention mechanism. Furthermore, Fang et al.[57] leveraged class activation maps and attention maps to demonstrate the robustness of the proposed structure. Chattopadhay et al.[116] advanced CAM with Grad-CAM++, which uses a weighted combination of positive partial derivatives from the last convolutional layer's feature map to generate visual explanations for class labels. Collectively, these methods enhance interpretability by analyzing internal parameters and activation mappings, enabling users to gain insights into the decision-making processes of the model.

Figure 16 presents the interpretability of two algorithm components: CAM for the CNN and the attention distribution from the non-local module. These visualizations indicate that the proposed model can effectively disregard consecutive signal errors while concentrating on valid information, highlighting its robustness and practical applicability.

The CAM generated from the GAP layer enhances classification explainability by identifying important regions in the input signals, with darker areas indicating higher importance. In the first scenario, valid input signals reveal two critical regions that significantly contribute to classification. To assess robustness, invalid data were added to the important regions of the voltage signal in Figures 16(b) and 16(c). This led the model to shift focus to unaffected areas, demonstrating its capacity to maintain robustness by adaptively selecting valid data. The attention maps from the non-local layer further illustrate this behavior, showing that the model effectively neglects error-affected parts while concentrating on relevant sections of the signal[57].

4 Knowledge adaptation and model evolution

4.1 Necessity and rationality

From the perspective of knowledge adaptation and model evolution, the spatial and temporal distribution of renewable energy output, fault patterns, and control switching of power electronic devices can significantly alter the typical operating range of the system. Time-domain simulations rely on calculations based on predetermined disturbances or expected fault scenarios. However, the differentiated operational modes resulting from the dual high characteristics may lead to misalignments in stability analysis derived from these simulations. In this context, both the system's topological structure and data distribution are critical to the generalization of stability analysis. The system's topology influences power flow and fault propagation, while data distribution variations—such as seasonal changes in wind turbine output or class imbalances—affect the model's generalization ability. These factors are captured by probabilistic mappings, which represent the likelihood of outcomes based on observed data. To address these challenges, adaptive updating methods should be employed to refine these mappings, enabling the model to generalize more effectively to new, unseen scenarios and ensuring robust stability assessments across diverse conditions.

AI models can effectively capture differences in data distributions under varying operating conditions. By fine-tuning knowledge from the source domain to the target domain, knowledge transfer can occur between different operational spaces and mapping relationships in power systems. This process enhances the model's generalization ability at new operating points, ensuring robust performance amid continuously changing system states. Furthermore, incorporating reinforcement learning allows the model to optimize strategies and self-correct based on evolving system conditions. In the face of complex faults and uncertain disturbances, reinforcement learning can adjust model parameters in real-time based on feedback, facilitating dynamic adaptation to transient stability states[117–119].

Given the variations in voltage levels, network characteristics, and power grid components across different systems, knowledge adaptation is crucial for establishing a unified representation of diverse power grid scenarios. This process enhances model generalization across various tasks and datasets.

4.2 Knowledge adaptation based on ensemble learning

Ensemble learning seeks to capitalize on the strengths of individual models, thereby enhancing adaptability across various tasks. For instance, Li et al.[120] and Chen et al.[121] applied ensemble learning to pre-fault dynamic security assessment, resulting in improved model reliability. In Ref. [121], performance was further enhanced by assigning greater weights to critical samples, allowing the model to concentrate on the most significant data points. To address data delays, Yu et al.[122] utilized a large LSTM for initial evaluations alongside an ensemble of smaller LSTM blocks. Zhang et al.[123,124] proposed ensemble models based on different PMU sets to sustain performance in the event of data loss. Additionally, Tan et al.[80] developed a PMU clustering method that accounted for feature importance. However, despite these benefits, ensemble learning approaches can be computationally intensive and time-consuming, complicating the implementation of machine learning models in real-time power system applications.

For example, Shen et al.[91] introduces an ensemble bagging classifier that operates across multiple time scales to effectively balance classification errors and enhance the system performance. Figure 17 depicts the processes involved in offline training and online testing for this multi-time-scale classifier. Initially, several base learners are developed. During the prediction phase, each base learner produces a probability vector, with each element indicating the likelihood of a specific category. The average of these probability vectors is then calculated. Once the predictions for each time scale are obtained, the final probability vector is determined by the time scale selections made by the prediction algorithm. The ultimate outcome is generated through a weighted voting process applied to these predictions[91].

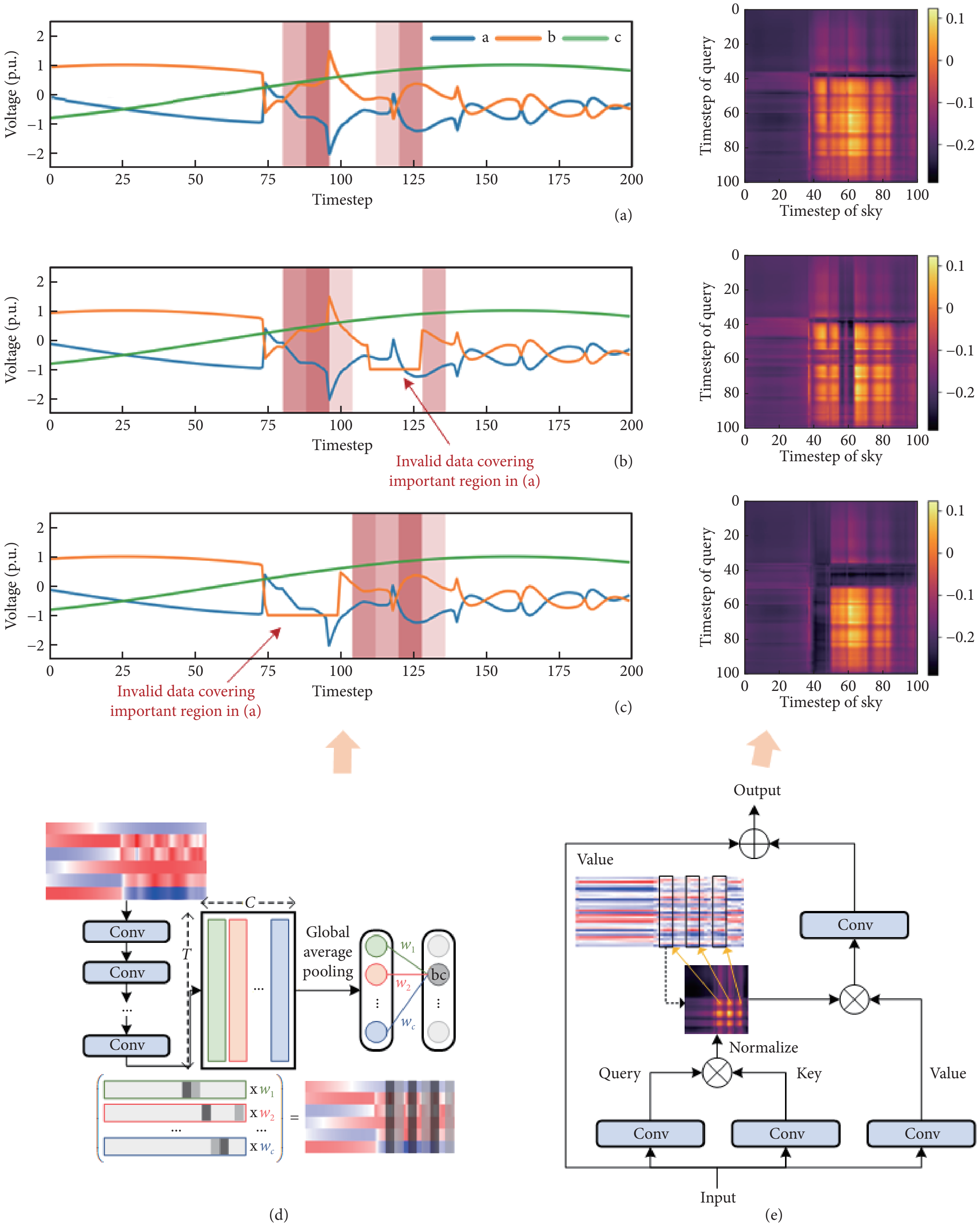

Figure 16 CAMs of the classification model. (a) Without data pollution and **(b)(c)** with data pollution. **(d)** and **(e)** illustrate the interpretability structures based on CAM and attention map, respectively. Reprinted with permission from Ref. [57], © 2023, IEEE.

4.3 Knowledge adaptation based on data recovery

The structural characteristics of wireless sensor networks can lead to various issues, including sensor failures, noise, PMU malfunctions, random data loss, and communication failures, resulting in incomplete measurement data[125,126]. In the daily operations of China's power grid, approximately 10% to 30% of PMU measurement data is reported as abnormal or missing[125], significantly undermining the reliability of AI models in online applications[80].

In power systems, measurement and transmission noise can

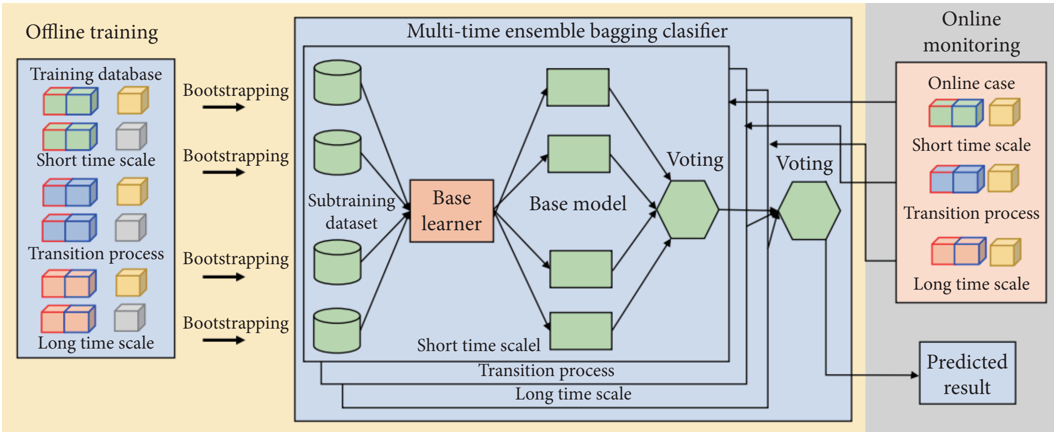

Figure 17 **An illustration of a multi-time-scale ensemble classifiers. Reprinted with permission from Ref. [91], © 2024, IEEE.**

interfere with data, adversely affecting the accuracy of AI models. To tackle this challenge, an adaptive data recovery model (ADRM) is introduced, which aims to restore noisy data to a low-noise state, independent of the noise distribution, thereby reducing its influence on TSA. As shown in Figure 18, the original dataset consists of simulation and historical operational data, which are used to train TSA classifiers. Each dataset D_1 to D_n, contaminated by different white Gaussian noises (WGNs), is employed to train distinct stacked denoising autoencoder (SDAE)-based targeted recovery models (TRMs). Additionally, a noise recognition model (NRM) is trained on data affected by all expected noise distributions D_1 to D_n. Upon receiving noisy data, the n TRMs generate n separate recovered datasets D_1 to D_n, while the NRM provides a corresponding set of weight values. The final recovered dataset D_w is then computed by applying these weights to the recovered data, which is subsequently input into the TSA classifiers to yield assessment results[127].

Moreover, to address the challenge of missing knowledge caused by incomplete data, advanced matrix optimization techniques that leverage spatiotemporal low-rank properties have been employed[128,129]. The alternating direction method of multipliers (ADMM) has also been applied to address the matrix completion problem specific to PMU data[130]. Moreover, an efficient algorithm for large matrix factorization was proposed to tackle equivalent problems[131]. However, these methods often encounter limitations in real-world applications, as actual conditions may not consistently meet the minimum measurement requirements[128].

With the advent of artificial intelligence technologies, deep learning-based data completion methods have emerged. For example, Miranda et al.[132] employed autoencoders to reconstruct missing values by encoding system knowledge within a nonlinear manifold defined by weights. Furthermore, Liao et al.[126] and Goodfellow et al.[133] implemented GANs to minimize distribution errors between generated and real data. To further exploit the spatiotemporal correlations within power systems,[115,134] focused on capturing the authenticity of each pixel in feature maps while accounting for value differences, leading to improved reconstruction performance.

Figure 19 depicts a case study of a data reconstruction algorithm. This proposed method acts as an initial online data recovery process and can be tailored for various tasks by modifying database parameters to suit specific needs, such as modifying the range of possible operating points and feature maps. The fundamental loss function and model structure can remain unchanged to effectively capture electrical spatio-temporal information across diverse applications.

Meanwhile, as shown in Figures 19(a)–19(d), Fang et al.[115] enhances the credibility of the proposed method by incorporating an interpretability module into the algorithm. The generated attention maps visualize the model weights within the non-local layer of the generator, highlighting the model's strong reconstruction performance. To model PMU failure scenarios, all data

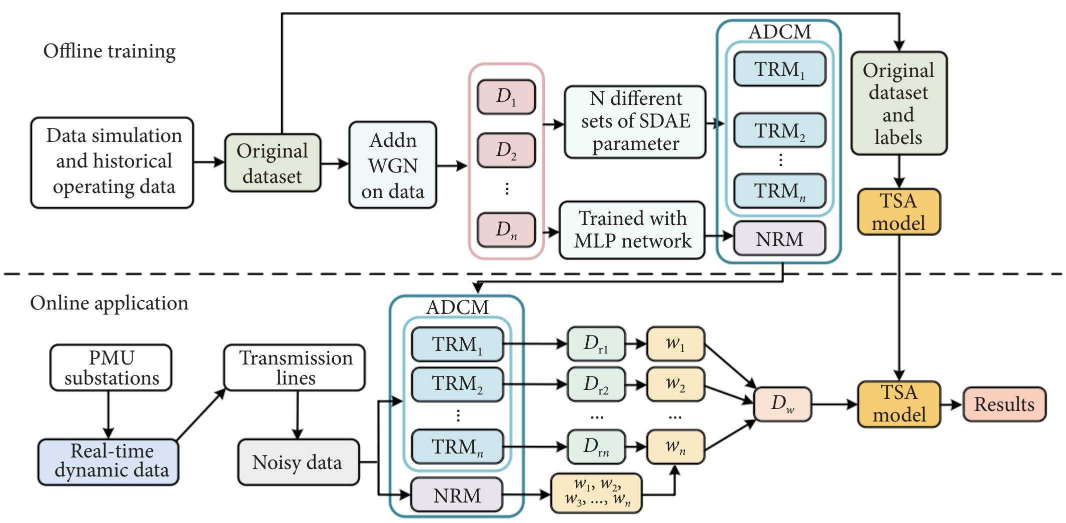

Figure 18 **An illustration of a denoising structure. Reprinted with permission from Ref. [127], © 2022, IEEE.**

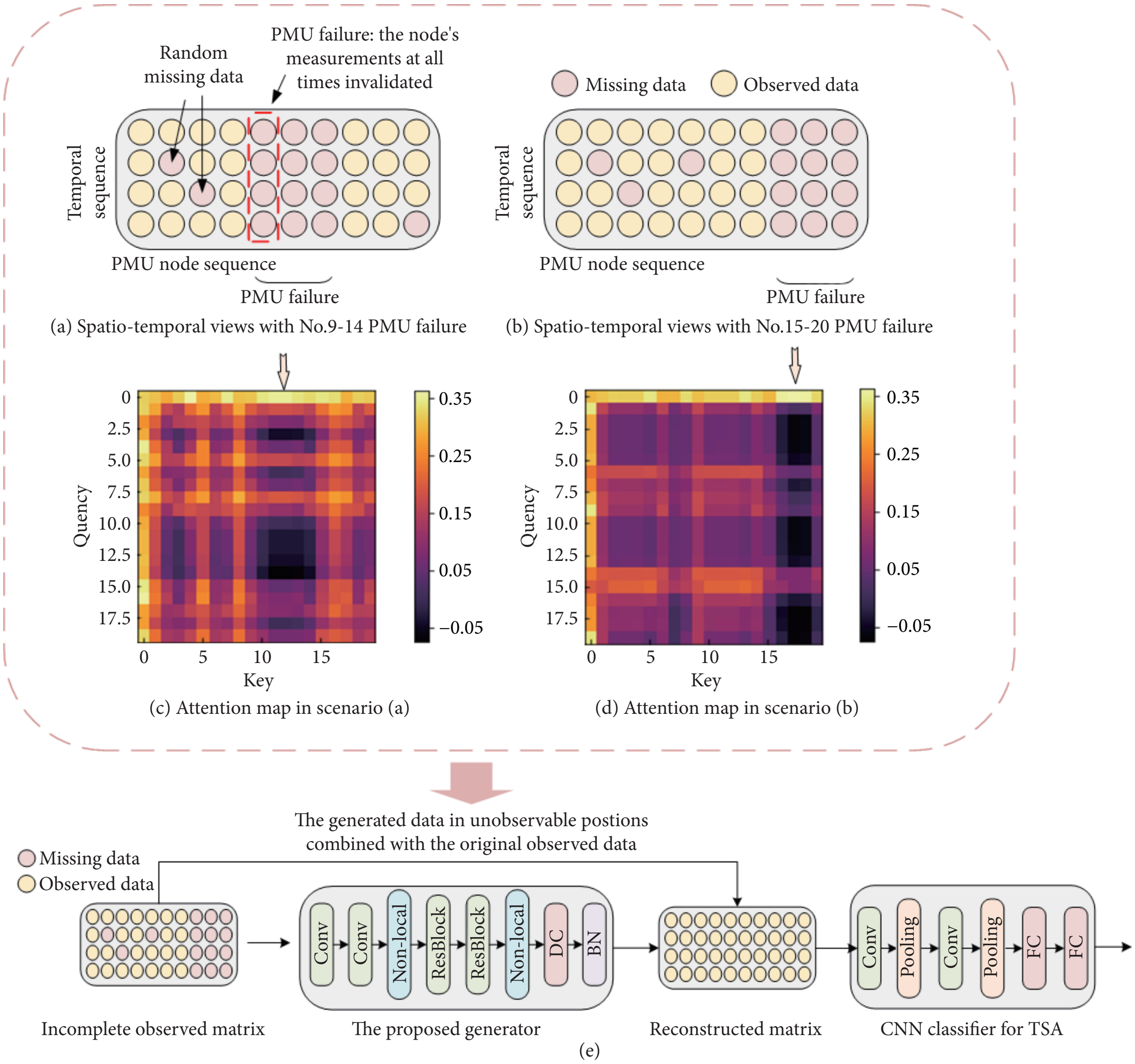

Figure 19 **An example of a data imputation model and its associated interpretabilit . Reprinted with permission from Ref. [115], © 2024, IEEE.**

from malfunctioning PMUs are set to zero. The attention maps (Figures 19(c) and 19(d)) depict the attention distribution across two samples experiencing different PMU failures, with the associated feature maps displayed in Figures 19(a) and 19(b). During the reconstruction of missing data in a partially observed sample, it is essential to ignore sequences from malfunctioning PMUs, as they lack valuable information for reconstruction. The attention maps in Figures 19(c) and 19(d) illustrate the algorithm's ability to effectively disregard the sequences from malfunctioning PMUs while focusing on the valid data[115].

4.4 Knowledge adaptation based on knowledge transfer

Conventional ML models often perform well within the specific domain or dataset on which they were trained. However, when faced with shifts in task or data distribution, these models typically necessitate retraining, a process that can be time-consuming and computationally intensive. This requirement for retraining is particularly impractical in real-world applications, such as power systems or industrial monitoring, where data continuously evolves. Therefore, Hu et al.[135] implemented a model update mechanism using the Sliced Cramér Preservation (SCP) algorithm with a deep residual shrinkage network (DRSN), constructing an SCP-DRSN-based model. This continuous learning approach allows the model to adapt to new data while maintaining performance, providing an effective solution for long-term model optimization.

Transfer learning (TL) harnesses knowledge from a source domain or task and applies it to a related target domain, facilitating model adaptation to new tasks with minimal retraining. This ability to transfer learned representations across domains significantly enhances model efficiency, particularly when labeled data in the target domain is scarce. In such instances, TL leverages the abundant labeled data from the source domain, thereby reducing the reliance on extensive labeled datasets in the target domain[136].

By aligning feature distributions between the source $\boldsymbol{D}_s$ and target domains $\boldsymbol{D}_t$, TL also alleviates the challenges associated with domain shifts that typically hinder the performance of conventional AI models. Each domain is characterized by a feature space X and a probability distribution $P(\boldsymbol{X})$, represented as $\boldsymbol{D}_s=\{\boldsymbol{X}_s, P(\boldsymbol{X}_s)\}$ and $\boldsymbol{D}_t=\{\boldsymbol{X}_t, P(\boldsymbol{X}_t)\}$, respectively. The learning tasks within both domains are defined by a label space and its corresponding prediction function, denoted as $\boldsymbol{T}=\{\boldsymbol{Y}, f\}$. In this context, TL aims to enhance the learning of $f(\cdot)$ in $\boldsymbol{D}_t$ using the knowledge in $\boldsymbol{D}_t$ and $\boldsymbol{T}_s$ [137], as indicated in Figure 20. For instance, Ren et al.[138] used transfer learning techniques to iteratively minimize the marginal and conditional distribution differences between the trained data and unknown data for stability assessment. Hao et al.[139] achieved feature adaptation by minimizing the multi-kernel maximum mean discrepancy (MK-MMD) between domains. Jiang et al.[59] proposed a mechanism-informed adversarial transfer learning (TL) approach, integrated with a domain-adversarial neural network, which seamlessly incorporates physics-embedded axis orbits corresponding to various modes within the domain adaptation process.

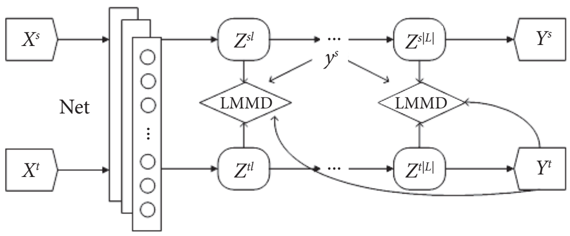

Figure 20 A typical domain adaption TL model structure.

Figure 21 presents a bidirectional active transfer learning (Bi-ATL) framework as proposed in Ref. [140]. This framework effectively combines data from both the target and source domains. The Bi-ATL module creates a mixed instance set that incorporates knowledge from the target domain through forward active learning, and retains relevant information from the source domain through backward active learning. The purpose of forward active learning is to identify the target instances that are most valuable for labeling, thereby improving performance compared to other methods. In contrast, backward active learning focuses on selecting suitable instances from the source domain to virtually expand the training set, which reduces the need for extensive labeling in the target domain. Moreover, the framework utilizes fine-tuning to adjust the pre-trained model for new operational conditions, using the actively created mixed instance set for enhanced efficiency compared to passive fine-tuning approaches. In summary, the Bi-ATL framework integrates information from original operating conditions and a limited number of labeled instances from new conditions to achieve more effective adaptation[140].

Furthermore, to overcome challenges related to data scarcity and enhance data generation efficiency, Figure 22 presents the workflow of a feature combination-based TL for data generation. In Stage I, a GAN is utilized as the pre-trained model, leveraging the original dataset that includes all features. Stage II focuses on selecting features, evaluating their importance in relation to the objectives. Stage III employs model-based transfer learning to create generative models for the target features. In Stage IV, the outputs from various models are combined to generate complete samples. Throughout the transfer learning process, the source generative model is fine-tuned using the target dataset to generate state features associated with the k-th target attribute. This method reduces the time and resources required to develop a new model from scratch while improving performance with limited training data. As a result, the model-based transfer learning strategy enables effective training with fewer target samples, while the proposed feature selection and integration process decreases computational complexity[141].

To address the limited coverage of model adaptation in the context of domain adaptation and reinforcement learning, additional transfer learning approaches, such as multi-task learning (MTL), offer valuable insights. Several studies have demonstrated the effectiveness of MTL in power systems, particularly in optimizing control strategies and enhancing task efficiency. For example, Wang et al.[142] introduced the causality-based multi-task neural network (CMTNN), which incorporates causal relationships between tasks while minimizing the introduction of extraneous information. This method employs a mask layer after the input layer to filter irrelevant information on a task-specific basis, thus ensuring more relevant task learning. Similarly, Ma et al.[143] developed a multi-task model aimed at optimizing emergency control strategies for frequency regulation in receiving-end power grids, significantly improving the online optimization efficiency of control strategies and highlighting the potential of MTL in complex power system control scenarios. In another approach, Liu et al.[79] utilized a multi-task attribution map to enable a RL agent to assign attention weights to different tasks based on the power system nodes involved. This allowed the model to address the multi-task adjustment problem effectively while achieving near-optimal operational costs. Furthermore, Li et al.[144] employed a multi-task learning model with progressive layered extraction, significantly reducing both training costs and evaluation time, further demonstrating the computational efficiency of MTL in power system applications.

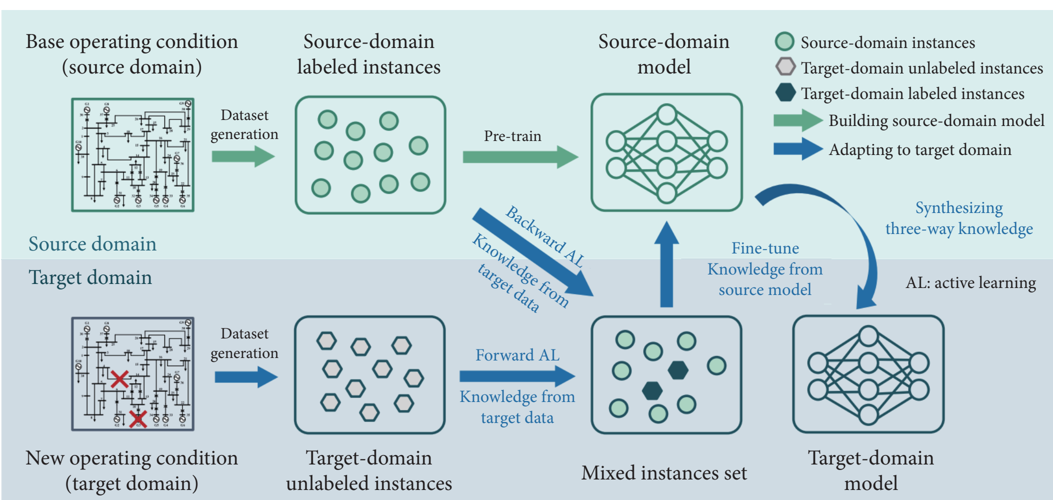

Figure 21 The Bi-ATL framework for adapting DL-based models to previously unlearned operating conditions. Reprinted with permission from Ref. [140], © 2023, IEEE.

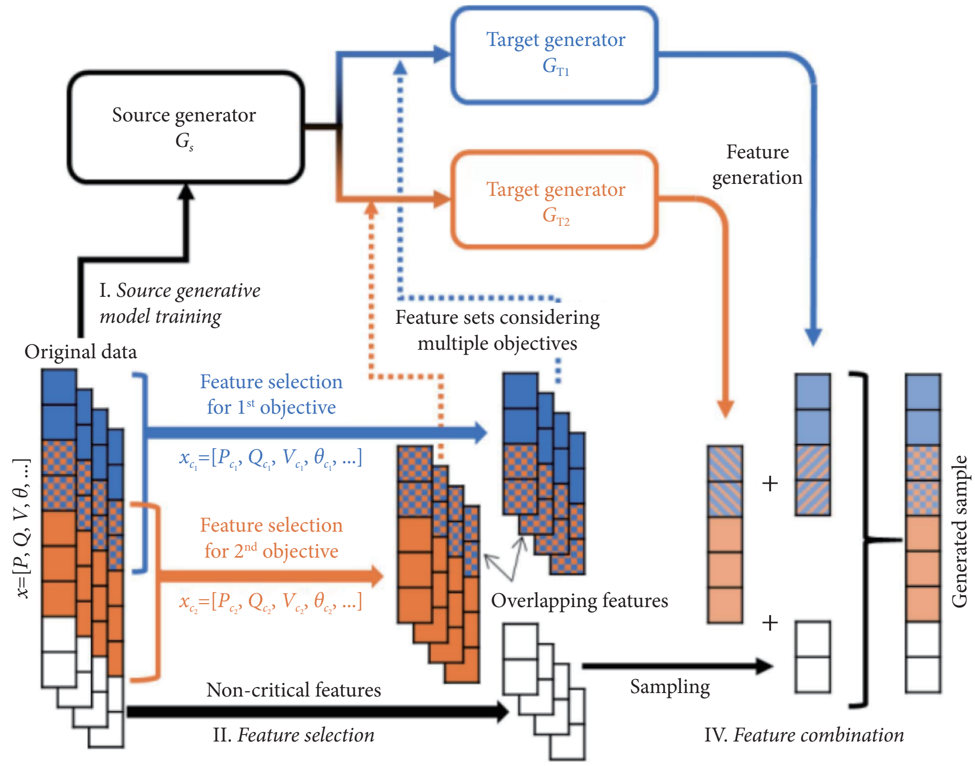

Figure 22 An algorithm structure for feature combination-based transfer learning. Reprinted with permission from Ref. [141], © 2024, IEEE.

5 Future prospects of AI in power systems

Recent reports have highlighted the successful deployment of AI techniques in real-world power systems, with a primary focus on enhancing grid resilience during extreme events and enabling rapid post-disaster recovery. Additionally, several regional grids have implemented real-time online power flow calculations with millisecond-level accuracy, dynamic identification of load and distributed energy sources at second-level resolution, data-driven transient voltage stability criteria with 100 ms response times, and stability margin estimation that does not rely on fault information[145].

Despite recent advancements, real-world power systems, particularly power distribution networks with large-scale integration of distributed energy resources (DERs) such as photovoltaic (PV) systems, microgrids, and energy storage, continue to face significant challenges. These challenges stem from the inherent uncertainty and dynamic nature of the operating environment, influenced by factors such as weather conditions, load variations, and equipment malfunctions, which introduce substantial uncertainties affecting power flow and complicating stability assessments. Additionally, power distribution networks with DERs are characterized by unpredictable topologies, frequent reconfigurations, and incomplete measurement data. Conventional stability assessment methods struggle to address these issues, as they rely on static topological models and predefined assumptions about system behavior, limiting their ability to adapt to the real-time changes in topology and generation-load variations that are critical for accurate stability analysis.

Addressing these challenges requires the development of flexible and robust AI algorithms to manage uncertainty. As noted, this involves transfer learning, spatiotemporal feature extraction, and improving online data quality. With power grid data now reaching terabyte scales, two primary challenges emerge: high-dimensional features and large datasets. To mitigate these, AI methods use dimensionality reduction techniques like autoencoders and PCA to preserve critical information while reducing complexity. Scalable algorithms, such as distributed computing frameworks (e.g., Apache Spark), enable efficient data processing across multiple nodes. Additionally, online learning techniques allow for incremental model updates, eliminating the need for retraining on entire datasets. These strategies effectively address the challenges of high-dimensionality and large-scale data in real-time power grid monitoring.

Therefore, future research on AI-driven transient stability analysis in power systems should focus on overcoming these limitations by improving algorithm robustness, enhancing data quality, and addressing the complexities of dynamic real-world environments.

5.1 Knowledge representation of AI-based models

In high-penetration AC/DC power systems, the interactions among various types of power electronic devices, along with the multi-scale nonlinear dynamics between these devices and the grid, emphasize the multi-time-scale coupling characteristics. Additionally, the inherent randomness and volatility of renewable energy outputs increase operational uncertainties within the grid. Moreover, control strategies for DC transmission and renewable generation introduce significant discrete switching behaviors in transient responses. This complexity poses challenges for AI models in comprehensively understanding the evolving stability characteristics of the grids. As a result, AI models often struggle to achieve the comprehensive analysis that is consistent with physics-based mechanistic models when learning the complex features of the power grid.

Thus, it is essential to explore methods that integrate physical and data-driven AI approaches, taking into account the uncertainties associated with renewable outputs and the intricate operational characteristics of power electronic devices. Furthermore, further research should aim to construct a parameter space for transient stability knowledge in high-penetration AC/DC power systems, effectively combining established rules and empirical insights in power system stability analysis.

5.2 Reduction and solution of AI-based models

The exponential growth in system dimensions poses significant challenges for model training. The increasing penetration of various power electronic devices has resulted in a substantial rise in the dimensionality of power system modeling, leading to heightened computational demands. Moreover, the complexity involved in equivalent modeling of power electronic clusters within energy units and generation unit clusters in renewable energy stations further complicates this task. Consequently, when AI models attempt to reduce dimensionality by mapping high-dimensional information to lower dimensions through extensive datasets, they often encounter difficulties in maintaining the consistency of stability characteristics and dynamic trajectories before and after dimensionality reduction. Furthermore, developing physics-data fusion models that balance simulation accuracy and timeliness requires further exploration.

To achieve dimension reduction and optimization of AI-based stability analysis models, it is essential to analyze the intrinsic mechanisms of various heterogeneous power electronic devices. This entails establishing evaluation metrics for the spatiotemporal similarity of dynamic behaviors within clusters. Future research should focus on characterizing the dimensionality reduction mapping of dominant features associated with transient instability in the parameter space. By incorporating these reduced mapping parameters into the loss function and optimization process of AI models, it is possible to develop intelligent algorithms that adaptively reduce features while preserving the structural characteristics and stability features of the high-dimensional system. This approach can alleviate the computational burden associated with model training.

5.3 Evolution and adaption of AI-based models

The operation scenarios of high-penetration renewable AC/DC power systems are both complex and variable. However, the internal parameters in AI algorithms are often determined based on typical operating conditions, generating analytical results by training on extensive historical data. This reliance on fixed conditions poses challenges in ensuring performance under changing circumstances.

Therefore, developing AI methods for transferring transient stability knowledge tailored to the diverse operational modes is essential. This includes researching methods for representing the transfer of operational information and dynamic responses in high-penetration renewable power systems. Additionally, exploring approaches for updating stability knowledge through broad inheritance across multiple scenarios and in-depth generation of knowledge models is crucial. These efforts aim to facilitate stability knowledge analysis and control of the system under complex operational conditions.

6 Conclusions

With the continuous advancement of modern grid construction, China's power system has evolved into a complex cyber-physical system characterized by its large scale, intricate structure, and multi-source information exchange. AI techniques are increasingly applied to characterize, discover, and adapt stability analysis knowledge, thereby facilitating the establishment and evolution of stability analysis models. This paper reviews recent advancements in AI technologies, including generative adversarial learning, transfer learning, and graph learning, in the context of stability analysis in power systems, leading to the following conclusions:

(1) AI technologies serve as universal tools for knowledge acquisition through extensive data learning. While significant theoretical research exists regarding classical stability analysis in grids, the increasing penetration of renewable energy and the integration of numerous power electronic devices introduce multi-scale nonlinear dynamics and multi-time-scale coupling characteristics. Consequently, AI methods diminish the reliance on precise simulations during model building, positioning AI-based techniques for learning and modeling stability knowledge as a critical research direction.

(2) The modeling of stability-related knowledge using AI still heavily relies on expert experience as prior knowledge, particularly in informing the selection of stability feature scales and model orders. However, there is a lack of adaptive algorithms capable of determining or adjusting the feature space and model order. Future AI approaches can explore incorporating evaluations of data similarity in dynamic response processes to determine model order and facilitate adaptive equivalent modeling.

(3) Current AI techniques exhibit a degree of adaptive evolution through model transfer and incremental learning. However, operational uncertainties arising from renewable energy outputs and control strategies for DC transmission introduce significant discrete switching behaviors in transient responses. As the underlying physical states changes during model transfer, a more robust intelligent model closely aligned with fundamental physical principles, or a model capable of automatically adapting to different operating states, may be essential for effective solutions. Future AI models need to evaluate dominant stability knowledge and dynamically update key parameters while transitioning between different model structures to enhance applicability.

Acknowledgements

This work is supported by the National Natural Science Foundation of China (No. U23B20126).

Article history

Received: 1 November 2024; Revised: 2 December 2024; Accepted: 5 December 2024

Additional information

Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

References

[1] Jufri, F. H., Widiputra, V., Jung, J. (2019). State-of-the-art review on power grid resilience to extreme weather events: Definitions, frameworks, quantitative assessment methodologies, and enhancement strategies. *Applied Energy*, 239: 1049–1065.

[2] Bilis, E. I., Kröger, W., Nan, C. (2013). Performance of electric power systems under physical malicious attacks. *IEEE Systems Journal*, 7: 854–865.

[3] Gomes, P. (2004). New strategies to improve bulk power system security: Lessons learned from large blackouts. In: Proceedings of the IEEE Power Engineering Society General Meeting, Denver, CO, USA.
[4] Xu, L., Guo, Q., Sheng, Y., Muyeen, S. M., Sun, H. (2021). On the resilience of modern power systems: A comprehensive review from the cyber-physical perspective. *Renewable and Sustainable Energy Reviews*, 152: 111642.
[5] Kundur, P., Paserba, J., Ajjarapu, V., Andersson, G., Bose, A., Canizares, C., Hatziargyriou, N., Hill, D., Stankovic, A., Taylor, C. et al. (2004). Definition and classification of power system stability IEEE/CIGRE joint task force on stability terms and definitions. *IEEE Transactions on Power Systems*, 19: 1387–1401.
[6] Yu, X., Xue, Y. (2016). Smart grids: A cyber–physical systems perspective. *Proceedings of the IEEE*, 104: 1058–1070.
[7] Chen, Q., Yin, X., You, D., Hou, H., Tong, G., Wang, B., Liu, H. (2009). Review on blackout process in China Southern area main power grid in 2008 snow disaster. In: Proceedings of the 2009 IEEE Power & Energy Society General Meeting, Calgary, AB, Canada.
[8] Haes Alhelou, H., Hamedani-Golshan, M. E., Njenda, T. C., Siano, P. (2019). A survey on power system blackout and cascading events: Research motivations and challenges. *Energies*, 12: 682.
[9] Sarkar, S., Saha, G., Pal, G., Karmakar, T. (2015). Indian experience on smart grid application in blackout control. In: Proceedings of the 2015 39th National Systems Conference (NSC), Greater Noida, India.
[10] Arnold, G. W. (2011). Challenges and opportunities in smart grid: A position article. *Proceedings of the IEEE*, 99: 922–927.
[11] Magnusson, P. C. (1947). The transient-energy method of calculating stability. *Transactions of the American Institute of Electrical Engineers*, 66: 747–755.
[12] Chiang, H. D., Wu, F., Varaiya, P. (1987). Foundations of direct methods for power system transient stability analysis. *IEEE Transactions on Circuits and Systems*, 34: 160–173.
[13] Xue, Y., Van Cutsem, T., Ribbens-Pavella, M. (1988). A simple direct method for fast transient stability assessment of large power systems. *IEEE Transactions on Power Systems*, 3: 400–412.
[14] Xue, Y., Wehenkel, L., Belhomme, R., Rousseaux, P., Pavella, M., Euxibie, E., Heilbronn, B., Lesigne, J. F. (1992). Extended equal area criterion revisited (EHV power systems). *IEEE Transactions on Power Systems*, 7: 1012–1022.
[15] Hu, J., Vasilakos, A. V. (2016). Energy big data analytics and security: Challenges and opportunities. *IEEE Transactions on Smart Grid*, 7: 2423–2436.
[16] Joshi, P. M., Verma, H. K. (2021). Synchrophasor measurement applications and optimal PMU placement: A review. *Electric Power Systems Research*, 199: 107428.
[17] Kabiri, M., Amjady, N. (2019). A new hybrid state estimation considering different accuracy levels of PMU and SCADA measurements. *IEEE Transactions on Instrumentation and Measurement*, 68: 3078–3089.
[18] Gungor, V. C., Lu, B., Hancke, G. P. (2010). Opportunities and challenges of wireless sensor networks in smart grid. *IEEE Transactions on Industrial Electronics*, 57: 3557–3564.
[19] Chen, K., He, Z., Wang, S. X., Hu, J., Li, L., He, J. (2018). Learning-based data analytics: Moving towards transparent power grids. *CSEE Journal of Power and Energy Systems*, 4: 67–82.
[20] LeCun, Y., Bengio, Y., Hinton, G. (2015). Deep learning. *Nature*, 521: 436–444.
[21] Shi, Z., Yao, W., Li, Z., Zeng, L., Zhao, Y., Zhang, R., Tang, Y., Wen, J. (2020). Artificial intelligence techniques for stability analysis and control in smart grids: Methodologies, applications, challenges and future directions. *Applied Energy*, 278: 115733.
[22] Tolle, K. M., Tansley, D. S. W., Hey, A. J. G. (2011). The fourth paradigm: Data-intensive scientific discovery. *Proceedings of the IEEE*, 99: 1334–1337.
[23] Russell, S., Norvig, P. (2009). *Artificial Intelligence: A Modern Approach*, 3rd Ed. USA: Prentice Hall Press.
[24] Roh, Y., Heo, G., Whang, S. E. (2021). A survey on data collection for machine learning: A big data—AI integration perspective. *IEEE Transactions on Knowledge and Data Engineering*, 33: 1328–1347.
[25] Vieira, S., Pinaya, W. H. L., Mechelli, A. (2020). Introduction to machine learning. In: Mechelli, A., Vieira, S. Eds. *Machine learning*. Academic Press.
[26] He, K., Zhang, X., Ren, S., Sun, J. (2015). Deep residual learning for image recognition. arXiv: 1512.03385.
[27] Radford, A., Kim, J. W., Xu, T., Brockman, G., McLeavey, C., Sutskever, I. (2022). Robust speech recognition via large-scale weak supervision. arXiv:2212.04356.
[28] Ranftl, R., Bochkovskiy, A., Koltun, V. (2021). Vision transformers for dense prediction. In: Proceedings of the 2021 IEEE/CVF International Conference on Computer Vision (ICCV), Montreal, QC, Canada.
[29] Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Illia Polosukhin, L., K. (2017). Attention is all you need. arXiv:1706.03762.
[30] Chen, K., Hu, J., He, J. (2018). A framework for automatically extracting overvoltage features based on sparse autoencoder. *IEEE Transactions on Smart Grid*, 9: 594–604.
[31] Fang, J., Zheng, L., Liu, C., Su, C. (2024). A data-driven case generation model for transient stability assessment using generative adversarial networks. *IEEE Transactions on Industrial Informatics*, 20: 14391–14400.
[32] Zhou, Y., Guo, Q., Sun, H., Yu, Z., Wu, J., Hao, L. (2019). A novel data-driven approach for transient stability prediction of power systems considering the operational variability. *International Journal of Electrical Power & Energy Systems*, 107: 379–394.
[33] Gomez, F. R., Rajapakse, A. D., Annakkage, U. D., Fernando, I. T. (2011). Support vector machine-based algorithm for post-fault transient stability status prediction using synchronized measurements. *IEEE Transactions on Power Systems*, 26: 1474–1483.
[34] Guo, T., Milanović, J. V. (2014). Probabilistic framework for assessing the accuracy of data mining tool for online prediction of transient stability. *IEEE Transactions on Power Systems*, 29: 377–385.
[35] Zhang, R., Wu, J., Shao, M., Li, B., Lu, Y. (2018). Transient stability prediction of power systems based on deep belief networks. In: Proceedings of the 2018 2nd IEEE Conference on Energy Internet and Energy System Integration (EI2), Beijing, China.
[36] Frimpong, E. A., Okyere, P. Y., Asumadu, J. (2018). On-line determination of transient stability status using multilayer perceptron neural network. *Journal of Electrical Engineering*, 69: 58–64.
[37] Zhu, L., Hill, D. J., Lu, C. (2019). Hierarchical deep learning machine for power system online transient stability prediction. *IEEE Transactions on Power Systems*, 35: 2399–2411.
[38] Luo, Y., Lu, C., Zhu, L., Song, J. (2023). Graph convolutional network-based interpretable machine learning scheme in smart grids. *IEEE Transactions on Automation Science and Engineering*, 20: 47–58.
[39] Samantaray, S. R., Kamwa, I., Joos, G. (2017). Phasor measurement unit based wide - area monitoring and information sharing between micro - grids. *IET Generation, Transmission & Distribution*, 11: 1293–1302.
[40] Tan, B., Yang, J., Tang, Y., Jiang, S., Xie, P., Yuan, W. (2019). A deep imbalanced learning framework for transient stability assessment of power system. *IEEE Access*, 7: 81759–81769.
[41] Douzas, G., Bacao, F., Last, F. (2018). Improving imbalanced learning through a heuristic oversampling method based on k-means and SMOTE. *Information Sciences*, 465: 1–20.
[42] Chawla, N. V., Bowyer, K. W., Hall, L. O., Kegelmeyer, W. P. (2002). SMOTE: Synthetic minority over-sampling technique. *Journal of Artificial Intelligence Research*, 16: 321–357.
[43] Zhang, H., Goodfellow, I., Metaxas, D., Odena, A. (2019). Self-attention generative adversarial networks. In: Proceedings of the

36th International Conference on Machine Learning, California, USA.

[44] Yan, C., Chang, X., Li, Z., Guan, W., Ge, Z., Zhu, L., Zheng, Q. (2022). ZeroNAS: Differentiable generative adversarial networks search for zero-shot learning. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 44: 9733–9740.

[45] Yan, C., Chang, X., Luo, M., Liu, H., Zhang, X., Zheng, Q. (2024). Semantics-guided contrastive network for zero-shot object detection. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 46: 1530–1544.

[46] Ouyang, X., Ying, C., Agam, G. (2021). Accelerated WGAN update strategy with loss change rate balancing. In: Proceedings of the 2021 IEEE Winter Conference on Applications of Computer Vision (WACV), Waikoloa, HI, USA.

[47] Fan, J., Yuan, X., Miao, Z., Sun, Z., Mei, X., Zhou, F. (2022). Full attention Wasserstein GAN with gradient normalization for fault diagnosis under imbalanced data. *IEEE Transactions on Instrumentation and Measurement*, 71: 3517516.

[48] Arjovsky, M., Chintala, S., Bottou, L. (2017). Wasserstein GAN. arXiv:1701.07875.

[49] Shao, S., Wang, P., Yan, R. (2019). Generative adversarial networks for data augmentation in machine fault diagnosis. *Computers in Industry*, 106: 85–93.

[50] Ren, C., Xu, Y. (2019). A fully data-driven method based on generative adversarial networks for power system dynamic security assessment with missing data. *IEEE Transactions on Power Systems*, 34: 5044–5052.

[51] Liu, J., Qu, F., Hong, X., Zhang, H. (2018). A small-sample wind turbine fault detection method with synthetic fault data using generative adversarial nets. *IEEE Transactions on Industrial Informatics*, 15: 3877–3888.

[52] Li, J., Yang, H., Yan, L., Li, Z., Liu, D., Xia, Y. (2020). Data augment using deep convolutional generative adversarial networks for transient stability assessment of power systems. In: Proceedings of the 2020 39th Chinese Control Conference (CCC), Shenyang, China.

[53] Zhu, L., Hill, D. J. (2022). Data/model jointly driven high-quality case generation for power system dynamic stability assessment. *IEEE Transactions on Industrial Informatics*, 18: 5055–5066.

[54] Gan, R., Li, X., Wei, W., Su, H., Zhan, Z. (2023). Grid transient simulation using attention-based data augmentation technique with supercomputing. In: Proceedings of the 2023 4th International Seminar on Artificial Intelligence, Networking and Information Technology (AINIT), Nanjing, China.

[55] Yuan, R., Wang, B., Sun, Y., Song, X., Watada, J. (2023). Conditional style-based generative adversarial networks for renewable scenario generation. *IEEE Transactions on Power Systems*, 38: 1281–1296.

[56] Kang, M., Zhu, R., Chen, D., Li, C., Gu, W., Qian, X., Yu, W. (2024). A cross-modal generative adversarial network for scenarios generation of renewable energy. *IEEE Transactions on Power Systems*, 39: 2630–2640.

[57] Fang, J., Chen, K., Liu, C., He, J. (2023). An explainable and robust method for fault classification and location on transmission lines. *IEEE Transactions on Industrial Informatics*, 19: 10182–10191.

[58] Chen, K., Hu, J., He, J. (2016). Detection and classification of transmission line faults based on unsupervised feature learning and convolutional sparse autoencoder. *IEEE Transactions on Smart Grid*, 9: 1748–1758.

[59] Jiang, X., Li, Y., Wang, Z., Hui, H., Cheng, X. (2023). Orbit-DANN: A mechanism-informed transfer learning method for automatic fault diagnosis of turbomachinery. *IEEE Sensors Journal*, 24: 2228–2241.

[60] Morales, J., Orduña, E. A., Rehtanz, C. (2014). Identification of lightning stroke due to shielding failure and back flashover for ultra-high-speed transmission-line protection. *IEEE Transactions on Power Delivery*, 29: 2008–2017.

[61] Soni, B. P., Saxena, A., Gupta, V., Surana, S. L. (2018). Identification of generator criticality and transient instability by supervising real-time rotor angle trajectories employing RBFNN. *ISA Transactions*, 83: 66–88.

[62] Shi, Z., Yao, W., Zeng, L., Wen, J., Fang, J., Ai, X., Wen, J. (2020). Convolutional neural network-based power system transient stability assessment and instability mode prediction. *Applied Energy*, 263: 114586.

[63] Guo, T., Milanović, J. V. (2016). Online identification of power system dynamic signature using PMU measurements and data mining. *IEEE Transactions on Power Systems*, 31: 1760–1768.

[64] Fang, J., Liu, C., Zheng, L., Su, C. (2023). A data-driven method for online transient stability monitoring with vision-transformer networks. *International Journal of Electrical Power & Energy Systems*, 149: 109020.

[65] An, J., Yu, J., Li, Z., Zhou, Y., Mu, G. (2020). A data-driven method for transient stability margin prediction based on security region. *Journal of Modern Power Systems and Clean Energy*, 8: 1060–1069.

[66] An, J., Mu, G., Li, Z., Liu, D. (2019). Power system transient stability margin assessment using steady-state information. In: Proceedings of the 2019 IEEE Innovative Smart Grid Technologies - Asia (ISGT Asia), Chengdu, China.

[67] Phootrakornchai, W., Jiriwibhakorn, S. (2015). Online critical clearing time estimation using an adaptive neuro-fuzzy inference system (ANFIS). *International Journal of Electrical Power & Energy Systems*, 73: 170–181.

[68] Sulistiawati, I. B., Priyadi, A., Qudsi, O. A., Soeprijanto, A., Yorino, N. (2016). Critical Clearing Time prediction within various loads for transient stability assessment by means of the Extreme Learning Machine method. *International Journal of Electrical Power & Energy Systems*, 77: 345–352.

[69] Zhu, L., Wen, W., Li, J., Hu, Y. (2023). Integrated data-driven power system transient stability monitoring and enhancement. *IEEE Transactions on Power Systems*, 39: 1797–1809.

[70] Chicco, G. (2012). Overview and performance assessment of the clustering methods for electrical load pattern grouping. *Energy*, 42: 68–80.

[71] Lever, J., Krzywinski, M., Altman, N. (2017). Principal component analysis. *Nature Methods*, 14: 641–642.

[72] Wan, Z., Zhang, Y., He, H. (2017). Variational autoencoder based synthetic data generation for imbalanced learning. In: Proceedings of the 2017 IEEE Symposium Series on Computational Intelligence (SSCI), Honolulu, HI, USA.

[73] Xu, C., Dai, Y., Xu, P., Gao, T., Zhang, J. (2023). Wind power scenario generation based on denoising diffusion probabilistic model. In: Proceedings of the 2023 IEEE International Conference on Systems, Man, and Cybernetics (SMC), Honolulu, Oahu, HI, USA.

[74] Dong, X., Mao, Z., Sun, Y., Xu, X. (2024). Short-term wind power scenario generation based on conditional latent diffusion models. *IEEE Transactions on Sustainable Energy*, 15: 1074–1085.

[75] Zhu, L., Wen, W., Qu, Y., Shen, F., Li, J., Song, Y., Liu, T. (2024). Robust representation learning for power system short-term voltage stability assessment under diverse data loss conditions. *IEEE Transactions on Neural Networks and Learning Systems*, 35: 6035–6047.

[76] Wang, Z., Zhou, Y., Guo, Q., Sun, H. (2022). Interpretable neighborhood deep models for online total transfer capability evaluation of power systems. *IEEE Transactions on Power Systems*, 37: 260–271.

[77] Vázquez-Canteli, J. R., Nagy, Z. (2019). Reinforcement learning for demand response: A review of algorithms and modeling techniques. *Applied Energy*, 235: 1072–1089.

[78] Qiu, D., Wang, Y., Wang, J., Zhang, N., Strbac, G., Kang, C. (2023). Resilience-oriented coordination of networked microgrids: A shapley Q-value learning approach. *IEEE Transactions on Power Systems*, 39: 3401–3416.

[79] Liu, S., Luo, W., Zhou, Y., Chen, K., Zhang, Q., Xu, H., Guo, Q., Song, M. (2024). Transmission interface power flow adjustment: A deep reinforcement learning approach based on multi-task attribution

map. *IEEE Transactions on Power Systems*, 39: 3324–3335.

[80] Tan, B., Yang, J., Zhou, T., Zhan, X., Liu, Y., Jiang, S., Luo, C. (2020). Spatial-temporal adaptive transient stability assessment for power system under missing data. *International Journal of Electrical Power & Energy Systems*, 123: 106237.

[81] Xie, H., Zhang, B. H., Yu, G. L., Li, Y. H., Li, P. (2006). Power system transient stability detection theory based on characteristic concave or convex of trajectory. *Proceedings of the CSEE*, 26(5): 38–42. (in Chinese)

[82] Zheng, C., Sun, H. D., Li, H. L. (2021). Response-based branch transient transmission capability index and transient stability emergency control. *Proceedings of the CSEE*, 41(2): 581–591. (in Chinese)

[83] Wang, Z. W., Sun, H. D., Yi, J., Zhao, B., Xu, S. Y. (2020). Real-time identification of transient angle instability in two machine groups using angular velocities. *Power System Technology*, 44(7): 2634–2642. (in Chinese)

[84] Ma, S. Y., Zhu, C. H., Zheng, C., Li, P. H., Chen, C. S. (2020). Analysis of extended phase trajectory characteristics and transient stability identification. *Proceedings of the CSEE*, 40(20): 6516–6526. (in Chinese)

[85] Hang, F., Huang, S., Chen, Y., Mei, S. (2017). Power system transient stability assessment based on dimension reduction and cost-sensitive ensemble learning. In: Proceedings of the 2017 IEEE Conference on Energy Internet and Energy System Integration (EI2), Beijing, China.

[86] Zhang, C., Li, Y., Yu, Z., Tian, F. (2016). Feature selection of power system transient stability assessment based on random forest and recursive feature elimination. In: Proceedings of the 2016 IEEE PES Asia-Pacific Power and Energy Engineering Conference (APPEEC), Xi'an, China.

[87] Sun, M., Konstantelos, I., Strbac, G. (2019). A deep learning-based feature extraction framework for system security assessment. *IEEE Transactions on Smart Grid*, 10: 5007–5020.

[88] Wu, S., Zheng, L., Hu, W., Yu, R., Liu, B. (2020). Improved deep belief network and model interpretation method for power system transient stability assessment. *Journal of Modern Power Systems and Clean Energy*, 8: 27–37.

[89] Tan, B., Yang, J., Pan, X., Li, J., Xie, P., Zeng, C. (2017). Representational learning approach for power system transient stability assessment based on convolutional neural network. *The Journal of Engineering*, 2017: 1847–1850.

[90] Shen, Y., Peng, Y., Shuai, Z., Zhou, Q., Zhu, L., Shen, Z. J., Shahidehpour, M. (2023). Hierarchical time-series assessment and control for transient stability enhancement in islanded microgrids. *IEEE Transactions on Smart Grid*, 14: 3362–3374.

[91] Yu, H., Xu, C., Geng, G., Jiang, Q. (2023). Multi-time-scale shapelet-based feature extraction for non-intrusive load monitoring. *IEEE Transactions on Smart Grid*, 15: 1116–1128.

[92] Gupta, A., Gurrala, G., Sastry, P. S. (2019). An online power system stability monitoring system using convolutional neural networks. *IEEE Transactions on Power Systems*, 34: 864–872.

[93] James, J. Q., Hill, D. J., Lam, A. Y., Gu, J., Li, V. O. (2017). Intelligent time-adaptive transient stability assessment system. *IEEE Transactions on Power Systems, 33*: 1049–1058.

[94] Yu, J. J. Q., Lam, A. Y. S., Hill, D. J., Hou, Y., Li, V. O. K. (2019). Delay aware power system synchrophasor recovery and prediction framework. *IEEE Transactions on Smart Grid*, 10: 3732–3742.

[95] Guo, X., Zhu, S., Yang, Z., Liu, H., Bi, T. (2021). Consecutive missing data recovery method based on long-short term memory network. In: Proceedings of the 2021 3rd Asia Energy and Electrical Engineering Symposium (AEEES), Chengdu, China.

[96] Gu, S., Qiao, J., Zhao, Z., Zhu, Q., Han, F. (2022). Power system transient stability assessment based on graph neural network with interpretable attribution analysis. In: Proceedings of the 2022 4th International Conference on Smart Power & Internet Energy Systems (SPIES), Beijing, China.

[97] Defferrard, M., Bresson, X., Vandergheynst, P. (2016). Convolutional neural networks on graphs with fast localized spectral filtering. In: Proceedings of the 30th International Conference on Neural Information Processing Systems, Red Hook, NY, USA.

[98] Hu, J., Wang, Q., Ye, Y., Wu, Z., Tang, Y. (2023). A high temporal-spatial resolution power system state estimation method for online DSA. *IEEE Transactions on Power Systems*, 39: 877–889.

[99] Pei, Y., Zhao, J., Yao, Y., Ding, F. (2023). Multi-task reinforcement learning for distribution system voltage control with topology changes. *IEEE Transactions on Smart Grid*, 14: 2481–2484.

[100] Zhu, L., Wen, W., Li, J., Zhang, C., Shen, Y., Hou, Y., Liu, T. (2024). Structure-aware recurrent learning machine for short-term voltage trajectory sensitivity prediction. *IEEE Internet of Things Journal*, 11: 15128–15139.

[101] Li, X., Jiang, T., Bai, L., Kou, X., Li, F., Chen, H., Li, G. (2020). Orbiting optimization model for tracking voltage security region boundary in bulk power grids. *CSEE Journal of Power and Energy Systems*, 8: 476–487.

[102] Jayasekara, B., Annakkage, U. D. (2006). Derivation of an accurate polynomial representation of the transient stability boundary. *IEEE transactions on Power Systems*, 21: 1856–1863.

[103] Lv, J., Pawlak, M., Annakkage, U. D. (2012). Prediction of the transient stability boundary using the lasso. *IEEE Transactions on Power Systems*, 28: 281–288.

[104] Liu, Y. L., Shi, X. J., Xu, Y. (2020). A hybrid data-driven method for fast approximation of practical dynamic security region boundary of power systems. *International Journal of Electrical Power & Energy Systems*, 117: 105658.

[105] Zheng, L., Wang, Z., Li, G., Xu, Y. (2022). Evaluating the significance of samples in deep learning-based transient stability assessment. *Frontiers in Energy Research*, 10: 925126.

[106] Genc, I., Diao, R., Vittal, V., Kolluri, S., Mandal, S. (2010). Decision tree-based preventive and corrective control applications for dynamic security enhancement in power systems. *IEEE Transactions on Power Systems*, 25: 1611–1619.

[107] Liu, C., Sun, K., Rather, Z. H., Chen, Z., Bak, C. L., Thøgersen, P., Lund, P. (2014). A systematic approach for dynamic security assessment and the corresponding preventive control scheme based on decision trees. *IEEE Transactions on Power Systems*, 29: 717–730.

[108] Thams, F., Venzke, A., Eriksson, R., Chatzivasileiadis, S. (2020). Efficient database generation for data-driven security assessment of power systems. *IEEE Transactions on Power Systems*, 35: 30–41.

[109] Lan, Y., Shi, Z., Yao, W., Zhou, R., Luo, F., Wen, J. (2023). SHAP algorithm for transparent power system transient stability assessment: Critical impact factors identification. In: Proceedings of the 2023 International Conference on Power System Technology (PowerCon), Jinan, China.

[110] Tan, B., Zhao, J., Su, T., Huang, Q., Zhang, Y., Zhang, H. (2022). Explainable Bayesian neural network for probabilistic transient stability analysis considering wind energy. In: Proceedings of the 2022 IEEE Power & Energy Society General Meeting (PESGM), Denver, CO, USA.

[111] Zeiler, M. D., Fergus, R. (2014). Visualizing and understanding convolutional networks. In: Fleet, D., Pajdla, T., Schiele, B., Tuytelaars, T. Eds. *Computer Vision – ECCV 2014*. Cham: Springer.

[112] Simonyan, K., Vedaldi, A., Zisserman, A. (2013). Deep inside convolutional networks: Visualising image classification models and saliency maps. arXiv:1312.6034.

[113] Sundararajan, M., Taly, A., Yan, Q. (2017). Axiomatic attribution for deep networks. In: Proceedings of the 34th International Conference on Machine Learning, PMLR, 70: 3319–3328.

[114] Zhou, B., Khosla, A., Lapedriza, A., Oliva, A., Torralba, A. (2016). Learning deep features for discriminative localization. In: Proceedings of the 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA.

[115] Fang, J., Zheng, L., Liu, C. (2024). A novel method for missing data reconstruction in smart grid using generative adversarial networks. *IEEE Transactions on Industrial Informatics*, 20:

4408–4417.

[116] Chattopadhay, A., Sarkar, A., Howlader, P., Balasubramanian, V. N. (2018). Grad-CAM: Generalized gradient-based visual explanations for deep convolutional networks. In: Proceedings of the 2018 IEEE Winter Conference on Applications of Computer Vision (WACV), Lake Tahoe, NV, USA.

[117] Glavic, M., Fonteneau, R., Ernst, D. (2017). Reinforcement learning for electric power system decision and control: Past considerations and perspectives. *IFAC-PapersOnLine*, 50: 6918–6927.

[118] Zhou, X., Lu, N., Wang, X., Luo, H., Yan, R. (2023). A time-adaptive method to transient stability assessment based on reinforcement learning. In: Proceedings of the 2023 International Conference on Power System Technology (PowerCon), Jinan, China.

[119] Hadidi, R., Jeyasurya, B. (2013). Reinforcement learning based real-time wide-area stabilizing control agents to enhance power system stability. *IEEE Transactions on Smart Grid*, 4: 489–497.

[120] Li, Q., Xu, Y., Ren, C., Zhao, J. (2019). A hybrid data-driven method for online power system dynamic security assessment with incomplete PMU measurements. In: Proceedings of the 2019 IEEE Power & Energy Society General Meeting (PESGM), Atlanta, GA, USA.

[121] Chen, Z., Ren, C., Xu, Y. (2022). An improved AdaBoost-based ensemble learning method for data-driven dynamic security assessment of power systems. In: Proceedings of the 2022 IEEE Power & Energy Society General Meeting (PESGM), Denver, CO, USA.

[122] Yu, J. J. Q., Lam, A. Y. S., Hill, D. J., Li, V. O. K. (2017). Delay aware intelligent transient stability assessment system. *IEEE Access*, 5: 17230–17239.

[123] Zhang, Y., Xu, Y., Dong, Z. Y. (2018). Robust ensemble data analytics for incomplete PMU measurements-based power system stability assessment. *IEEE Transactions on Power Systems*, 33: 1124–1126.

[124] Zhang, Y., Xu, Y., Dong, Z. Y. (2017). Robust classification model for PMU‐based on‐line power system DSA with missing data. *IET Generation, Transmission & Distribution*, 11: 4484–4491.

[125] Zhu, L., Hill, D. J. (2021). Cost-effective bad synchrophasor data detection based on unsupervised time-series data analytic. *IEEE Internet of Things Journal*, 8: 2027–2039.

[126] Liao, W., Salinas, S., Li, M., Li, P., Loparo, K. A. (2017). Cascading failure attacks in the power system: A stochastic game perspective. *IEEE internet of things journal*, 4: 2247–2259.

[127] Wang, H., Ouyang, Y. (2022). Adaptive data recovery model for PMU data based on SDAE in transient stability assessment. *IEEE Transactions on Instrumentation and Measurement*, 71: 2519611.

[128] Gao, P., Wang, M., Ghiocel, S. G., Chow, J. H., Fardanesh, B., Stefopoulos, G. (2016). Missing data recovery by exploiting low-dimensionality in power system synchrophasor measurements. *IEEE Transactions on Power Systems*, 31: 1006–1013.

[129] Hao, Y., Wang, M., Chow, J. H. (2020). Modeless streaming synchrophasor data recovery in nonlinear systems. *IEEE Transactions on Power Systems*, 35: 1166–1177.

[130] Liao, M., Shi, D., Yu, Z., Yi, Z., Wang, Z., Xiang, Y. (2019). An alternating direction method of multipliers based approach for PMU data recovery. *IEEE Transactions on Smart Grid*, 10: 4554–4565.

[131] Hastie, T., Mazumder, R., Lee, J. D., Zadeh, R. (2015). Matrix completion and low-rank SVD via fast alternating least squares. *The Journal of Machine Learning Research*, 16: 3367–3402.

[132] Miranda, V., Krstulovic, J., Keko, H., Moreira, C., Pereira, J. (2012). Reconstructing missing data in state estimation with autoencoders. *IEEE Transactions on power systems*, 27: 604–611.

[133] Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., Bengio, Y. (2020). Generative adversarial networks. *Communications of the ACM*, 63: 139–144.

[134] Yoon, J., Jordon, J., Schaar, M. (2018). Gain: Missing data imputation using generative adversarial nets. In: Proceedings of the 35th International Conference on Machine Learning, PMLR, 80: 5689–5698.

[135] Hu, B., Hao, Z., Chen, Z., Zhang, J. (2022). Combination with continual learning update scheme for power system transient stability assessment. *Sensors*, 22: 8982.

[136] Pan, S. J., Tsang, I. W., Kwok, J. T., Yang, Q. (2011). Domain adaptation via transfer component analysis. *IEEE transactions on neural networks*, 22: 199–210.

[137] Pan, S. J., Yang, Q. (2010). A survey on transfer learning. *IEEE Transactions on knowledge and data engineering*, 22: 1345–1359.

[138] Ren, C., Xu, Y. (2020). Transfer learning-based power system online dynamic security assessment: Using one model to assess many unlearned faults. *IEEE Transactions on Power Systems*, 35: 821–824.

[139] Hao, Q., Wang, J., Wang, X., Li, J., Su, C., Liu, C. (2023). Localization of sub/super-synchronous oscillation sources in wind power systems based on deep adaptation network. In: Proceedings of the 2023 4th International Conference on Advanced Electrical and Energy Systems (AEES), Shanghai, China.

[140] Shi, Z., Yao, W., Tang, Y., Ai, X., Wen, J., Cheng, S. (2023). Bidirectional active transfer learning for adaptive power system stability assessment and dominant instability mode identification. *IEEE Transactions on Power Systems*, 38: 5128–5142.

[141] Lan, J., Zhou, Y., Guo, Q., Sun, H. (2024). Data augmentation for data-driven methods in power system operation: A novel framework using improved GAN and transfer learning. *IEEE Transactions on Power Systems*, 39: 6399–6411.

[142] Wang, Z., Zhou, Y., Guo, Q., Sun, H. (2024). The total transfer capability assessment of transmission interfaces combining causal inference and multi-task learning. *IEEE Transactions on Power Systems*, 39: 453–464.

[143] Ma, H., Tian, H., Cheng, D., Zhao, K., Xing, F., Qi, H., Su, R., Li, C. (2023). Data-driven multiple-task dynamic security assessment and its application on optimization of emergency control strategy for frequency. In: Proceedings of the 2023 International Conference on Power System Technology (PowerCon), Jinan, China.

[144] Li, B., Xu, S., Sun, H., Li, Z., Yu, L. (2024). System strength assessment based on multi-task learning. *CSEE Journal of Power and Energy Systems*, 10: 41–50.

[145] Han, Y. D., Lu, C., Song, W. C., Wu, P. X., Fang, H. N., Liu, W. C. (2024). Review and prospects of online calculation and analysis techniques for power system security and stability. *Proceedings of the CSEE*, 44(17): 6733–6761. (in Chinese)