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Topical Review

A systematic review on bottleneck identification in complex networks

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Abstract

Complex network bottlenecks, as core constraints governing system efficiency, stability, and resilience, reflect structural imbalances among network topology, functional flows, and inter-component coupling. They substantially affect the performance and reliability of critical infrastructure and socioeconomic systems. As a prominent research topic, current studies remain fragmented in theories and methodologies, making it difficult to formulate targeted bottleneck mitigation strategies for diverse network scenarios. Meanwhile, the proliferation of big data, artificial intelligence, and other emerging technologies has reshaped traditional analytical paradigms. This paper systematically reviews state-of-the-art research, which classifies bottlenecks by their identification object, origin, scope, and temporal characteristics, and categorizes identification methods into topology-based, flow/load-based, dynamics-based, machine learning-based, and deep learning-based approaches. We further summarize future development trends and highlight key unresolved challenges.

Keywords: complex networks, bottleneck identification, critical infrastructure, network resilience, network systems

1. Introduction

1.1. Background

In today's highly interconnected world, system structures and their interactions are typically characterized in the form of networks. Complex networks, serving as a pivotal tool for understanding and analyzing interconnectivity in modern society, have been extensively applied in natural, social, and engineering systems [1, 2], ranging from biological neural networks [3] and social networks [4] to power grids [5] and transportation networks [6]. Endowed with large scale, high connectivity, and structural heterogeneity, complex networks facilitate efficient information transmission and resource sharing. However, they also impose considerable challenges on the investigation of system reliability [7].

In most real-world networks, structure and function are tightly coupled with system performance depending critically on a small set of critical nodes and links [8–13]. Nevertheless, the topological structure and distribution in these networks

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are extremely inhomogeneous, with a small number of hub nodes undertaking the core function of maintaining network connectivity. Owing to inherent structural heterogeneity, network functions, loads, and other properties tend to concentrate on specific nodes or links, forming a highly uneven functional-load distribution that intrinsically constitutes structural and functional bottlenecks [14]. Once certain nodes, links, or subsystems become functionally constrained or fail, the network often experiences significant performance degradation or even systemic collapse. For example, in urban transportation networks, bottlenecks manifest as persistent congestion at key intersections or highway entrances, leading to stagnant transport efficiency across the entire region. In global supply chain networks, delays at a single core manufacturer or logistics hub can rapidly amplify, resulting in production chain disruptions and substantial economic losses.

Identifying bottlenecks is central to understanding network dynamics and improving system-level performance. This problem has attracted sustained interest in complex systems, network science, computer science, and control theory. In the context of network optimization, bottlenecks often emerge as critical constraints that limit system performance. Identifying these bottlenecks enables targeted resource allocation and scheduling strategies, thereby significantly improving overall network efficiency and quality of service [15]. In risk prevention and control, identifying bottlenecks enables early warning of vulnerable points in the network [16], supporting network survivability design and emergency fault response [8, 17].

Despite the significant research value of identifying bottlenecks in complex networks, traditional analytical methods have gradually revealed their limitations as networks expand in scale, become more structurally heterogeneous, and exhibit increasingly prominent dynamic characteristics. Early identification methods based on single static metrics, such as degree centrality [18] and betweenness centrality [19], fail to fully characterize the complex functional roles of nodes or links within networks. Meanwhile, dedicated identification models tailored to domain-specific networks [20] lack universality across different types of complex networks.

Given the emergence of numerous new methods in this field in recent years, there is an urgent need to summarize and synthesize these advances. This paper focuses on the identification of bottlenecks in complex networks and integrates recently developed dynamic bottleneck identification techniques, particularly machine learning (ML) and deep learning approaches, within a unified network science and complex systems framework. Its primary objective is to disseminate the latest theoretical methods in this field, pinpoint future research directions, and provide a valuable reference for relevant scholars.

1.2. Review methodology

This paper defines three specific research questions (RQs) as the backbone for constructing the review framework.

(1) ***RQ1***: What types and forms of bottlenecks exist in complex networks?

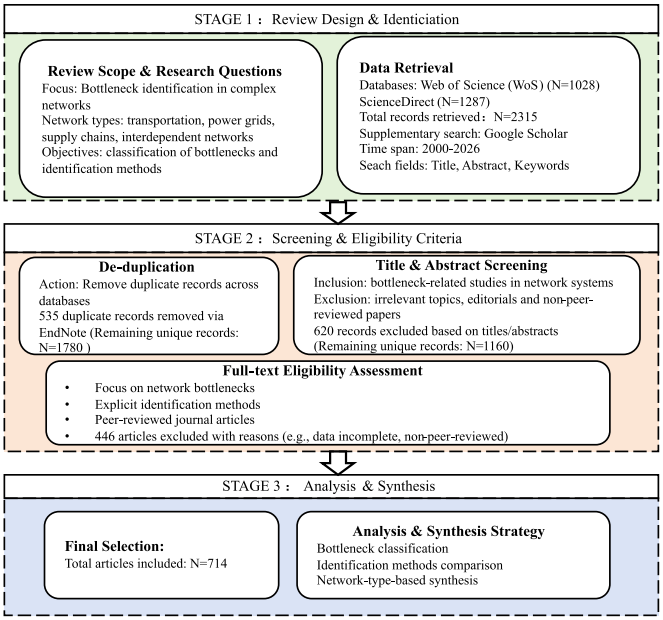


Figure 1. Research methodology according to PRISMA.

(2) ***RQ2***: What similarities and differences in bottleneck manifestations exist across different network types (e.g. transportation, power, supply chain, Internet of Things)?

(3) ***RQ3***: What are the mainstream methods currently available for bottleneck identification?

To ensure standard research practice, we adopted a systematic survey methodology inspired by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. The literature selection process was structured into three distinct phases: identification, screening, and analysis, as shown in figure 1.

Step 1. Review design and Identification. The review was designed to focus on bottleneck identification in complex networks, covering network types including transportation systems, power grids, supply chains, and interdependent networks, with the core objectives of classifying bottleneck types and summarizing identification methods. Literature retrieval was conducted using three primary databases: Web of Science, IEEE Xplore, and ScienceDirect, supplemented by a search in Google Scholar. The time span was set from 2000 to 2025, and searches were performed in the fields of title, abstract, and keywords to ensure comprehensive coverage.

Multiple combinations of keywords were employed for retrieval, categorized into three groups:

1. **Network object level**: ‘Complex Network’, ‘network system’, ‘Traffic Network’, ‘Biological Network’, ‘Maritime Network’, ‘Internet of Things network’, ‘IoT network’, ‘Supply Chain Network’, ‘Social Network’, ‘interdependent network’, ‘multilayer network’.
2. **Bottleneck feature level**: ‘Bottleneck’, ‘Key Node’, ‘Critical Node’, ‘Key Link’, ‘Critical Link’, ‘Key Component’, ‘Critical Component’, ‘Subnetworks’.

3. **Research objective level**: 'Identification', 'Detection', 'Recognition','Localization', 'Evaluation', 'Diagnosis'.

Step 2. Screening and eligibility criteria. First, duplicate records retrieved across different databases were removed. Then, title and abstract screening was performed to include studies related to bottlenecks in network systems, while excluding irrelevant topics, editorials, and non-peer-reviewed papers. Finally, full-text eligibility assessment was conducted, where final eligibility was determined based on three criteria: (1) focus on network bottlenecks, (2) explicit presentation of identification methods, and (3) publication as peer-reviewed journal articles.

Step 3. Analysis and synthesis. Following the screening process, a total of 714 articles were selected for final analysis and synthesis. In particular, the analysis strategy included the classification of network bottlenecks, the comparison of different bottleneck identification methods, and the synthesis of findings based on different network types. This approach provides support for the systematic and comprehensive review of the research progress in the field of bottleneck identification in complex networks.

To systematically review the research progress on bottleneck identification in complex networks, this section adopts a bibliometric approach, utilizing the visualization tool VOSviewer to analyze relevant literature. [21]. Based on temporal keyword co-occurrence analysis, the evolution of bottleneck identification research can be divided into three stages:

- **Stage 1 (2000–2017)**: Research primarily relied on classical topological metrics to identify node bottlenecks in single-layer networks.
- **Stage 2 (2018–2021)**: Functional and dynamic methods increased significantly, with research focusing on bottleneck analysis in power, transportation and other engineering networks.
- **Stage 3 (2022–2025)**: Research shifted toward data-driven intelligent identification and applications in interdependent and multilayer networks.

Figure 2 shows the publication trend of research on bottleneck identification in complex networks over time. As illustrated, the number of related publications has increased steadily, reflecting the growing academic and industrial interest in this field.

Figure 3 shows the timeline visualization of keyword co-occurrence, which reveals the primary research topics in the field of bottleneck identification for complex networks. Three distinct thematic clusters are identified: core concepts and theoretical analysis, methodologies and identification techniques, and application domains and advanced technologies. The cluster of core concepts and theoretical analysis focuses on fundamental theories involving complex networks, vulnerability, robustness, and cascading failure. It aims to clarify the underlying mechanisms of network evolution, failure propagation, and system resilience. The cluster of methodologies and identification techniques centers on identification-oriented research, covering typical indicators and approaches such as critical node recognition, network robustness assessment, and various centrality measures, which support the detection and evaluation of key functional components in complex networks. The cluster of application domains and advanced technologies encompasses typical engineering scenarios including power grids, transportation networks, and cybersecurity systems. Combined with advanced analytical methods such as deep learning and data mining, it promotes the practical deployment and interdisciplinary integration of network bottleneck identification analysis technologies.

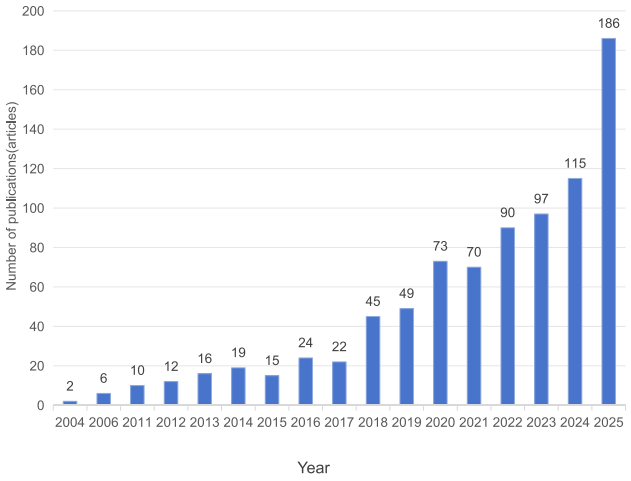


Figure 2. Trend of the number of published literatures.

1.3. Related work and contributions

With the wide application of complex networks in transportation, power grids, communications, supply chains, biological systems, and other fields, the identification of bottlenecks has become an important direction in complex network research. Existing reviews have systematically summarized the related work, which can be divided into two categories: one type focusing on structural properties and node importance, and the other type on domain-specific bottleneck identification.

The first category of reviews primarily focuses on structural properties and node importance evaluation. Lü *et al* [22] summarized critical node identification techniques based on structural centrality, iterative optimization, and dynamical process-based approaches. Chen *et al* [23] reviewed critical node identification methods. Ait Rai [24] focused on influential node identification from the perspective of influence propagation. The second category concentrates on domain-specific bottleneck identification. Wang *et al* [25] reviewed bottlenecks in production networks. Tang *et al* [26] discussed static, simulation-based, and data-driven bottleneck identification in manufacturing systems. Gong *et al* [27] reviewed bottleneck formation mechanisms in transportation networks. However, existing reviews suffer from several limitations:

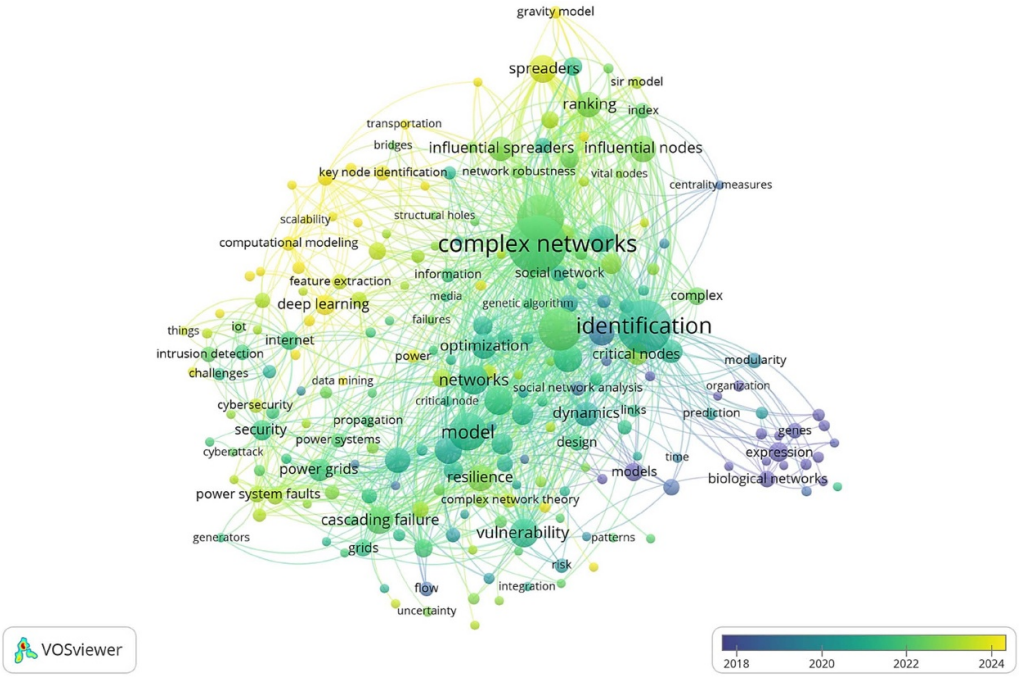


Figure 3. Keyword co-occurrence network revealing major research topics.

1. Most reviews focus on a single bottleneck type, lacking integrated classification across nodes, links, and components.
2. Methods are discussed in isolation without horizontal comparison across modeling assumptions and application scenarios.
3. Cross-domain and interdependent network bottleneck mechanisms remain insufficiently analyzed.
4. The practical effectiveness, adaptability to complex network dynamics, and interpretability of results of emerging technologies such as artificial intelligence (AI) and ML in bottleneck identification remain insufficiently explored.

To address the aforementioned limitations, the main contributions of this paper are as follows:

1. This paper expands bottleneck objects to nodes, links, and components, constructing a multidimensional classification framework.
2. It systematically integrates structural, functional, dynamic, ML, and deep learning-based bottleneck identification methods.
3. It conducts comparative analysis across network types and application scenarios, identifying challenges and future research directions.

2. Classification framework of network bottlenecks

A typical network consists of nodes and links, where nodes correspond to various entities in real-world systems, and links represent the interrelationships or interactions between these entities [23]. Although the basic components of a network are relatively simple, bottlenecks in practical engineering and natural systems often emerge from structural topology, dynamical processes, and external perturbations. Scientific classification of bottlenecks is a prerequisite for understanding their nature and developing targeted identification methods.

The multi-dimensional classification framework of network bottlenecks established in this study is intuitively illustrated in figure 4. We divide network bottlenecks from four complementary dimensions: object type, formation origin, impact scope, and temporal status. It should be emphasized that this framework is a multi-dimensional characterization scheme rather than a mutually exclusive taxonomy. These four dimensions capture distinct behavioral attributes of network bottlenecks and are not strictly independent of one another. In real-world systems, a single bottleneck can simultaneously exhibit multiple cross-dimensional characteristics. Accordingly, dimensional overlaps across the tables in this section do not represent conceptual redundancy or repetitive categorization. Rather, they reflect the inherently multi-faceted nature of bottleneck phenomena. These tables should be interpreted as single-perspective projections of a unified literature dataset onto the multi-dimensional characterization space, with each table focusing on one specific axis to maximize presentation and categorical clarity.

2.1. Types of bottlenecks

Bottlenecks in complex networks typically exist in the form of nodes, links, or components, and these objects play critical roles in network connectivity, functional integrity, or robustness.

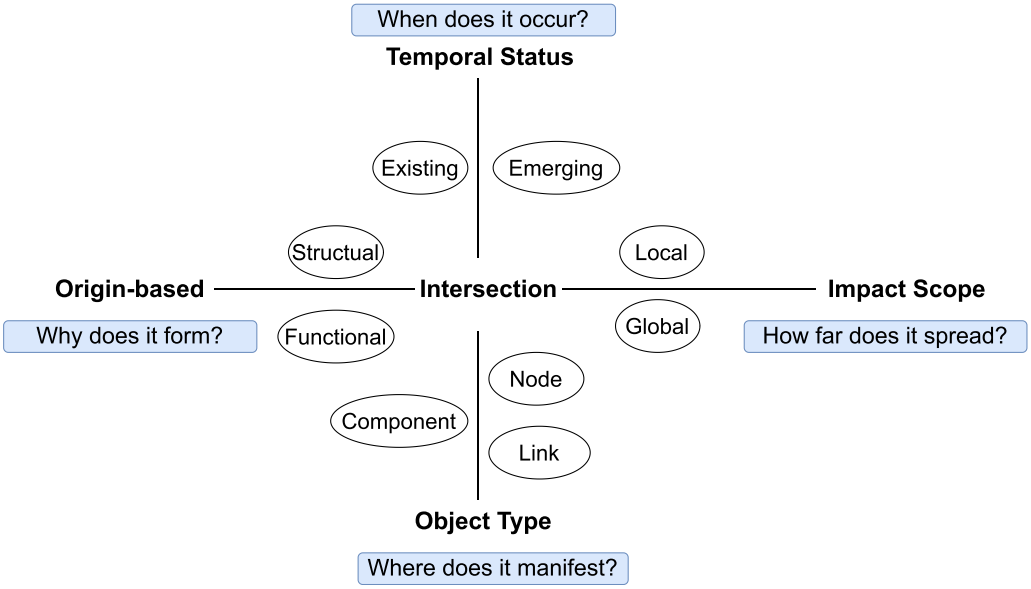


Figure 4. Classification framework of bottlenecks in complex networks.

2.1.1. Critical node. In complex network research, traditional studies on critical nodes have primarily aimed to maximize node influence, enhance information propagation efficiency, or mitigate performance degradation under perturbations [28–30]. When considering bottlenecks, the definition and focus of critical nodes change. A critical node refers to a node that plays an important role in network structure and information transmission, and whose influence can significantly affect the propagation efficiency and performance of the entire network [31, 32]. Such critical nodes have distinct characteristics in network topology. They are usually located at path junctions or traffic concentration points, and are also the vulnerable parts of the entire system where risks are most likely to accumulate, congestion occurs, and cascading failures are induced. Based on these core topological properties, methods for identifying critical nodes mainly focus on how to quantify or map these characteristics.

A variety of representative topological centrality metrics and improved identification algorithms have been proposed successively in existing research. Betweenness Centrality [19] quantifies the frequency of a node acting as an intermediary in the shortest paths, directly measuring its criticality in controlling network traffic and information circulation. Eigenvector centrality [33] focuses on the importance of a node's neighbors, identifying indirect influence bottlenecks that have few connections themselves but are connected to a large number of important nodes. In contrast, information centrality [34] evaluates node importance based on the efficiency of information transmission over all possible paths in the network. When dealing with highly heterogeneous networks, the *k*-shell decomposition method [35] provides an effective hierarchical analysis tool by iteratively stripping low-degree peripheral nodes from the network, and can clearly identify the nodes located at the core of the network. To balance identification accuracy and computational complexity, Chen *et al* [36] proposed Semi-local Centrality, which effectively

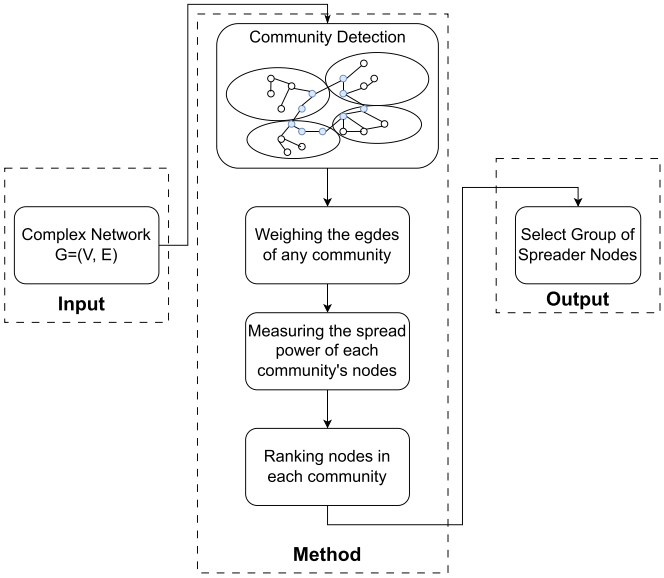


Figure 5. Framework of the HKCD method based on *k*-shell decomposition.

compensates for the limitations of traditional local and global metrics by fusing first-order and second-order neighbor information of nodes. To address the problem that a single metric is difficult to capture both local and global characteristics simultaneously, Zhao *et al* [37] proposed the structural holes *k*-shell index by combining structural hole theory with *k*-shell decomposition, which can significantly improve the identification accuracy of 'bridge-type' critical nodes connecting different communities. HamaKarim *et al* [38] proposed the hybrid *k*-shell based community detection (HKCD) method relying on *k*-shell decomposition. As shown in the methodological framework in figure 5, the method takes the original complex network as input, partitions it into multiple sub-communities, assigns weights to intra-community links,

evaluates node spreading capability within each community, and finally outputs a ranked list of influential spreader nodes, forming a complete workflow from decomposition to node ranking.

2.1.2. Critical link. A critical link, also often referred to as a bridge edge or bottleneck edge, is a connecting channel that has an important impact on network connectivity, traffic transmission, or function execution, whose failure or removal will lead to network fragmentation and a significant decline in transmission efficiency [39–43]. Compared with critical nodes that focus on the 'point' convergence and control capabilities, key links highlight the 'line' bridging properties and load limits. In weighted networks with high path dependence, such links usually carry the highest effective traffic or serve as sparse channels between different communities, geographical regions, or functional modules, and thus their destructiveness is far greater than that of node failure.

For example, in transportation networks, critical links correspond to trunk highways, river-crossing bridges, or important tunnels, whose congestion or interruption will lead to large-scale traffic paralysis. Shen *et al* [44] proposed the critical link disruptor model, which formulates link disruption as an optimization problem to minimize the total pairwise connectivity under weight constraints, and developed the hybrid iterative linear programming rounding algorithm to detect key links with higher destructiveness than traditional centrality methods. Edge betweenness centrality proposed by Girvan [42] efficiently identifies inter-community bridges and traffic throats by counting the frequency of each edge in global shortest paths. The max-flow min-cut theorem established by Elias *et al* [45] and Lord *et al* [46] points out that the links in the min-cut set are exactly the transmission bottlenecks with the strongest capacity constraints even if their edge betweenness centrality is not high, which may become actual functional bottlenecks due to the excessively high load-to-capacity ratios. Xiao *et al* [47] showed that traditional edge betweenness centrality is significantly underestimated in high-load heterogeneous networks, and proposed a dynamic evaluation framework integrating edge betweenness centrality and the load-capacity model, proving that min-cut set links and high load or capacity ratio links are the real bottlenecks that trigger large-scale cascading failures.

2.1.3. Critical components. Critical components refer to a set of nodes with dense internal connections, high functional coupling, but relatively sparse connections with the rest of the network. Their overall failure can lead to network fragmentation into multiple isolated regions, weaken cross-module connectivity, or trigger large-scale cascading failures in interdependent networks [48, 49]. Unlike critical nodes and key links, the risk of critical components does not come solely from individual elements. These components have tight internal structures, undertake common tasks, and often span multiple subsystems or multilayer networks. Once a component fails, its impact is no longer limited to the local area, but will be amplified into a system-level performance decline through inter-module dependencies. When the coupling strength exceeds a critical threshold, failure of critical components induces a transition from a second-order continuous phase transition to a first-order catastrophic collapse [50].

Existing methods for identifying critical components include community detection, *k*-shell decomposition, min-cut set analysis, and combined metrics based on traffic and betweenness centrality. In typical infrastructure networks, critical components often appear in the form of submodules or regional clusters. Fu *et al* [51] proposed the component importance and interdependence analysis framework, which quantifies critical components in three types of subnetworks (Transmission network, Distribution network, Communication network) and their cross-layer coupling effects through physically embedded multilayer network metrics, providing an operable basis for the priority recovery order after failures. Dunn and Wilkinson [52] developed a comprehensive evaluation metric integrating three core network attributes, namely node original traffic, betweenness centrality, and node degree, for identifying critical vulnerable components in infrastructure networks. The Summary-bAsed deNsest Subgraph discovery method proposed by Niu *et al* [53] avoids graph data materialization through node neighborhood summarization and can efficiently mine the densest subgraphs in relational graphs. This method performs excellently in fraud detection scenarios, and densest subgraphs often correspond to potential critical subnetworks or risk concentration areas in the context of functional networks.

Overall, table 1 summarises related research on network bottleneck identification. These methods provide effective tools for detecting critical nodes, links, and components in complex networks and achieve decent performance in structural and functional analysis through diverse centrality, optimization, and learning-based paradigms.

2.2. Origin-based bottleneck classification

According to the dominant factors governing bottleneck emergence, network bottlenecks are generally classified into structural bottlenecks and functional bottlenecks.

2.2.1. Structural Bottlenecks. Structural bottlenecks are determined by the geometric and topological properties of network structure and are directly associated with degree distributions, shortest-path distributions, connectivity patterns, and other static structural attributes, independent of traffic dynamics or temporal evolution [22, 43]. They typically manifest as sparse inter-module channels (cut sets), vertex separators, high-betweenness hubs, or bridging links connecting different communities, submodules, or functional regions. The failure or saturation of such structures can directly induce global connectivity disruption, path length explosion, or functional module isolation. Sreenivasan *et al* [54] first formally introduced the concept of structural bottlenecks, demonstrating that the upper bound of packet injection rate in any network is constrained by the minimum vertex separator. They derived a rigorous mathematical upper bound scaling with network size N

Table 1. Classification and comparison of network bottleneck types.

References	Bottleneck Object	Definition	Method Paradigm	Core Approach	Network Type	Computational Complexity	Advantages	Limitations
[18, 19, 33, 34]	Node	Nodes whose removal significantly degrades global network performance	Centrality-based metrics	Degree, Betweenness, Eigenvector-based node control quantification	General complex networks	Low	Theoretically mature Low computational cost	Neglects dynamic load and functional processes
[35, 37, 38]	Node	Structurally and functionally core nodes	*k*-shell decomposition and extensions	Iterative pruning + Community detection + Weighted edges + Diversity measures	Highly heterogeneous networks	Low–Medium	Uncovers true structural cores	Low discrimination within same *k*-shell layer
[36]	Node	Nodes with balanced local-global influence	Semi-local centrality	First- and second-order neighborhood integration	General complex networks	Medium	Balances local and global influence	Sensitive to neighborhood order selection
[39, 40]	Node	System-critical nodes	Reinforcement learning	DRL / GNN+ Q-learning global optimization	Large-scale complex networks	High	Detects potential bottlenecks	Low interpretability Training required
[44]	Link	Links whose failure causes fragmentation	Optimization attack models	Connectivity minimization under constraints	General / Weighted networks	High	Stronger destructive power than edge centrality	Computationally intensive
[45, 46]	Link	Capacity-constrained transmission links	Max-flow–Min-cut	Minimum cut-set identification	Flow and transportation networks	Medium	Direct functional bottleneck localization	Ignores topological heterogeneity
[47]	Link	High-load failure-prone edges	Load-capacity hybrid models	Edge betweenness + Load/capacity ratio	High-load heterogeneous networks	Medium–High	Corrects heavy-load bias	High ional burden
[48, 50]	Component	System-critical node groups	Interdependent percolation models	Mutually connected components + Phase transition theory	Interdependent networks	Medium	Uncovers systemic fragility	Idealized assumptions
[49, 51]	Component	Cross-layer critical components	Multilayer network analysis	Inter-layer dependency modeling	Multilayer networks	High	Unified multilayer framework	High data and computation demand
[52]	Component	Functionally critical subsystems	Topology-flow hybrid indicators	Flow × (betweenness/degree)	Infrastructure networks	Medium	Engineering interpretability	Strong real-data dependence
[53]	Component	Dense functional substructures	Dense subgraph discovery	Densest subgraph extraction	Relation / functional networks	Low	Scalable to large graphs	Generalizability uncertain

and obtained explicit scaling forms for scale-free networks, establishing a fundamental linkage between topological constraints and global transport capacity.

In real-world networks, structural bottlenecks are often located along unavoidable transmission corridors or critical hubs for resource, information, or signal propagation. They determine whether effective connectivity between submodules can be sustained and constitute the structural carriers of global connectivity and functional integrity. Accordingly, identification of structural bottlenecks primarily relies on static topological analysis. Hamedmoghadam *et al* [55] employed a heterogeneous flow percolation model to analyze structural bottlenecks in infrastructure networks, showing that flow-weighted link criticality scores can accurately localize transmission-bottleneck links. Through long-term analysis of the structural evolution of power distribution networks, Hartmann *et al* [56] constructed an undirected and unweighted graph model with degree, closeness and betweenness centrality metrics calculated to analyze the evolution of their probability density functions, identifying structurally bottlenecked nodes and links in the power grid. Meanwhile, the vulnerability induced by structural bottlenecks was evaluated by quantifying the attenuation of network efficiency. In the context of social information diffusion, Kang *et al* [57] proposed a directed network model to analyze the association between the structure of online social networks and information access, quantitatively investigate the information adoption rate of friends, and unravel the formation mechanisms of structural and cognitive bottlenecks. For urban transportation systems, Kwon *et al* [58] performed a comparative analysis of the real-world traffic flow network against its structurally randomized null model, and investigated the quality disparities between high- and low-betweenness links across different time periods, as well as the impact of congestion on high-betweenness links on the network's global efficiency. In communication networks, Aghaei and Lohrasebi [59] defined the traffic percolation threshold based on the load of system nodes, systematically investigated the impacts of network structures, different routing strategies and transmission capacity distributions on the efficiency of communication networks, and verified the effect of regulatory approaches related to node load distribution on the organization of traffic loads.

2.2.2. Functional bottlenecks. Functional bottlenecks are induced by operational dynamics, arising from the joint effects of flow distributions, capacity constraints, and routing or scheduling mechanisms. Their core does not lie in static network geometry, but in the emergence of load saturation states, where node or link loads exceed their functional carrying capacities under specific operational conditions. Unlike structural bottlenecks, even networks with identical topologies may exhibit substantially different bottleneck locations, intensities, and evolution trajectories due to variations in demand levels, flow allocation strategies, and operational rules.

Crucitti *et al* [60] proposed a cascading failure model based on dynamic load redistribution, identifying functional bottlenecks as nodes whose loads exceed capacity thresholds. Saberi *et al* [61] proposed an analytical framework for the propagation of urban traffic congestion based on a simple contagion process and constructed a system of ordinary differential equations analogous to the susceptible-infected-recovered (SIR) model; they identified congested links and conducted curve fitting to validate the proposed model. In power systems, Schäfer *et al* [62] developed a dynamic cascading failure framework based on swing equations, showing that short-timescale failure propagation is governed by instantaneous maximum flow constraints. Zhang *et al* [63] proposed a distributed robust optimization framework for transmission grid bottleneck identification. Li *et al* [64] reviewed fifty years of bottleneck modeling in transportation systems and proposed a unified functional bottleneck criterion based on functional performance deviation rather than structural positional attributes.

As shown in table 2 , we summarize and classify existing studies on network bottlenecks, and compare different methods in terms of their applicable scenarios, advantages, and limitations, which supports the identification and analysis of network bottlenecks in this paper.

2.3. Impact-scope based bottleneck classification

The destructive consequences induced by bottleneck failure exhibit significant heterogeneity across networks. According to the spatial and functional range of impact, network bottlenecks can be classified into local bottlenecks and global bottlenecks. Local bottlenecks primarily affect confined subnetworks or local neighborhoods, whereas global bottlenecks impose systemic constraints on overall network functionality and integrity.

2.3.1. Local bottlenecks. Local bottlenecks refer to critical nodes or links that impose significant constraints on information, resource, or flow transmission within specific subgraphs or neighborhood regions of a network. The failure of such elements leads to a pronounced degradation of local efficiency, without necessarily causing a collapse of global connectivity. Structurally, local bottlenecks typically manifest as high-load hubs or bridging units within local communities or neighborhoods. Their intrinsic vulnerability arises from a structural contradiction in that they play an indispensable role in local connectivity yet often lack redundancy and alternative routing paths, making them highly susceptible to disturbance and overload. In many subnetworks, neighboring nodes rely on a single or a few critical nodes or links for mutual connectivity. Once these core elements fail, local information transmission and functional interaction are immediately disrupted. The identification of local bottlenecks does not rely on global topological information but primarily adopts local structural indicators. Common approaches include semi-local centrality measures that evaluate node influence across multi-order neighborhoods.

Burt [65] analyzed the distribution of structural holes within enterprises and the associated characteristics of the brokerage role, demonstrating that nodes occupying structural hole positions-which connect otherwise disconnected local groups-naturally form local bottleneck units. To

Table 2. Classification and comparison of network bottlenecks based on origin.

References	Type	Temporal Variability	Method Category	Network Type	Cascading Failure	Advantages	Limitations
[54]	Structural	Low	Bottleneck percolation theory	Communication networks	No	First formal definition rigorous theoretical bound	No practical identification tools
[55]	Structural	Low	Heterogeneous flow percolation	Infrastructure networks	Yes	Cross-domain applicability	Parameter sensitivity
[56]	Structural	Low	Long-term structural evolution	Power networks	No	Persistent vulnerability identified	Domain-specific long-term data dependence
[57]	Structural	Low	Social information bottleneck analysis	Social networks	No	Integrates cognitive constraints	Subjective indicators
[58]	Structural	Medium	Empirical percolation analysis	Urban transportation networks	Yes	Topology-flow coupling mechanism	High-resolution data required
[59]	Structural	Medium	Percolation transition analysis	Communication networks	Yes	Topology-load sensitivity linkage	Limited large-scale validation
[60–62]	Functional	High	Cascading failure / dynamic spreading	Complex networks	Yes	Realistic operational simulation	Parameter sensitive computationally intensive
[63]	Functional	High	Distributed robust optimization	Power grids	Yes	Strong robustness engineering relevance	Domain-specific applicability
[64]	Functional	Medium	Unified bottleneck framework	Transportation systems	No	Cross-model integration	Conceptual-level framework

overcome the limited discriminative power of traditional structural hole metrics in complex networks, Yu *et al* [66] proposed the improved structural holes (ISH) method, which relies solely on node degree and neighborhood information. By introducing edge weights based on neighbor positional differences, ISH characterizes the local resource investment structure of nodes and enables refined identification of local bridging nodes. Meghanathan *et al* [67] explicitly formulated local bottlenecks as a bridge-node problem and proposed the neighborhood-based bridge node centrality framework, which hierarchically quantifies local bottleneck intensity using neighborhood graph connectivity components, algebraic connectivity ratios, and neighborhood scale indicators.

2.3.2. Global bottlenecks. Global bottlenecks are critical components that constrain overall network connectivity, systemic functional integrity, and macroscopic transmission efficiency at the network scale. Their failure typically propagates beyond local disturbances and triggers cross-regional, cross-modular, and even cross-system cascading failures through load redistribution, functional dependency, or inter-layer coupling mechanisms. Unlike local bottlenecks, global bottlenecks commonly manifest as high-betweenness bridging structures, single points of failure in network topology, or core nodes and links responsible for inter-layer coupling in interdependent networks. They are characterized by high replacement costs, long recovery cycles, and dominant systemic risk contributions, making them primary risk sources in complex system resilience design. The identification of global bottlenecks relies on global topological indicators, system-level connectivity assessment, and cascading failure simulations. The core objective is to evaluate the system-wide functional impact induced by component failure, rather than local structural perturbations or isolated performance indicators.

Buldyrev *et al* [48] based on percolation theory, constructed interdependent network models, simulated the cascading effects of node failures, analyzed the percolation properties of networks under different coupling modes, investigated the impacts of coupling strength on global failures, and revealed the formation and evolution patterns of local failures triggering global bottlenecks and leading to global network collapse. Kim *et al* [68] constructed four basic supply network structures, designed a resilience measurement index, analyzed the impact of network structures on global bottlenecks via simulation, and proposed the proposition that networks with node degree distributions following a power law are more resistant to global bottlenecks. Rivas-Dávalos *et al* [69] proposed a global bottleneck identification method based on natural connectivity, quantifying the degradation of global network connectivity induced by single-line removal to assess its impact on systemic robustness. Zhao *et al* [70] reviewed failure-dependency mechanisms and classified global bottlenecks into structural global bottlenecks, triggered by direct dependency failure, and functional global bottlenecks, induced by load redistribution dynamics.

2.4. Temporal-status based bottleneck classification

The timing of bottleneck manifestation fundamentally determines identification strategies and intervention policies. Bottlenecks can be classified into three categories, namely existing bottlenecks, potential bottlenecks, and emerging bottlenecks.

2.4.1. Existing bottlenecks. Existing bottlenecks refer to constraints that are already explicitly manifested under the present network topology and load conditions, whose overload or failure has led to observable performance degradation or functional limitations. In complex systems, such bottlenecks typically appear as congestion points, saturated links, or anomalous-performance nodes identified through real-time monitoring, such as peak-hour traffic segments, overloaded transmission lines in power grids, or blocked workstations in manufacturing systems.

The explicit observability of existing bottlenecks enables their direct identification from operational data, making them highly valuable for immediate intervention and resource reallocation to prevent further performance deterioration or cascading failures [71]. ML-based approaches dominate the identification, relying on real-time monitoring data, performance indicators, and load measurements to localize bottleneck positions. Li *et al* [72] proposed a bottleneck detection method for short-term and long-term bottlenecks in manufacturing systems, using real-time production-line records of blockage probability, starvation probability, and buffer content to directly identify existing bottleneck locations. Subramaniyan *et al* [73] developed a real-time algorithm for shifting bottlenecks, extracting existing bottlenecks, average bottlenecks, and non-bottlenecks from manufacturing execution systems (MES) data to support dynamic scheduling and resource optimization. Patounas *et al* [74] built a prototype testbed for cloudified mobile networks, adopted ML combined with distributed/centralized analytical approaches to explore bottleneck identification schemes, and provided an intelligent monitoring framework for existing bottleneck detection. Tu *et al* [75] designed an optimization-based scheme to identify transmission bottlenecks that limit power network performance under extreme events, demonstrating that capacity limits of a few critical links act as inherent existing bottlenecks in power transmission systems.

2.4.2. Potential bottlenecks. Potential bottlenecks refer to hidden risk components that do not exhibit performance degradation under current steady-state conditions, but may rapidly evolve into explicit bottlenecks under slight load growth, topological perturbations, or local failures due to insufficient redundancy or parameter sensitivity. Unlike existing bottlenecks, potential bottlenecks are characterized by structural concealment and conditional activation. Their risks originate not from present abnormal states, but from the system's high sensitivity to perturbations. Once activated, their impacts often propagate rapidly through cascading and amplification

mechanisms, severely affecting overall system performance and reliability [60].

The identification of potential bottlenecks therefore requires abstraction beyond single operational scenarios. It relies on topological feature extraction, parameter sensitivity analysis, and stress-testing frameworks to evaluate the amplification effects of small perturbations on global system performance, reliability, and availability. Such bottlenecks do not necessarily correspond to current congestion points but may become dominant performance constraints under load escalation, resource reconfiguration, or localized failures. Zacarias *et al* [76] analyzed performance bottlenecks in large-scale HPC systems, showing that resource contention in memory and cache can significantly limit system efficiency. They further demonstrated that optimized resource scheduling and workload colocation strategies are effective in mitigating such bottlenecks. Li *et al* [77] employed percolation theory combined with real-time urban traffic speed data to construct functional networks based on speed thresholds, identifying bridging links at critical thresholds as potential bottlenecks. Bucur *et al* [78] proposed a simulation-based stress-testing framework in wireless networks, identifying topological bottlenecks that remain hidden under normal operation but dominate performance degradation under stress scenarios. Matos *et al* [79] developed a hierarchical-model-based bottleneck identification method for cloud systems, using systematic parameter sensitivity ranking to detect components that are not yet failing but exhibit high sensitivity to performance and availability. Zio [80] analyzed vulnerability and risk in critical infrastructures, highlighting that latent structural and functional weaknesses can act as potential bottlenecks, which may trigger system-wide failures under disturbances.

2.4.3. Emerging bottlenecks. Emerging bottlenecks refer to potential bottleneck units that have not yet appeared explicitly under the current network structure and operational state, but are expected to form key constraints on system connectivity, transmission efficiency, or functional execution within a specific future period based on network evolution trends, demand growth patterns, or planning scenario analysis. Unlike existing or potential bottlenecks, emerging bottlenecks do not rely on abnormal performance in current operational data; instead, their identification is entirely based on predictions of temporal network evolution, load growth trajectories, and structural change trends, thus exhibiting strong forward-looking and planning-oriented characteristics.

The identification of such bottlenecks depends on predictive models, which evaluate the medium- and long-term trends of the system and conduct scenario deduction of future network states to proactively locate nodes, links, or functional modules that may evolve into key constraints. Kosasih [81] used graph neural networks (GNNs) to predict hidden supply relationships, finding that newly formed critical dependencies may transform into emerging bottlenecks after demand growth with the expansion of enterprises or changes in cooperation structures. Ma *et al* [82] proposed a critical link detection method in airway networks based on complex network

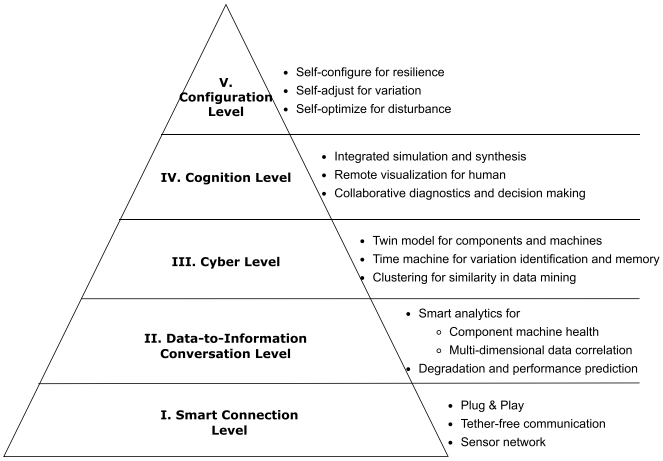


Figure 6. 5 C architecture for implementation of CPS.

theories. Anjaneyulu and Kubendiran [83] proposed a hybrid deep learning model utilizing principal component analysis, stacked auto-encoder, long short term memor, and k-nearest neighbors named PALKNN for short-term traffic flow prediction. Yin *et al* [84] conducted predictive analysis of task networks based on spatiotemporal graph convolutional networks (GCNs), pointing out that with the dynamic changes in the structure and execution sequence of production tasks, some resource nodes may evolve into system bottlenecks under scenarios of future task intensification or structural adjustment. Ragazzini *et al* [85] focused on emerging bottlenecks in manufacturing systems and proposed a prediction and control framework centered on digital twins (DT). By synchronizing real-time data, simulating future behaviors with DT, and predicting bottlenecks combined with the activity cycle method, the framework dynamically adjusts order release and scheduling rules. Lee *et al* [86] proposed a unified five-layer 5 C cyber-physical system (CPS) architecture for Industry 4.0 manufacturing. As illustrated in figure 6, the framework integrates data acquisition, information transformation, network transmission, cognitive decision-making, and system reconfiguration, where the cognition layer is responsible for predictive analytics and future constraint estimation in emerging bottleneck identification.

Overall, as shown in table 3, we divide related work into existing, potential, and emerging bottlenecks based on their developmental stages. Various methods including anomaly detection, ML-based learning, optimization, and predictive modeling are compared, highlighting their advantages and limitations in different network scenarios.

3. Identification methods for network bottlenecks

3.1. A general mathematical formulation for bottleneck identification

Although bottleneck identification methods differ substantially in their theoretical foundations and implementation strategies, they share a common objective: evaluating the criticality of network elements based on available network

Table 3. Classification and comparison of network bottlenecks from a temporal perspective.

References	Temporal type	Scientific nature	Method paradigm	Trigger condition	Network type	Advantages	Limitations
[71]	Existing	Anomaly detection	Manufacturing bottleneck survey	Current performance degradation	Manufacturing networks	Comprehensive classification framework	/
[72, 73]	Existing	Machine learning-based detection	Shifting bottleneck analytics	Blockage/starvation anomalies	Manufacturing systems	Model-free, real-time efficient	Data-quality sensitivity
[74]	Existing	ML + distributed analytics	Multi-layer data fusion	Performance anomalies	Cloud mobile networks	Distributed processing	Data integration complexity
[63]	Existing	Optimization-based identification	Transmission bottleneck identification via greedy optimization	Transmission capacity limits	Power transmission networks	Resilience-oriented constraint analysis	Computational demand, scenario specificity
[76]	Potential	Resource-constrained bottlenecks	Scheduling optimization under resource contention	System performance degradation under limited shared resources	Large-scale computing networks	Efficient utilization of constrained resources	Sensitivity to workload heterogeneity
[77]	Potential	Percolation analysis	Speed-threshold functional networks	Speed degradation	Urban road networks	Threshold-based real-time identification	Subjective threshold selection
[78, 79]	Potential	Stress testing / Sensitivity analysis	Simulation-based frameworks	Perturbation/ Parameter variation	Wireless/Cloud networks	Hidden-risk exposure	Multi-scenario testing cost
[80]	Potential	Vulnerability and risk analysis	System-level risk modeling	Latent defect activation	Critical infrastructure networks	Potential failure assessment	Uncertainty and system complexity
[81]	Emerging	Evolutionary prediction	GNN hidden-link forecasting	Network expansion/cooperation change	Supply-chain networks	Hidden dependency prediction	Training-data demand
[82–84]	Emerging	Spatiotemporal forecasting	Deep learning prediction models	Demand growth/task densification	Aviation/traffic/task networks	High prediction accuracy	Model complexity
[85, 86]	Emerging	Predictive identification	Cyber-physical system modeling with predictive analytics	Disturbance propagation and capacity constraints	Manufacturing systems	Real-time monitoring and foresight	System integration complexity

information. From this perspective, different bottleneck identification paradigms can be generalized as a unified mapping from network information to the bottleneck score of a network element.

Accordingly, a general mathematical formulation can be expressed as

$$B(\alpha) = f(G, A, t, M), \tag{1}$$

where $B(\alpha)$ denotes the bottleneck score of a network element α, which may represent a critical node, critical link, or critical component. $G = (V, E)$ represents the network topology, where V and E denote the sets of nodes and links, respectively. A denotes the network attributes associated with the topology, such as flow, load, capacity, traffic demand, transmission state, or node features. t represents the temporal state of the network and is optional for static networks but essential for dynamic bottleneck identification. M denotes the model parameters or decision rules adopted by different bottleneck identification methods. For topology-based, flow-based, and spreading dynamics-based methods, M corresponds to predefined topological metrics, physical models, or empirical decision rules. For ML and deep learning methods, M represents the model parameters learned from historical data during the training process. The mapping function $f(\cdot)$ transforms the available network information into the corresponding bottleneck score.

3.2. Topology-based bottleneck identification methods

Topology-based bottleneck identification methods represent one of the most classical categories in complex network research. Their core idea is to characterize node importance solely based on network connectivity, without introducing node attributes or dynamic processes. These approaches typically rely on structural features such as centrality measures, hierarchical decomposition, and community structures to identify key elements that play critical roles in network connectivity and structural stability.

Existing surveys, such as Saxena *et al* [87], systematically reviewed centrality-based measures and provided comprehensive classifications of classical node importance indicators. Representative indicators include degree centrality [18], betweenness centrality [18, 19], closeness centrality [18], eigenvector centrality [33], information centrality [34], k-shell decomposition [35], structural holes [65, 66], H-index [88], and community or modularity-based methods [89]. Since these analytical techniques have been extensively applied in complex network studies and their theoretical foundations and algorithms are relatively mature, this paper does not provide detailed introductions to each specific method.

Overall, topology-based approaches rely exclusively on network connectivity, requiring low data dependency and offering high computational efficiency, which makes them particularly suitable for large-scale static networks. Moreover, they provide strong interpretability at the structural level. However, due to the neglect of dynamic characteristics and load evolution during network operation, these methods are typically used as basic analytical tools or preliminary screening approaches in complex system bottleneck identification. Therefore, topology-based methods are generally regarded as foundational techniques that should be integrated with dynamic-process-based or ML-based methods to improve the reliability and practical interpretability of bottleneck identification results.

3.3. Flow-and load-based bottleneck identification methods

In real-world complex networks, system performance limitations are not determined solely by topological structure, but are closely related to the functional loads carried by nodes or links and their transmission capacities. Flow- and load-based identification methods focus on resource flow and capacity constraints, identifying bottlenecks by characterizing local overload phenomena and transmission limitations.

The max-flow–min-cut method [46], derived from classical network flow theory, abstracts complex systems as directed graphs with capacity constraints. By computing the maximum transmissible flow between a source-sink pair and simultaneously identifying the minimum cut-set that disconnects the source and sink, this approach precisely locates the 'chokepoints' or key node sets that restrict global transmission capacity.

Motter *et al* [8] proposed the load-capacity model, in which load is defined using dynamic flux measures based on betweenness centrality or real traffic flows, while capacity is set to $(1+\alpha)$ times the initial load. The load-capacity ratio is then used as the key evaluation metric. When the ratio exceeds a threshold, node failure is triggered, leading to load redistribution and cascading failures. Cascading failure models simulate the dynamic redistribution of loads after initial failures when the updated load of a node (or link) exceeds its capacity threshold, subsequent failures occur, leading to chain propagation effects. By evaluating cascade thresholds, these models identify trigger nodes that pose the greatest threat to overall system robustness, thereby characterizing potential system-level failure pathways.

Edmonds and Karp [90] introduced a breadth-first search (BFS)-based augmenting path algorithm, significantly improving computational efficiency and enabling minimum-cut localization in large-scale networks. Abdullah and Hua [91] integrated this framework with shortest-path algorithms for bottleneck identification in urban transportation networks. Kinney *et al* [92] applied the framework to simulations on real North American power grid topologies, empirically validating its reliability and applicability for bottleneck identification in engineering networks. Ren *et al* [93] developed a stochastic cascading failure model based on state-transition theory, representing node failures as probabilistic state transitions and applying it to the study of dynamic cascading processes in communication networks.

3.4. Spreading dynamics-based bottleneck identification methods

In complex networks, bottlenecks often manifest as critical constraints within spreading processes. Spreading

dynamics-based identification methods model networks as dynamically evolving systems, using classical differential equation frameworks to simulate state transitions and propagation paths. These methods quantify the contributions of nodes or edges to global diffusion scale, speed, and thresholds, thereby identifying high-impact bottlenecks. Classical frameworks include the SIS, SIR, and SEIR models.

Pastor-Satorras *et al* [94] systematically analyzed the core mechanisms of SIS, SIR, SEIR, and their extended models, examining the effects of network topology and real-world factors on spreading thresholds, outbreak scales, and propagation speeds. Newman *et al* [95] reformulated SIR/SEIR models as bond percolation problems and applied generating function techniques to obtain exact solutions for networks with arbitrary degree distributions and bipartite structures, promoting their application in bottleneck analysis of heterogeneous networks. Mauro Aliano *et al* [96] proposed a delayed dynamic SIR variant incorporating 'financial immunity' delay effects for bottleneck identification in financial risk propagation networks, demonstrating the amplifying role of time delays on bottleneck impacts. Granell *et al* [97] introduced the cycle unaware-aware-unaware–susceptible-infected-susceptible processes (UAU–SIS) multilayer model, clarifying the regulatory role of information diffusion on epidemic thresholds and infection prevalence in coupled virtual social networks and physical contact networks. Zhao *et al* [98] focused on dynamic bottleneck identification in urban transportation systems, proposing the traffic congestion diffusion (TCD) model, which integrates multisource data to capture the spatiotemporal propagation of traffic flow impacts (TFI). By simulating congestion diffusion processes, bottleneck identification is reformulated as an influence maximization problem, as shown in figure 7. Soares and Estrada [99] investigated bottleneck identification in nonconservative spreading dynamics on complex networks and proposed an analytical method based on the Lemann-Ghosh Laplacian operator. They defined the navigation bottleneck index by deriving the analytical solution of non-conservative diffusion equations over time, quantifying a vertex's short-term particle-spreading capability, where vertices with high values are identified as potential bottlenecks.

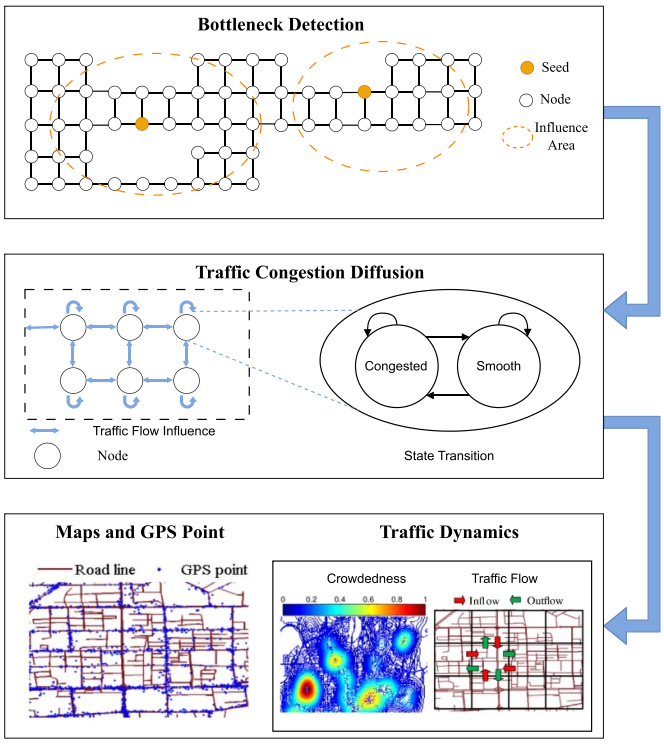


Figure 7. Integration of bottleneck analysis for continuous improvement planning during the pilot study.

3.5. *ML-based bottleneck identification methods*

With the continuous growth of large-scale network operation data, ML-based approaches have gradually become an important technical paradigm for bottleneck identification in complex networks. These methods typically formulate bottleneck identification as a supervised classification or regression task, where statistical learning models are trained to capture the mapping between network features and bottleneck states from historical operational data, thereby enabling the identification and prediction of high-risk nodes or links. Traditional ML methods, such as support vector machines, random forests, and decision trees, are widely adopted. Topological indicators, including degree centrality, betweenness centrality, closeness centrality, connectivity metrics, and local structural properties, are typically integrated into high-dimensional feature vectors, allowing ML models to discover latent bottleneck patterns within the feature space.

Zhao *et al* [100] proposed a supervised ML framework for critical node identification in complex networks by training classification models based on node topological features, as shown in figure 8. Rezaei *et al* [101] employed support vector regression to integrate multidimensional features under limited labeled samples, enabling fine-grained prediction of potential bottlenecks in real networks. Yang *et al* [102] combined network embedding techniques with classical ML models by integrating low-dimensional representations generated by DeepWalk with local centrality indicators, thereby achieving bottleneck discrimination in continuous vector spaces. Ungern-Sternberg and Teriete [103] proposed a ML-assisted dynamic bottleneck analysis framework for order-based value streams, which integrates utilization analysis and active period analysis to identify dynamic bottlenecks using IoT and production-order data. Lai *et al* [104] extended the turning point method by introducing heuristic rules for complex manufacturing structures. By extracting real-time blocking, starvation, throughput data, their method enables bottleneck localization in both main production lines and subsystems. Subramaniyan *et al* [105] proposed a ML-based maintenance diagnosis framework that identifies operational bottlenecks through downtime feature extraction from MES logs, combining k-means clustering, boxplot visualization, and expert knowledge.

Overall, ML-based methods exhibit strong adaptability to real operational environments and engineering systems. A key characteristic of this paradigm is its reliance on handcrafted feature engineering, where structural, topological, and

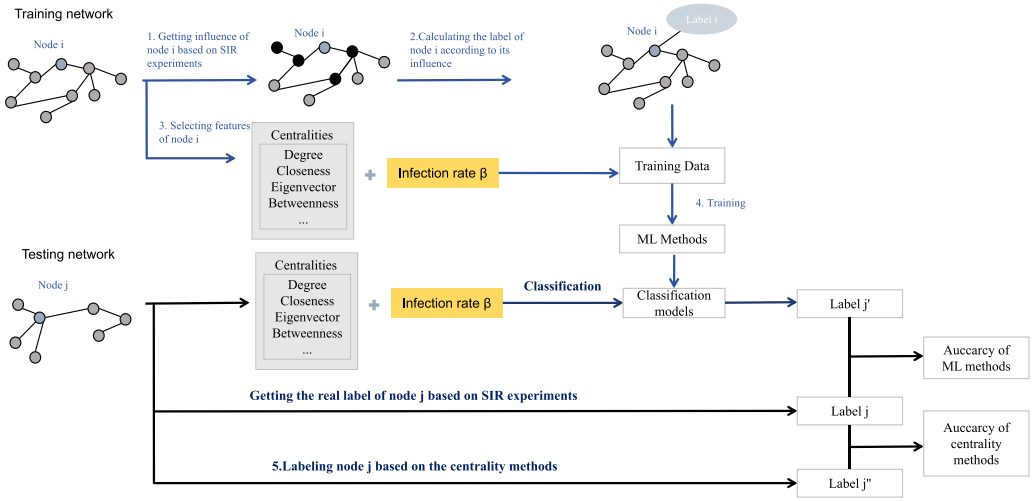


Figure 8. Framework for identifying influential nodes in complex networks based on machine learning methods.

functional indicators are manually designed to construct discriminative feature vectors for bottleneck classification. Compared with deep learning approaches, conventional ML models generally provide better interpretability, since the contribution of individual features can be explicitly quantified using feature importance analysis and post-hoc explanation techniques such as SHapley Additive exPlanations-based attribution methods [106]. This improves the transparency of bottleneck identification results and supports more reliable decision interpretation in engineering systems. However, such methods depend heavily on expert-designed features and labeled datasets, and suffer weak generalization across diverse networks and operating conditions.

To mitigate this generalization limitation and broaden data-driven network analysis, scholars apply ML to various intelligent network scenarios beyond bottleneck recognition. Recent works embed learning algorithms into comprehensive intelligent network systems for data analysis and adaptive decision-making. For instance, blockchain-aided software-defined vehicular networks adopt distributed, privacy-protected learning to enhance security amid volatile traffic environments [107]. Beyond vehicular networks, IoT intrusion detection also leverages ML to spot network threats yet suffers from the same poor generalization on heterogeneous traffic [108]. These cross-domain efforts demonstrate that ML has shifted from an independent forecasting tool to a core module of intelligent network control. The stable distributed learning frameworks verified in vehicular communications can provide viable solutions to the poor generalization of current bottleneck detection algorithms in complex CPSs, a dilemma further validated by research on cloud-integrated CPS operating on large-scale shared service clusters [109].

3.6. Deep learning-based bottleneck identification methods

With the rapid development of deep learning and reinforcement learning, bottleneck identification has gradually evolved from conventional feature-engineering-based learning toward an end-to-end representation learning paradigm capable of

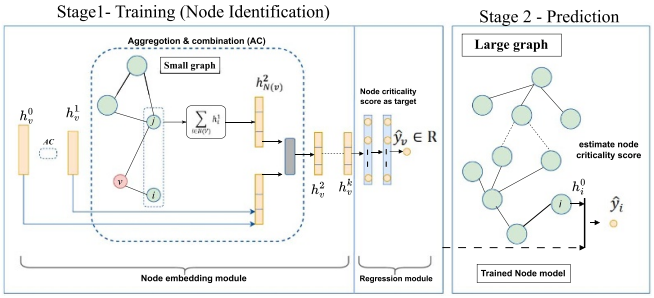


Figure 9. ILGR framework for node identification.

explicitly modeling complex network structures, temporal evolution, and adaptive decision-making processes. Deep learning-based methods can automatically capture high-order topological dependencies and nonlinear interaction mechanisms that are difficult to characterize using handcrafted features, thereby demonstrating stronger expressive capability in large-scale dynamic networks.

GNNs form the core of this paradigm. Via iterative message passing, they aggregate neighborhood signals to learn high-order topological representations automatically. Unlike traditional ML requiring manual feature engineering, GNNs realize end-to-end learning from raw graph data and capture multi-scale structural relations without hand-designed indicators. Munikoti *et al* [110] put forward the ILGR framework to learn node embeddings and predict component criticality, generalizing from small synthetic graphs to large networks (figure 9). Representative variants include spectral/spatial GCNs [111], attention-weighted graph attention networks (GATs) [112], and inductive GraphSAGE [113]. Spatio-temporal GNNs such as Graph WaveNet [114] combine adaptive graph learning and dilated temporal convolutions to capture traffic bottleneck evolution.

Deep reinforcement learning (DRL) further extends deep learning-based bottleneck identification toward sequential decision-making scenarios by formulating the problem as a Markov decision process [115]. Agents interact with dynamic

environments to identify critical nodes or links while simultaneously learning intervention strategies such as rerouting and load redistribution. Huang *et al* [116] proposed the heterogeneous information networks importance value estimation network (HIVEN) model for heterogeneous bottleneck estimation using meta-path-guided graph learning. Wu *et al* [117] incorporated GNNs into heterogeneous supply chain networks through multi-task learning to jointly optimize critical node identification and risk prediction. Fan *et al* [39] proposed a DRL framework named FINDER (finding key players in networks through DRL) for critical node identification in complex networks. Wang *et al* [118] developed a centralized actor-critic-based DRL framework to jointly optimize ramp metering and variable speed limit control, thereby reducing total travel time and alleviating highway congestion with relatively low computational complexity. Hong *et al* [119] proposed the GAT integrated with shortcut connections, an unsupervised GAT framework that mitigates vanishing-gradient issues and learns node dismantling scores without labeled supervision.

Deep learning fundamentally revolutionizes bottleneck analysis, moving from static descriptive research to intelligent prediction and adaptive decision support. Equipped with representation learning and temporal modeling, these methods excel at analyzing large, time-varying networks. Two critical drawbacks still exist: poor model interpretability and reliance on massive labeled data, which limit cross-scenario generalization. To tackle this issue, scholars adopt graph-oriented XAI tools. GNNExplainer and PGExplainer extract decisive subgraph structures and generate human-readable reasoning for graph model outputs [120].

Apart from bottleneck detection, recent work combines deep learning with self-organized optimization for intelligent networks. Firefly synchronization and traveling-wave pulse-coupled oscillators enhance coordination and energy efficiency in wireless sensor networks [121, 122]. Random traveling-wave pulse-coupled oscillator algorithms further improve distributed synchronization and energy efficiency through decentralized self-organizing mechanisms in wireless sensor networks [123]. One existing review sorted out self-organized intelligent algorithms and discussed their combination with lightweight AI for distributed network optimization [124]. Though these studies do not target bottlenecks directly, they offer valuable references for building resilient intelligent network analysis systems. Though these studies do not target bottlenecks directly, they offer valuable references for building resilient intelligent network analysis systems. Such generalization obstacles are not exclusive to communication networks but also emerge in educational cloud platforms equipped with AI-driven self-paced learning systems [125].

As summarized in tables 4 and 5, this paper categorizes mainstream complex network bottleneck identification approaches. Table 4 lists classic methods covering topological, flow-load, propagation dynamics, ML and deep learning branches. Table 5 establishes a unified evaluation standard that compares all paradigms on computational complexity, data demand, scalability, robustness, interpretability and adaptability to dynamic networks.

4. Bottlenecks in different types of networks

This section provides a systematic review of bottleneck identification methods from the perspective of different network types, highlighting the structural forms, functional characteristics, identification paradigms, and failure consequences across diverse application domains.

4.1. Single-layer networks

Single-layer networks represent the most fundamental and earliest-studied form in complex network research. Such networks consist of a single type of nodes and links, and are commonly observed in traditional infrastructures such as transportation systems and power grids.

4.1.1. Traffic networks. Traffic networks constitute one of the earliest and most extensively studied application domains in bottleneck research. The core objective is to identify critical nodes and links that are most likely to induce congestion, delays, or system efficiency degradation under normal or high-load operating conditions.

Early studies primarily relied on topological structures, using indicators such as betweenness centrality and weighted degree centrality to identify hub nodes that play key roles in traffic flow transmission. Laudanna and Scardoni [126] proposed the concepts of centrality interference and centrality robustness to characterize the variability of node importance under structural perturbations, demonstrating that topology-driven bottlenecks exhibit strong systemic impacts in regional transportation networks and validating the explanatory power of topological centrality for bottleneck attributes.

Abdullah and Hua [91] constructed weighted road networks using manual traffic counts and online map data, and combined the Ford-Fulkerson and Dijkstra algorithms to identify critical road segments that constrain overall network throughput. Yang *et al* [127] adopted an input-output analytical framework and employed the Leontief inverse matrix to quantify the sensitivity of nodes to global flow variations, thereby identifying nodes that are most likely to evolve into bottlenecks under network perturbations. Zhu *et al* [128] proposed a node importance evaluation method integrating betweenness, shortest paths, and the maximum connected subgraph. Lai and Zhang [129] compared multiple identification approaches and showed that the *k*-shell degree neighborhood identification method, which integrates local and global information, exhibits superior performance in identifying bottlenecks in urban rail transit systems. In the aviation domain, Ma *et al* [82]. constructed spatio-temporal weighted networks based on flight trajectories and identified dynamically evolving bottleneck links using edge centrality and penetration indicators. With the explosive growth of traffic data, deep learning techniques have been increasingly introduced into traffic bottleneck analysis. The spatio-temporal bottleneck mining (STBM) model proposed by Lee *et al* [130] enables detection of dynamic congestion evolution in cities, as shown in figure 10.

Table 4. Summary of bottleneck identification methods in complex networks.

References	Method category	Core method/model	Core mechanism	Network domain	Graph features	Complexity
[18]	Topology-based	Centrality framework	Unified degree, betweenness, closeness, centralization	Social, info networks	Undirected; unweighted	Low
[19]		Betweenness centrality	Shortest-path-based control capability	Social networks	Directed/undirected; unweighted	High
[33]		Eigenvector centrality	Recursive importance via neighbors	Social networks	Undirected; weighted/unweighted	Medium
[34]		Information centrality	Path efficiency via matrix inversion	Social networks	Undirected; weighted/unweighted	Medium-high
[35]		k-shell decomposition	Iterative peeling for core detection	Complex networks	Undirected; unweighted	Low
[65]		Structural holes	Non-redundant connections	Social networks	Undirected; unweighted	Low-medium
[66]		Improved structural holes	Optimizes structural hole indices to identify key nodes	Complex networks	Undirected; unweighted	Medium
[88]		H-index	Degree + neighborhood hierarchy	Large-scale networks	Directed/undirected; unweighted	Low-medium
[89]		Modularity	Spectral decomposition	Modular networks	Undirected	$O(n^2 \log n)$
[8]	Flow and load-based	Cascading failure model	Load redistribution	Infrastructure networks	Undirected; unweighted	Medium-high
[46]		Max-flow method	Max-flow min-cut bottleneck detection	Transport networks	Directed; weighted	Medium-high
[90]		Edmonds-Karp	BFS-based augmenting paths	General networks	Directed; weighted	$O(VE^2)$
[91]		Shortest Path + Max Flow	Path selection with capacity constraints	Urban traffic	Directed; weighted	Medium
[92]		Power Grid Cascading	Simulate linked failures in power grids	Power transmission networks	Undirected; weighted	Medium-High
[93]		Stochastic Cascading	Random propagation	Communication networks	Directed/Undirected; unweighted	Medium
[94]	Spreading dynamics	Epidemic models	SIR/SIS-based spreading processes	Complex networks	Directed/undirected; weighted/unweighted	—
[95]		SIR analytical model	Mapping to percolation	Social networks	Undirected; unweighted	Medium

(Continued.)

Table 4. (Continued.)

References	Method category	Core method/model	Core mechanism	Network domain	Graph features	Complexity
[96]		Delay SIR Model	Introduces incubation and immunity delays	Financial networks	Undirected	Medium
[97]		Multi-layer Awareness-epidemic Model	MMCA method for awareness-epidemic interaction	Multi-layer networks	Undirected; unweighted	Medium
[98]		Traffic Congestion Diffusion + Influence Maximization	TCD model with TFI propagation	Urban traffic networks	Directed; unweighted	Medium-high
[99]		Non-conservative Diffusion	Laplacian-based diffusion analysis	Complex networks	Undirected	Medium
[100]	Machine learning-based	ML-based identification	Learning from topology + simulation	Complex networks	Directed/undirected; weighted/unweighted	Medium-high
[101]		ML-based identification	Learning from topology + simulation	Complex networks	Directed/undirected; weighted/unweighted	Medium-high
[102]		DeepWalk+NLC	Embedding + node ranking	Complex networks	Undirected; unweighted	Medium
[103]		Utilization	Machine-buffer diagnosis	Manufacturing systems	—	Medium
[104]		Turning point method	Blocking/starvation time analysis	Manufacturing systems	—	Medium
[105]		Clustering diagnosis	K-means analysis of downtime	Manufacturing systems	—	Medium
[110]	Deep learning-based	GNN-based methods	Graph representation learning	Large-scale networks	Undirected	Medium-high
[111]		GCN	Spectral graph convolution	Complex networks	Undirected; weighted/unweighted	Medium
[112]		GAT	Attention-based aggregation	Complex networks	Directed/undirected	Medium-high
[113]		GraphSAGE	Inductive representation learning	Large-scale networks	Undirected	Medium-high
[114]		Graph WaveNet	Adaptive & dilated convolution	Traffic networks	Directed; weighted	High
[116]		Heterogeneous GNN	Multi-relation feature learning	Heterogeneous networks	Multi-relational	High
[117]		Supply Chain GNN	Meta-path + temporal modeling	Supply chain networks	Directed; weighted	High
[39]		DRL (FINDER)	Minimize network connectivity to identify key nodes	General complex networks	Undirected	High
[118]		Actor-Critic based DRL	RM and VSL	Freeway traffic network	Directed	Low
[119]		Graph Attention + Shortcut Connections	GAT with shortcut for unsupervised scoring	Transportation, infrastructure, social	Undirected	Low

Table 5. Comparative analysis of bottleneck identification methods in complex networks.

Category	Data Requirements	Complexity	Scalability	Robustness	Interpretability	Dynamic Applicability	Advantages	Limitations
Topology-based	Low	Low	High	Medium	High	Low	Efficient and interpretable structural analysis	Limited to static topology; ignores dynamics
Flow and load-based	Medium	High	Medium	High	Medium	Medium	Captures physical constraints and failure propagation	High computational cost; parameter sensitivity
Spreading dynamics-based	Medium	Medium–High	Medium	Medium	Medium	High	Models diffusion and congestion processes	Sensitive to parameters and interference effects
Machine learning-based	High	Medium	High	Medium	Low–Medium	High	Handles noisy data and nonlinear patterns	Limited interpretability; generalization issues
Deep learning-based	Very High	Very High	Medium–High	High	Low	High	Strong representation learning for complex systems	High training cost; low interpretability

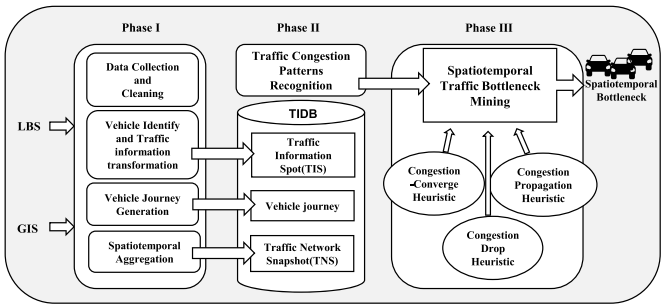


Figure 10. STBM model for traffic bottleneck identification.

4.1.2. Power grids. Power systems represent one of the most classical and extensively studied domains in complex network bottleneck research. Unlike traffic networks, where bottlenecks are primarily driven by topological constraints, bottlenecks in power grids are jointly determined by physical laws, operational states, and network structural properties. Typical bottlenecks manifest as critical transmission nodes, key transmission lines, or congested corridors, whose failures may trigger large-scale blackouts or cascading failures. Therefore, constructing identification methods that balance structural characteristics with physical constraints and accurately reflect real operational mechanisms remains a core challenge in this field.

Chen *et al* [131] proposed a weighted line betweenness metric to identify vulnerable transmission lines that have significant impacts on large-scale blackouts. Liu *et al* [132] proposed the node electrical centrality (NEC) index by integrating electrical betweenness and eigenvector centrality to improve bottleneck node identification. Fan *et al* [133] proposed a critical nodes identification algorithm considering electrical topology and power flow distribution (ETPD-CNIA) algorithm, which integrates electrical topology and power flow distribution through a node interaction model and adaptive fusion strategy, significantly enhancing bottleneck localization performance in large-scale power grids. Chen *et al* [134] introduced the power flow transmission network (PFTN) model, constructing a critical component identification framework based on transmission distance, transmission capacity, and capacity degree metrics. Fan *et al* [135] further partitioned power-communication networks into three layers, namely physical topology, flow carrying capacity, and service importance, and proposed a multilayer critical node identification algorithm by evaluating node importance across layers. As shown in figure 11, Zhang *et al* [17] developed a robust bottleneck identification framework based on node resilience. The model integrates multi-criteria evaluation under an ANP-G structure, capturing interactions among safety, economy, and structural stability, while coupling node-level and system-level risk indicators such as load variation and voltage deviation. Liu *et al* [136] proposed a wind power prediction errors correlation-aware grid bottleneck identification method for real-time dispatch warning and security control in high-renewable power systems.

With the increasing availability of high-resolution measurement data, ML-based and deep learning-based methods have been introduced into power grid bottleneck identification. Jafarzadeh *et al* [137] proposed a data-driven framework using Koopman mode analysis with PMU measurements for real-time transient stability prediction, instability alarm detection, and coherent generator identification in power systems. Wang *et al* [138] proposed a modified graph attention network for identifying critical components in power grids, demonstrating the effectiveness of deep graph learning in capturing complex spatio-temporal dependencies and nonlinear interactions in power system bottlenecks.

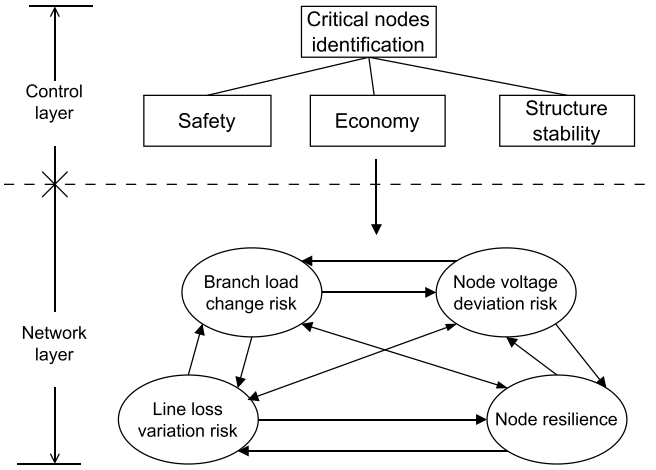


Figure 11. Network structure diagram of identification index based on ANP.

4.1.3. Supply chain networks. Supply chain networks consist of multiple types of entities, including suppliers, manufacturers, distributors, and logistics nodes, forming a typical multi-node and multi-level complex network structure. Bottlenecks in such systems usually correspond to key nodes or enterprises that play decisive roles in logistics continuity, production stability, and demand fulfillment. Once these critical components are disrupted, impacts rapidly propagate along upstream and downstream relationships, inducing production stagnation and systemic risks. Consequently, supply chain networks constitute an important application domain in complex network bottleneck research.

Early studies primarily adopted topological perspectives, using complex network centrality measures to identify hub nodes or intermediary nodes that perform core coordination functions. Ou *et al* [139] employed a cascading failure-based approach to identify critical nodes in automotive supply chain networks, revealing that firms with high connectivity and structurally central positions dominate disruption propagation and act as key bottlenecks that determine network invulnerability. Arora and Ventresca [140] adopted a topological resilience modeling approach and demonstrated the critical role of node centrality distributions in bottleneck formation by simulating node removal impacts on supply availability and functional network scale.

Beyond topology, researchers have begun to incorporate functional information including logistics flows, supply

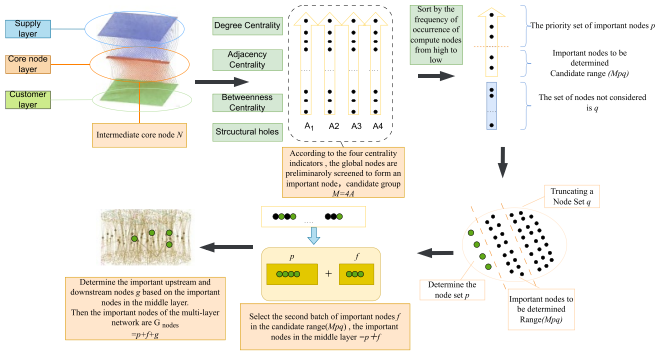


Figure 12. Framework for identifying critical nodes in multi-layer supply chain networks.

relationships, and external risks. Ledwoch *et al* [141] integrated multiple centrality indicators with geographic risks and transportation distances in systemic risk assessment to identify high-risk hubs and key intermediaries in complex supply chains. Hua *et al* [142] further constructed a multi-layer supply chain network model that jointly considers supply relationships and intra-layer competition, forming a composite node importance index and validating the dominant role of key nodes in bottleneck evolution through cascading failure experiments. Li *et al* [143] systematically analyzed forward and backward disturbance propagation mechanisms in supply chains based on the ripple effect, demonstrating the strong coupling between node functional roles and bottleneck attributes. Chen and Wen [144] focused on knowledge-intensive supply chains and combined risk propagation models with network cohesion analysis to identify critical nodes that significantly affect system resilience, further proposing structural optimization pathways. Wang *et al* [145] constructed a multi-layer supply chain network model with cross-scale indicators for critical node identification. The framework models interdependencies across different layers and evaluates node importance through integrated structural and functional metrics, as illustrated in figure 12.

4.2. Interdependent networks

In real-world engineering systems, critical infrastructures and functional networks rarely operate in isolation. Instead, they are interconnected through physical dependencies, information dependencies, or functional couplings, forming interdependent networks. Such systems consist of multiple interacting network layers, where the failure of nodes in one layer can propagate across layers and trigger cascading failures. Their percolation properties differ fundamentally from those of isolated networks, while single scale-free networks typically exhibit high robustness. Interdependent networks are intrinsically fragile. Under strong coupling conditions, the percolation transition shifts from a continuous (second-order) phase transition to a discontinuous (first-order) phase transition [146]. Typical examples include the dependence of power grids on communication networks, the co-evolution of transportation systems and information systems, and the deep coupling among logistics, production, and digital platforms in modern supply chains. Compared with single-layer networks, bottlenecks in interdependent networks are not determined solely by intra-layer topology or load distribution, but are strongly shaped by inter-layer dependency structures. Failures are amplified through cascading propagation processes, leading to systemic risk amplification and large-scale functional collapse. To systematically organize the existing research on bottleneck characteristics under different dependency structures, this study classifies interdependent networks according to the forms of inter-layer dependencies and constructs a comparative analytical framework, as summarized in table 6. Existing studies commonly categorize interdependent networks into fully interdependent, partially interdependent, unidirectionally dependent, and multilayer interdependent systems.

In partially interdependent networks, where dependencies are incomplete or asymmetric, bottlenecks tend to concentrate on highly dependent nodes, and overall system robustness exhibits strong sensitivity to coupling strength. Parshani *et al* [147] proposed an iterative cascading failure model quantifying robustness via percolation transitions (first-order vs second-order) and validating it on ER and scale-free networks. Dong *et al* [148] investigated percolation in partially interdependent networks under targeted attacks, and demonstrated that increasing coupling strength significantly reduces network robustness. Meanwhile, highly interdependent nodes dominate the cascading failure process and act as critical bottlenecks that determine system resilience. Li *et al* [149] developed a betweenness-coupled cascading failure model showing assortative coupling maximizes robustness while disassortative coupling minimizes it. In fully interdependent networks, one-to-one bidirectional dependencies amplify local perturbations, with core nodes/links acting as bottlenecks triggering large-scale cascades. Buldyrev *et al* [48] demonstrated that fully interdependent networks exhibit significantly lower robustness than isolated networks, with first-order percolation transitions and higher collapse thresholds, where the removal of a small fraction of nodes can induce catastrophic cascades. Gao *et al* [150] investigated cascading dynamics in systems composed of n fully connected random networks and analyzed the effects of network number and degree distributions on the critical percolation threshold and mutual giant component formation. In unidirectional networks, upstream critical nodes dominate bottlenecks, driving hierarchical cascades. In multilayer networks, cross-layer connectors and coupling structures create new bottlenecks, and single-layer key nodes may lose system-level importance. Fu *et al* [151] constructed an interdependent network model incorporating directionality, redundancy, and dependency range, and showed through numerical simulations that unidirectional dependency structures are more fragile than bidirectional ones. Zhao *et al* [152] developed a directed higher-order network model with full and partial dependencies, clarifying the existence of hybrid phase transitions in partially dependent systems. Ferrari and Santagata [153] identified critical nodes in multilayer interdependent networks using efficiency loss, articulation points, and betweenness centrality, and demonstrated the structural vulnerability of intermodal transportation systems.

Table 6. Classification of interdependent network types and bottleneck characteristics.

References	Network Type	Dependency Mechanism	Typical Bottleneck Pattern	Application Domains
[146–148]	Partially interdependent	Partial/asymmetric dependency	High-dependency nodes dominate vulnerability	Weakly coupled infrastructures
[48, 149]	Fully interdependent	One-to-one bidirectional coupling	Core nodes trigger cascading collapse	Power-communication systems
[150]	Unidirectional dependency	Hierarchical support relations	Upstream nodes dominate systemic risk	Power-dependent transport systems
[151–153]	Multilayer interdependent	Cross-layer functional coupling	Cross-layer bridge-node bottlenecks	Integrated transport–energy–ICT systems

Overall, table 7 summarizes representative studies on bottleneck identification in typical networks, including traffic, power grid, supply chain, and interdependent infrastructure networks. This table compares the corresponding network type, primary bottleneck, identification method, consequence of failure, and data characteristics, revealing the common features and application differences of bottleneck analysis in various complex network scenarios.

5. Challenges and future directions

5.1. Major challenges

Although research on identifying bottlenecks in complex networks has gradually evolved from static topological analysis to dynamic, ML-based, and intelligent methods, several core obstacles still limit practical applications.

Challenge 1. Conflict between computational complexity and real-time performance in ultra-large-scale and highly dynamic networks

With the rapid expansion of networks such as the Internet of Things, global supply chains, and smart cities, network nodes and interactions exhibit high dimensionality and dynamics. On the one hand, traditional topological metrics and cascading failure simulations usually require global traversal on large-scale networks, and their computational complexity grows sharply with network size. On the other hand, in highly dynamic scenarios such as peak-hour traffic congestion propagation or power transient fluctuations, bottleneck locations evolve rapidly with load and topology changes. Identification must be completed within seconds or even milliseconds. Otherwise, results lag behind real bottleneck evolution and lose decision-making value, or even fail at critical moments [154]. Although inductive learning methods such as GCN have alleviated learning pressure in some scenarios, the conflict between inference latency and resource constraints on edge nodes remains prominent when dealing with dynamic networks with high-frequency evolution [111].

Challenge 2. Lack of stable mapping between bottleneck identification and intervention decisions

Locating bottlenecks is only the first step, and the ultimate goal is to design effective interventions based on identification results. However, most current studies focus on localization without establishing a stable mapping mechanism from bottleneck identification to intervention strategies. In infrastructure networks, improving the capacity of strong or weak bottlenecks does not always delay system collapse and may sometimes accelerate it, indicating that the system response after bottleneck enhancement is not linearly related to the bottleneck impact [155]. This phenomenon shows that 'being identified as a bottleneck' does not necessarily mean 'prioritized intervention'. Most existing methods assume strong consistency between the two, which does not always hold in complex systems. Therefore, systematic analysis and feedback mechanism design for bottleneck intervention effects are needed to truly guide optimization and control strategies.

Challenge 3. Complex and non-uniform bottleneck formation mechanisms under multi-network coupling

Real-world systems are rarely isolated networks but form multi-layer or interdependent networks through various dependencies. For example, interdependencies between power systems and communication networks amplify failure impacts during propagation. Studies on interdependent networks show that node dependencies significantly increase system vulnerability to local disturbances, and the complexity of coupled structures makes indicators and protection strategies for single-layer networks difficult to generalize to the system level [151]. Under multi-network coupling, a node that is not a bottleneck in a single network may trigger a system-level bottleneck via cross-layer dependencies. Therefore, constructing a bottleneck judgment mechanism that reflects scenario details and connects different layers remains a major challenge.

Challenge 4. Lack of causal and traceable explanations for bottleneck identification

Bottleneck identification requires not only 'where bottlenecks are' but also 'why nodes or links become bottlenecks'. Although methods such as graph attention mechanisms have preliminarily improved model transparency, mainstream approaches remain at the correlation level and struggle to provide causally traceable explanations [120]. In high-risk human-machine collaboration scenarios, the lack of interpretability in complex models prevents operators from understanding causal mechanisms and key influencing factors, thereby hindering their integration into real-time decision-making and limiting the transition from passive identification to proactive intervention [156].

Challenge 5. Lack of long-term time-series modeling for predicting potential and emerging bottlenecks

This paper classifies bottlenecks into existing, potential, and emerging types, emphasizing their temporal dynamics. However, current methods mainly use snapshot or short-term analysis and cannot capture long-term structural evolution and bottleneck migration. The absence of long-range prediction models for 'how potential bottlenecks evolve into dominant ones under certain disturbances and time scales, and when they migrate' limits network planning, preventive maintenance, and proactive resilience design [157].

Challenge 6. Real-time bottleneck detection under dynamic and imperfect data conditions

With the increasing scale and temporal dynamics of real-world complex networks, bottleneck identification has gradually shifted from static analysis to real-time and continuously evolving settings. However, practical deployment is fundamentally constrained by three interrelated aspects: computational efficiency, data quality, and measurement uncertainty.

First, large-scale temporal networks significantly increase computational burden, making it difficult for classical graph algorithms to support real-time bottleneck detection. Recent advances in temporal GNNs, such as TGN and EvolveGCN,

Table 7. Summary of related works on bottleneck in typical networks.

References	Network Type	Primary Bottleneck	Identification Methods	Consequence of Failure	Data Characteristics
[82]	Spatio-temporal airline network	Key links (navigation connections)	Weighted spatio-temporal network, edge betweenness, percolation filtering	Massive flight rerouting and airspace congestion causing delays	Dynamic temporal spatial network, time-series & streaming data
[91]	Urban road traffic network	Bottleneck paths (capacity-limited segments)	Max-flow (Ford-Fulkerson), max-flow min-cut, Dijkstra	Road saturation triggers congestion diffusion and regional imbalance	Static spatial heterogeneous network
[126]	Highway network	Key nodes (regional hubs & highway exits)	Betweenness interference, centrality robustness, node removal	Loss of regional connectivity and overloaded alternatives	Static spatial heterogeneous network
[127]	Urban road network	Key nodes (main intersections & flow convergence)	Virtual input-output model, efficiency validation	Drop in network efficiency and secondary congestion	Static spatial heterogeneous network
[128]	Urban traffic network	Key nodes (network hubs & core transfer stations)	Integrated normalized centrality framework	Decreased connectivity, longer paths, reduced reliability	Static spatial heterogeneous network
[129]	Urban traffic network	Key nodes (metro transfers & bus hubs)	Degree & k-shell neighborhood methods, dynamic attack	Giant component reduction and network efficiency collapse	Static spatial heterogeneous network
[130]	Urban road network	Spatio-temporal bottlenecks (congestion hotspots)	STBM	Congestion diffusion causing longer commute times	Dynamic temporal spatial network, time-series, heterogeneous demand
[131]	Power grid	Vulnerable lines (critical transmission corridors)	Weighted line betweenness, adjacent edge correction	Cascading failures and large-scale blackout risk	Static spatial power grid, heterogeneous nodes/lines
[132]	Power grid	Key nodes (topological & electrical critical)	NEC, power flow index	Cascading overload and system stability collapse	Static power grid, electrical coupling, heterogeneous nodes
[133]	Power system	Topological & flow critical nodes	ETPD-CNIA	Cascading overload, disordered flow, and widespread outages	Static power grid, electrical coupling, heterogeneous nodes
[134]	Power grid	Key nodes & branches (backbone & cross-regional)	PFTN, multi-dimensional indicators	Load loss and network disintegration	Static spatial power grid, heterogeneous nodes/branches
[135]	Power-communication network	Key nodes (dispatch centers & high-priority)	Multi-layer identification with evidence theory fusion	Service interruption and network splitting	Multi-layer logical network, heterogeneous roles
[17]	Active distribution network	Key nodes (power outlets, PV access & heavy-load)	ANP-based resilience evaluation	Voltage deviation, overload and increased line loss	Time-series dynamic data, heterogeneous nodes

(Continued.)

Table 7. (Continued.)

[136]	Wind-integrated power system	Marginal bottlenecks (line limits, ramping & reserve)	Stochastic optimization, iterative max-max-min LP	Scheduling infeasibility and voltage instability	Uncertain wind data, dynamic constraints, multi-scenario
[137]	Power system	Transient stability bottlenecks	Measurement-based modeling (Koopman, DMD, PMU)	Instability evolution and alarm identification	PMU streaming time-series data
[138]	Power system	Key links (backbone & high-load lines)	Improved graph attention network (IGAT)	Disordered flow, cascading overload, hard recovery	Static grid with renewables, time-series, heterogeneous elements
[139]	Automotive supply chain network	Structural bottlenecks (core firms & central positions)	Cascading failure-based identification, improved k-shell, resilience evaluation	Risk propagation	Heterogeneous enterprise roles, Tesla supply chain data
[140]	Supply chain network	Topological weak nodes/links	Action-based network generation, multi-objective optimization	Extended paths and delivery delays	Multi-layer topology, heterogeneous roles
[141]	Supply chain network	Systemic risk key nodes	Multi-centrality fusion with risk-weighted propagation	Risk diffusion and supply chain disruption	Dual-network, risk-weighted data
[142]	Supply chain network	Cascading failure key nodes	Entropy-weighted fusion of supply-demand metrics	Cascading under-load and resource misallocation	Multi-layer directed network, heterogeneous roles
[143]	Supply chain network	Bidirectional propagation key nodes	Markov bidirectional model with agent-based simulation	Bidirectional disturbance causing production interruption	Dynamic time-series, agent-based simulation
[144]	Knowledge-intensive supply chain	Knowledge propagation bottlenecks	Weighted knowledge network, centrality evaluation	Reduced knowledge diffusion and delayed innovation	Multi-layer knowledge network, heterogeneous attributes
[145]	Multi-layer green supply chain	Key nodes (mid-layer manufacturers & cross-layer hubs)	Multi-scale centrality fusion (FMSM) with ESG	Cascading failures, weakened network structure	Static multi-layer supply chain, transaction & ESG data
[48]	Interdependent networks	Coupling-dependent bottlenecks	Percolation model, generating function, cascade simulation	First-order discontinuous phase transition, catastrophic cascading	Static heterogeneous topologies, coupling parameters, large-scale simulation
[146]	Interdependent network system	Inter-network coupling weak links	Percolation-based interdependent framework	First-order phase transition and loss of scale-free robustness	Multi-type topologies, coupling parameters

(Continued.)

Table 7. (Continued.)

References	Network Type	Primary Bottleneck	Identification Methods	Consequence of Failure	Data Characteristics
[147]	Dual interdependent networks	Coupling strength bottlenecks	Partial interdependence model, generating function	First-order abrupt transition under strong coupling	Dual-network coupling parameters, large-scale simulation
[148]	Partially interdependent networks	Coupling and dependency bottlenecks	Percolation analysis under targeted attack with cascading failure	Abrupt collapse and robustness degradation	Coupling strength, node degree, simulation data
[149]	Interdependent networks	Coupling & node-related bottlenecks	Betweenness-coupled cascading model	Irreversible network fragmentation under assortative coupling	Static topologies, heterogeneous centrality
[150]	Multi-network interdependent system	Coupling & node structure bottlenecks	Percolation on n-layer fully interdependent networks	First-order discontinuous phase transition and network disintegration	Static multi-type topologies, n-layer coupling
[151]	Interdependent infrastructure networks	Dependency structure bottlenecks	Dependency structure analysis (directionality, redundancy, extent)	Lower robustness in directed networks and high vulnerability to hub attacks	Static ER/SF topologies, 3D dependency
[152]	Directed higher-order interdependent networks	Higher-order coupling bottlenecks	Higher-order directed model with GIN/GOUT/GSCC percolation	Higher vulnerability and discontinuous phase transition	Directed higher-order network, hyperedges, Monte Carlo
[153]	Multi-modal interdependent transportation network	Geo-functional dependency bottlenecks	Geo-functional interdependent modeling, centrality robustness	Faster collapse and regional connectivity breakdown	Multi-modal static network, geospatial data

partially alleviate this issue by enabling incremental and event-driven updates for dynamic graph representation learning [158, 159].

Second, real-world systems often suffer from incomplete observations due to sensor failures, communication delays, or privacy constraints. Such partial observability introduces structural uncertainty, which may affect the reliability of bottleneck detection results. To mitigate this issue, recent studies explore graph-based inference and representation learning methods to approximate missing information from incomplete data streams [160, 161].

Finally, measurement noise and stochastic fluctuations further complicate real-time decision-making, as transient disturbances may be misinterpreted as structural bottlenecks. Robust graph learning methods are therefore required to enhance stability under noisy and uncertain environments [162].

5.2. Future directions

1. Develop lightweight and efficient dynamic graph models for real-time bottleneck detection

Future work can draw on lightweight dynamic graph inference [163], using structural sparsification, key temporal feature selection, and attention compression to build lightweight models. Such models can greatly reduce computation and inference delay while maintaining accuracy, enabling millisecond-level online bottleneck tracking and prediction. They can also reduce global monitoring overhead and support real-time early warning in transportation and power systems.

2. Establish a reliable link from bottleneck identification to intervention for dynamic evaluation and adaptive optimization

Combining DTs, simulation and reinforcement learning, intervention strategies such as bottleneck enhancement and structural reconstruction can be tested and risk-assessed. DTs simulate the effect of bottleneck modification, and learning algorithms evaluate corresponding risks. Through an iterative 'identification, simulation, feedback, and optimization' mechanism, cost-effective and stable strategies can be automatically selected [155], thereby transforming bottleneck identification results into actionable schemes for maintenance arrangement, resource allocation, and system optimization.

3. Design unified multi-layer bottleneck judgment methods

Integrating structural and functional indicators of single-layer networks with inter-layer coupling relationships will establish a unified, multi-scale bottleneck representation system. This can more accurately trace how local disturbances spread across layers, compensate for the limitations of single-layer analysis, improve the accuracy and consistency of bottleneck localization in interdependent networks, and provide a theoretical basis for risk assessment, collaborative protection, and robust design of cross-domain coupled infrastructures.

4. Causally enhanced bottleneck explanation

Integrating causal representation learning and GNN explainability modules (e.g. generating explanations for GNN Explainer and counterfactual validation) can generate causal subgraphs and counterfactual explanations for bottleneck formation. Combined with visualization tools for human-machine verification, this improves the reliability of GNN-based bottleneck identification and promotes the shift from passive localization to active interpretable intervention, supporting decision-making in high-risk scenarios.

5. Capture migration trends from potential to emerging bottlenecks

This study integrates continuous-time dynamic graph models with the spatiotemporal modeling logic of the bottleneck spatiotemporal attention network [164], and focuses on the slow migration of traffic bottlenecks caused by long-term structural changes, such as dependency evolution and node addition and deletion. By capturing spatial correlations and temporal evolution, long-range prediction of bottleneck migration can be achieved, supporting long-term network planning, preventive maintenance, and proactive resilience design.

6. Synergistic integration for intelligent infrastructure resilience

Beyond traditional graph-theoretic and centralized deep learning identification approaches, an emerging paradigm integrates GNNs, federated learning, and DT for intelligent infrastructure management, shifting research focus from static local bottleneck recognition to proactive whole-network resilience enhancement. Large critical infrastructures like power grids and logistics networks face a conflict between dynamic bottleneck monitoring and data privacy. Federated graph learning solves this problem, allowing distributed subnetworks to jointly train graph models without exposing private topology and traffic data. Privacy-preserving edge models such as Fed-DT-EdgeGNN realize cross-domain collaborative optimization while protecting routing information [165]. Collaborative temporal GNN training extracts spatiotemporal features and detects hidden graph anomalies without sacrificing local data sovereignty [166]. Analysis outputs and model weights from decentralized graph models are imported into the integrated DT platform. The high-fidelity synchronized virtual copy of physical infrastructures leverages embedded graph intelligence to run real-time counterfactual simulations on topological flaws and cascading risks [167]. This integrated system forms a complete data-decision loop rather than conducting passive bottleneck detection only. Combining federated graph analysis and DT feedback, the system automatically executes resilience strategies including dynamic rerouting and topology adjustment, transforming infrastructure management from passive risk inspection to autonomous cyber-physical protection.

5.3. Management perspective

One practical value of bottleneck identification lies in supporting timely management decisions and proactive interventions to lift system resilience and operational efficiency. As

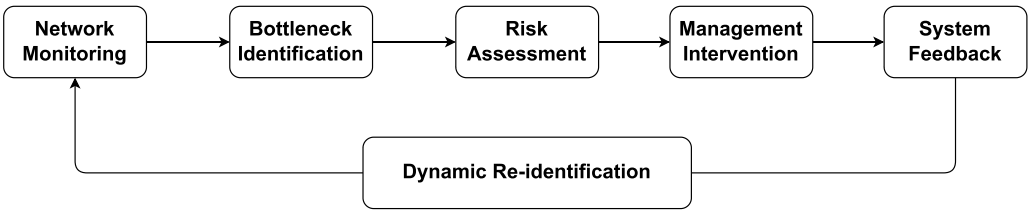


Figure 13. Closed-loop framework for bottleneck management.

shown in figure 13, bottleneck management may be understood via a closed-loop decision-making workflow. After network monitoring and bottleneck detection, identified bottlenecks can be analyzed via multi-dimensional characterization. Multi-dimensional characterization lay a foundation for subsequent risk evaluation, where bottlenecks can be prioritized according to their criticality, propagation risk and potential system influence for reference. In light of the ranking results, various intervention schemes can be chosen for different practical scenarios. Common optional management measures cover resource allocation, capacity enhancement, structural optimization, traffic rerouting, preventive maintenance and redundancy deployment. Instead of adopting identical solutions for all bottlenecks, intervention strategies should balance implementation cost, operability feasibility, and expected resilience improvement. After implementation, intervention effects can be tracked through real-time monitoring and performance feedback. The updated network operating state may be reused for subsequent bottleneck detection, constructing a dynamic closed-loop structure that can offer support for adaptive decision-making within time-varying complex networks. This closed-loop structure suggests that bottleneck identification is better viewed as an ongoing management cycle containing detection, evaluation, intervention and feedback, rather than a separate analytical task. From a management science perspective, this closed-loop structure may offer a conceptual reference for integrating bottleneck identification with intervention planning, resource allocation, and adaptive feedback, thereby helping translate identification results into practical management actions.

6. Conclusion

Bottleneck identification in complex networks is a fundamental issue for understanding system operation, improving performance, and enhancing resilience. This paper systematically reviews bottleneck types and identification methods from the perspectives of object, origin, impact scope, and temporal status, and summarizes progress in transportation, power and supply chain networks. Comparative analysis shows that with increasing network scale, structural heterogeneity, and dynamic uncertainty, bottlenecks have evolved from single static components to complex systemic constraints driven by topology, load, dynamics, and cross-layer dependencies.

Existing studies have achieved remarkable progress in structural analysis and local function identification, but challenges remain in characterizing dynamic evolution, predicting potential and emerging bottlenecks, and collaborative identification in multi-layer interdependent networks. Future research should integrate ML-based and deep learning-based models, introduce temporal evolution and cross-layer coupling, and shift bottleneck identification toward proactive prediction and intervention. A systematic understanding and intelligent identification of bottlenecks will play an increasingly important role in supporting the safe operation of critical infrastructures and optimal decision-making in complex systems.

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References

[1] Sun P G, Gao L and Han S S 2011 Identification of overlapping and non-overlapping community structure by fuzzy clustering in complex networks *Inf. Sci.* **181** 1060–71
[2] Ma L, Xu L, Fan X, Li L, Lin Q, Li J and Gong M 2025 Multifactorial evolutionary deep reinforcement learning for multitask node combinatorial optimization in complex networks *Inf. Sci.* **702** 121913
[3] Sun J, Gan L, Ding J, Ma R, Qian J and Xue K 2023 Identification of non-coding RNAs and their functional network associated with optic nerve invasion in retinoblastoma *Heliyon* **9** e13813
[4] Zhao J and Cheong K H 2023 Early identification of diffusion source in complex networks with evidence theory *Inf. Sci.* **642** 119061
[5] Zhao Y *et al* 2020 Identification of critical lines for enhancing disaster resilience of power systems with renewables based on complex network theory *IET Gener. Transm. Distrib.* **14** 4459–67
[6] Wang L, Zhang S, Szűcs G and Wang Y 2024 Identifying the critical nodes in multi-modal transportation network with a traffic demand-based computational method *Reliab. Eng. Syst. Saf.* **244** 109956
[7] Yin H, Zhang A and Zeng A 2023 Identifying hidden target nodes for spreading in complex networks *Chaos Solit. Fractals* **168** 113103
[8] Motter A E and Lai Y C 2002 Cascade-based attacks on complex networks *Phys. Rev. E* **66** 065102
[9] Liu Y, Liu D, Jin Di, Wang W, Zheng X and Yu. C 2026 LWDiffusion: node role detection in complex networks via legendre wavelet diffusion model *Inf. Sci.* **726** 122749
[10] Pastor-Satorras R and Vespignani A 2002 Immunization of complex networks *Phys. Rev. E* **65** 036104
[11] Zhao M, Zhou T, Wang B-H and Wang W-X 2005 Enhanced synchronizability by structural perturbations *Phys. Rev. E* **72** 057102

[12] Zamora-López G, Zhou C and Kurths J 2010 Cortical hubs form a module for multisensory integration on top of the hierarchy of cortical networks *Front. Neuroinform.* **4** 1

[13] Zemanová L, Zhou C and Kurths J 2006 Structural and functional clusters of complex brain networks *Physica D.* **224** 202–12

[14] Yang Z, Tian Y, Xiong J, Li M, Niu K, Zhou D and Ma J 2026 Complex network evolution with node strategies driven by information entropy *Inf. Sci.* **724** 122713

[15] Wang Y, Wang X, Huang Z, Li W and Xu S 2022 Joint optimization of dynamic resource allocation and packet scheduling for virtual switches in cognitive internet of vehicles *EURASIP J. Adv. Signal Process.* **2022** 32

[16] Goldenberg J, Han S, Lehmann D R and Hong J W 2009 The role of hubs in the adoption process *J. Mark.* **73** 1–13

[17] Zhang W, Liu K-Y, Sheng W, Du S and Jia D 2020 Critical node identification in active distribution network using resilience and risk theory *IET Gener. Transm. Distrib.* **14** 2771–8

[18] Freeman L C 1978 Centrality in social networks conceptual clarification *Soc. Netw.* **1** 215–39

[19] Freeman L C 1977 A set of measures of centrality based on betweenness *Sociometry* **40** 35–41

[20] Chai Y , Yu H, Dong Y, Wen Y and Lv C 2025 Key node identification and network simplification modelling method for optimal power flow analysis of active distribution network *Electr. Power Syst. Res.* **238** 111066

[21] Wong D 2018 Vosviewer *Tech. Serv. Q.* **35** 219–20

[22] Lü L, Chen D, Ren X-L, Zhang Q-M, Zhang Y-C and Zhou T 2016 Vital nodes identification in complex networks *Phys. Rep.* **650** 1–63

[23] Chen D, Chen J, Zhang X, Jia Q, Liu X, Sun Y and Yu W 2025 Critical nodes identification in complex networks: a survey *Complex Eng. Syst.* **5** 11

[24] Rai K A, Machkour M and Antari J 2023 Influential nodes identification in complex networks: a comprehensive literature review *Beni-Suef Univ. J. Basic Appl. Sci.* **12** 18

[25] Wang Y, Zhao Q and Zheng D 2005 Bottlenecks in production networks: an overview *J. Syst. Sci. Syst. Eng.* **14** 347–63

[26] Tang J, Dai Z, Jiang W, Wu X, Zhuravkov M A, Xue Z and Wang J 2024 A comprehensive review of theories, methods and techniques for bottleneck identification and management in manufacturing systems *Appl. Sci.* **14** 7712

[27] Gong X, Raadsen M P H and Bliemer M C J 2025 A systematic review of node models for macroscopic network loading of traffic flows *Transp. Res. B* **199** 103273

[28] Zhang S, Hanjalic A and Wang H 2024 Predicting nodal influence via local iterative metrics *Sci. Rep.* **14** 4929

[29] Jiang Z-Y , Zeng Y, Liu Z-H and Ma J-F 2019 Identifying critical nodes' group in complex networks *Physica A* **514** 121–32

[30] Yang A J, Deng S, Wang H, Zhang Y and Yang W 2023 Disruptive coefficient and 2-step disruptive coefficient: novel measures for identifying vital nodes in complex networks *J. Informetr.* **17** 101411

[31] Lalou M, Tahraoui M A and Kheddouci H 2018 The critical node detection problem in networks: A survey *Comput. Sci. Rev.* **28** 92–117

[32] Ullah A and Meng Y 2025 Finding influential nodes via graph embedding and hybrid centrality in complex networks *Chaos Solitons Fractals* **194** 116151

[33] Bonacich P 1972 Factoring and weighting approaches to status scores and clique identification *J. Math. Sociol.* **2** 113–20

[34] Stephenson K and Zelen M 1989 Rethinking centrality: methods and examples *Soc. Netw.* **11** 1–37

[35] Kitsak M *et al* 2010 Identification of influential spreaders in complex networks *Nat. Phys.* **6** 888–93

[36] Chen D, Lu L, Shang M-S, Zhang Y-C and Zhou T 2012 Identifying influential nodes in complex networks *Physica A* **391** 1777–87

[37] Zhao Z, Li D, Sun Y, Zhang R and Liu J 2023 Ranking influential spreaders based on both node k-shell and structural hole *Knowl. Based Syst.* **260** 110163

[38] HamaKarim B R, Mohammadiani R P, Sheikhahmadi A, Hamakarim B R and Bahrami M 2023 A method based on *k*-shell decomposition to identify influential nodes in complex networks (https://doi.org/10.21203/rs.3.rs-2242049/v1)

[39] Fan C, Zeng L, Sun Y and Liu Y-Y 2020 Finding key players in complex networks through deep reinforcement learning *Nat. Mach. Intell.* **2** 317–24

[40] Manchanda S, MITTAL A, Dhawan A, Medya S, Ranu S and Singh A 2020 GCOMB: learning budget-constrained combinatorial algorithms over billion-sized graphs *Advances in Neural Information Processing Systems (NeurIPS 2020)* vol 33 (Curran Associates, Inc) pp 20000–11

[41] Yu E-Y, Chen D-B and Zhao J-Y 2018 Identifying critical edges in complex networks *Sci. Rep.* **8** 14469

[42] Girvan M and Newman M E J 2002 Community structure in social and biological networks *Proc. Natl Acad. Sci.* **99** 7821–6

[43] Boccaletti S, Latora V, Moreno Y, Chavez M and Hwang D-U 2006 Complex networks: structure and dynamics *Phys. Rep.* **424** 175–308

[44] Shen Y, Nguyen N P, Xuan Y and Thai M T 2013 On the discovery of critical links and nodes for assessing network vulnerability *IEEE/ACM Trans. Netw.* **21** 963–73

[45] Elias P, Feinstein A and Shannon C 1956 A note on the maximum flow through a network *IEEE Trans. Inf. Theory* **2** 117–9

[46] Ford L R and Fulkerson D R 1956 Maximal flow through a network *Can. J. Math.* **8** 399–404

[47] Xiao F, Li J and Wei B 2022 Cascading failure analysis and critical node identification in complex networks *Physica A* **596** 127117

[48] Buldyrev S V, Parshani R, Paul G, Stanley H E and Havlin S 2010 Catastrophic cascade of failures in interdependent networks *Nature* **464** 1025–8

[49] Boccaletti S *et al* 2014 The structure and dynamics of multilayer networks *Phys. Rep.* **544** 1–122

[50] Gao J, Buldyrev S V, Stanley H E and Havlin S 2012 Networks formed from interdependent networks *Nat. Phys.* **8** 40–48

[51] Fu T, Wang D, Fan X and Huang Q 2022 Component importance and interdependence analysis for transmission, distribution and communication systems *CSEE J. Power Energy Syst.* **8** 488–98

[52] Dunn S and Wilkinson S M 2013 Identifying critical components in infrastructure networks using network topology *J. Infrastruct. Syst.* **19** 157–65

[53] Niu Y, Li Y, Jiang J and Lakshmanan L V S 2025 SANS: efficient densest subgraph discovery over relational graphs without materialization *Proc. ACM on Web Conf. 2025 (Sydney NSW Australia)* (ACM) pp 4250–63

[54] Sreenivasan S, Cohen R, López E, Toroczkai Z and Stanley H E 2007 Structural bottlenecks for communication in networks *Phys. Rev. E* **75** 036105

[55] Hamedmoghadam H, Jalili M, Vu H L and Stone L 2021 Percolation of heterogeneous flows uncovers the bottlenecks of infrastructure networks *Nat. Commun.* **12** 1254

[56] Hartmann B, Soha T, Cirunay M T and Erdei T 2025 Inherent structural vulnerabilities in power distribution networks: a longitudinal complex network analysis *Appl. Netw. Sci.* **10** 31

[57] Kang J H and Lerman K 2013 Structural and cognitive bottlenecks to information access in social networks *Proc. 24th ACM Conf. Hypertext and Social Media* pp 51–59

[58] Kwon Y, Jung J-H and Eom Y-H 2023 Global efficiency and network structure of urban traffic flows: a percolation-based empirical analysis *Chaos* **33** 113104

[59] Aghaei F and Lohrasebi A 2024 Analysis of traffic in communication networks based on percolation transition *Eur. Phys. J. B* **97** 17

[60] Crucitti P, Latora V and Marchiori M 2004 A model for cascading failures in complex networks *Phys. Rev. E* **69** 045104

[61] Saberi M *et al* 2020 A simple contagion process describes spreading of traffic jams in urban networks *Nat. Commun.* **11** 1616

[62] Schäfer B, Witthaut D, Timme M and Latora V 2018 Dynamically induced cascading failures in power grids *Nat. Commun.* **9** 1975

[63] Zhang Q, Liu Y S, Gao H O and You F 2024 A data-aided robust approach for bottleneck identification in power transmission grids for achieving transportation electrification ambition: a case study in new york state *Adv. Appl. Energy* **14** 100173

[64] Li Z-C, Huang H-J and Yang H 2020 Fifty years of the bottleneck model: a bibliometric review and future research directions *Transp. Res. B: Methodol.* **139** 311–42

[65] Burt R S 2004 Structural holes and good ideas *Am. J. Sociol.* **110** 349–99

[66] Yu H, Cao X, Liu Z and Li Y 2017 Identifying key nodes based on improved structural holes in complex networks *Physica A* **486** 318–27

[67] Meghanathan N 2021 Neighborhood-based bridge node centrality tuple for complex network analysis *Appl. Netw. Sci.* **6** 47

[68] Kim Y, Chen Y and Linderman K 2015 Supply network disruption and resilience: a network structural perspective *J. Oper. Manage.* **33–34** 43–59

[69] Rivas-Dávalos F, Sánchez-Jaime J, Acosta-Reyes P and Alvarez-Farias L 2024 Identifying critical transmission lines in cascading outages using the natural connectivity index *Discov. Electron.* **1** 29

[70] Zhao Y, Cai B, Cozzani V and Liu Y 2025 Failure dependence and cascading failures: a literature review and research opportunities *Reliab. Eng. Syst. Saf.* **256** 110766

[71] Ibidunmoye O, Hernández-Rodriguez F and Elmroth E 2015 Performance anomaly detection and bottleneck identification *ACM Comput. Surv.* **48** 1–4:35

[72] Li L, Chang Q and Ni J 2009 Data driven bottleneck detection of manufacturing systems *Int. J. Prod. Res.* **47** 5019–36

[73] Subramaniyan M, Skoogh A, Gopalakrishnan M, Salomonsson H, Hanna A, Lämkull D and Guo J 2016 An algorithm for data-driven shifting bottleneck detection *Cogent Eng.* **3** 1239516

[74] Patounas G, Foukas X, Elmokashfi A and Marina M K 2020 Characterization and identification of cloudified mobile network performance bottlenecks *IEEE Trans. Netw. Serv. Manag.* **17** 2567–83

[75] Tu H, Zhang X, Xia Y, Gu F and Xu S 2022 Bottlenecks identification and resilience improvement of power networks in extreme events *Front. Phys.* **10** 941165

[76] Zacarias F V, Petrucci V, Nishtala R, Carpenter P and Mossé D 2021 Intelligent colocation of HPC workloads *J. Parallel Distrib. Comput.* **151** 125–37

[77] Li D, Fu B, Wang Y, Lu G, Berezin Y, Stanley H E and Havlin S 2015 Percolation transition in dynamical traffic network with evolving critical bottlenecks *Proc. Natl Acad. Sci.* **112** 669–72

[78] Bucur D, Iacca G and De Boer P-T 2015 Characterizing topological bottlenecks for data delivery in CTP using simulation-based stress testing with natural selection *Ad Hoc Netw.* **30** 22–45

[79] Matos R *et al* 2020 Bottleneck detection in cloud computing performance and dependability: sensitivity rankings for hierarchical models *J. Netw. Syst. Manage.* **28** 1839–71

[80] Zio E 2016 Challenges in the vulnerability and risk analysis of critical infrastructures *Reliab. Eng. Syst. Saf.* **152** 137–50

[81] Kosasih E E and Brintrup A 2022 A machine learning approach for predicting hidden links in supply chain with graph neural networks *Int. J. Prod. Res.* **60** 5380–93

[82] Ma C, Alam S, Cai Q and Delahaye D 2022 Critical links detection in spatial-temporal airway networks using complex network theories *IEEE Access* **10** 27925–44

[83] Anjaneyulu M and Kubendiran M 2023 Short term traffic flow prediction using hybrid deep learning *Comput. Mater. Contin.* **75** 1641–56

[84] Yin J, Ma R and Ge S 2025 Predicting task bottlenecks in digital manufacturing enterprises based on spatio-temporal graph convolutional networks *Front. Eng. Manag.* **12** 736–53

[85] Ragazzini L, Negri E, Fumagalli L and Macchi M 2024 Digital twin-based bottleneck prediction for improved production control *Comput. Ind. Eng.* **192** 110231

[86] Lee J, Bagheri B and Kao H-A 2015 A cyber-physical systems architecture for industry 4.0-based manufacturing systems *Manuf. Lett.* **3** 18–23

[87] Saxena A and Iyengar S 2020 Centrality measures in complex networks: a survey arXiv: 2011.07190

[88] Lü L, Zhou T, Zhang Q-M and Stanley H E 2016 The *h*-index of a network node and its relation to degree and coreness *Nat. Commun.* **7** 10168

[89] Newman M E J 2006 Modularity and community structure in networks *Proc. Natl Acad. Sci.* **103** 8577–82

[90] Edmonds J and Karp R M 1972 Theoretical improvements in algorithmic efficiency for network flow problems *J. ACM* **19** 248–64

[91] Abdullah N and Hua T K 2017 The application of the shortest path and maximum flow with bottleneck in traffic flow of kota kinabalu *J. Comput. Sci. Comput. Math.* **7** 37–43

[92] Kinney R, Crucitti P, Albert R and Latora V 2005 Modeling cascading failures in the north American power grid *Eur. Phys. J. B* **46** 101–7

[93] Ren W, Wu J, Zhang X, Lai R and Chen L 2018 A stochastic model of cascading failure dynamics in communication networks *IEEE Trans. Circuits Syst. II: Express Br.* **65** 632–6

[94] Pastor-Satorras R, Castellano C, Van Mieghem P and Vespignani A 2015 Epidemic processes in complex networks *Rev. Mod. Phys.* **87** 925–79

[95] Newman M E J 2002 Spread of epidemic disease on networks *Phys. Rev. E* **66** 016128

[96] Aliano M, Cananà L, Cestari G and Ragni S 2023 A dynamical model with time delay for risk contagion *Mathematics* **11** 425

[97] Granell C, Gomez S and Arenas A 2013 Dynamical interplay between awareness and epidemic spreading in multiplex networks *Phys. Rev. Lett.* **111** 128701

[98] Zhao B, Xu C, Liu S, Zhao J and Li L 2021 Dynamic traffic bottlenecks identification based on congestion diffusion model by influence maximization in metro-city scales *Concurr. Comput.: Pract. Exp.* **33** e5790

[99] Soares G G and Estrada E 2024 Navigational bottlenecks in nonconservative diffusion dynamics on networks *AIMS Math.* **9** 24297–325

[100] Zhao G, Jia P, Huang C, Zhou A and Fang Y 2020 A machine learning based framework for identifying influential nodes in complex networks *IEEE Access* **8** 65462–71
[101] Rezaei A A, Munoz J, Jalili M and Khayyam H 2023 A machine learning-based approach for vital node identification in complex networks *Expert Syst. Appl.* **214** 119086
[102] Yang X-H, Xiong Z, Ma F, Chen X, Ruan Z, Jiang P and Xu X 2021 Identifying influential spreaders in complex networks based on network embedding and node local centrality *Physica A* **573** 125971
[103] Ungern-Sternberg R and Teriete T 2023 Data-driven analysis of dynamic bottlenecks in order-based value streams *Procedia CIRP* **120** 183–8
[104] Lai X, Shui H, Ding D and Ni J 2021 Data-driven dynamic bottleneck detection in complex manufacturing systems *J. Manuf. Syst.* **60** 662–75
[105] Subramaniyan M, Skoogh A, Muhammad A S, Bokrantz J, Johansson B and Roser C 2020 A data-driven approach to diagnosing throughput bottlenecks from a maintenance perspective *Comput. Ind. Eng.* **150** 106851
[106] Lundberg S M and Lee S-I 2017 A unified approach to interpreting model predictions *Advances in Neural Information Processing Systems (NIPS 2017)* vol 30 (Curran Associates, Inc) pp 4765–74
[107] Al-Mekhlafi Z G 2022 Software-defined vehicular networks (SDVN) *Int. J. Comput. Sci. Netw. Secur.* **22.9** 231–43
[108] Al-Mekhlafi Z G and Alfhaid S A 2025 Innovative security measures: a comprehensive framework for safeguarding the internet of things *AI-Driven: Social Media Analytics and Cybersecurity, Volume 1180 of Studies in Computational Intelligence*, ed W M S Yafooz and Y Al-Gumaei (Springer) pp 175–85
[109] Ma S, Li J, Li J and Xie M 2025 Cloud-integrated cyber-physical systems: reliability, performance and power consumption with shared-servers and parallelized services *Front. Eng. Manag.* **12** 272–90
[110] Munikoti S, Das L and Natarajan B 2022 Scalable graph neural network-based framework for identifying critical nodes and links in complex networks *Neurocomputing* **468** 211–21
[111] Kipf T N and Welling M 2017 Semi-supervised classification with graph convolutional networks *Int. Conf. on Learning Representations* https://openreview.net/forum?id=SJU4ayYgl
[112] Veličković P, Cucurull G, Casanova A, Romero A, Lio P and Bengio Y 2017 Graph attention networks *ICLR* (https://doi.org/10.17863/CAM.48429)
[113] Hamilton W, Ying Z and Leskovec J 2017 Inductive representation learning on large graphs *Advances in Neural Information Processing Systems (NIPS 2017)* vol 30 pp 1025–35
[114] Wu Z, Pan S, Long G, Jiang J and Zhang C 2019 Graph wavenet for deep spatial-temporal graph modeling *28th Int. Joint Conf. on Artificial Intelligence (IJCAI-19). Int. Joint Conf. on Artificial Intelligence (IJCAI)* 1907–13
[115] Kaelbling L P, Littman M L and Moore A W 1996 Reinforcement learning: a survey *J. Artif. Intell. Res.* **4** 237–85
[116] Huang C, Fang Y, Lin X, Cao X, Zhang W and Orlowska M 2022 Estimating node importance values in heterogeneous information networks *Proc. IEEE 38th Int. Conf. on Data Engineering (ICDE)* pp 846–58
[117] Wu X, Huang Y and Bao W 2025 Using GNN to identify supply chain network structure *Int. J. Big Data Intell. Technol.* **6** 060205
[118] Wang C, Xu Y, Zhang J and Ran B 2022 Integrated traffic control for freeway recurrent bottleneck based on deep reinforcement learning *IEEE Trans. Intell. Transp. Syst.* **23** 15522–35
[119] Hong Li, Xu M, Liu Y, Zhang X and Fan C 2025 A deep learning dismantling approach for understanding the structural vulnerability of complex networks *Chaos Solitons Fractals* **194** 116148
[120] Ying Z, Bourgeois D, You J, Zitnik M and Leskovec J 2019 Gnnexplainer: Generating explanations for graph neural networks *Advances in Neural Information Processing Systems (NeurIPS 2019)* vol 32 (Curran Associates, Inc)
[121] Al-Mekhlafi Z G, Hanapi Z M, Othman M and Zukarnain Z A 2016 A firefly-inspired scheme for energy-efficient transmission scheduling using a self-organizing method in a wireless sensor networks *J. Comput. Sci.* **12** 482–94
[122] Al-Mekhlafi Z G, Hanapi Z M, Othman M, Zukarnain Z A and Song H 2017 Travelling wave pulse coupled oscillator (TWPCO) using a self-organizing scheme for energy-efficient wireless sensor networks *PLoS One* **12** e0167423
[123] Al-Mekhlafi Z G, Hanapi Z M, Othman M, Zukarnain Z A and Saleh A M S 2018 Random traveling wave pulse-coupled oscillator algorithm of energy-efficient wireless sensor networks *Int. J. Distrib. Sens. Netw.* **14** 8991
[124] Al-Mekhlafi Z G, Hanapi Z M and Saleh A M S 2019 Firefly-inspired time synchronization mechanism for self-organizing energy-efficient wireless sensor networks: a survey *IEEE Access* **7** 115229–48
[125] Fernando E, Hassan R, Murad D F and Al-Mekhlafi Z G 2025 Exploring the artificial intelligence era in influencing self-paced learning: systematic and bibliometric review of literature *Educ. Process: Int. J.* **18** 2025
[126] Laudanna C and Scardoni G 2012 Identifying critical traffic jam areas with node centralities interference and robustness *Netw. Heterog. Media* **7** 463–71
[127] Yang F, Yan F, Zhang C, Tang X, Li J, Zhang X, Gan Y and Javaid M 2021 Applying the virtual input-output method to the identification of key nodes in busy traffic network *Complexity* **2021** 5559857
[128] Zhu L, Luo J, Zhao Y and Yang Y 2015 A new method to determine node importance of an urban traffic network *15th COTA Int. Conf. of Transportation Professionals* (American Society of Civil Engineers) pp 2827–38
[129] Lai Q and Zhang H-H 2022 Analysis of identification methods of key nodes in transportation network *Chin. Phys. B* **31** 068905
[130] Lee W-H, Tseng S-S, Shieh J-L and Chen H-H 2011 Discovering traffic bottlenecks in an urban network by spatiotemporal data mining on location-based services *IEEE Trans. Intell. Transp. Syst.* **12** 1047–56
[131] Chen X, Sun K, Cao Y and Wang S 2007 Identification of vulnerable lines in power grid based on complex network theory *2007 IEEE Power Engineering Society General Meeting* pp 1–6
[132] Liu B, Li Z, Chen X, Huang Y and Liu X 2018 Recognition and vulnerability analysis of key nodes in power grid based on complex network centrality *IEEE Trans. Circuits Syst. II: Express Br.* **65** 346–50
[133] Fan B, Shu N, Li Z and Li F 2023 Critical nodes identification for power grid based on electrical topology and power flow distribution *IEEE Syst. J.* **17** 4874–84
[134] Chen C, Zhou X, Li Z, He Z, Li Z and Lin X 2018 Novel complex network model and its application in identifying critical components of power grid *Physica A* **512** 316–29
[135] Fan B, Zheng C, Tang L and Wu R 2020 Critical nodes identification for vulnerability analysis of power communication networks *IET Commun.* **14** 703–13

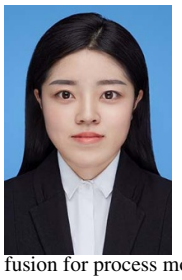
[136] Liu B, Meng K, Dong Z Y and Zhang W 2020 Marginal bottleneck identification in power system considering correlated wind power prediction errors *J. Mod. Power Syst. Clean Energy* **8** 187–92
[137] Jafarzadeh S, Genc I and Nehorai A 2021 Real-time transient stability prediction and coherency identification in power systems using koopman mode analysis *Electr. Power Syst. Res.* **201** 107565
[138] Wang C, Wang X, Cao Y, Li Y, Lv Q and Zhang Y 2024 Critical link identification of power system vulnerability based on modified graph attention network arXiv: 2409.07785
[139] Ou C, Pan F and Lin S 2024 Cascade failure-based identification and resilience of critical nodes in automotive supply chain networks *Sustainability* **16** 5514
[140] Arora V and Ventresca M 2018 Modeling topologically resilient supply chain networks *Appl. Netw. Sci.* **3** 19
[141] Ledwoch A, Brintrup A, Mehnen J and Tiwari A 2018 Systemic risk assessment in complex supply networks *IEEE Syst. J.* **12** 1826–37
[142] Hua Z, Xia Y, Chen Y and Sun W 2025 Identification of critical nodes in supply chain networks *AIP Adv.* **15** 015224
[143] Li Y, Chen K, Collignon S and Ivanov D 2021 Ripple effect in the supply chain network: forward and backward disruption propagation, network health and firm vulnerability *Eur. J. Oper. Res.* **291** 1117–31
[144] Chen J and Wen H 2023 The application of complex network theory for resilience improvement of knowledge-intensive supply chains *Oper. Manag. Res.* **16** 1140–61
[145] Wang S, Ai R, Khattak S I and Tariq S 2025 Green supply chains: feature analysis and key node identification in multi-layer supply chain networks based on fused multi-scale metric *IEEE Access* **13** 85363–79
[146] Kenett D Y, Gao J, Huang X, Shao S, Vodenska I, Buldyrev S V and Havlin S 2014 *Network of Interdependent Networks: Overview of Theory and Applications* (Springer) pp 3–36
[147] Parshani R, Buldyrev S V and Havlin S 2010 Interdependent networks: reducing the coupling strength leads to a change from a first to second order percolation transition *Phys. Rev. Lett.* **105** 048701
[148] Dong G, Gao J, Tian L, Du R and He Y 2012 Percolation of partially interdependent networks under targeted attack *Phys. Rev. E* **85** 016112
[149] Li C, Li W, Cao C and Yu W 2019 Robustness analysis of interdependent networks for cascading failure *J. Syst., Simul.* **31** 538–48
[150] Gao J, Buldyrev S V, Havlin S and Stanley H E 2012 Robustness of a network formed by *n* interdependent networks with a one-to-one correspondence of dependent nodes *Phys. Rev. E* **85** 066134
[151] Fu G, Dawson R, Khoury M and Bullock S 2014 Interdependent networks: vulnerability analysis and strategies to limit cascading failure *Eur. Phys. J. B* **87** 148
[152] Zhao D, Ling X, Peng H, Zhong M, Han J and Wang W 2024 Robustness of interdependent directed higher-order networks against cascading failures *Physica D.* **462** 134126
[153] Ferrari C and Santagata M 2023 Vulnerability and robustness of interdependent transport networks in north-western Italy *Eur. Transp. Res. Rev.* **15** 6
[154] El-Shamy A, El-Fishawy N, Attiya G and Mohamed M A A 2021 Anomaly detection and bottleneck identification of the distributed application in cloud data center using software–defined networking *Egypt. Inform. J.* **22** 417–32
[155] Zhu T, Yang X, Ma Z, Gao J and Wu J 2025 Can a bottleneck capacity enhancement policy postpone infrastructure network collapse? *Transp. Policy* **163** 1–13
[156] Rudin C 2019 Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead *Nat. Mach. Intell.* **1** 206–15
[157] Mao J *et al* 2024 Identify critical nodes in complex network with large language models arXiv: 2403.03962
[158] Rossi E, Chamberlain B, Frasca F, Eynard D, Monti F and Bronstein M 2020 Temporal graph networks for deep learning on dynamic graphs arXiv: 2006.10637
[159] Pareja A, Domeniconi G, Chen J, Ma T, Suzumura T, Kanezashi H, Kaler T, Schardl T B and Leiserson C E 2020 Evolvegcn: evolving graph convolutional networks for dynamic graphs *Proc. AAAI Conf. Artif. Intell.* **34** 5363–70
[160] Wang W-X, Lai Y-C and Grebogi C 2016 Data based identification and prediction of nonlinear and complex dynamical systems *Phys. Rep.* **644** 1–76
[161] Ding X, Kong L W, Zhang H F and Lai Y C 2024 Deep-learning reconstruction of complex dynamical networks from incomplete data *Chaos* **34** 043115
[162] Holme P and Saramäki J 2012 Temporal networks *Phys. Rep.* **519** 97–125
[163] Chen H, Alhinai Y, Jiang Y, Na E and Hao C 2022 Bottleneck analysis of dynamic graph neural network inference on CPU and GPU *2022 IEEE Int. Symp. on Workload Characterization (IISWC)* (IEEE) pp 130–45
[164] Lai X, Qiu T, Shui H, Ding D and Ni J 2023 Predicting future production system bottlenecks with a graph neural network approach *J. Manuf. Syst.* **67** 201–12
[165] Thenmozhi I J C S M C and Nawaz G M K 2026 Fed-DT-EdgeGNN: privacy-preserving federated digital twin edge intelligence for secure VANET communication *Int. J. Comput. Sci. Mob. Comput. (IJCSMC)* **15** 18–27
[166] Haider S Z, Shah A, Arif M, Iftikhar H and Ali W 2026 Privacy-preserving federated temporal graph learning with digital twin-guided adaptive deception for cyber-resilient IoMT arXiv: 2606.21513
[167] Sellitto G P, Masi M, Pavleska T and Aranha H 2021 A cyber security digital twin for critical infrastructure protection: the intelligent transport system use case *The Practice of Enterprise Modeling, Volume 432 of Lecture Notes in Business Information Processing*, ed E Serral, J Stirna, J Ralyté and J Grabis (Springer) pp 212–27



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