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Analysis of Fire Propagation and Risk Network Based on Sensor Technology

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As China's urban landscape evolves, the frequency and complexity of fire incidents have increased, causing severe secondary disasters and widespread damage. Fire-induced disaster chains present cumulative and unpredictable risks, exacerbated by environmental, structural, and human factors. We construct a fire propagation model based on disaster chain theory, integrating hazard-causing elements, vulnerable assets, and disaster-inducing environments. Using data from 75 government-reported fire incidents and on the basis of complex network theory, we identified key risks and analyzed their fire propagation capabilities using comprehensive degree, clustering coefficient, and eigenvector centrality. Thirty-nine interconnected risks were identified, and their effect on fire propagation was assessed. Several risks, despite high propagation potential, had minimal influence, while others with strong connectivity required extensive monitoring. The role of sensor networks in early detection and control was emphasized, and simulation results supported targeted risk management strategies. The results of this study emphasize the need for data-driven fire control, optimizing sensor deployment, and prevention strategies to mitigate the cascading effects of fire disasters.

1. Introduction

As community functions, structures, and landscapes continue to evolve in China, the number of fire incidents has been increasing significantly. The causes of fires are diverse with strong interdependencies affected by numerous factors. Fires cause disasters in time, space, and environmental conditions,(1) leading to secondary hazards, such as smoke and toxic gas emissions, explosions, and environmental pollution, and severe consequences, including infrastructure damage, public panic, and casualties. For example, the '1·24' fire disaster in Jialeyuan Community, Xinyu, Jiangxi, China in 2024 caused secondary and derivative impacts, including smoke and toxic gas release, structural damage, and combustible explosions, resulting in 39 fatalities, 9 injuries, and an economic loss of 43.53 million yuan (USD 6.0 million).(2) Fires cause interconnected secondary and derivative disasters, which is referred to as a fire-induced disaster chain.(3) Such incidents show cumulative effects and unpredictability, making their progression difficult to forecast and control. The absence of effective intervention in disasters

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escalates risks and severely damages and disrupts the community system. Therefore, it is important to understand the fire-induced disaster chains and develop strategies to minimize losses. Being different from natural disasters such as floods and earthquakes, fires are triggered by multiple causes, including humans, objects, management failure, and environmental factors, resulting in a series of disasters.[4]

Recently, research on fire risk assessment and analysis has been conducted using fire risk assessment and simulation, correlation analysis, and prediction. However, the complex relationships between risk factors have rarely been studied. To explore these relationships, complex network theory is employed owing to its inherent advantages in analyzing the coupling effects and pathways generated by various factors. This theory is widely applied to study the development of fire-induced disaster chains, such as those in urban environments, fire propagation in underground commercial complexes, and oil tank accidents.[5–8] While existing research contributes to fire risk assessment, it presents several limitations.

First, most studies concentrate on the analysis of a single risk factor, lacking a systematic characterization of the coupling effects between secondary risk factors that initiate a fire-induced disaster chain. This insufficient understanding of the disaster propagation chain makes it challenging to study the cross-layer transmission mechanisms of secondary disasters, such as explosions and toxic smoke spread. Second, traditional assessment methods heavily rely on static network models, which fail to capture the dynamic characteristics of fire propagation. Furthermore, common risk identification methods depend solely on single topological indicators such as risk level and the clustering coefficient of risks. While these metrics reflect the characteristics of risks, information on sensor data is not considered.

Therefore, we constructed a fire propagation model based on the disaster chain theory, which presents the risk connectivity level, the propagation effect of each risk in a disaster, and vulnerable assets to disaster. The model can address the limitations of topological indicators and identify risks that require extensive monitoring with sensor data. The results of this study provide a basis for formulating a strategy to prevent a fire and minimize the secondary disaster and for optimizing sensor deployment for effective monitoring and preventing fires.

2. Fire Propagation Model

2.1 Disaster chain theory

A disaster chain is a complex system affected by hazard-causing factors, disaster-inducing environments, vulnerable assets to disaster, and disaster events.[9] In the chain, hazard-causing factors are defined as elements that might trigger or exacerbate disasters and cause losses, including extreme climate changes and human activities, which are unpredictable and sudden; disaster-inducing environments refer to collective environmental conditions that might lead to disasters in natural and social environments; vulnerable assets are entities, such as residents and infrastructure, that directly suffer severe losses from hazard-causing factors.[10] A hazard-causing factor can cause a disaster that can damage multiple vulnerable assets. Vulnerable assets might trigger continuous disasters in a disaster chain or disaster cluster.[11] On the basis of the interaction mechanism that involves the elements, the factor set of a fire-induced disaster chain is expressed as

$$G = \{C, E, R, S\}, \tag{1}$$

where G is the fire-induced disaster chain system, C is the hazard-causing factor, E is the disaster-inducing environment, R is the disaster event caused by the coupling of C and E, and S is the vulnerable assets to disaster.

The topological structure of a disaster chain consists of multiple risks that have complex structural characteristics. A simple model is required to analyze fire development and propagation paths in the chain. Fire incidents can trigger secondary and derivative disasters on the interconnected path that resembles a topological network. Therefore, it is necessary to explore the fire propagation chain. In the developed model, risks with a high level of connection and fire propagation effect on other risks were identified.

2.2 Sensor network for fire control

The sensor network plays an important role in early warning and fire control. The sensor network monitors smoke, temperature, or flame in real time and issues alarms in the early stage of a fire for effective evacuation and fire control. The integrated sensor network detects fire hazards and activates suppression mechanisms, including water spraying, inert gas release, oxygen supply cutoff, and ventilation duct closure, effectively preventing fire propagation before human intervention is required. However, its effectiveness is limited by sensor sensitivity, system response speed, fire control device functions, and equipment maintenance, which requires manual intervention. Nevertheless, owing to early detection, the sensor network significantly strengthens proactive fire protection and control and rapid response, and plays an essential role in reducing fire-related losses. The structure of a fire detection and control system is shown in Fig. 1. The roles of the components of the system are described in alphabetical order as follows.

- Broadcast line: This is part of the fire alarm system's public address or voice evacuation system. Its role is to broadcast prerecorded or live messages to guide people to safety during an emergency.
- Bus short-circuit isolator: This device isolates a short circuit on a communication bus. It prevents a fault in one section of the circuit from disabling the entire loop, ensuring that other devices on the bus continue to function correctly.
- Bus telephone extension: This is an extension of the internal communication system, allowing for direct voice communication with the fire alarm control panel from various locations within a building.
- Bus telephone jack: This is the connection point for a bus telephone extension.
- Cable-type line-type heat detector: This uses a heat-sensitive cable to sense a fire. When the temperature along the cable exceeds a certain threshold, it triggers an alarm.

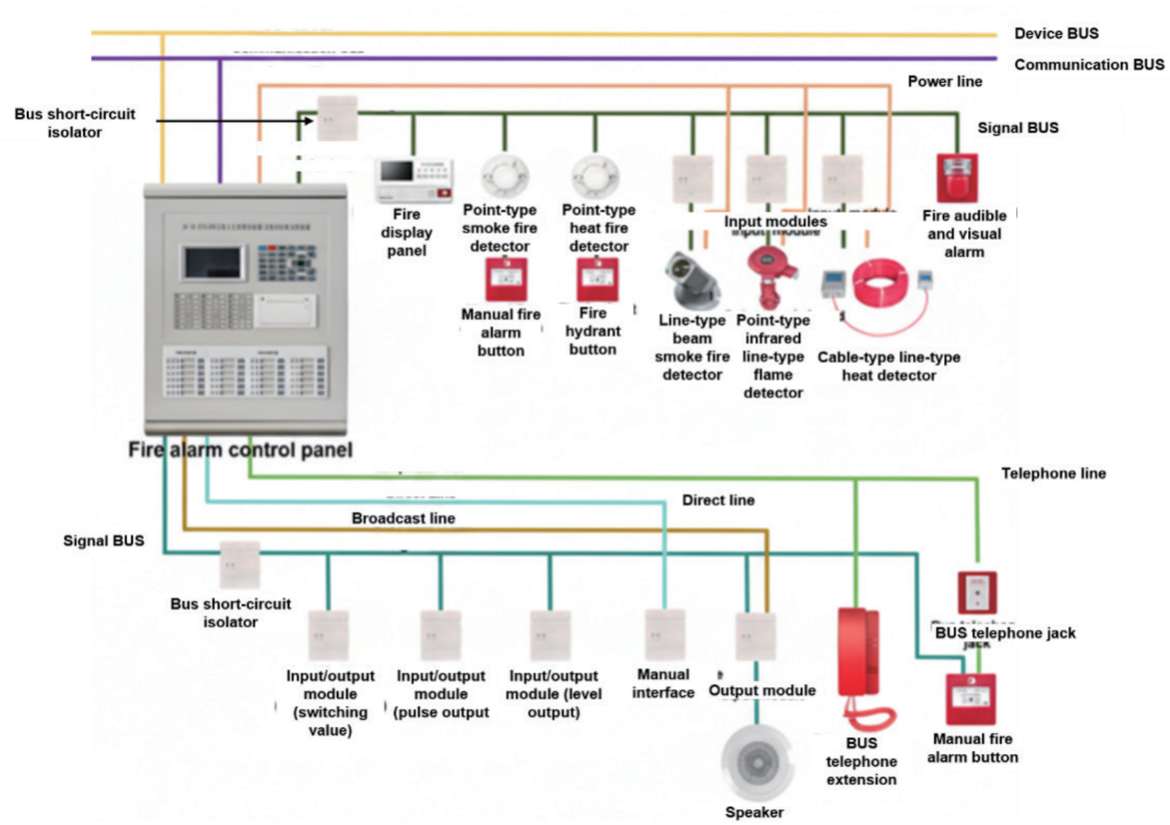

Fig. 1. (Color online) Fire detection and control system with sensor network (from this study).

- Communication bus: This is the primary communication pathway for all devices connected to the fire alarm control panel. It transmits data and signals between detectors, modules, and the panel.
- Device bus: This is a specialized bus for communication with specific intelligent or addressable devices, often carrying more complex data than a standard signal bus.
- Direct line: This is a dedicated telephone line used for direct, private communication between specific points in the system, typically used by emergency personnel.
- Fire alarm control panel: This is the brain of the system. It receives signals from detectors, initiates alarms, and monitors the entire fire alarm system.
- Fire audible and visual alarm: Also known as a horn/strobe, this device provides both an audible alert (siren or horn) and a visual warning (flashing strobe light) to alert building occupants of a fire.
- Fire display panel: This is an ancillary display unit, typically a simplified version of the main control panel. It shows the status of the system and the location of a fire without requiring access to the main control panel.
- Fire hydrant button: This is a device used to signal the fire alarm control panel that a fire hydrant is being used, often activating related systems such as pumps.

- Input module: This module connects non-addressable devices (e.g., a sprinkler flow switch or a manual pull station) to the addressable communication bus, allowing the fire alarm control panel to monitor their status.
- Input/output module (level output): This provides a continuous or variable output signal, often used to control systems that require a specific voltage or current level.
- Input/output module (pulse output): This provides a series of electrical pulses, often used to control or interface with equipment that operates on the basis of a pulsed signal.
- Input/output module (switching value): This can be used for both input and output functions. It provides a simple on/off or open/close signal, often used to activate or monitor other building systems such as fans or dampers.
- Line-type beam flame detector: This is a specialized detector that uses an infrared or ultraviolet light beam to detect the presence of an open flame over a long distance.
- Line-type beam smoke fire detector: This is used in large open areas (e.g., warehouses) and uses a beam of light to detect smoke. When smoke obstructs the beam, an alarm is triggered.
- Manual fire alarm button: This is a manually operated device that allows a person to activate the fire alarm system by pulling a lever or pressing a button.
- Manual interface: This is a device that allows for manual control or input into the fire alarm system, often used for specialized functions.
- Output module: This receives a signal from the fire alarm control panel and activates other external systems, such as magnetic door locks, smoke dampers, or elevators.
- Point-type heat fire detector: This senses a fire when the temperature at a specific point in a room reaches a predefined threshold or when the temperature rises quickly.
- Point-type infrared: This is a detector that senses the infrared radiation emitted by a fire at a specific location.
- Point-type smoke fire detector: This is a common detector that senses a fire by detecting smoke particles at a specific location, using either ionization or photoelectric technology.
- Power line: This is the wiring that supplies electrical power to all the devices in the system.
- Signal bus: This is a simple communication pathway that carries signals from detectors and other devices to the fire alarm control panel.
- Speaker: This is part of the voice evacuation system. It plays prerecorded messages or live announcements to guide building occupants to safety.
- Telephone line: This is a standard telephone line used to connect the fire alarm system to an external monitoring station or for internal communication.

2.3 Fire propagation

To improve the fire detection and control capability, the comprehensive degree, clustering coefficient, and eigenvector centrality of risks need to be evaluated to analyze the risk network's characteristics. The results are used to evaluate the risk's connectivity level and the fire propagation effect on other risks.

2.3.1 Key risk identification

Key risks are those that exert the greatest effect on a network's topological structure and functionality. Accurately identifying these risks enhances control over fire propagation efficiency and optimizes network performance.(12) Although the traditional K-shell method determines the importance of risks by calculating their positions in the network and assigning different shell values, it does not reveal the importance of risks in the same layer. This method heavily relies on risk characteristics while ignoring the impact of risks on fire propagation, thereby failing to accurately identify the propagation capabilities of the risks. The model developed in this study integrated local and global fire propagation characteristics to evaluate the importance of risks.(13) This method aligns with the disaster chain theory. The calculation method of the developed model is as follows:

$$C(i) = K(i) + \mu_i D(i) + \theta S_i, \tag{2}$$

$$\mu_i = \frac{K(i)}{N(i)}, \tag{3}$$

where $C(i)$ is the risk degree for risk i, $K(i)$ is the total number of risks within the two-step neighborhood of risk I, $N(i)$ is the number of subneighbor risks (or direct neighbors) of risk I, μ_i is the neighborhood influence coefficient, calculated as the ratio of risks in the two-step neighborhood to the number of direct neighbors, $D(i)$ represents the direct influence degree, which is the number of risks directly connected to risk I, θ is the sensor correlation coefficient, and S_i is the sensor correlation strength, S_i indicates the relationship between risk i and a sensor deployment point. If a risk is directly connected to a sensor deployment point, $S_i = 1$, while $S_i = 0.5$ if a risk is indirectly connected (or related to) a sensor deployment point.

2.3.2 Vulnerability

Vulnerability refers to the degree of change in the risk network structure and connectivity of the risks. Risk propagation efficiency declines when risks are randomly distributed. We examined the connectivity level and the level of fire propagation effect of risks.

The risk connectivity level is determined by the fire propagation capability of risks to other risks [Eq. (4)].

$$k(G) = \min\{|S| : S \text{ is a node cut set of } G\}, \tag{4}$$

where $k(G)$ represents the network connectivity of graph G (the network of risks), $|S|$ denotes the number of risks in set S, and the "node cut set" is a set of nodes (risks) whose removal disconnects the graph.

The stability of the network with risks is affected by the ratio of the number of risks connected (N') to others to the total number of risks (N) (5).

$$S = \frac{N'}{N} \tag{5}$$

The level of the propagation effect of risk represents the fire propagation speed, reflecting the level of connection between risks,[14] and is calculated as

$$e = \frac{1}{N(N-1)} \sum\nolimits_{i \neq j} \frac{1}{d_{ij}}, \tag{6}$$

where d_{ij} is the shortest path between risks i and j.

3. Risk Identification and Model Construction

In this study, the Octopus data collector was used to obtain 75 fire incident analysis reports published by government emergency management departments over the past five years. A corpus was constructed as a fire disaster event dataset. Relationships between the identified risks were analyzed on the basis of the elements (C, E, R, and S) of the disaster chain and extracted risk factors. The elements and factors were mapped to identify direct and indirect causes, casualties and losses, and secondary disasters. Identified factors were coded and transformed into an $n \times n$ co-occurrence matrix A, where A_{ij} represents the number of times of the occurrence of event i that might trigger event j. A was then converted into an adjacency matrix C using Eq. (7).

$$C_{ij} = \begin{cases} 0, & A_{ij} = 0 \\ 1, & A_{ij} > 0 \end{cases} \tag{7}$$

When $C_{ij} = 1$, risk i leads to risk j. If $C_{ij} = 0$, there is no relationship between risks i and j.

Nine hazard-causing factors, 21 disaster-inducing environments, five vulnerable assets to disaster, and four disaster events were identified in this study (Table 1 and Fig. 2).[15] The Kappa index of the risks was higher than 0.8, indicating reliable coding results. Out of 75 reports, 10 reports were analyzed to extract and code the number of risks. Until the increasing rate of the number of extracted risks reached 0, texts were coded and analyzed.

On the basis of the adjacency matrix C, the network structure was constructed using Gephi software (Fig. 2). The network consisted of 39 risks. The PageRank algorithm was used to identify risks and present the correlation and level of connection between risks. The five most severe risks were identified as R1, R2, S1, E19, and E13. These risks were critical factors in fire incidents, requiring extensive monitoring and preventive measures to avoid disaster.

Table 1
Fire-induced disaster chain event risks.

Factor	Risk		Factor	Risk		Factor	Risk	
Hazard-causing factors	C1	Electrical failure	Disaster-inducing environments	E5	Blocked fire escape	Disaster-inducing environments	E18	Delayed rescue response
	C2	Gas leakage		E6	Lack of fire protection design		E19	Poor emergency escape ability
	C3	Improper use of electrical appliances		E7	Improper accumulation of flammable materials		E20	Unclear management responsibility
	C4	Unattended ignition source		E8	Illegal modification of electric bicycles		E21	Insufficient professional skills
	C5	Battery fire		E9	Poor fire resistance performance of building materials	Disaster events	R1	Sudden fire
	C6	Nonstandard flammable materials used		E10	Nonstandard installation of electrical wiring		R2	Flammable material deflagration
	C7	Formation of explosive gas mixture		E11	Inadequate ventilation measures		R3	Generation of toxic smoke
	C8	Delayed alarm		E12	Lack of anti-static measures		R4	Explosion
	C9	High fire load		E13	Poor living habits	Vulnerable assets to disaster	S1	Casualties
Disaster-inducing environments	E1	Lack of safety awareness		E14	Insufficient safety education and training		S2	Property damage
	E2	Lack or failure of fire-fighting facilities		E15	Inadequate implementation of safety supervision responsibilities		S3	Daily life inconvenience
	E3	Illegal construction		E16	Ineffective inspection and rectification		S4	Online public opinion
	E4	Illegal leasing		E17	Inadequate fulfillment of safety responsibilities		S5	Building collapse and damage

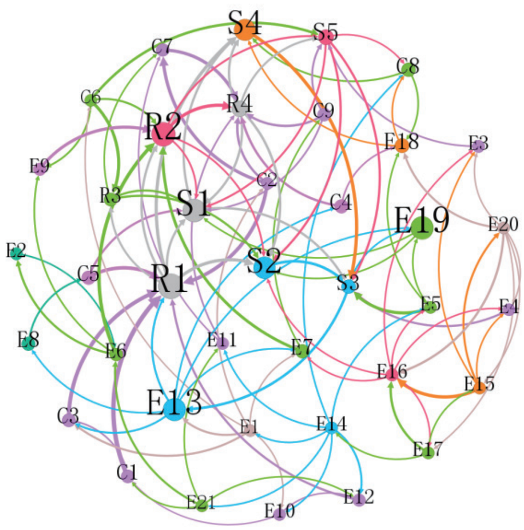

Fig. 2. (Color online) Risk network identified in this study.

4. Fire Propagation Model

The comprehensive degree of risk is presented as the sum of its out-degree and in-degree. In-degree represents the number of other risks that can trigger it, suggesting that it is easily triggered, while out-degree represents the number of risks it can trigger, suggesting a strong fire propagation effect. Risks with high in-degrees (higher than out-degrees) included S1, S3, S4, and S2, indicating that these risks were easily triggered. Risks with high out-degrees (significantly higher than in-degrees) include E1, E13, E14, and E20, suggesting that these risks had strong fire propagation effects (ability to trigger other risks) and must be monitored with well-defined preventive measures. The clustering coefficient represents the similarity in fire propagation and relationships between risks.(16)

The clustering coefficient presents the degree to which nodes (risks) in a graph tend to cluster. It is calculated for a single node or for the entire graph based on the number of connections between a node's immediate neighbors.

The average clustering coefficient for the entire network is the average of the local clustering coefficients for all nodes in the graph and is calculated as(17)

$$C = \frac{1}{N}\sum_{v \in G} C_v, \tag{8}$$

where, N is the number of nodes (risks) in the graph and C_v is the local clustering coefficient of each node. A high average clustering coefficient for a network indicates a highly interconnected and structured network, whereas a low average coefficient suggests a more sparse and less connected network where nodes' neighbors are not necessarily neighbors with each other.

The clustering coefficient of the network was small (0.162), indicating low connectivity levels of the risks.(16) Risks with the highest clustering coefficients (R1, E15, and E3) exhibited close connections with adjacent risks (Fig. 3). Controlling such risks effectively reduces the possibility of secondary disaster.

The importance of risks is determined by the mutual influence and measured by eigenvector centrality. Eigenvector centrality is a measure of a risk's influence within a network. Unlike degree centrality (which just counts direct connections), eigenvector centrality considers the quality of those connections. A risk receives a higher score if it is connected to other risks that

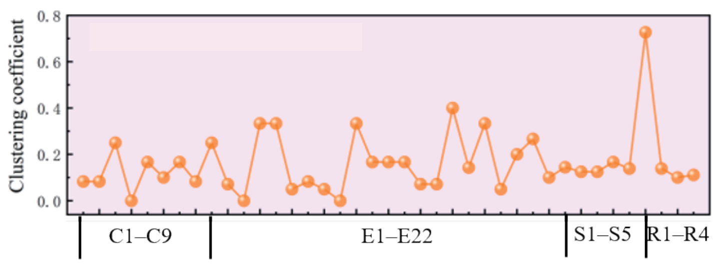

Fig. 3. (Color online) Clustering coefficients of risks.

are themselves highly connected and influential. Eigenvector centrality is a recursive calculation. The score for a node is proportional to the sum of the scores of all the nodes connected. For a given network represented by an adjacency matrix, the eigenvector centrality of all the nodes is the eigenvector corresponding to the largest eigenvalue of that matrix. The top five risks in eigenvector centrality included S3, S1, S2, S4, and E19. These risks showed close relationships, and their eigenvector centralities were used to identify adjacent risks to prevent fire propagation and determine preventive measures (Fig. 4). Comprehensive degrees of the risks calculated using Eqs. (2) and (3) were used to identify risks with high potentials of causing a disaster. R1, S1, R4, R2, and S5 were identified as the risks with high comprehensive degrees and require prevention and control measures (Fig. 5).

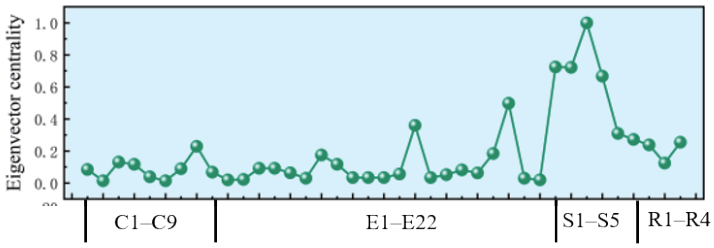

Fig. 4. (Color online) Eigenvector centralities of risks.

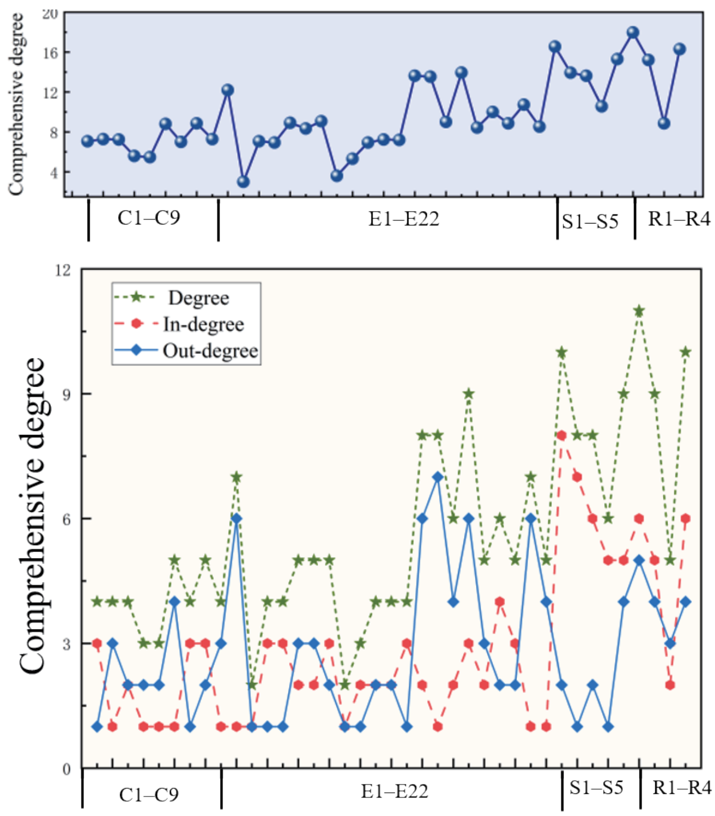

Fig. 5. (Color online) Comprehensive degrees of risks.

5. Vulnerability of Risk Network

To evaluate the performance of the fire propagation network, we assessed its vulnerability. This involved identifying vulnerability indicators and analyzing how they relate to one another. The results of this assessment were then used to guide the development of targeted fire control measures designed to reduce the risk and spread of fire.

Figure 6 illustrates how four different metrics, namely, risk hedging degree, comprehensive degree, eigenvector centrality, and clustering coefficient, are related to the overall risk connectivity level across 39 identified risks. The risk hedging degree, represented by the black line with triangle markers, starts at a high connectivity level and gradually declines. This trend suggests that as risk hedging increases, the network becomes less interconnected. In other words, random hedging can effectively reduce systemic fire risk by weakening the pathways through which fire might propagate. The comprehensive degree, shown as a red line with circle markers, exhibits a stepwise decline. This pattern indicates that some risks are significantly more connected than others. On the basis of this metric, three distinct groups of risks were identified: C1–C8, E1–E11, and E12–S5. Additionally, risks C9 and E1 were found to fall between the first and second groups, suggesting that they serve as transitional nodes within the network.

The eigenvector centrality, represented by the green line with star markers, fluctuates but generally trends downward. This metric reflects the varying influence of individual risks within the network. The analysis revealed five connectivity clusters: C1–C8, C9–E3, E5–E15, E16–E20, and E21–S4. These groupings help identify which risks are most central to fire propagation and therefore require closer monitoring and control. The clustering coefficient, depicted by the blue line with square markers, also shows a stepwise decline with some fluctuations. This suggests that certain risks are embedded in tightly knit clusters, while others are more isolated. Two

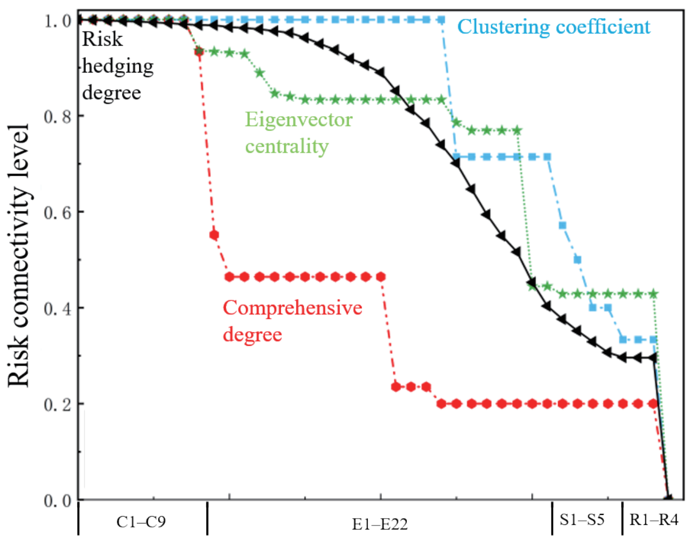

Fig. 6. (Color online) Groups of risks by risk connectivity levels of comprehensive degree (red), eigenvector centrality (green), clustering coefficient (blue), and under risk hedging (black).

primary groupings were observed on the basis of this metric: C1–E15 and E16–E21. These clusters represent localized zones of vulnerability where fire could spread rapidly if triggered.

We evaluated the fire propagation effect across 39 identified risks in the network. On the basis of simulation results and the figure provided, the average level of the fire propagation effect was estimated to be 49.02%. The average level of the fire propagation effect was calculated as the overall mean propagation effect after the normalization of all risk levels of the four metrics (Fig. 7). Among the risks analyzed, R1, E6, E14, R4, and R2 exhibited the highest levels of the fire propagation effect.

For the comprehensive degree, two distinct groups were identified on the basis of this metric, namely, E3 to E12 and E13 to E18. Risks in the first group exhibited higher propagation effects, indicating their stronger effect on the network's structure and function. For clustering coefficients, the risk effects were grouped into C1 to E14 and E16 to R3, reflecting localized clusters where fire could spread more rapidly owing to tight interconnections. Five propagation effect groups were observed for the eigenvector centrality: C1 to C8, C9 to E1, E4 to E20, E21 to R2, and R3 to S2. These groupings highlight varying levels of influence and centrality within the network, helping to identify which risks are most critical to monitor. When risk hedging is applied randomly, the overall propagation effect decreases. This suggests that hedging strategies effectively reduce systemic vulnerability by weakening the connectivity between high-risk nodes. These risks are particularly influential in accelerating fire spread and triggering chain reactions. As such, they must be prioritized for targeted control measures to reduce their impact and enhance the network's resilience. In contrast, 17 risks demonstrated a low fire propagation effect. Although these risks pose less immediate danger in terms of spread, they require substantial resource allocation to prevent initial fire outbreaks. Their presence in the network underscores the importance of proactive fire prevention strategies, even for seemingly minor threats.

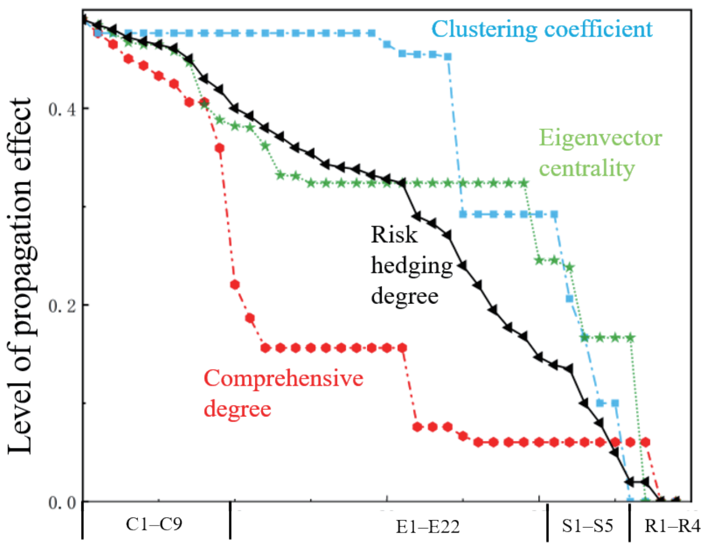

Fig. 7. (Color online) Groups of risks by propagation effect in risk network of comprehensive degree (red), eigenvector centrality (green), clustering coefficient (blue), and under risk hedging (black).

Overall, the results suggest that while a small number of risks have a disproportionately high influence on fire propagation, the majority exhibit lower levels of connectivity and impact. This distribution indicates that the fire propagation network possesses a degree of robustness, which helps mitigate the risk of widespread fire incidents and supports the effectiveness of strategic intervention.

The results underscore the importance of understanding how different metrics affect the fire propagation network. Risks with higher comprehensive degrees play a pivotal role in shaping the network's structure and functionality. If these risks are mismanaged or overlooked, the network's integrity may be compromised, making it more susceptible to rapid fire spread. Therefore, it is essential to develop corresponding control measures for these influential risks. By doing so, we can minimize the likelihood of fire propagation and delay the progression of chain reactions, ultimately enhancing the safety and resilience of the entire system.

6. Key Risk Control Measures

Fire incidents are caused by diverse causes, and fire control strategies need to be selected according to their characteristics (Table 2). On the basis of the identification of risks in the risk propagation network and the results of risk propagation simulations, sudden fire (R1), casualties (S1), explosion (R4), building collapse and damage (S5), and flammable material deflagration (R2) were identified as high-propagation risks. However, such risks showed a low level of effect on propagation in the risk network. Insufficient safety education and training (E14) and a lack of safety awareness (E1) were classified as mid-propagation risks. Risks with low comprehensive degrees showed no impact on network risk connectivity level and the propagation effect in the risk network. Electrical failure (C1) and the formation of an explosive gas mixture (C7) were

Table 2
Management strategies for different risks.

Risk	Strategy
R1	Link smoke sensors with intelligent sprinkler systems to detect smoke concentration in real time and automatically activate sprinklers to suppress fire spread. Use infrared thermal imaging cameras to locate high-temperature fire sources, integrate with ventilation systems to exhaust toxic gases, and guide personnel evacuation through acoustic-optic alarms.
S1	Deploy wearable vital sign sensors (heart rate, blood oxygen) and positioning tags to monitor personnel status in real time. Trigger emergency broadcasts on the basis of environmental data, dynamically adjust evacuation route indicator lights, and dispatch rescue robots to accurately locate trapped individuals and reduce casualty risks.
R4	Monitor hazardous environments using gas concentration and dust concentration sensors, and link explosion-proof ventilation equipment to rapidly dilute combustible gases. Install pressure sensors to detect pipeline overlimits, automatically cut off gas sources, and trigger explosion suppression devices to prevent explosions.
S5	Install vibration sensors and stress-strain sensors to monitor building structure deformation data in real time. Analyze load-bearing limits using digital twin models, issue warnings, and integrate hydraulic support systems to reinforce weak areas and avoid sudden collapses.
R2	Deploy temperature-humidity sensors and static electricity monitors in flammable material warehouses, and link environmental control systems to maintain low-temperature and low-static conditions. Use ultraviolet flame sensors to detect abnormal fire sources, trigger fire-resistant rolling shutters to isolate hazard zones, and inject nitrogen to reduce oxygen concentration and block deflagration conditions.

identified as low-propagation risks. Optimized risk management strategies are required by integrating real-world scenarios and selecting appropriate sensor types and deployment.

The simulation results summarized that 25% of the identified risks had a low propagation effect in the risk network, 55% showed a high risk connectivity level, and 45% required preemptive prevention strategies.

7. Conclusions

We analyzed fire-induced disaster chains through the development and simulation of a fire propagation model based on disaster chain theory and complex network analysis. By integrating empirical data from 75 official fire incident reports, we developed a model that identifies and quantifies the fire propagation capabilities of 39 interconnected risks, highlighting their roles in triggering secondary and derivative disasters. Comprehensive degree, clustering coefficient, and eigenvector centrality were measured, revealing that several risks were highly connected and critical to fire propagation, while others had minimal impact. Simulation results confirmed the robustness of the fire propagation network and underlined the importance of risk control measures. The deployment of sensor networks plays a pivotal role in early detection, risk suppression, and proactive fire management, although it is limited by system response and maintenance constraints. The results emphasize the need for tailored risk prevention strategies based on the specific propagation characteristics of each risk. As fire disasters become increasingly complex in urban environments, a systematic, data-informed approach is essential to enhance disaster resilience. The results of this study provide a basis for the development of predictive modeling, sensor optimization, and integrated disaster prevention systems to minimize loss and disruption from fire-induced disasters.

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