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Theoretical Research Review on Artificial Intelligence-Enhanced Power System Dynamic Resilience

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Abstract. Power systems face unprecedented complex challenges against the dual backdrop of accelerating energy transition and intensifying global climate change. To achieve "dual carbon" goals, large-scale integration of intermittent and volatile renewables like wind and solar is essential, increasing operational and dynamic stability challenges for power systems. Simultaneously, more frequent and intense extreme weather events heighten risks to power infrastructure and raise the likelihood of large-scale blackouts. The combined effect of these two factors drastically increases the risk of power systems suffering complex, variable, and highly dynamic disturbance impacts, posing severe challenges to their safe and stable operation. Traditional resilience enhancement methods have real-time performance and adaptability limitations, while artificial intelligence technology provides a new paradigm for building a dynamic resilience enhancement system. This paper systematically reviews the application of AI in power system dynamic resilience, focusing on analyzing AI-enabled dynamic resilience frameworks, key technologies, and development pathways. Comparing traditional methods reveals the advantages of AI technology in improving power system stability, enhancing scheduling decision accuracy, and reducing operation and maintenance costs. Simultaneously, it discusses current technical bottlenecks and future research directions, providing theoretical references for constructing a new generation of resilient power grids.

Keywords: Artificial Intelligence, Power System, Dynamic Resilience

1. Introduction

Compared to traditional power grids, new power systems exhibit new characteristics in various aspects, posing new challenges to comprehensive voltage sag assessment [1]. As power systems expand and interconnect, ensuring grid security and stability during extreme disasters becomes more challenging. Recently, low-probability, high-risk blackouts from such disasters have occurred more frequently [2]. Traditional physics-model-based resilience enhancement methods struggle to adapt to this rapidly changing operating environment. At the same time, AI technology, leveraging its powerful data processing and intelligent decision-making capabilities, offers new solutions for enhancing power system dynamic resilience. This paper compares traditional resilience enhancement methods with AI-based methods to ensure AI technology can deliver its intended

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effects and address existing deficiencies in current power system operation. It explores how to effectively utilize AI technology to enhance the dynamic resilience of power systems and identifies future research directions for AI in this field. This paper employs a systematic review approach to comprehensively analyze the technical pathways and theoretical frameworks for AI-enhanced dynamic resilience. The literature review analyzes traditional and AI-based dynamic resilience enhancement methods, emphasizing AI-driven frameworks, key technologies, and application strategies in power systems. This study offers theoretical guidance for next-generation resilient grids, fosters AI integration in power systems, and improves system stability and disaster resistance.

2. Fundamental theory of power system resilience

2.1. Definition of resilience

Resilience was first proposed by ecologist C.S. Holling to measure ecosystem sustainability and the ability to absorb changes and maintain population relationships after disturbances [3]. Derived from this, power system resilience refers to preserving and restoring normal functions when facing severe accidents, extreme disasters, or external attacks [4]. The most concerning aspect for people is enhancing urban power system resilience, which involves taking specific measures and strategies to strengthen the system's ability to withstand external disturbances, respond to emergencies, and quickly restore regular operation. This holistic concept involves multiple levels from theory to practice, encompassing six key characteristics: perception, adaptability, defense, recovery, coordination, and learning capability. The system must identify potential risks, coordinate resources to address disturbances, and optimize through experiential learning, thereby minimizing operational impacts and ensuring continuous, secure urban power supply [5]. A resilient urban power system should possess the capability for rapid and accurate assessment of system damage and inference of failure scope, and be able to coordinate multiple emergency management strategies to facilitate a faster recovery of normal function from a damaged state [6].

2.2. Dynamic resilience assessment steps

Traditional resilience theory primarily focuses on static resilience, i.e., the system's recovery capability under specific conditions. In contrast, dynamic resilience highlights the system's capacity for adaptation and recovery over varying temporal scales. Dynamic resilience assessment mainly includes the following steps: First, collect basic data such as distribution network structure, load data, basic parameters of Distributed Generation (DG) and energy storage, earthquake simulation scenarios, and perform data standardization. Then, the weights of primary and secondary resilience indicators under the three-state model will be determined, and a static comprehensive evaluation matrix composed of the three-state models will be established to quantify dynamic resilience indicators. Based on this, the three-state and dynamic resilience assessments can be performed [7].

3. Limitations of traditional dynamic resilience enhancement methods

3.1. Static nature defect in structural resilience assessment

3.1.1. Lack of functional correlation in transmission line assessment

Existing methods define damage states based on "component buckling degree" [8] (e.g., deformation of K-shaped braces on the tower body [9]), but the functional indicators are detached from power

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supply reality, failing to establish a quantitative relationship with power interruption. Furthermore, studies often only select "representative tower sections," lacking assessment for entire lines, thus failing to reflect a specific transmission line's actual post-earthquake functionality and recovery process. Additionally, secondary disaster mechanisms are overlooked. No research has yet explored the mechanism of secondary disasters on transmission towers and lines, a major factor in transmission tower damage identified in past earthquake disasters [10].

3.1.2. Neglect of substation building-equipment coupling effect

On the one hand, the building-equipment coupling effect in substations is neglected. Most substation designs primarily focus on the electrical part while failing to consider building structures and electrical components [11] simultaneously. Most existing analyses assume that damage to different equipment is uncorrelated, which is inconsistent with reality.

3.2. Fragmented management coordination bottleneck in resilience recovery

3.2.1. Rigidity of emergency plan rules and lack of dynamic mechanism

Existing resilience recovery schemes in emergency management suffer from rigid recovery priority rules. According to the State Grid Corporation's "Large-scale Blackout Emergency Plan," during power system restoration, large power plants must be restored first, followed by the planned restoration of power supply to important areas, key cities, and critical users. This approach lacks a dynamic assessment of damage severity. For example, in the process of power system restoration, certain assets located in proximity to substations may sustain extensive damage, resulting in protracted repair durations. Consequently, prioritizing the restoration of such equipment may not be the most effective strategy [12]. This exposes the current lack of regular revision and updating of emergency plans and the absence of a dynamic adjustment mechanism. After all, when emergency plans are applied to actual incidents, new problems may emerge, necessitating summary, induction, modification, and improvement based on shortcomings revealed in practical operations.

3.2.2. Fragmented cross-system data and absence of coordination mechanism

In emergency situations, heterogeneous data formats among various departments and agencies substantially impede the effectiveness of adaptive resilience restoration. Concurrently, there is no unified, comprehensive system for resilience recovery, and opportunities for cooperation and communication between departments and agencies under standard management are limited. In summary, fragmented plans and cross-system disconnection delay recovery and harm enhancing dynamic resilience.

3.3. Contradiction between computational accuracy and timeliness of resilience models

Existing models for resilience enhancement, such as various post-disaster repair models [13] and emergency assessment models [14], all face the dilemma where high physical model accuracy and real-time requirements cannot be simultaneously satisfied.

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4. Artificial intelligence enhancing dynamic resilience

4.1. Overview of AI and its advantages

Through big data analysis, artificial intelligence technology can generate programs analogous to human thinking to handle complex problems. Its characteristics, like parallelism and memory, give it significant advantages in enhancing power system dynamic resilience. Leveraging its powerful capabilities in data mining, pattern recognition, and real-time decision-making, AI provides a novel pathway for improving the grid's dynamic resilience against sudden disturbances (e.g., faults, extreme disasters). Dynamic resilience emphasizes the system's ability to rapidly predict, withstand, recover from, and adapt to disturbances. AI applications in this field are mainly manifested in the advanced perception of grid status, rapid fault blocking, and intelligent generation of recovery strategies.

4.2. AI-enabled dynamic resilience framework

The AI-enabled dynamic resilience framework consists of four links: data acquisition, model training, decision optimization, and execution feedback. Dynamic resilience enhancement can be achieved by collecting real-time power system operational data and utilizing AI algorithms for model training and optimization.

4.3. Role of AI in enhancing dynamic resilience

4.3.1. AI-enabled resilience perception and advanced defense

Enhancing grid dynamic resilience first relies on accurately perceiving potential risks and advanced defense (preventive control). Conventional physics-based preventive control strategies frequently encounter limitations in model fidelity and computational efficiency when addressing the intricate, dynamic instability phenomena introduced by high levels of renewable energy integration and widespread deployment of power electronic devices.

AI technology, particularly deep learning, offers possibilities to break through these bottlenecks.

First, AI enables data-driven security risk assessment. AI can deeply mine implicit stability patterns and risk features from the massive historical operational and simulation data accumulated by the grid, freeing itself from dependence on precise physical models, to achieve fast and accurate security state assessment. For example, models based on Deep Belief Networks (DBN) [15] or Artificial Neural Networks (ANN) [16] can establish mapping relationships between system state variables and transient stability margin, voltage stability index, frequency stability risk, etc. They are capable of evaluating a range of stability risks—including power angle, voltage, frequency, and wide-band oscillatory instabilities—encountered by the power grid under both present and anticipated future operational scenarios in real time, thereby establishing a critical basis for informed control strategies.

Based on risk assessment results, AI can generate intelligent preventive control decisions, such as assisting in developing economical and efficient preventive control strategies. Algorithms like Decision Trees (DT) [17] based on rule learning can learn stability rules from data to guide generator rescheduling scope and direction, such as identifying critical units and their output adjustment thresholds. Embedding AI-trained stability evaluators (e.g., ANN models predicting Critical Clearing Time CCT [18]) as "black-box constraints" [19] into intelligent optimization algorithms, like Bayesian Optimization [20], can solve optimal power flow problems considering

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multiple security constraints, minimizing preventive control costs (e.g., generation rescheduling cost) while satisfying stability margin requirements.

Furthermore, integrating big data analysis and AI (such as LSTM) [21] enables high-precision short-term prediction of load, renewable energy output, and critical equipment status (such as temperature and vibration). This advanced perception capability allows the system to anticipate potential overloads, voltage limit violations, or equipment failure risks, providing a basis for proactive operational adjustments and reserved safety margins, which is key to resilience defense.

4.3.2. AI-driven real-time disturbance blocking and fast recovery

Fast and accurate emergency control is the core for preventing accident escalation and maintaining system stability when faults or disturbances occur in the grid. It is also the core manifestation of dynamic resilience. The core value of AI in this phase lies in its decision-making speed, which far exceeds traditional methods.

AI models can achieve millisecond-level emergency control decisions. Utilizing AI models like Support Vector Machines (SVM) [22] or Random Forests [23] to rapidly calculate the sensitivity of stability indices to control variables, combined with optimization models, can quickly generate emergency control strategies. Deep Reinforcement Learning (DRL) (such as combining CNN and Q-network) [24] can also achieve "end-to-end" control. Interacting and learning with grid simulation environments can directly map observed system states to optimal control actions, such as which unit to trip, how much load to shed, or whether to deploy braking resistors. This method bypasses complex modeling and optimization solving processes, achieving near-real-time optimal control decisions after training convergence, particularly suitable for time-critical transient stability emergency control. AI can also perform intelligent fault diagnosis and location. Computer vision (CV)-driven artificial intelligence leverages the analysis of both visible spectrum and infrared imagery captured during drone-based inspections to autonomously and efficiently detect anomalies and malfunctions in transmission lines and substation apparatus. This approach markedly reduces the time required for fault localization and delivers essential data to expedite the isolation of fault sites and the development of restoration protocols [25].

AI can significantly assist in coordinated recovery and resource scheduling. AI can optimize resource scheduling and network reconfiguration strategies during post-disaster recovery. Integrating multi-source data such as grid topology, fault information, available resources, and traffic conditions, AI algorithms can plan optimal repair routes and restoration sequences to maximize the scope and speed of power supply restoration, enhancing system recovery resilience [26].

4.3.3. Cyber-physical integration and resilience coordination optimization

Enhancing grid dynamic resilience relies on the deep synergy between the power physical system and the information and communication system, i.e., establishing a Cyber-Physical System (CPS). Utilizing AI and simulation technology to study the mutual influence between the information network and the physical power grid under faults or disasters, coupled modeling and simulation can identify how information layer failures trigger or exacerbate physical layer collapse, and vice versa, thereby identifying overall system vulnerabilities. Establishing an information technology-based unified dispatch mechanism for power information and communication ensures that critical control commands and status information can be transmitted quickly and accurately through multiple reliable paths (including ground fiber optics, satellite communication, and drone relay temporary

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networks) during extreme events, guaranteeing control system availability and ensuring unified dispatch and emergency communication [26].

AI provides new ideas for solving the coordination problem between preventive and emergency control. The coordination problem can be transformed into a bi-level optimization [27]. For instance, DT identifying stability region boundaries and sensitivity analysis [28] can narrow the control search space. Alternatively, AI can solve sub-problems separately, aiming to minimize total control costs globally and achieve the optimal balance between economy and security.

4.4. Challenges and prospects

Despite AI's enormous potential in enhancing grid dynamic resilience, key challenges remain. The first is AI model reliability. Power systems have extremely high safety requirements. Key challenges include poor interpretability of AI models, particularly "black-box" deep learning models, misclassification of unsafe states under sample imbalance, and insufficient generalization to novel operating modes or rare faults [29]. Critical future directions include continuous online learning, transfer learning, incorporating physical rules using knowledge graphs, and rigorous model verification and robustness testing.

Furthermore, high-performance AI relies on high-dimensional, high-quality data. This necessitates deploying high-precision intelligent sensors and employing data cleaning and augmentation techniques.Data privacy and security are paramount. Differential privacy, homomorphic encryption, and federated learning are recommended to safeguard sensitive data and mitigate adversarial and poisoning attacks on AI models. In the future, with breakthroughs in Large Language Models (LLM) [30] in complex pattern recognition, reasoning, and multi-source information fusion, and the maturation of edge computing and digital twin technologies, AI will play a more central role in building smart resilient grids with "autonomous perception-cognition-decision-recovery" capabilities, promoting the safe and stable operation of new power systems in highly uncertain environments.

5. Conclusion

This paper reviews AI's theoretical frameworks, key technologies, application advantages, and challenges in enhancing power system dynamic resilience. Traditional physics-based methods face limitations due to high renewable penetration and extreme events. AI offers a new paradigm via data mining, real-time decision-making, and self-learning. Deep learning enables dynamic perception and risk assessment for intelligent control. Deep reinforcement learning facilitates millisecond-level emergency control. Computer vision accelerates fault diagnosis and optimizes resource scheduling. AI enhances cyber-physical synergy, ensuring communication reliability and coordinating control through bi-level optimization. Compared to traditional methods, AI improves stability, decision speed, reduces costs, and enhances self-adaptation, breaking resilience bottlenecks.

This paper needs more empirical case studies, broader literature coverage, and deeper discussion of AI's reliability and ethical risks. Future work should enhance AI model trustworthiness, deepen cyber-physical resilience, explore applications of large language models in regulation, planning, and decision-making, and investigate edge intelligence and digital twin-driven resilience. It should also build knowledge graphs integrating physical rules and multi-agent decision frameworks, promote standardization and ethical norms, and drive power systems toward smart resilience with autonomous perception-cognition-decision-recovery-evolution capabilities to address energy transition and climate change.

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