Load Allocation Strategy for Command and Control Networks based on Interdependence Strength

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Abstract

Command and control networks(C2N) exhibit evident multi-network interdependencies owing to their complex hierarchical associations, interleaved communication links, and dynamic network changes. However, the existing command and control networks do not consider the effects of dependent nodes on the load distribution. Thus, we proposed a command and control networks load allocation strategy based on interdependence strength. First, a new measure of interdependence strength was proposed based on the edge betweenness, which was followed by proposing the inter-layer load allocation strategy based on the interdependence strength. Eventually, the simulation experiments of the aforementioned strategy were designed to analyze the network invulnerability with different initial load capacity parameters, allocation model parameters, and allocation strategies. The simulation indicates that the strategy proposed in this study improved the node survival rate of the interdependent command and control networks model and successfully prevented cascade failures.

Keywords: command and control networks, interdependence strength, load distribution strategy.

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1. Introduction

In the 6G[1] era, the interaction between different networks becomes more intricate and shows obvious characteristics of dependence, which is usually studied by the method of dependency networks. Interdependent networks are characterized by a certain dependency relationship between one another, making them more vulnerable than general networks considering cascade failures. Command and control networks(C2N) are featured by complex hierarchical associations, interleaved communication links, and dynamic network changes[2]. Moreover, they exhibit dependencies on multiple types of networks such as sensor, command and control, and firepower strike networks. Consequently, if a single failure were to spread across a network, cascade failures would be triggered, leading to risks such as destroyed nodes, broken links, and a destructed network. As a result, the combating effectiveness would be significantly affected. Thus, it is critical to develop a load allocation strategy for interdependent C2N to effectively address the problem of cascade failures and improve their invulnerability.

Research regarding interdependent networks started in 2010 when Buldyrev[3] et al. proposed a one-to-one cascade failure model for grid and communication networks for large-scale power outages. Currently, research regarding the cascade failure of dependent networks primarily focuses on the cascade failure model, coupling mode, coupling strength, and load-capacity(ML) model.

1) Regarding cascade failure models, researchers have primarily built different network models to analyze the cascade failure process of interdependent networks. Wang et al. [4] considered the direction of interdependent edges, and analyzed the cascade failure model of dependent networks based on asymmetric dependency relationships. Kang et al. [5] constructed a two-layer interdependence network model for the command information system and established a dynamic failure-recovery model. Tian et al. [6] considered the energy support relationship between the interdependent networks, and a load-based energy support cascade failure model was proposed. Yu et al. [7] proposed a cascade failure model for interdependent networks based on the load of interdependent edges and applied it to an interdependent metro-bus network to analyze the load distribution induced by the interchange between different transportation networks. In another study[8], the authors constructed a cascade failure model for interdependent networks based on actual data on urban clusters in the Chengdu-Chongqing region and compared the cascade failure of a single network with that of a coupled network. In addition, the non-uniformity of network structures owing to spatial factors in the real world was considered[9], and the cascade failure of spatially modular interdependent networks was investigated.

2) Regarding the coupling strength and modes, researchers have primarily analyzed the invulnerability of interdependent networks under varying coupling strengths and modes. The robustness of two-layer interdependent networks was analyzed under different attack strengths, coupling strengths, and topologies[10]. In another study[11], 14 methods of adding edge-linking strategies were proposed to improve the robustness of scale-free networks considering deliberate attacks. Li et al. [12] analyzed the robustness of scale-free interdependent networks under three coupling strategies: assortative link, disassortative link, and random link. Xu et al. [13] generated different types of directed–undirected interdependent networks with varying coupling modes and investigated the cascading failure robustness of these types of networks. Chen et al. [14] proposed an internal link additional strategy and a coupling link additional strategy based on low relative betweenness. Yang et al. [15] identified the key vulnerable edges by relying on the centrality, degree, betweenness, and PageRank of the nodes at both

ends of the interdependent edges and proposed a strategy to remove the vulnerable coupling edges. Lin et al. [16] calculated coupling coefficients based on the proportion of intra- and inter-layer load allocation and introduced a dynamic coupling strategy based on these coupling coefficients. Hao et al. [17] proposed assortative coupling with harmonic closeness (ACH) and disassortative coupling with harmonic closeness (DCH) considering the shortest paths between the nodes.

3) Regarding the ML model, researchers have primarily studied the initial load on the nodes and the load allocation strategies. Zhang et al. [18] proposed a load redistribution strategy for interdependent networks based on the maximum remaining capacity of neighboring nodes. Kumar et al. [19] considered a multi-layer interdependent network model and proposed an optimal load redistribution strategy for intra-layer and inter-layer links. Xing et al. [20] constructed a double-layer networked command information system with weights and analyzed the performance of three different load allocation strategies and the integrated allocation strategy. Liu et al. [21] constructed an asymmetric interdependent C2N and communication network and proposed a capacity allocation method for resource-constrained nodes. In a previous study[22-23], a cascading failure model of interdependent networks based on mutual traffic redistribution under fluctuant load was proposed. Besides, the interdependence between coupled layers is realized by mutual traffic redistribution. Fu et al. [24] proposed an interdependent cascade model and analyzed the effects of different attack strategies on the robustness of the interdependent network. Liu et al. [25] proposed a partially interdependent network model of multimode rail transit, and developed a novel cascading overload failure model with tunable parameters of load redistribution inter subnetwork. Considering the residual capacity, Zhang et al. [26] proposed a dynamic load redistribution strategy based on the local load factor of the nodes. Nevertheless, most of the aforementioned studies present improvements in the load distribution strategies based on the node degree, betweenness, and residual capacity of a single network, and thus cannot reflect the effects of the interdependence strength of the nodes on cascade failure.

Although presenting a foundation for the study of cascade failures of interdependent C2N, the aforementioned studies merely considered the dependent edges as the connected edges between the networks, and failed to consider that the connected edges of different interdependent nodes would generate different interdependence strengths. Meanwhile, most existing load distribution strategies have not considered the effects of dependent nodes on load redistribution. Thus, we defined the interdependence strength of the C2N in this study considering the edge betweenness and the shortest path between the interdependent nodes and proposed a load allocation strategy for the C2N based on the interdependence strength, which consequently improved the invulnerability performance of the C2N. The primary contributions of this study are as follows:

1) A new definition of the interdependence strength of C2N was given based on the edge betweenness and the shortest path between the interdependent nodes, and a measurement method for the interdependence strength based on the edge betweenness was proposed.

2) A C2N load allocation strategy based on interdependence strength was proposed to address the discord between load allocation and interdependence.

3) Algorithm simulation experiments were designed to analyze the parameter changes of the initial load definition, allocation model parameter changes, and the performance of different allocation strategies considering the network invulnerability.

Section 2 presents an analysis of the characteristics of the C2N and a respective two-layer interdependent model. Section 3 provides a new definition of the interdependence strength and proposes a measurement method for the interdependence strength based on the edge betweenness. In Section 4, based on the ML model, we established the initial load definition method considering the layer degree and proposed a C2N load allocation strategy based on the interdependence strength. Section 5 presents the simulation analysis; simulation experiments were designed to compare and analyze the changes of the initial load definition parameters, distribution model parameters, and the network invulnerability performance under different allocation strategies. Section 6 concludes this study with a summary and outlook.

2. Two-layer interdependent C2N model

A C2N system is composed of a battlefield command and control entities at all levels and of all types that have a command and control, as well as the coordination relationship and their associated relationships[27]. Based on the complex network theory, the rules for constructing an interdependent command and control network were set up as follows:

Rule 1: Treat all levels of command entities and their functional units as nodes of the network without considering individual differences.

Rule 2: The command and control relationship within the system serves as the edge of the network, including the command information flow and the feedback letter flow, with no direction of the edge in the network.

Rule 3: All edges have the same weight of 1 and there are no edges connected to the node itself.

Moreover, it is also necessary to consider the two primary information flows of the C2N [28]: (i) the command and control relationship from the higher to lower hierarchy, and (ii) the coordination relationship between the same hierarchy. Based on this, a two-layer interdependent C2N model was constructed, as presented in **Fig. 1**. To simplify the analysis, the connection between two sub-networks was established by random coupling, and the inter-layer coupling edge was only set up as a command and control relationship between two layers, which characterizes the command and control information flow.

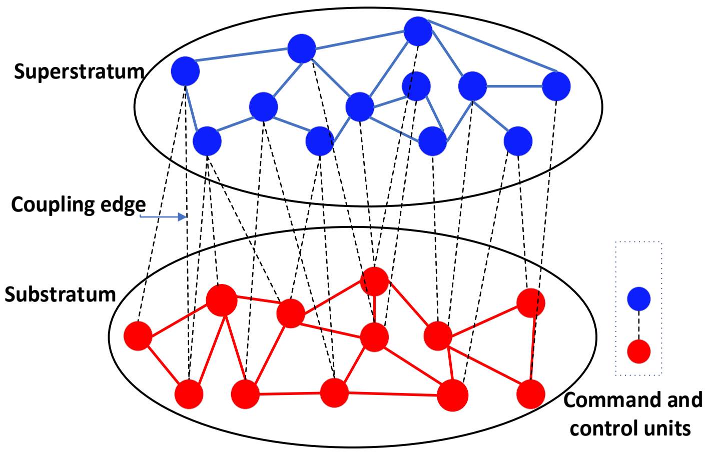


Fig. 1. Two-layer interdependent command and control network model.

The two-layer sub-networks are denoted as Network A and Network B. The network is denoted by $\boldsymbol{G}=(V, E)$. The set of all nodes in the network is denoted by $V=N_A \cup N_B$, $V_A=\{v_i, i\in[1,N_A]\}$, $V_B=\{v_i, i\in[1,N_B]\}$. The number of nodes in Network A and

Network B is denoted by N_A and N_B, respectively. $E=E_{connectivity} \cup E_{dependency}$ denotes the set of the intra-layer connected edges and inter-layer dependent edges in the network, where the intra-layer connected edges represent the coordination of the nodes within a layer while the inter-layer dependent edges characterize the command and control relationship of the upper layer to the lower layer. The adjacency matrix $\boldsymbol{W}$ denotes the network G, and the two-layer interdependent command and control network model is represented as follows:

$$\boldsymbol{W}=(\mathrm{w}_{\mathrm{ij}})_{\mathrm{N}\times\mathrm{N}} = \begin{pmatrix} \mathrm{w}_{A} & \mathrm{w}_{AB} \\ \mathrm{w}_{BA} & \mathrm{w}_{B} \end{pmatrix}_{N\times N}, \quad \mathrm{N}=\mathrm{N}_{\mathrm{A}} \cup \mathrm{N}_{\mathrm{B}} \tag{1}$$

Where $w_{\mathrm{ij}} = \begin{cases} 1, (v_i, v_j) \in E \\ 0, \quad others \end{cases}$.

3. Edge betweenness-based interdependence strength

Interdependent edges reflect the association between sub-networks in terms of the exchange of material, energy, and information[29]. The more frequent the exchange, the greater the mutual influence between networks. The strength of mutual influence between such networks is called interdependence strength.

The interdependence strength measures the tightness of the connection between the nodes in the two networks that are coupled to one another and also indicates the degree of influence and control of one network on the other. Literature [30] argues that the more important the interdependent nodes i and m are, the greater impact their failures will have on the occurrence and propagation of cascading failures in interdependent networks. It is pointed out that the node importance is positively correlated with the interdependency strength. Besides, the node degree is used to measure the node importance, and the definition of interdependency strength is given as follows:

$$Q_{im} = w_i w_m = k_i^{\delta} k_{\mathrm{m}}^{\delta}, \delta \in [0,1] \tag{2}$$

where Q_{im} denotes the interdependency strength between two nodes with a coupling relationship,and $W_i = k_i^{\delta}$ represents the weight of node i . k_i^{δ} represents the degree of node i, and δ is the adjustable parameter of the interdependence strength. The degree only measures the local importance of the node and does not measure the global information of the network. We propose a novel definition of interdependency strength based on the physical significance of interdependent edges in the exchange of material energy information between subnetworks. It takes into account the global information associated with these edges starting from the frequency of information flow passing through interdependent edges between subnets.

First, the definition of edge betweenness centrality is given. The edge betweenness is the ratio of the number of the shortest paths passing through the edge to the total number of shortest paths in the network. Supposedly, if the shortest path through the edge e_{ij} between nodes g and k is $\boldsymbol{L}(g,k,e_{ij})$ then the edge betweenness B_{ij} of e_{ij} can be expressed as follows:

$$\mathrm{B}_{ij} = \frac{\sum_{g}^{n}\sum_{k}^{n}\frac{L(g,k,e_{ij})}{L(g,k)}}{n(n-1)/2} \tag{3}$$

The edge betweenness reflects the transmission and control capacities of the path relative to the network resources. The larger the edge betweenness, the more times any node in the network passes through the edge, the stronger the transmission and control capacities of the edge to network resources, and the greater its role in the network[31].

Secondly, a new definition of the interdependence strength of the interdependent C2N was given based on the definition method of the edge betweenness and frequency of passing through the dependent edge when the information energy is transferred between:

$$Q_{mn} = b_{mn} = \sum_{i}^{N_A} \sum_{j}^{N_B} \frac{\theta_{ij}(e_{mn})}{\theta_{ij}} \tag{4}$$

Where Q_{mn} is the strength of the dependence between nodes m and n. b_{mn} is the proportion of the paths passing through the interdependent edge e_{mn} relative to the total number of the shortest paths from nodes in Network A to nodes in Network B, and θ_{ij} denotes the number of the shortest paths from node i in Network A to node j in Network B. $\theta_{ij}(e_{mn})$ is the number of the shortest paths from node i in Network A to node j in Network B that pass through the interdependent edge e_{mn}. The larger the b_{mn}, the higher the frequency of information interaction between subnetworks flowing through the dependent edge, indicating that the dependent edge plays a stronger role in the network information flow process, and the stronger the interdependence strength between the nodes.

4. C2N load allocation strategy based on the interdependence strength

4.1 ML model

Existing initial load methods mostly rely on metrics such as node degree and betweenness to define the initial load of nodes. However, C2N is different from transportation networks, power grids, etc., as it possesses strict hierarchical characteristics. The higher the command hierarchy level a node occupies, the more important it is, and it will bear a relatively larger initial load. However, nodes in the upper layers may not necessarily have larger degrees, and nodes in the lower layers may not necessarily have smaller degrees. Therefore, referring to the initial load definition method based on the hierarchical degree of literature [32], and the initial load on the nodes of the two-layer interdependent C2N based on the node degree and node hierarchy were defined as follows:

$$\mathrm{L}_i(0) = \alpha \times \mathrm{k}_i{}^{\lambda} + (1-\alpha) \times (D+1-d_i)^{\gamma} \tag{5}$$

Here, k_i represents the degree of the node, D represents the two-layer interdependent command and control network (D=2), and d_i represents the hierarchy at which the node is located. d_i =1 indicates that the node i is at the upper node of the interdependent command and control network, and d_i=2 indicates that the node i is at the lower node. $\alpha \in [0,1]$ and $\lambda, \gamma \in [0,+\infty]$ denote the initial load regulation parameters， which is used to adjust the influence of degree value and level on the initial load of nodes. When $1-\alpha$ is relatively large, the initial load of nodes in the network primarily depends on the node hierarchy, making the hierarchical structure of the initial load distribution more pronounced. However, in this case α is relatively small and it may lead to negligible differences in the initial load among nodes belonging to the same hierarchy level. Conversely, when α is relatively large, the situation is reversed. When $\alpha = 1$, the initial load of nodes is not affected by their organizational positions and is solely determined by their degrees. On the other hand, when $\alpha = 0$, the initial load of nodes is independent of their degrees and is entirely dependent on their organizational positions.

The node capacity represents the maximum load that the node can carry and is strictly controlled by the costs. Accurately defining the capacity of the node provides the network a better resistance to invulnerability without utilizing additional costs and resources. In this study, the node capacity was defined using the linear relationship in the ML model as follows:

$$\mathrm{C}_i = L_i(0) + \beta L_i(0) \tag{6}$$

Among them, β is the capacity adjustment parameter, which is used to measure the remaining capacity of the node in the initial state. The larger β is, the larger the remaining capacity of the node in the initial state is, and the stronger the ability of the network to resist cascading failures. However, the larger β is, the higher the network construction cost will be. Considering the network cost, generally β ranges from 0 to 1.

4.2 Load allocation strategy

The C2N has strict hierarchical characteristics, and each node has itself ability to participate in the task matching its organizational status. The organizational status and performance among the upper layer nodes is higher than that of the lower layer nodes. In the two-layer interdependent C2N model, after the lower layer nodes fail, their loads are distributed to the interdependent nodes of the upper layer and neighboring nodes of the same layer. The residual capacity allocation strategy was adopted within the same layers. When allocating to the upper layer nodes, the interdependence strength between the interdependent nodes is considered as follows: the stronger the interdependence between the nodes, the stronger the connection. The equation is defined as follows:

$$\mathrm{L}(\mathrm{C}_j, \eta, Q_{ik}, \mathrm{L}_j) = \begin{cases} \dfrac{\mathrm{C}_j\text{-}\mathrm{L}_j}{\sum_{m\in\Gamma_i} \mathrm{C}_m\text{-}\mathrm{L}_m}, \Gamma_i \neq \varnothing, \mathrm{U}_i = \varnothing \\ \eta \dfrac{\mathrm{C}_j\text{-}\mathrm{L}_j}{\sum_{m\in\Gamma_i} C_m - L_m} + (1-\eta)\dfrac{Q_{ik}}{\sum_{n\in U_i} Q_{in}}, \Gamma_i \neq \varnothing, \mathrm{U}_i \neq \varnothing \\ \dfrac{Q_{ik}}{\sum_{n\in U_i} Q_{in}}, \Gamma_i = \varnothing, \mathrm{U}_i \neq \varnothing \end{cases} \tag{7}$$

Where C_j is the capacity of node j, and L_j is the load of node j at a moment; Q_{ik} is the interdependence strength of the interdependent nodes i and k, and $\eta \in (0,1)$ is the load distribution adjustment factor. Γ_i is the set of sibling nodes of the failed node i, and U_i is the set of the upper-hierarchy dependent nodes of the failed node i. When $\Gamma_i \neq \varnothing$,$U_i = \varnothing$, indicating that the failed node has no dependent nodes, the load is assigned only to the sibling nodes. When $\Gamma_i = \varnothing$,$U_i \neq \varnothing$, indicating that the failed node has no neighbors, its load is assigned only to the upper-hierarchy dependent nodes. When $\Gamma_i \neq \varnothing$, $U_i \neq \varnothing$, indicating that the failed node has both neighbors and the upper-hierarchy dependent nodes, the load of the failed node will be assigned according to the interdependence strength and peer-level cooperative strength; this assignment strategy integrates the influence of the interdependence strength and cooperative strength on the load redistribution of the failed node, and the weights of the influencing factors can be adjusted according to the coefficient η.

According to the aforementioned load distribution policy, the additional load by the sibling neighbor node or upper layer dependent node j of the failed node is as follows:

$$L_j(t+1) = L_j(t) + \Delta L_{i\to j} = L_j(t) + L_i\left(t\right) \times \mathrm{L}(\mathrm{C}_j, \eta, Q_{ik}, \mathrm{L}_j) \tag{8}$$

Where ΔL_j is the load assigned to node j after the failure of node i, $L_i(t)$is the load of node i at time t, and if $L_j(t+1)>C_j$ is considered as the node overload failure, it will trigger the next round of the cascade failure.

4.3 Invulnerability evaluation index

4.3.1 Node survival rate

When the network cascade failure reaches the steady state, most researchers use the giant component to measure the resistance of the network to invulnerability; however, the nodes or connected edges that are not part of the giant component in real networks do not necessarily fail. As long as the nodes are not isolated and overloaded, they remain normal nodes. Therefore, the node survival rate F, which was obtained from previous literature[4], was used to measure the invulnerability of the network and is defined as follows:

$$F = \frac{N_A^* + N_B^*}{N_A + N_B} \tag{9}$$

Here, N_A and N_B and N_A* and N_B* indicate the total number of nodes in networks A and B before and after failure, respectively. A larger node survival rate F indicates a smaller impact of the cascade failure on the network and better robustness of the network.

4.3.2 Network carrying capacity

Simultaneously, the remaining capacity of the nodes after cascade failure needs to be considered. The network carrying capacity indicator CF is used to measure the capacity of the nodes to withstand additional load after the network reaches a steady state, which is defined as follows:

$$CF = \frac{\sum_{i=1}^{N_A^*+N_B^*} (\mathrm{C}_i - L_i)}{conL_i(0)} \tag{10}$$

where C_i is the node capacity, L_i is the initial node load and $conL_i(0)$ is the sum of the initial loads of all the nodes in the network.

4.3.3 Node deletion rate

The node deletion rate, denoted as p, represents the extent to which the network is under attack. The larger the node deletion rate, the more nodes are under attack in the network, indicating a higher level of damage to the network. The definition is as follows:

$$p = \frac{N^*}{N} \tag{11}$$

Where N represents the total number of nodes in the network, and N^* represents the number of nodes under attack.

5. Simulation analysis

The C2N has scale-free and small-world characteristics. The two-layer interdependent C2N in this study uses a combination of scale-free (BA) and small-world network (NW) for the simulation analysis. The dependency edges are constructed by random coupling, and the coupling pattern is many-to-many, with an average of four dependency edges between one node.

5.1 Impact of the load capacity parameters on the network's anti-invulnerability performance

The initialization parameter settings are shown in **Table 1**. D represents the total number of hierarchical levels in the command network. This paper considers a double-layer structure, that is D=2. λ and γ are used to adjust the importance of nodes' degree and hierarchy in the initial load. In this paper, the command hierarchy consists of two layers, and the node degrees are much larger compared to the hierarchy levels. To achieve a relatively balanced proportion between node degree and hierarchy, the principle of $\lambda<\gamma$ is adopted, initializing the value of λ=0.9, γ=1.9. β is the capacity parameter, and it is initialized as 0.4, following the principle that it should not exceed twice the cost constructed by the initial network. The total number of nodes in networks A and B is the same, which is 200. A random attack strategy was used to attack the lower-level network; the values of the parameters were adjusted. Each group of experiments was conducted 100 times to determine the average value.

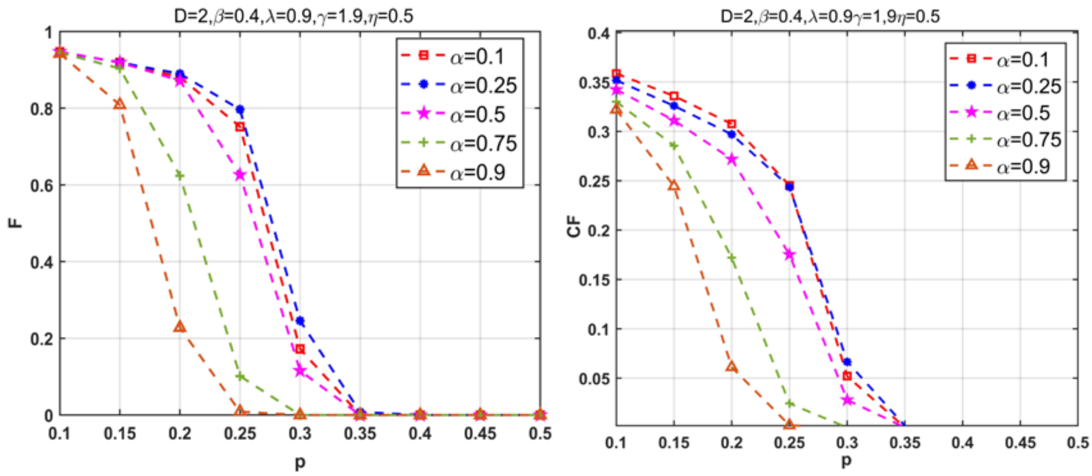
Table 1. Initial parameter settings

Name	Layers of the C2N	Initial load regulation parameters		Capacity parameter	load distribution adjustment parameter	The number of nodes in network A	The number of nodes in network B
Parameter	D	λ	γ	β	η	N_A	N_B
Value	2	0.9	1.9	0.4	0.5	200	200

5.1.1 The effect of the initial load parameter α on the invulnerability performance of the network

α is adjusted based on the importance of the node degree and layer level in the load capacity model. If α is too small, the node load depends on the node hierarchy, the node load of the same layer cannot be distinguished, and the lower layer nodes with larger degree values do not have a larger capacity, thus the fault will rapidly propagate within the layer. If α is too large, the initial load and capacity of the nodes depend on the node degree, the initial load of the upper and lower layer nodes with the same degree value cannot be distinguished, and the upper layer nodes with smaller degree values have a smaller capacity, thus the fault will rapidly spread in the upper layer.

To determine the value of α, **Fig. 2(a)** and **Fig. 2(b)** demonstrate the effect of the node survival rate F and the network carrying capacity CF for α as {0.1, 0.25, 0.5, 0.75, 0.9}. As the node deletion rate p increases, both F and CF gradually decrease. When the α values range from 0.1 to 0.25, the decreasing trend of F and CF becomes slower; when $\alpha \geq 0.25$, the decreasing trend of F and CF increases more rapidly, and the network performance sharply deteriorates. The network performance is observed to be optimal when α is 0.25.

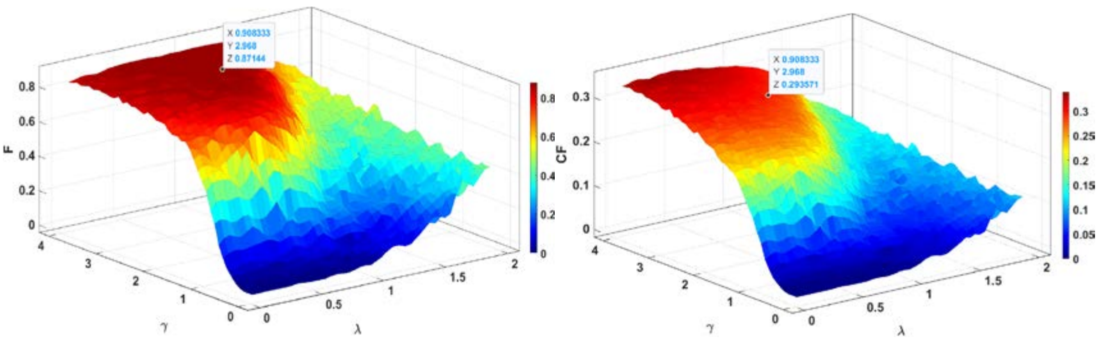


(a)Variation of F with α fetching (b)Variation of CF with α fetching

Fig. 2. The relationship between the invulnerability and the α.

5.1.2 The effect of the initial load parameter α on the invulnerability performance of the network

Based on the previous analysis, the parameters were set as α=0.25, D=2, η=0.5, and β=0.4. **Fig. 2(a)** demonstrates that when the node deletion rate is less than 0.2, the effect of the parameter changes on the network performance changes is insignificant. For the convenience of determining the values of λ and γ, the node deletion probability should be greater than 0.2; p=0.23 was selected in this subsection.



(a)Variation of F under different λ, γ (b)Variation of CF under different values λ, γ

Fig. 3. The relationship between the invulnerability and the λ, γ

Fig. 3 demonstrates the effects of the initial load regulation parameters λ and γ on the network performance. As λ and γ increase, both F and CF increase. When the values of λ and γ are approximately 0.9 and 2.9, both F and CF values are larger, and the network performance is better. Meanwhile, at λ=0.9, there is no significant change in F and a slight change in CF as the value of γ increases. Therefore, considering the constrained network cost, the following values were selected: λ=0.9, and γ = 2.9.

5.1.3 The effect of the capacity parameter β on the invulnerability performance of the network

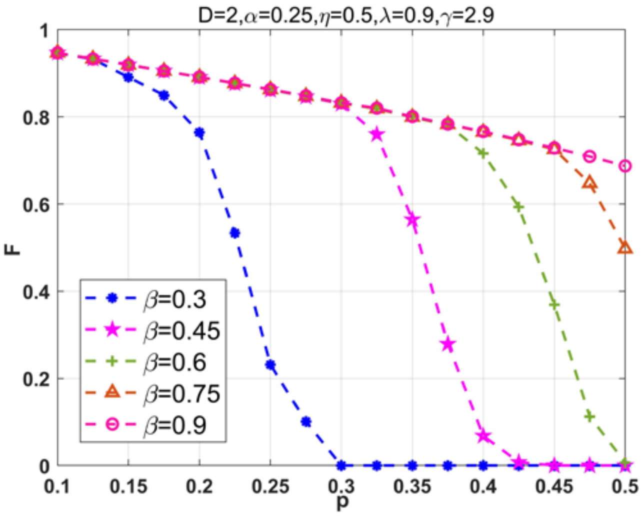
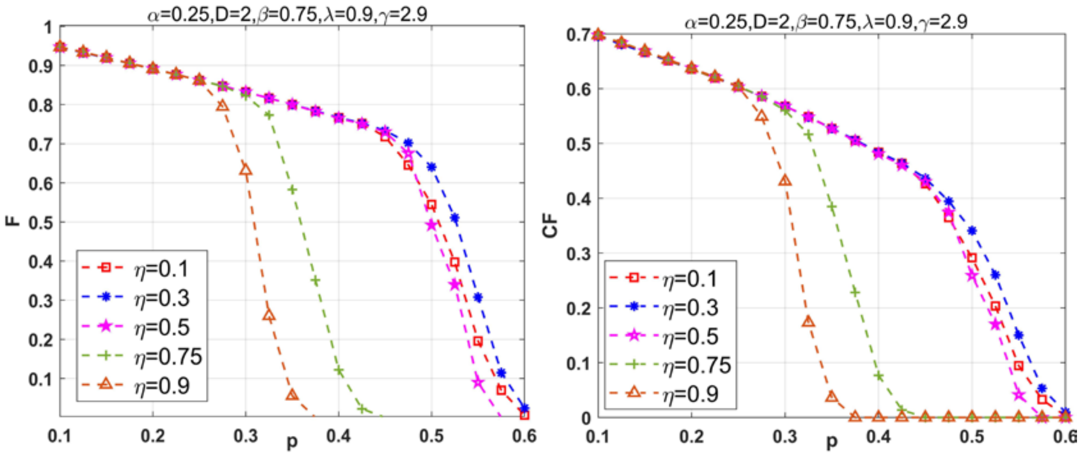


Fig. 4. Variation of F for β values

Fig. 4 demonstrates the effect of the capacity parameter β on the invulnerability of the network. β has values ranging from [0,1], where α=0.25, D=2, η=0.5, λ=0.9, and γ=2.9. If β is too small, the network will be very fragile. If β is too large, it can improve the network invulnerability but requires a significantly high construction cost. Fig.4 demonstrates that as β increases, F decreases more slowly, and the invulnerability performance of the network further increases. Moreover, as β increases, the rate of decrease for F becomes less and less. When β ranges from 0.75 to 0.9, there is no difference in F at $p \leq 0.45$, indicating that continuing to increase the value of β at this time does not significantly improve the network's resistance to invulnerability. Therefore, the value of β was set to be 0.75 while considering the construction cost.

5.2 Impact of the load distribution regulation factor on the network resistance to invulnerability

The following parameters were selected: α=0.25, D=2, λ=0.9, and γ=2.9, and β=0.75. The impact of the load distribution regulation coefficient η on the network invulnerability under BA-BA with a network size of 200 using a random attack strategy on the lower layer network is shown in **Fig. 5**.



(a)Variation of *F* under different values of η (b)Variation of *CF* under different values of η

Fig. 5. The relationship between the invulnerability and the η

η regulates the ratio of the load distribution to intra-layer and inter-layer. When an excessive load is distributed to upper layers, it will lead to an overload failure of the upper layer nodes without a sufficient capacity. When an excessive load is distributed on the same layer, it will also tend to cause an overload failure of the neighboring nodes on the same layer. Both cases will lead to a rapid spread of cascade failures in the network. **Fig. 5** demonstrate that as η increases, the invulnerability performance of the network increases and then decreases; when η=0.3, the load distribution ratio between the layers within a layer is balanced and the invulnerability performance of the network is optimal.

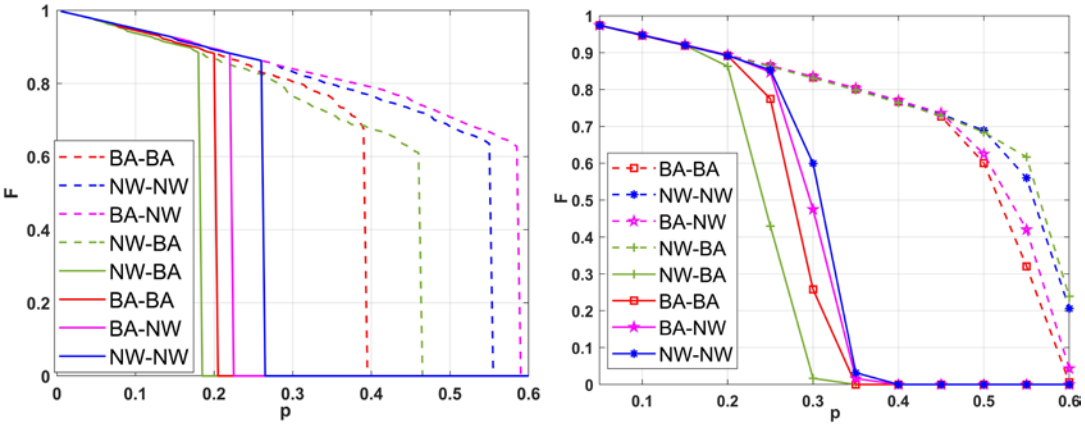
5.3 Impact of the load distribution regulation factor on the network resistance to invulnerability

5.3.1 Analysis of the invulnerability performance of different interdependent network models

The following parameters were selected: α=0.25, D=2, η=0.3, β=0.75, λ=0.9, γ=2.9, N_A=N_B=200. The four two-layer interdependent C2N models are BA-BA, NW-NW, BA-NW, and NW-BA; the residual capacity allocation strategy is used within the layers. In this study, the network invulnerability performance of the four network models was compared under deliberate and random attacks with and without the allocation strategy of this study as shown in **Table 2**.

Table 2. Comparative analysis of different interdependent network models

network models	Intra-layer load distribution strategy	Inter-layer load distribution strategy
BA-BA NW-NW BA-NW NW-BA	Remaining capacity	No inter-layer load distribution policy / Inter-layer load distribution based on dependency strength(Our method)



(a)Deliberate attack (b)Random attack

Fig. 6. Effect of having an inter-layer allocation strategy on the network resilience

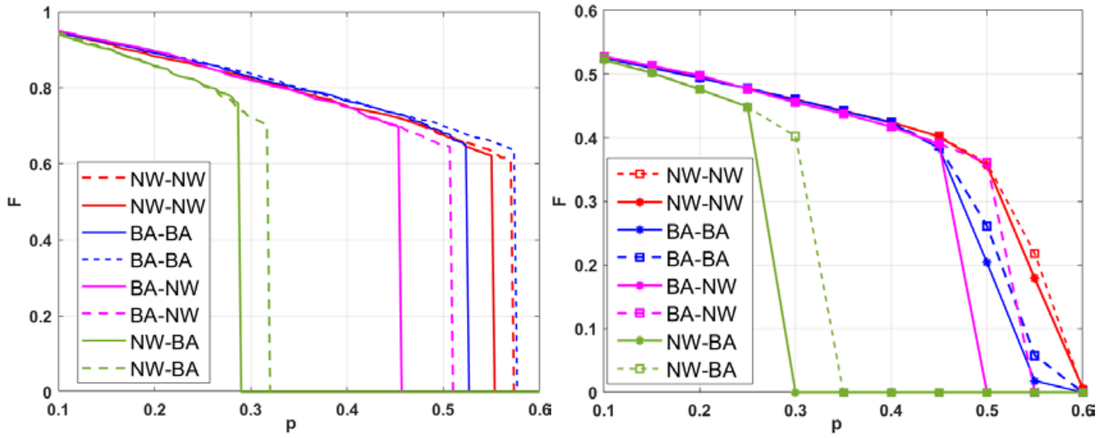
The solid line in **Fig. 6** indicates no inter-layer load distribution policy, and the dashed line indicates the use of an inter-cascade allocation policy based on the interdependence strength. As shown in **Fig. 6(a)**, there is a critical attack value for the network under deliberate attacks; when this value is reached, the network performance abruptly changes and cascade failures rapidly spread within the network, causing the network to instantaneously collapse. As shown in **Fig. 6(a)** and **Fig. 6(b)**, with the adoption of the inter-cascade load allocation strategy based on the cascade strength, the invulnerability of all four cascade network models is significantly improved during both random and deliberate attacks. Under a deliberate attack, the most significant improvement in the invulnerability of the BA-NW dependent network model is observed. Under random attacks, the most significant improvement in the invulnerability of the NW-BA dependent network model is observed.

5.3.2 Analysis of the invulnerability of different phase dependent strengths

The following parameters were selected: α=0.25, D=2, η=0.3, β=0.75, λ=0.9, γ=2.9, N_A=N_B=300; the robustness of the BA-BA interdependent network gradually increases as the interdependence strength adjustment parameter δ becomes larger in (2). Therefore, the interdependence strength adjustment parameter of δ=1 is considered in this subsection. As shown in **Table 3**, four network models(BA-BA,NW-NW,BA-NW,NW-BA) are also selected; The residual capacity allocation strategy remains to be used within the layer to compare the invulnerability performance of the two interdependence strength metrics in this study with that obtained in the literature[30].

Table 3. Comparative analysis of different dependent strength

network models	Intra-layer load distribution strategy	Inter-layer load distribution strategy
BA-BA NW-NW BA-NW NW-BA	Remaining capacity	The dependence strength based on the degree value/ The dependence strength based on the edge betweenness（Our method）



(a)Deliberate attack (b)Random attack

Fig. 7. Comparison of different phase dependent strengths

As shown in **Fig. 7**, the solid line indicates degree value method of reference [30], and the dashed line indicates the methods of this study.

From **Fig. 7**, it can be seen that the strategy in this paper can better improve the network invulnerability than the method in reference [30] under the four network models. Moreover, in the case of heterogeneous networks BA-NW and NW-BA, the strategy in this paper has significant advantages. Because the previous study[30] uses the node degree values at both ends of the dependent edges to measure the interdependence strength between nodes, considering that the larger the node degree value, the greater the impact caused by the failure at that point. However, only the local importance of the nodes is measured, ignoring that there may be some nodes of low degree that occupy the central position in the network, while other nodes of high degree may be located at the edge of the network. And two nodes with the same degree value will have different influences in the network. Especially in the case of large differences in network structures, the degree of mutual influence and control between nodes is not accurate because of the lack of consideration of the global leading to poor network invulnerability. The strategy used in this study is based on the edge betweenness, which considers the role and influence of nodes in the entire network starting from the frequency of information flow passing through interdependent edges between subnets. The dependence strength definition based on edge betweenness can more accurately define the degree of interaction between dependent nodes in the process of cascade failure. Therefore, the four network models which adopt the dependent strength method based on edge betweenness have obvious advantages in the anti-invulnerability.

6. Conclusion

In this study, we constructed a two-layer interdependent C2N model, for which a load allocation strategy was proposed based on the interdependence strength. In addition, simulation experiments were designed to verify the effectiveness of the strategy and references were provided for the cascade failure analysis of the interdependent command and control network. With the continuous improvement of information, the organizational structure of C2N is increasingly complex. In the next step, we will thoroughly study the load allocation problem of a multi-layer interdependent command and control network and consider the effects of the coupling mode on the strategy.

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References

[1] V. K. Quy, A. Chehri, N. M. Quy, et.al, "Innovative trends in the 6G era: a comprehensive survey of architecture, Applications, Technologies, and Challenges," *IEEE Access*, vol. 11, pp. 39824-39844, 2023. Article (CrossRef Link)

[2] X. E. Gao, B. Chen, P. L. Jiang, et al, "Hierarchy-entropy based method for command and control networks reconfiguration," *Journal of Supercomputing*, vol.78, no.13, pp.15229-15249, April 2022. Artical (CrossRef Link)

[3] S. V. Buldyrev, R. Parshani, G. Paul, et al, "Catastrophic cascade of failures in interdependent networks," *Nature*, vol.464, no.7291, pp.1025-1028, April. 2010. Article (CrossRef Link)

[4] C. Wang, J. L. Guo, A. W. Shen, "Analysis of cascading failures of interdependent network based on asymmetric dependency," *Journal of Systems Engineering and Electronics*, vol.42, no.05, pp.1093-1101, May 2020.

[5] D. Kang, J. H. Li, Z. Wang, et al, "A resilience recovery strategy of a double-layer interdependent network model of C^4KISR," *Electronics Optics & Control*, vol.28, no.12, pp.22-26, Dec. 2021. Article (CrossRef Link)

[6] M. Tian, Z. C. Dong, M. J. Cui, et al, "Energy-supported cascading failure model on interdependent networks considering control nodes," *Physica A: Statistical Mechanics and its Applications*, vol.522, pp.195-204, May 2019. Article (CrossRef Link)

[7] R. B. Yu, Y. Jiang, Y. W. Yan, et al, "Research on robustness of interdependent networks considering dependent side load," *Journal of University of Electronic Science and Technology of China*, vol.51, no.05, pp.774-785, Sep. 2022. Article (CrossRef Link)

[8] S. Liu, C. S. Yin, D. Chen, et al, "Cascading failure in multiple critical infrastructure interdependent networks of syncretic railway system," *IEEE Transactions on Intelligent Transportation Systems*, vol.23, no.6, pp.5740-5753, Jun. 2022. Article (CrossRef Link)

[9] D. Vaknin, A. Bashan, L. A. Braunstein, et al, "Cascading failures in anisotropic interdependent networks of spatial modular structures," *New Journal of Physics*, vol.23, no.11, pp.113001, Nov. 2021. Article (CrossRef Link)

[10] N. Wang, Z. Y. Jin, J. Zhao, "Cascading failures of overload behaviors on interdependent networks," *Physica A: Statistical Mechanics and its Applications*, vol.74, pp.125989, July 2021. Article (CrossRef Link)

[11] C .Y. Chen, Y. Zhao, H. M. Qin, et al, "Robustness of interdependent scale-free networks based on link addition strategies," *Physica A: Statistical Mechanics and its Applications*,vol.604, pp.127851,Oct. 2022. Article (CrossRef Link)

[12] M. N. Li, J. L. GUO, "Study on load-induced robustness of interdependent networks," *Application Research of Computers*, vol.36, no.08, pp.2388-2391, Aug. 2019. Article (CrossRef Link)

[13] X. J. Xu, X. W. Fu, "Analysis on cascading failures of directed–undirected interdependent networks with different coupling patterns," *Entropy*, vol.25, no.3, pp.471, Apr. 2023. Article (CrossRef Link)

[14] S. M. Chen, Y. M. Dai, H. Y. Cheng, "Research of the link addition strategies for improving the Robustness of Interdependent Networks," *Journal of University of Electronic Science and Technology of China*, vol.48, no.01, pp.103-109, Jan. 2019. Article (CrossRef Link)

[15] X. H. Yang, W. H. Feng, G. Chen, et al, "Enhancing coupled networks robustness via removing Key fragile dependency links," *IEEE Transactions on Circuits and Systems II: Express Briefs*, vol.68, no.3, pp.953-957, Mar. 2021. Article (CrossRef Link)
[16] I. C. Lin, O. Yağan, J. W, Carlee, "dynamic coupling strategy for interdependent network systems against cascading failures," *IEEE Transactions on Network Science and Engineering*, vol.10, no.4, pp. 2265-2282, Aug. 2023. Article (CrossRef Link)
[17] Y. C. Hao, L. M. Jia, Y. H. Wang, "Cascading failures in interdependent scale-free networks of different coupling preferences with the harmonic closeness," *EPL (Europhysics Letters)*, vol.127, no.3, pp.38003. Sep. 2019. Article (CrossRef Link)
[18] Z. H. Zhang, Y. F. Yin, X. Zhang, et al, "Optimization of robustness of interdependent network controllability by redundant design," *PloS one*, vol.13, no.2, pp. e0192874, Feb. 2018. Article (CrossRef Link)
[19] R. Kumar, S. Kumari, M. Bala, "Minimizing the Effect of Cascade Failure in Multilayer Networks with Optimal Redistribution of Link Loads," *Journal of Complex Networks*, vol.9, no.6, pp. cnab043, Dec. 2021. Article (CrossRef Link)
[20] J. C. Xing, C. X. Chen, Z. L. Zhu, et al, "Cascading failure of double layer networked command information system," *Control and Decision*, vol.35, no.12, pp.3017-3025, Dec. 2020. Article (CrossRef Link)
[21] F. Z. Liu, B. Xiao, J. J. Liu, et al, "Robustness of asymmetric dependent network under cascading failure," *Journal of National University of Defense Technology*, vol. 43, no.01, pp.49-56, Feb. 2021. Article (CrossRef Link)
[22] Y. Shen, G. Ren, N. Zhang, et al, "Effects of mutual traffic redistribution on robustness of interdependent networks to cascading failures under fluctuant load," *Physica A: Statistical Mechanics and its Applications*, vol.560, pp.125138, Dec. 2020. Article (CrossRef Link)
[23] Y. F. Chen, D. Zhang, K. Che, et al, "Cellular automaton model considering the effect of brake light and traffic light at the intersection," *International Journal of Communication Systems*, vol.35, no.12, pp. e4251, Aug. 2022. Article (CrossRef Link)
[24] D. L. Fu, S. H. Zhu, Z. F. Yuan, et al, "Robustness of interdependent networks based on different subnet cascade mechanisms," *Computer Engineering & Science*, vol.40, no.03, pp.439-444, Mar. 2018. Article (CrossRef Link)
[25] S. Liu, C. S. Yin, D. J. Chen, et al, "Modelling and impact analysis of interdependent characteristics on cascading overload failure of syncretic railway networks," *Plos one*, vol.15, no.9, pp.e0239096, Sep.2020. Article (CrossRef Link)
[26] Q. Zhang, J. H. Cao, T. L. Song, et al, "Cascading failure analysis considering load redistribution in equipment support network," *Journal of Ordnance Equipment Engineering*, vol.42, no.06, pp.86-90, Jun. 2021. Article (CrossRef Link)
[27] C. Y. Sun, M. X. Shen, "Research on dynamic evolution Modeling of command and control networks," *Military Operations Research and Systems Engineering*, vol.31, no.01, pp.39-45, Mar. 2017.
[28] H. Y. Han, R. N. Yang, H. L. Li, et al, "Cascading failure of two-layered interdependent command and control network," *Journal of Central South University (Science and Technology)*, vol.46, no.12, pp.4542-4547, Dec. 2015.
[29] S. Y. lao, J. D. Wang, L. Bai, "Review of the interdependent networks," *Journal of National University of Defense Technology*, vol.38, no.01, pp.122-128, Feb. 2016. Article (CrossRef Link)
[30] J. W. Wang, L. Cai, C. Jiang, "Cascading model in interdependent networks with edge weight and coupled strength," *Journal of Industrial Engineering*, vol.32, no.04, pp.149-157, 2018. Article (CrossRef Link)
[31] J. A. Pichardo-Corpus, "The concentration of edge betweenness in the evolution of planar graphs and street networks," *Journal of Complex Networks*, vol.11, no.2, pp. cnad004, April 2023. Article (CrossRef Link)
[32] X. E. Gao, D. P. Zhang, K. Q. Li, et al, "A cascading failure model for command and control networks with hierarchy structure," *Security and Communication Networks*, Mar. 2018. Article (CrossRef Link)

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