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Risk Identification of Critical Infrastructures Considering Dual Interdependency: A Complex Network Approach

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Abstract

Critical Infrastructures (CIs) are exposed to various risks, which hinder their successful operation and induce great losses. Due to the interdependency between risks and that between CIs, the identification of the most prominent risks becomes complex and challenging. However, existing studies rarely considered the dual interdependency of risks and CIs. This study proposes a double-layer network for multiple interdependent risks and CIs. The Design Structure Matrix (DSM) and Restart Random Walk (RRW) algorithm are combined to determine the impact of risks on CIs by incorporating the strength of dual interdependency. The LeaderRank algorithm is then used to rank these risk factors and an illustrative example is given to validate the model. The proposed model and algorithms can systematically quantify complex interdependencies embedded in the operation of CIs susceptible to multiple risks, and provide decision-makers with evidence to prioritize risks.

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Keywords: Critical infrastructure; Risk identification; Interdependency; Complex network

1. Main text

Critical Infrastructures (CIs) are exposed to various risks varying from natural hazards to human factors [1]. For instance, the 2011 earthquake in Japan with the following-up nuclear power plant explosion and natural gas leakages triggered widespread system breakdowns and substantial losses [2]. Due to the geopolitical conflicts between Russia and Ukraine and the rupture of the North Stream pipelines, disruptions on the natural gas system, electricity system and other CIs of EU persist, inducing severe damages on the its normal operation [3]. To guarantee public security, an

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effective identification of prominent risks is necessary for developing risk mitigation strategies and preventing the failure of CIs.

However, risk identification for CIs is immensely complex due to intricate interdependencies. On the one hand, interdependency exist between risk factors. For example, extremely cold weather often raises the probability of damages in water pipelines [3]. On the other hand, CIs are also interdependent. For example, electricity system relies on water system for hydropower generation, while water pumps and machinery in turn depend on electricity for activation [1]. Current studies mainly focused on either interdependent risks or CI interdependency. For instance, looking into electricity systems susceptible to earthquakes and hurricanes, Salman and Li constructed a framework for modelling multi-hazard risks [4]. Alon et al. proposed a comprehensive framework of multi-hazard risk assessment and management of mitigation strategies [5]. Based on graph theory, Johansson and Hassel proposed a modelling approach for risks in railway systems that captures function and geographic interdependencies [6]. Roni et al. proposed a conceptual framework to quantify risks in integrated water-electricity systems [7]. Whereas, the composite effects of dual interdependency are often underestimated, which hinders the systematic identification and prioritization of risks that have the most severe impacts on CIs.

Based on the above analysis, a complex network approach will be designed for determining the most prominent risks affecting multiple CIs considering dual interdependency. A research framework is first proposed for clarifying the research procedures, then the model for quantifying dual interdependency is constructed, followed by a Restart Random Walk (RRW) algorithm to solve the model. Finally, a LeaderRank algorithm is adopted for ranking the collection of risks, and an example is illustrated to validate the model.

2. Methodology

2.1. Research framework

Fig. 1. demonstrates the four-step research framework. First, interdependent CIs are clarified, and risk factors affecting these CIs are extracted based on literature reviews, expert interviews and close track of news. Second, the dual interdependency between risks and that between CIs, as well as the occurrence of risks in each CI are quantified using the Design Structure Matrix (DSM). Third, the model is solved using RRW algorithm and a steady-state probability matrix is generated that reflects the impact of each individual risk factor on each CI by incorporating dual interdependency. Finally, based on the results obtained from the RRW algorithm, a LeaderRank algorithm is adopted to rank the risk factors.

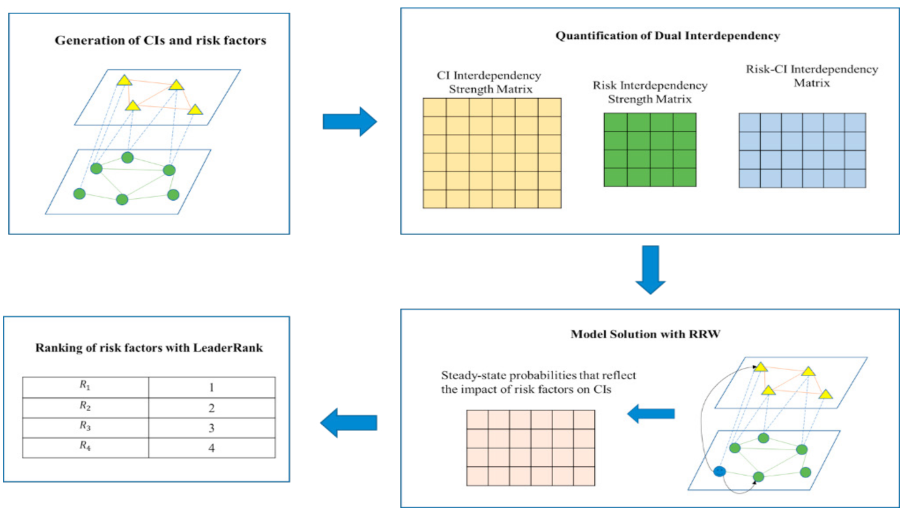

Fig. 1. Research framework

2.2. Quantification of dual interdependency

Due to the various categories of interdependencies, this paper adopts the DSM method for quantifying the interdependency between CIs and that between risks. A strong interdependency that denotes the direct connection between two CIs and a weak interdependency that denotes an indirect connection between two CIs are clarified. The calculation of the strength of strong interdependency is shown in formulation (1), where $DSM(i,j)$ represents the strength of the dependency from CI_i to CI_j, and N represents the number of CIs.

$$SI(CI_i,CI_j)=\frac{DSM(i,j)}{\sum_{k=1}^{N}(DSM(i,k)+DSM(k,i))}, i\neq j \tag{1}$$

The weak interdependency refers to the connection between CIs through a third-party CI as the intermediary node. The calculation of the interdependency strength is shown in formulation (2), where N_1 is the number of adjacent nodes from CI_i to CI_j, N_2 represents the number of CIs affecting CI_i in the network, and N_3 represents the number of CIs affected by CI_j.

$$WI(CI_i,CI_j)=\frac{\sum_{m=1}^{N_1}(SI(CI_m,CI_i)\times SI(CI_i,CI_m))}{\sum_{q=1}^{N_2}SI(CI_i,CI_q)+\sum_{k=1}^{N_3}SI(CI_\mathrm{k},CI_j)-2SI(CI_i,CI_j)} \tag{2}$$

The overall interdependency strength from CI_i to CI_j can then be calculated as in formulation (3):

$$TS(CI_i,CI_j)=SI(CI_i,CI_j)+WI(CI_i,CI_j) \tag{3}$$

The interdependency strength between risk factors can also be calculated using the above method and $R(i,j)$ is then generated.

2.3. Model solution with RRW

This paper uses the RRW algorithm to analyze the impact of one specific risk factor on each CI. The basic principle is that one actor starting from any node in the network can choose to move to adjacent nodes or to return to the starting point with a certain probability and start a new walk [8]. Firstly, a random walk matrix is constructed in formulation (4):

$$W=\begin{pmatrix}(1-\beta)\tilde{R} & \beta\tilde{A}\\ \beta\tilde{A}^T & (1-\beta)\tilde{CI}\end{pmatrix} \tag{4}$$

where β is the probability that the actor chooses to jump to another layer (from the risk layer to the CI layer), and $1-\beta$ is the probability that the actor continues to walk in the current layer (in the interdependent risk layer or the CI layer). CI denotes matrix of interdependency strength between CIs, R denotes the matrix of dependency strength between risks, and A denotes the matrix of interdependency from risks to CIs. $\tilde{CI},\tilde{R},\tilde{A}$ are the standardized matrices obtained from the above matrices, and $\tilde{A}^T$ is the transposition of $\tilde{A}$.

$$p^{(0)} = \begin{pmatrix} \lambda \tilde{A}^T \\ (1-\lambda)\tilde{R} \end{pmatrix} \tag{5}$$

$$p^{(t+1)} = (1-v)W^T p^{(t)} + vp^{(0)} \tag{6}$$

$$\Delta = \left| p^{(t+1)} - p^{(t)} \right| < \varepsilon \tag{7}$$

Formulation (5) indicates that starting from any risk factor in the risk layer, the initial probability matrix $p^{(0)}$ can be constructed by simulating n times, where n is the number of risk factors, and λ indicates the weight of interdependency between the risk layer and the CI layer. The iteration is performed according to Formulation (6), where W denotes the random walk matrix of the actor, and v represents its probability of returning to the starting point to begin a new walk, while $1-v$ is the probability of continuing to walk in the network. The iteration ceases when formulation (7) is satisfied, and the obtained matrix $p^{(t+1)}$ denotes the probability matrix in the steady state.

2.4. Risk ranking with LeaderRank algorithm

LeaderRank introduced a ground node and bidirectional edges between that node and all other nodes in the network, solving the problems of parameter generality and equal transition probability for each node. Based on the steady-state probability matrix obtained in the RRW algorithm, the weighted LeaderRank algorithm is used to rank the risk factors. Formulation (8) describes the specific calculation formulation, with each node denoting a risk factor, s_i means the score of node i, and ω_{ij} means the path weight from node j to i.

$$s_i(t+1) = \sum_{j=1}^{N+1} \frac{\omega_{ji}}{\sum_{l=1}^{N+1} \omega_{jl}} s_j(t) \tag{8}$$

3. Illustrative example

To validate the model, an illustrative example of risk identification for CIs in city B is shown to construct a dual-layer network of CIs and risks. The risk layer consists of four factors, which are hurricane, flood, design defect, and pipeline failures, represented by R_1, R_2, R_3, R_4, respectively. The CI layer consists of six CIs susceptible to these risk factors. The CI interdependency strength matrix, risk interdependency strength matrix, and risk-CI interdependency matrix are shown in Fig. 2.

a

	CI_1	CI_2	CI_3	CI_4	CI_5	CI_6
CI_1	CI_1	0.089	**0.121**	0.160	0.149	0.231
CI_2	0.167	CI_2	0.159	0.203	0.264	0.177
CI_3	0.137	0.137	CI_3	0.225	0.146	0.204
CI_4	0.120	0.111	0.124	CI_4	0.192	0.048
CI_5	0.037	0.113	0.126	0.179	CI_5	0.031
CI_6	0.237	0.041	0.120	0.166	0.05	CI_6

b

	R_1	R_2	R_3	R_4
R_1	R_1	0.547	0.803	0.504
R_2	0.241	R_2	1.361	1.242
R_3	0.401	1.383	R_3	1.584
R_4	0.267	1.907	2.375	R_4

c

	CI_1	CI_2	CI_3	CI_4	CI_5	CI_6
R_1	0	1	0	0	0	0
R_2	1	0	0	1	0	1
R_3	0	0	1	1	1	1
R_4	1	1	1	0	0	1

Fig. 2. (a) CI interdependency strength matrix; (b) risk interdependency strength matrix; (c) risk-CI interdependency matrix.

After applying the RRW algorithm, the steady-state probability matrix can be obtained in Fig. 3. To comprehensively consider the impact of risk factors on CIs, this paper adopts the LeaderRank algorithm to rank the risk factors, with the order from low to high being R_1, R_2, R_3, R_4.

	CI_1	CI_2	CI_3	CI_4	CI_5	CI_6
R_1	0.001	0.118	0.007	0.005	0.005	0.001
R_2	0.120	0.014	0.021	0.129	0.014	0.127
R_3	0.005	0.026	0.138	0.138	0.133	0.126
R_4	0.121	0.126	0.133	0.016	0.010	0.124

Fig. 3. Steady-state probability matrix

4. Conclusions

Accurately clarifying the impact of multiple risks on CIs is extremely challenging due to the complex interdependency between risks and that between CIs. A double-layer risk-CI network was constructed and the DSM method was adopted to calculate the interdependency strength. By using the RRW algorithm to analyze the constructed network, the impact of specific risks on each CI was calculated by incorporating dual interdependency. The LeaderRank algorithm was applied to rank the risk factors. This study contributes to the community by providing a systematic framework for quantifying dual interdependency in risk identification of CIs, yet the interdependency between each CI components have been ignored due to the complexity, which will be the focus of the future research.

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