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Complex Network Approaches for Vulnerability Assessment and Resilience Enhancement in Power Systems

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ABSTRACT

The growing scale and complexity of modern power systems have created an urgent need for new frameworks capable of characterizing their structural, functional, and dynamic behaviors. Complex network theory offers such a paradigm by viewing the grid as an interconnected system where topology, physics, and dynamics collectively determine performance and resilience. This review summarizes the evolution of complex network approaches in power system analysis, emphasizing topology-based modeling, cascading-failure mechanisms, vulnerability assessment, and critical-component identification. It highlights how small-world and scale-free properties influence fault propagation and robustness, while betweenness- and flow-based indicators provide tools to identify vulnerable nodes and transmission corridors. These insights have advanced the understanding of cascading failures and vulnerability quantification through connectivity, load-loss, and efficiency metrics. However, challenges persist, including static assumptions, high computational demands, and limited integration with real-time data. Future progress will require coupling multilayer network models with dynamic simulations, high-performance computation, and artificial intelligence to enable predictive diagnostics and adaptive control. Complex network theory is poised to evolve into a unified analytical and engineering framework supporting the design of resilient, intelligent, and self-adaptive renewable power systems.

Introduction

As a critical infrastructure of modern society, the power system not only provides the fundamental driving force for daily life and industrial production but also plays an indispensable role in national economic development [1]. However, with the continuous growth of electricity demand and the expansion of power grid scale, the system has become increasingly complex, leading to new challenges in its operation and security. Under such circumstances, the vulnerability of power systems has become more evident, especially when confronted with large-scale blackout events [2].

Over the past two decades, numerous large-scale blackouts have occurred worldwide, such as the North American blackout in 2003 [3] and the Indian power outage in 2012 [4]. These incidents, often originating from local failures [5], evolved into cascading failures characterized by serial, stochastic, and unpredictable propagation dynamics [6]. Such events not only caused severe economic and social disruptions but also exposed the limitations of traditional analytical methods in assessing the security of modern, large-scale power systems [7]. Conventional approaches, typically based on deterministic modeling and reductionist principles, rely on component-level mathematical equations and differential models. Although effective in analyzing small-scale faults, they struggle to capture the complex mechanisms underlying large-scale cascading failures triggered by localized disturbances [8,9].

As the scale and operational complexity of power systems increase, researchers have gradually recognized that the occurrence of large-scale

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Nomenclature

k_i	Degree of node i; number of edges connected to node i
A_{ij}	Element of the adjacency matrix
C	Clustering coefficient
C_i	Mean value of the Clustering coefficients of all nodes
d_{ij}	Shortest path length (or weighted distance) between nodes i and j
E	Total number of edges in the network
E_i	Actual number of edges among neighbors of node i
L	Average path length of the network
L_a	Weighted total length of a transmission path
L_T	Physical length of a branch
n	Total number of nodes in the subnetwork
N	Total number of nodes in the network
P(k)	Degree distribution
W_l	Weight of branch (e.g., power flow or impedance value)

blackouts is closely related to the intrinsic topological properties of the grid [10]. A power system is not merely a collection of physical components, generation, transmission, distribution, and consumption but a highly interconnected network whose structure determines the pathways and extent of fault propagation, as well as the system's capacity for recovery and stability [11]. Investigating these structural and dynamic characteristics helps reveal the mechanisms of cascading failure and provides scientific guidance for system optimization and control [12,13].

Complex network theory has therefore emerged as a powerful framework for systematically studying the topological and dynamical behaviors of power systems [14]. It focuses not only on individual components (nodes and edges) but also on global network properties such as degree distribution, clustering coefficient, average path length, and betweenness centrality [15]. These metrics capture essential aspects of the grid's robustness and vulnerability. Furthermore, by integrating dynamic modeling, complex network analysis enables simulation of how power systems respond to external disturbances and how cascading failures evolve near critical thresholds [16]. These capabilities make complex network theory a valuable tool for evaluating grid vulnerability, understanding fault propagation mechanisms, and improving both efficiency and resilience, as shown in Fig. 1.

Recent research has demonstrated the effectiveness of complex network methods in analyzing power system topologies, identifying critical nodes and lines, and optimizing fault prevention strategies [17]. Nevertheless, current studies remain largely theoretical and are often insufficiently integrated with real-world grid operations. Challenges persist in modeling dynamic behaviors, achieving real-time analysis, and designing comprehensive resilience metrics [18]. Additionally, combining the physical properties and topological features of the grid into an integrated model that accurately reflects real-world operation remains a key research frontier.

Complex network theory in power system

Background of complex network

The study of complex networks originates from scientists' attempts to abstract and understand the structural and behavioral characteristics of real-world complex systems. Early work was grounded in classical graph theory, where systems were represented as sets of nodes and edges to analyze how the pattern of connectivity influences overall system performance. However, these traditional graph models, mostly regular or purely random networks, failed to capture the heterogeneity and dynamic evolution present in real systems. The classical Erdős-Rényi (ER) random network model assumes a uniform connection probability between any node pair. While mathematically elegant [19], this assumption fails to reproduce the heterogeneous connectivity patterns, clustering behavior, and preferential attachment processes prevalent in real-world systems such as power grids.Such deficiencies became evident in describing phenomena such as epidemic spreading, internet traffic, and large-scale power grid failures [20].Consequently, modern complex network theory has emerged as an interdisciplinary framework that integrates graph theory [21], statistical physics [22], and nonlinear dynamics [23] to study how local connectivity rules drive global system behavior [24].

Core concepts

Complex network theory investigates both the topological structure and dynamic behavior of interconnected systems, using quantitative

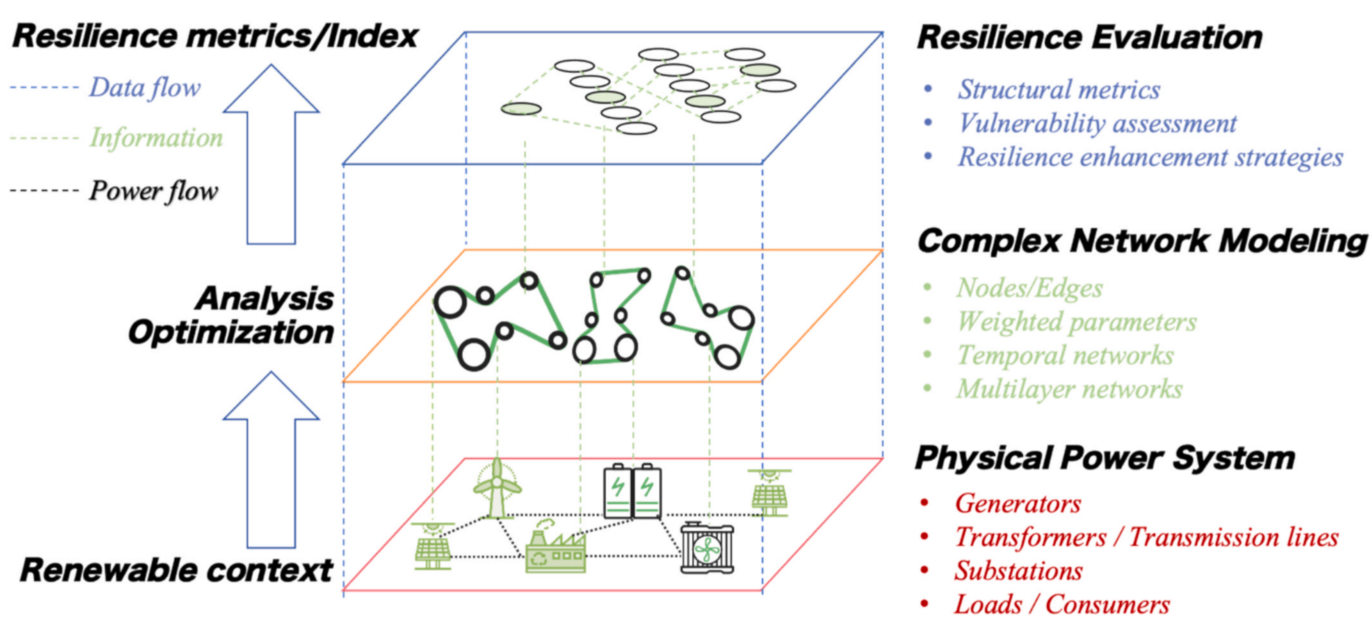

Fig. 1. Conceptual framework of complex network modeling and resilience assessment for renewable energy systems

measures to characterize their local and global properties. A network consists of a set of nodes connected by edges, and its efficiency, robustness, and vulnerability can be evaluated through several key indicators. The first metric is the average path length, which represents the mean shortest distance between any two nodes in the network, reflecting the overall efficiency and transmission speed of information or energy within the system. The evolutionary history and methodological framework of complex network applications in renewable-energy power systems have been shown in Fig. 2.

where N refers to the total number of nodes in the network, and d_{ij} represents the shortest path length between nodes i and j. The degree of a node is defined as the number of edges connected to it [25], while the degree distribution describes the statistical characteristics of node connectivity within the entire network. In scale-free networks, the degree distribution typically follows a power-law form [26].

$$L = \frac{1}{N(N-1)}\sum_{i\neq j} d_{ij}$$

$$k_i = \sum_j A_{ij}$$

$$P(k) = \frac{n_k}{N} \tag{1}$$

where Aij denotes an element of the adjacency matrix, indicating whether nodes i and j are connected. $Aij = 1$, if they are connected, and $Aij = 0$ otherwise. The degree distribution $P(k)$ represents the fraction of nodes in the network with degree k [27]. The clustering coefficient reflects how closely a node's neighbors are interconnected, quantifying the degree of local compactness or modularity. A higher clustering coefficient indicates tighter local coupling, which facilitates information exchange but can also accelerate local fault propagation [28].

$$C_i = \frac{2E_i}{k_i(k_i-1)} \tag{2}$$

where E_i represents the actual number of edges among the neighbors of node i, and k_i denotes the degree of node i. The average clustering coefficient (C_i) of the network is defined as the mean value of the clustering coefficients of all nodes [29].

The betweenness centrality of nodes and edges measures the frequency with which they appear on the shortest paths between other node pairs, revealing their critical roles in maintaining connectivity and identifying potential bottlenecks or weak points in the system. These indicators provide a quantitative foundation for analyzing how micro-level interactions determine macro-level properties in complex systems. They are particularly relevant to power and renewable energy systems, where structural topology governs the spread of disturbances and the overall system resilience [30].

Small-world and scale-free properties

Two key topological features, small-world and scale-free properties, are ubiquitous in natural and engineered networks. The small-world property, introduced by Watts and Strogatz, describes networks that combine high clustering coefficients with short average path lengths. In such networks, a few long-range connections drastically reduce the average distance between nodes, allowing fast and efficient transmission of energy or information [31]. While this property enhances performance and coordination, it also increases the likelihood that local disturbances will spread rapidly throughout the network. Thus, small-world networks serve as valuable models for studying cascading failures and blackout propagation in power grids, which can be shown as follows [32]:

$$\begin{cases} C >> C_{random} \\ L >> L_{random} \end{cases} \tag{3}$$

where C is the clustering coefficient, L is the average distance of the network, and the subscript random represents a random network [33]. By contrast, scale-free networks exhibit a degree distribution that follows a power law, lacking a characteristic scale and evolving according to the principle of self-organized criticality. In these networks, a few hub nodes possess an extremely high number of connections, while most nodes have relatively few. This architecture reflects the hierarchical and uneven structure of real systems, such as internet infrastructures or electric power grids, where rare but high-impact events occur more frequently than in random systems [34]. However, this same structure introduces vulnerability: while scale-free networks are robust against random failures, they are extremely fragile under targeted attacks on hubs. This duality between robustness and fragility makes the scale-free model highly relevant for analyzing systemic risks and resilience strategies in renewable energy systems [35].

Through this characters, complex network theory provides a

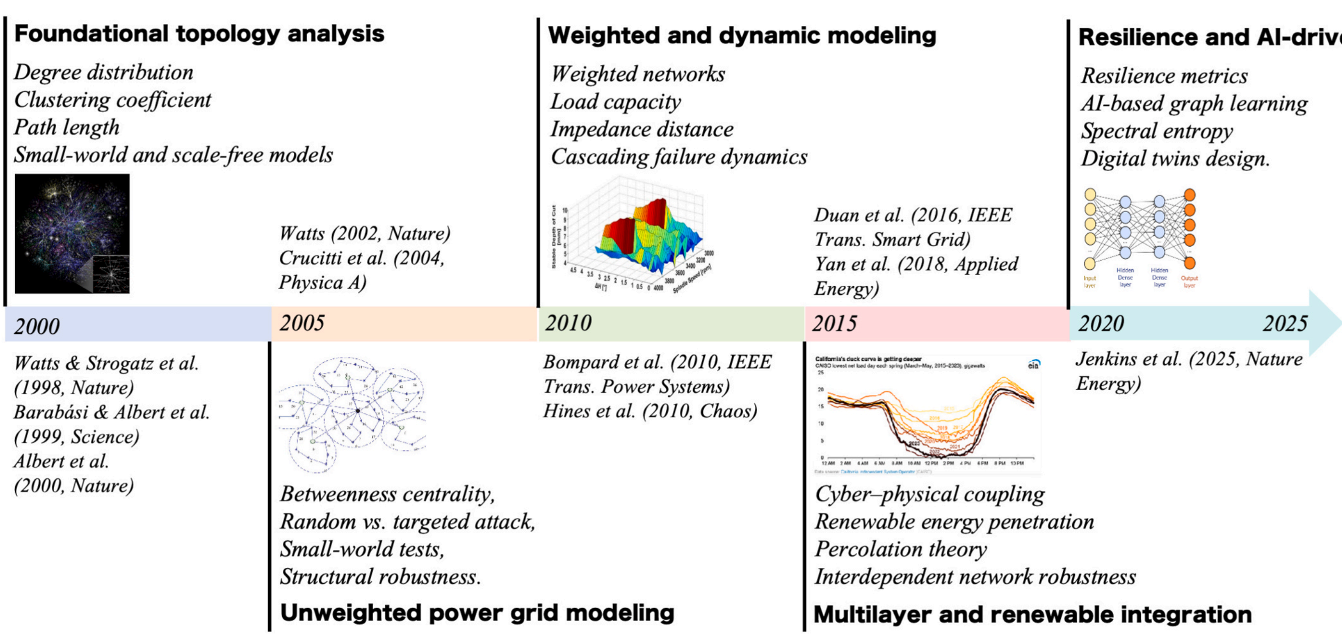

Fig. 2. Evolution and methodological pathway of complex network applications in renewable-energy power systems (2000–2025)

powerful analytical framework for understanding how local connectivity patterns and global structural organization jointly determine the robustness, efficiency, and vulnerability of large-scale systems [36]. When applied to renewable-energy-based power grids, this theory enables researchers to identify critical nodes and transmission paths, assess vulnerability under dynamic disturbances, and design resilient architectures capable of balancing efficiency and stability [37]. These theoretical foundations serve as a bridge between topological modeling and resilience-oriented design, laying the groundwork for subsequent analysis and optimization of complex renewable energy networks.

The core of complex network theory lies in exploring the intricate relationships between microscopic attributes of nodes and edges (such as degree and weight) and the macroscopic properties of networks (such as efficiency and stability) [38]. For modern power systems, the network topology largely determines how faults propagate and how efficiently the system can recover after disturbances. Current research on the application of complex network theory to power systems can be broadly categorized into three major directions [39].

First, topological modeling and cascading-failure analysis abstract the electrical network into a graph where nodes represent buses and edges correspond to transmission lines or transformers. This approach enables the study of fault propagation pathways and dynamic behaviors, helping to explain the mechanisms underlying cascading failures from a structural perspective [40].

Second, correlation studies between network metrics and fault evolution examine how topological indicators like node degree, betweenness centrality, and clustering coefficient, relate to the initiation and expansion of grid disturbances. For example, nodes with high betweenness often serve as critical hubs in cascading failure propagation, while highly clustered sub-networks may accelerate the transition from local to system-wide faults [41].

Third, vulnerability assessment and indicator development focus on constructing quantitative metrics that evaluate the relative importance of nodes and edges [42]. These metrics help identify weak links within the grid, providing guidance for preventive maintenance, risk mitigation, and structural optimization. This review will specially analyze these parts as following [43].

Complex network-based modeling

Early studies on complex network modeling of power systems typically simplified the grid into an undirected and unweighted topological model, in which buses were abstracted as network nodes, while transmission lines and transformers were represented as edges (multiple parallel lines were usually merged into a single link) [44]. Although this approach reduced modeling complexity and offered theoretical insight into the structural characteristics of power grids, it overlooked the physical and electrical attributes defining real systems. As a result, such simplified models faced limitations when applied to quantitative analyses of grid performance, fault propagation, and operational dynamics,

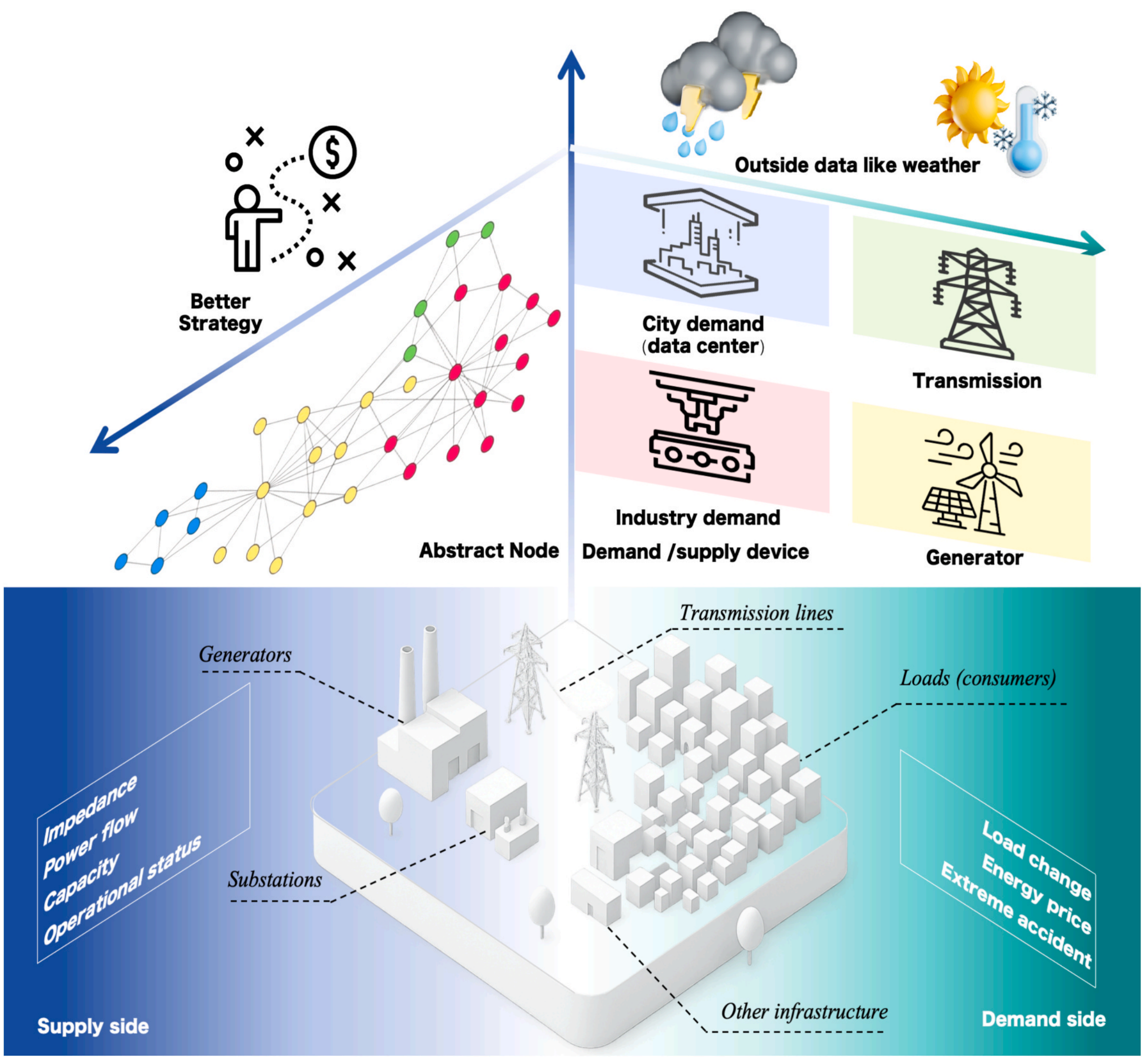

Fig. 3. Complex network-based modeling framework for power systems

and could not fully capture the real operating states of power networks [45].

With further research progress, scholars began to incorporate physical properties into complex network models, leading to the development of weighted network representations that more accurately reflect the operational characteristics of real power systems. In weighted network models, both nodes and edges are assigned physical weights [46], which may represent parameters such as impedance or power flow. Among the most common weighting methods are those based on branch impedance and power flow states [47], the framework has been shown in Fig. 3.

When impedance is used as the weighting factor, it captures the electrical distance between nodes, an essential measure of system connectivity [48]. Several studies adopted line reactance as the edge weight to evaluate electrical distance between nodes. In such models, the computation of shortest paths no longer depends on purely topological distance but on the sum of reactance values along each path. This modification alters traditional shortest-path calculations and, consequently, affects the estimation of metrics such as average path length, node betweenness, and edge betweenness [49].

$$L = \frac{1}{n(n-1)}\sum_{i\neq j} d_{ij}$$

$$\varepsilon = \frac{1}{n(n-1)}\sum_{i\neq j} \frac{1}{d_{ij}} \tag{4}$$

where n is the total number of nodes, and d_{ij} is the total reactance of the shortest path between nodes i and j, with branch reactance taken as the edge weight [50]. Another approach employs power flow and generation states as weighting parameters, reflecting the dynamic behavior of the power system. In this case, the ratio of power flow to line capacity is often used as an edge weight, accounting for each line's relative significance within the network. Node weights are typically defined as the sum of the weights of all connected edges, which can then be used to analyze clustering coefficients, edge betweenness, and average path lengths under realistic operational conditions. In addition, some studies combine both methods, defining composite edge weights as the product of line betweenness and power flow magnitude to evaluate the "activity level" of critical nodes and branches [51].

$$L_a = \frac{L_T}{\sum_{v\in V} P_v} = \frac{\sum_{l\in L} w_l P_l}{\sum_{v\in V} P_v} \tag{5}$$

where w_l is the weight of branch (e.g., power flow or impedance value), L_T is the physical length of branch, and L_a represents the weighted total length of transmission path. Although the introduction of weighted models effectively addresses the shortcomings of early unweighted topological models, current complex network representations of power systems still face several major limitations [52]. One persistent limitation is the neglect of power-flow directionality. Many models assume bidirectional or undirected links, overlooking the fact that real power grids exhibit distinct flow directions that strongly affect line importance, load redistribution, and the propagation of cascading failures. Additionally,neglecting power-flow directionality can lead to inaccurate importance assessments of certain transmission corridors, especially in meshed networks or multi-source supply configurations, potentially causing vulnerability assessment results to deviate from actual operational risks.A second weakness lies in the lack of differentiation among node types and their corresponding weights [53]. In practice, power grids consist of diverse functional nodes, such as generators, substations, and load centers, whose structural roles and operational impacts vary considerably. Yet most models treat all nodes uniformly, leading to oversimplified representations of the system's internal hierarchy and energy flow. Third, the coupling between static and dynamic parameters remains insufficiently addressed. Impedance is typically modeled as a fixed attribute, while its interaction with dynamic variables such as real-time power flow and load fluctuations is ignored [54]. In reality, load growth or redistribution alters line loading and voltage profiles, thereby influencing network stability and potentially triggering cascading events. Finally, the integration of topological and physical properties is still limited by the mathematical tools of traditional graph theory, which emphasize structural connectivity rather than the physics of electrical interactions. As a result, current models often fail to capture how physical constraints and network topology jointly determine fault propagation, especially in systems with meshed structures or parallel transmission corridors [55].

Topological characteristics and system faults analysis

The topological configuration of power grids plays a decisive role in determining their operational efficiency and fault propagation dynamics. From the perspective of complex network theory, extensive research has examined the structural properties of power grids and revealed several critical characteristics, most notably, scale-free and small-world behaviors, that help explain the intrinsic mechanisms underlying large-scale failures [56]. For example, statistical analyses of major blackouts in the North American power grid from 1984 to 1999 demonstrated that the relationship between outage size and occurrence probability follows a power-law distribution. This indicates that a small number of extreme events occur far more frequently than would be expected under a Gaussian or linear assumption. Such findings highlight the dominant role of a limited number of highly connected nodes, often referred to as hub nodes, in maintaining system connectivity. The failure of these hubs can initiate cascading processes that ultimately result in large-scale blackouts [57]. This scale-free characteristic underscores the need for targeted protection, redundancy design, and hierarchical planning strategies to safeguard critical nodes within the grid.

Another essential topological feature of power grids is their small-world property, characterized by a high clustering coefficient and a short average path length [58]. Studies based on unweighted and undirected network models have consistently shown that most real-world power grids display small-world characteristics. While this property enhances transmission efficiency and facilitates rapid information and energy exchange, it simultaneously increases systemic exposure by accelerating the spread of local disturbances to the global scale. A high clustering coefficient indicates dense local connectivity, which promotes rapid fault diffusion within clusters, whereas short average path lengths amplify the spatial reach of such disturbances across the network. Consequently, although the small-world property contributes positively to overall efficiency, it also heightens the grid's vulnerability, emphasizing the necessity of integrating fault-propagation risk assessment into grid design and operational management [59].

Further insights into the interplay between topology and fault behavior can be obtained through network partitioning analysis. By dividing the grid into robust regions and vulnerable regions based on node count and load magnitude, researchers have shown that robust regions generally consist of high-load or hub nodes with strong resistance to perturbations, whereas vulnerable regions are dominated by low-redundancy load nodes that are more susceptible to cascading failures and require longer recovery times [60]. This regional differentiation supports the formulation of targeted protection and optimization strategies, strengthening robustness where stability is essential, and enhancing redundancy in weak zones to mitigate the overall risk of cascading blackouts [61].

Comparative studies reveal that power grids in different countries exhibit distinct topological patterns. Many foreign grids display clear scale-free and small-world characteristics, whereas certain regional grids in China show degree distributions closer to exponential forms, deviating from a purely scale-free nature. This divergence arises largely from differences in planning philosophy and operational hierarchy [62]. Specifically,China's power grid has long adhered to a 'centralized planning, hierarchical dispatch' paradigm, emphasizing transmission efficiency of the backbone grid and direct connections to regional load centers. While this planning philosophy enhances power transfer efficiency, it also creates a high structural dependency on a limited number of hub nodes, leading to distinct vulnerability patterns under extreme events.For example ,failure of a single hub node can trigger wide-area cascading outages.Therefore, future grid planning should prioritize distributed and hierarchical designs to reduce hub-node dependency and enhance overall resilience [63].

The choice of modeling framework also significantly affects the identification of topological features. For instance, when weighted small-world models incorporating line impedance as edge weights are employed, some Chinese regional grids previously classified as non–small-world are found to satisfy small-world criteria [64]. This observation demonstrates that unweighted models tend to underestimate structural complexity, while weighted models more accurately capture the physical and operational characteristics of real systems. Hence, both unweighted and weighted modeling approaches should be jointly applied to provide a comprehensive and realistic representation of grid topology and to guide optimization and planning practices, as shown in Fig. 4.

Despite substantial progress, several challenges remain in characterizing and applying topological features of power grids [65]. First, inconsistent conclusions may arise from different modeling assumptions and weighting schemes, as some networks do not conform strictly to either scale-free or small-world structures [66]. The classification and optimization of such hybrid topologies warrant further investigation. Second, most existing studies rely on static representations and fail to account for dynamic behaviors such as load fluctuations, temporal evolution, and system adaptation. Moreover, the influence of main-bus configurations, hierarchical sub-topologies, and inter-regional coupling on cascading dynamics remains insufficiently understood [67]. Future research should integrate temporal network modeling and regionalized topology analysis to enhance the understanding of fault evolution and improve the design of resilient, adaptive power systems [68].

Cascading failure mechanisms

The study of cascading failure mechanisms represents a central issue in understanding large-scale power grid disruptions [69]. Traditional models, such as the OPA, CASCADE, and other implicit fault models, mainly rely on static security analyses (e.g., DC power flow) and stochastic failure distributions to simulate system reconfiguration following disturbances. While these approaches can reproduce the general statistical patterns of cascading failures, they provide limited insight into the intrinsic relationship between network topology and failure dynamics [70].

In contrast, complex network theory offers a structural-dynamic framework that links network topology with the temporal evolution of failures [71]. This approach focuses on how the connectivity, shortest paths, and power flow redistribution evolve before and after component failures. By defining node and edge failure criteria and dynamically updating network weights, it captures the sequential propagation of cascading events and the resulting degradation of system performance [72].

Past research introduced a performance degradation model to describe adaptive weight adjustments of nodes and edges under varying operational conditions. When a node or edge operates within capacity, its weight remains constant; when overloaded, the weight decreases proportionally to the stress level [73]; and when the failure threshold is reached, the component is removed, triggering a new cascade stage. Similarly, subsequent studies employed betweenness centrality as a surrogate for load to simulate power redistribution after line outages. Once a branch's load exceeds its operational limit, it is considered failed, leading to further propagation. Other works have extended the OPA framework by introducing upper and lower capacity constraints at the node level, enabling dynamic simulation of load redistribution and cascading sequences. These efforts collectively demonstrate how topology-dependent load redistribution governs failure evolution in complex power networks [74].

Another active research avenue applies percolation theory to characterize the emergence and evolution of cascading failures. In this framework, an initial fault may evolve into a percolating cluster, a connected subnetwork whose disruption compromises overall system integrity. Probabilistic fault modeling allows the identification of critical thresholds where local disturbances transition into global outages, providing a theoretical foundation for understanding the avalanche-like behavior often observed in large-scale power systems, as shown in Fig. 5.

Despite these advances, several challenges remain. Many complex

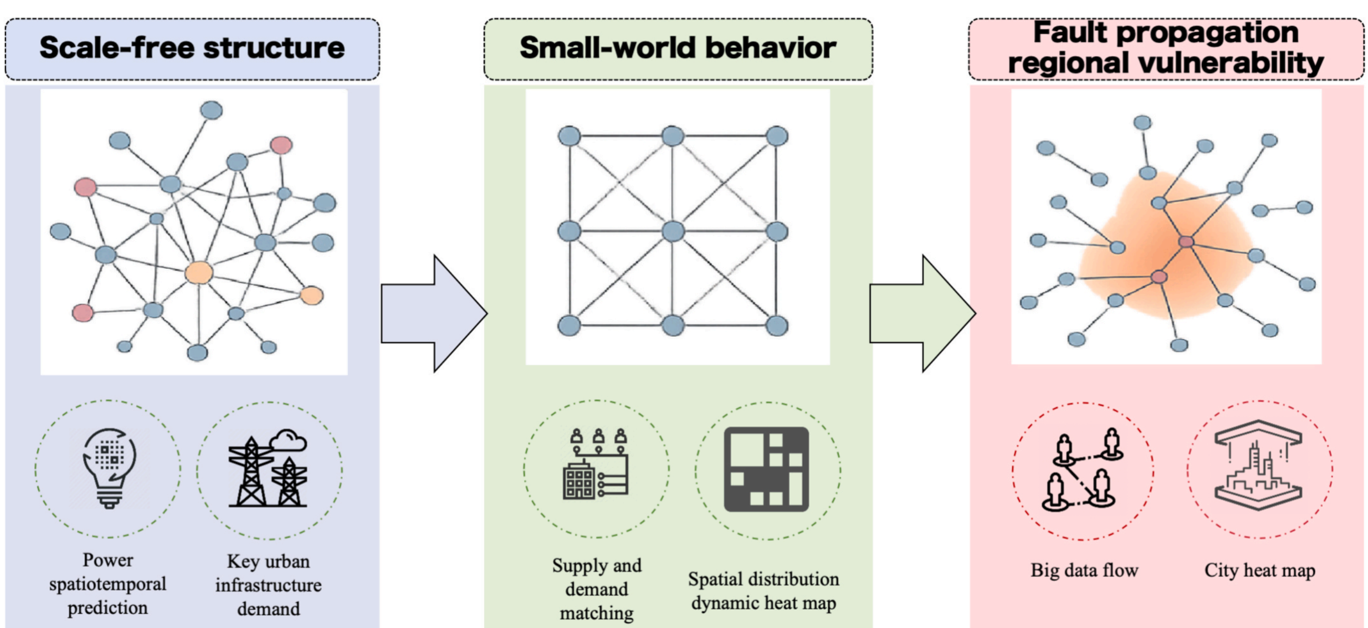

Fig. 4. Topological characteristics and fault propagation behavior of power grids based on complex network analysis

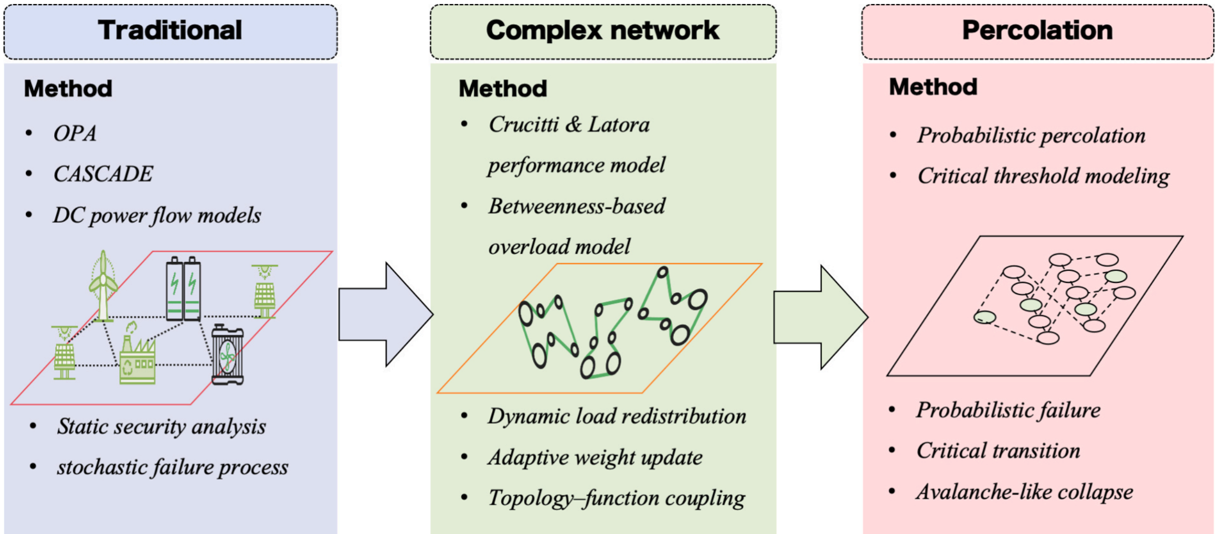

Fig. 5. Modeling and propagation mechanisms of cascading failures in power grids from traditional to complex network approaches.

network-based models still rely heavily on structural indicators (e.g., degree or betweenness centrality) as proxies for load or capacity, which lack rigorous justification from the standpoint of power system physics. Moreover, most models adopt uniform failure thresholds for all components, neglecting the heterogeneity of nodes and lines in capacity [75], dynamic response [76], and load distribution [77]. Such simplifications limit the accuracy of simulating how localized overloads and directional power transfers contribute to cascading propagation [78].

Furthermore, current studies often focus on deterministic attack scenarios, with limited attention to critical transition states and their quantitative correlation with structural metrics. Threshold parameters that define the onset of cascading failures remain largely heuristic, preventing a consistent identification of tipping points. Consequently, while complex network theory provides valuable qualitative insights and a powerful conceptual framework, further theoretical refinement and quantitative coupling with physical models are essential to overcome the limitations of traditional approaches and to enable more systematic [79], predictive strategies for cascading failure prevention and grid resilience enhancement [80].

Vulnerability metrics and assessment methods

Vulnerability assessment of power grids based on complex network theory

The overall framework of complex network-based vulnerability assessment methods for power systems is illustrated in Fig. 6. Its primary objective is to evaluate system performance and resilience under diverse fault or attack scenarios, thereby estimating the likelihood and scale of

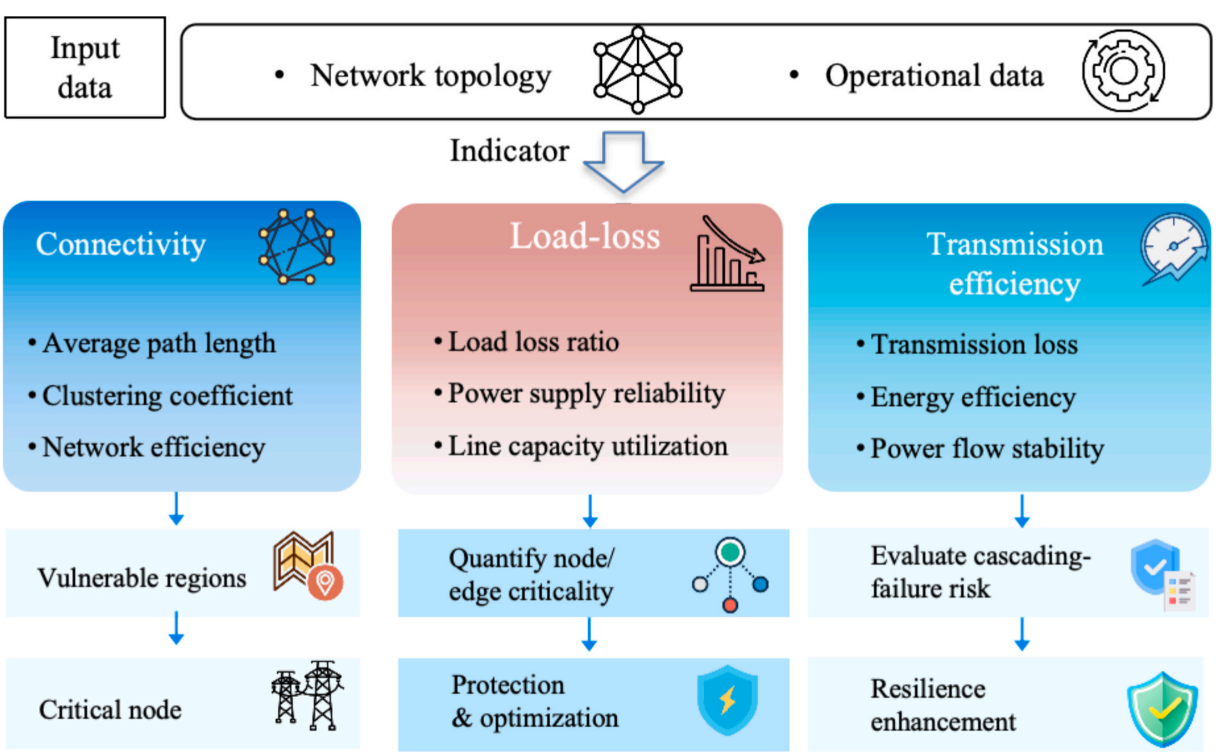

Fig. 6. Framework of complex network-based vulnerability assessment

cascading failures [81]. Empirical studies reveal that networks exhibiting scale-free and small-world properties possess a "robust-yet-fragile" nature: they remain relatively stable under random failures but are highly vulnerable to deliberate attacks targeting high-betweenness nodes or critical transmission corridors. This fragility typically manifests through abrupt changes in four key structural indicators, namely, the average shortest-path length, clustering coefficient, relative size of the largest connected component, and subnetwork cluster size distribution [82].

According to their underlying physical and operational principles, current vulnerability indicators can be broadly categorized into three main groups [83]. (1) Connectivity-Based Indicators, The average shortest-path length is a fundamental measure of overall network connectivity, representing the mean electrical distance between any two nodes. During cascading events, variations in this indicator intuitively reflect structural degradation [84]. Studies abstracted power grids into weighted or unweighted small-world networks and quantified vulnerability by comparing path lengths before and after targeted or random attacks. Nodes and edges are typically ranked by parameters such as degree, node betweenness, or edge betweenness, thereby quantifying how their removal affects global connectivity and network integrity. This indicator effectively captures the topological dimension of grid vulnerability, although it neglects physical loading constraints [85]. (2) Load-Loss Indicators, Vulnerability can also be expressed in terms of load loss or the number of failed nodes following a disturbance. Some studies [86] adopted the number of deactivated nodes as a direct vulnerability index, whereas others [87] introduced the maximum supply area after islanding, which measures the grid's ability to maintain supply–demand balance across separated regions. This family of indicators directly reflects the system's physical performance during fault propagation, providing a practical means to quantify operational degradation under partitioned conditions [88]. and (3) Transmission-Efficiency Indicators, Other approaches integrate power-flow data to assess vulnerability through efficiency-based measures. For instance, Some paper [89] proposed the concept of mean transmission distance, defined as the ratio between weighted path length and total transmitted power. When combined with local voltage and reactive power variations, this method yields a comprehensive indicator capturing both transfer efficiency and voltage stability. Simulation studies have verified that such metrics effectively represent system degradation under targeted attacks, offering a more physically meaningful supplement to purely structural analyses [89].

Most vulnerability studies assess the impact of different attack strategies—random failures, high-betweenness edge removals, or high-degree node removals—by observing changes in the above indicators. However, these methods rely on computationally intensive shortest-path and betweenness calculations, which restrict real-time applicability. Moreover, they lack universal thresholds that clearly differentiate between stable and vulnerable states, thus remaining largely theoretical rather than operational tools [90].

Additional challenges persist. The effects of ring structures, bus-bar configurations, and regional heterogeneity on vulnerability indicators are often overlooked, leading to discrepancies between model predictions and observed grid behavior [91]. Furthermore, most analyses treat network topology as static, disregarding regional dynamics and temporal evolution that strongly influence the spatial–temporal patterns of cascading failures [92]. Future research should aim to develop computationally efficient, dynamically updated, and empirically validated indicators supported by large-scale simulations and operational data. Such developments will significantly enhance both the accuracy and practical value of vulnerability assessments in modern power systems.

Identification of critical nodes and transmission lines

Another pivotal application of complex network theory lies in identifying critical control nodes and transmission corridors that are structurally or functionally vital to grid stability. The goal is to pinpoint components whose disruption could trigger widespread cascading failures, and thereby guide protective reinforcement and network optimization strategies [93].

Betweenness-Based identification methods, one of the most commonly used metrics is betweenness centrality, which quantifies the frequency with which a node or line appears on the shortest paths between all node pairs [94]. Studies have shown that high-betweenness elements serve as crucial "bridges" for power transfer and fault propagation. Building on this, subsequent research introduced the concept of structural load, defining operational and failure thresholds for each node based on its betweenness value and load level. These analyses confirm that small-world networks rely heavily on a limited number of high-betweenness nodes, underscoring the necessity of protecting these hubs to prevent cascading events [95].

Because grid operation depends strongly on the spatial distribution of power flow, integrating electrical state information into structural analysis produces more realistic and actionable insights. Some studies have incorporated real power-flow data as edge weights in betweenness computations, resulting in an efficiency-oriented vulnerability index that better identifies critical transmission lines [96]. Others extended this concept by analyzing node dependencies under multiple contingency scenarios, integrating load, capacity coefficients, and operational margins. These hybrid approaches demonstrated higher fidelity and engineering relevance than purely structural models, effectively bridging the gap between topological abstraction and physical system behavior [97].

Besides, the identification of critical components fundamentally relies on baseline network models and vulnerability indicators. Although a universal theoretical foundation is still lacking, this research line's major contribution is to transform experience-driven engineering judgment into quantitative, reproducible assessments [98]. By using network-based indicators, particularly betweenness centrality, the relative importance of nodes and lines can be evaluated systematically, offering a theoretical basis for decision support in grid operation and planning. Nonetheless, current methods face three persistent obstacles: (i) high computational complexity, (ii) limited generalizability across different network topologies and operational states, and (iii) sensitivity to time-varying topology and power-flow dynamics during cascading events, which often leads to unstable or inconsistent rankings [99,100].

In practical engineering contexts, critical-node identification remains constrained by computational and modeling limitations. Calculating betweenness centrality requires enumerating nearly all shortest paths in the network, causing computational costs to rise rapidly with system size, making real-time or large-scale analysis challenging. A second major limitation lies in the lack of dynamic adaptability [101]. During fault propagation, both network topology and power-flow distribution evolve continuously, yet most models remain static, failing to capture these rapid, coupled dynamics. Moreover, accurately ranking parallel transmission circuits remains problematic [102,103]. Because parallel lines often differ in impedance, load, or flow direction, their betweenness values may vary significantly, resulting in inconsistent identification outcomes [104].

To address these challenges, future studies should pursue a more integrated and adaptive analytical framework. Algorithmic optimizations or approximate computation methods could substantially enhance computational efficiency, enabling near real-time applications in large systems. Equally important is the development of dynamic network models that update weights and structural parameters as system conditions evolve, providing a more faithful representation of real-time grid operations [105]. Incorporating multiple indicators into a unified vulnerability framework will further improve the precision and robustness of critical-component identification. Finally, large-scale simulations and field data validation will be essential to calibrate parameters, test generalizability, and ensure engineering applicability

[106].

In summary, the identification of critical nodes and transmission lines provides a crucial foundation for structural optimization, cascading-failure prevention, and resilience enhancement in modern power systems [107]. With continuing advances in algorithmic efficiency, dynamic modeling, and multi-criteria integration, the application of complex network theory in this domain is expected to evolve from theoretical exploration toward practical, data-driven solutions that enable more secure, adaptive, and resilient grid operations.

Conclusion and prospects

Complex network theory provides a powerful framework for understanding the electric power system as a complex engineering network that integrates physical, informational, and socio-economic dimensions. At the macro level, it reveals the intrinsic interconnections among network topology, vulnerability, cascading failures, and operational efficiency. At the micro level, it offers quantitative tools for identifying critical nodes and transmission lines, assessing fragility, and guiding network optimization. Over the past two decades, research in this field has evolved from static topological characterization to dynamic modeling of fault propagation, laying a solid theoretical foundation for the secure, resilient, and intelligent operation of modern power systems.

Despite these advances, a considerable gap still exists between theoretical exploration and practical application. Current research remains constrained by limited theoretical systematization, weak coupling with real-world dynamics, and insufficient engineering applicability. Many models still rely on static topologies, which fail to represent the time-varying characteristics and nonlinear interactions of actual power grids. The correspondence between network theory and the physical mechanisms governing grid operations remains incomplete, impeding the full integration of structural analysis and operational physics. Furthermore, achieving real-time situational awareness and coordinated control in cyber–physical power systems continues to pose significant challenges, particularly under uncertain and rapidly changing conditions.Future research should strengthen the linkage between complex network theory and practical grid planning, operation, and control. For instance, topological resilience metrics could be incorporated into grid expansion planning, or dynamic network models could be used for real-time identification of vulnerable components during system operation, thereby closing the loop from theoretical analysis to engineering practice.

Looking forward, the development of complex network theory for power systems is expected to advance toward deeper interdisciplinary integration, intelligence-driven evolution, and systematic engineering application. A promising direction is the establishment of unified multilayer and heterogeneous network frameworks that couple physical grids, communication infrastructures, energy markets, and control systems to capture cross-domain dependencies and risk propagation mechanisms. Equally important is the advancement of dynamic network modeling and high-performance simulation platforms that can incorporate real-time operational data to analyze temporal vulnerability, cascading failures, and recovery behaviors. As artificial intelligence continues to reshape energy systems, machine learning and reinforcement learning will become powerful tools for predictive diagnostics, adaptive topology optimization, and autonomous resilience control.For example, graph neural networks can be employed for dynamic node ranking and failure prediction, while digital twin technology can establish high-fidelity simulation environments for coupled multi-layer grids, enabling joint optimization from topology to physical behavior. Meanwhile, the establishment of a theory-to-practice closed loop—linking modeling, data-driven analysis, and experimental validation will be crucial for translating academic insights into actionable engineering solutions for smart grid planning, disaster prevention, and resilient infrastructure design. Ultimately, the transformative significance of complex network theory lies not only in its analytical depth but also in its capacity to reshape the research paradigm of power systems, from static structural analysis to dynamic, intelligent cognition. As the era of the energy internet and digitalized power grids unfolds, this theoretical foundation will serve as a cornerstone for realizing a safer, more resilient, and more intelligent energy future.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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