Interlayer Coupling Strategy for Two-Layer Interdependent Command-and-Control Networks: Balancing Node Walk Betweenness and Operational Attributes

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***Abstract*—In system-of-systems operations, command-and-control networks (C2Ns) increasingly exhibit hierarchical interdependence and cross-network coupling. Designing effective interlayer coupling strategies is therefore essential for improving the survivability of interdependent C2Ns under attacks. However, most existing coupling strategies are predominantly topology-driven and fail to jointly capture multipath information transmission characteristics and operational compatibility among heterogeneous nodes. To address this issue, this study proposes an interlayer coupling strategy for two-layer interdependent C2Ns, referred to as PRO, by integrating node walk betweenness and operational attributes. Specifically, a walk-betweenness-based dependency strength metric is constructed to characterize node importance from the perspective of multipath information transmission, while an operational attribute matching mechanism is introduced to evaluate the functional compatibility of cross-layer nodes. Based on these two components, the PRO strategy is developed for survivability-oriented interlayer coupling design. Simulation experiments on an air-defense command-and-control scenario are conducted under both deliberate and random attacks. The results of repeated simulations show that the proposed strategy consistently outperforms the compared baseline methods in node survival rate, observe-orient-decide-act (OODA)-oriented functional chain retention ratio, and combat link efficiency degradation rate. Compared with the baseline random strategy, under random attack, PRO improves node survival rate by 50.00%, improves the OODA-oriented functional chain retention ratio by 19.40%, and reduces the combat link efficiency degradation rate by 3.53%. These results indicate that the PRO strategy improves not only structural robustness but also the preservation of sensing–command–firepower coordination under cascading failures. The proposed method provides a joint structural–functional framework for mitigating cascading failure risks and enhancing survivability in interdependent C2Ns.**

***Keywords*—Interdependent command and control networks; interlayer coupling strategy; walk betweenness; operational attributes**

I. Introduction

In system-of-systems operations, command-and-control networks (C2Ns) increasingly exhibit hierarchical interdependence and cross-network coupling. Sensing, command-and-control, and firepower subnetworks interact through information sharing, command dissemination, strike execution, and feedback, thereby forming an observe-orient-decide-act (OODA) process [1], [19]. Because different combat units are functionally heterogeneous and strongly interdependent, local failures may propagate across subnetworks through dependency relationships, eventually degrading not only structural connectivity but also mission-oriented coordination capability. Therefore, introducing the perspective of interdependent networks is important for understanding the survivability of C2Ns, while the design of interlayer dependency relationships becomes a key factor affecting cascading-failure propagation and mission-oriented coordination.

Existing studies have shown that coupling patterns and coupling preferences significantly affect the robustness of interdependent networks. However, command-and-control networks differ from generic interdependent networks because they contain heterogeneous operational units, hierarchical command relationships, and mission-oriented sensing–command–firepower coordination. As reviewed in Section II, existing coupling strategies are still insufficient for interdependent C2Ns because they usually rely on topology-driven criteria and rarely integrate multipath information transmission characteristics with operational compatibility among heterogeneous nodes.

To address this gap, this study proposes an interlayer coupling strategy for two-layer interdependent C2Ns, referred to as PRO. The proposed strategy integrates walk-betweenness-based dependency strength and operational attribute matching. The former characterizes node importance from the perspective of multipath information transmission, whereas the latter evaluates the functional compatibility of cross-layer heterogeneous nodes. In this way, PRO supports survivability-oriented interlayer dependency design from a joint structural–functional perspective. The main contributions of this study are as follows:

- A dependency strength metric was proposed based on node walk betweenness, considering the multipath characteristics of node information transmission.

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- A node operational attribute matching metric was established to characterize the functional compatibility among heterogeneous combat units.
- An interlayer coupling strategy for two-layer interdependent C2Ns was developed by integrating dependency strength and operational attribute matching.
- Simulation experiments under deliberate and random attacks are conducted to evaluate the proposed strategy from the perspectives of node survival rate, OODA-oriented functional chain retention ratio, and combat link efficiency degradation rate, thereby verifying its structural and functional survivability advantages.

The remainder of this study is organized as follows. Section II reviews related studies on interdependent-network coupling strategies and C2N survivability analysis and clarifies the research gap. Section III abstracts the two-layer interdependent C2N model. Section IV defines the walk-betweenness-based dependency strength, operational attribute matching metric, and the proposed PRO coupling strategy. Section V presents simulation experiments and comparative results. Section VI discusses the mechanisms, practical applicability, and scalability of the proposed method. Section VII presents future research directions. Finally, Section VIII concludes the study.

II. Related Work

A. Coupling Strategies in Interdependent Networks

In recent years, studies have reported that the robustness of interdependent networks is closely related to the choice of coupling strategies [2]-[4]. Existing coupling strategies can be broadly divided into coupling-pattern-based methods and topology-preference-based methods. Coupling-pattern-based methods mainly focus on how dependency edges are organized between networks. For example, Xu and Fu [5] compared one-to-one, one-to-many, and many-to-many coupling patterns in directed-undirected interdependent networks and analyzed their effects on cascading-failure robustness. Liu et al. [6] compared assortative, disassortative, and random coupling strategies. Chen and Du et al. [7] further showed that different coupling preferences may lead to different robustness behaviors under sparse and dense coupling conditions.

Topology-preference-based methods further optimize interlayer dependency relationships according to the structural properties of nodes or edges. Hao et al. [8] proposed assortative and disassortative coupling strategies based on node proximity and shortest-path information. Wang et al. [9] proposed a locally optimized coupling strategy based on neighbor node priority connection (NPC), and Zang et al. [10] further developed a low-degree neighbor node priority connection (LDNPC) strategy. Li et al. [11] investigated edge-coupled interdependent networks under different coupling modes. Lin et al. [12] introduced a stepwise optimization strategy to dynamically adjust coupling coefficients during cascading failures. Gao et al. [13] proposed a globally homogeneous coupling strategy based on node degree and average network degree. Ji et al. [14] defined inter-degree differences and proposed random inter-degree–degree difference (RIDD) and low inter-degree–degree difference (LIDD) strategies.

These studies demonstrate that coupling patterns, coupling preferences, and topology-based optimization rules can significantly affect the robustness of interdependent networks. However, most of these strategies are developed for generic interdependent networks. Their coupling criteria are mainly derived from static topology, local connectivity, shortest-path proximity, or degree-related indicators. Therefore, they are insufficient for command-and-control networks, where interlayer dependency relationships not only represent structural connections but also reflect information transmission, command support, and operational coordination among heterogeneous combat units.

B. Command-and-Control Network Modeling and Survivability Analysis

Compared with generic interdependent networks, C2Ns have stronger mission semantics, functional heterogeneity, and hierarchical organization. Sensing, command-and-control, and firepower nodes perform different operational roles and jointly support the observe–orient–decide–act (OODA) process. Therefore, survivability analysis of C2Ns should consider not only structural connectivity but also the preservation of mission-oriented sensing–command–firepower functional chains.

Existing studies have investigated C2Ns from different perspectives. Wang et al. [15] proposed an invulnerability measure for C2Ns based on mission links. Chen et al. [16] developed a dual-layer interdependent C2N model for integrated reconnaissance-strike and OODA-loop capabilities. Chen et al. [17] investigated the dynamic evolution of C2Ns using a hypernetwork-based model. Pan et al. [18] proposed a multi-attribute-weighted modeling method for C2Ns. Ling et al. [19] discussed network-centric warfare metrics from connectivity to the OODA cycle. Zhao et al. [20] further highlighted the importance of robustness analysis of C2Ns under cascading failures.

These studies provide important foundations for C2N modeling, mission-oriented performance evaluation, and cascading-failure analysis. Nevertheless, most of them focus on network abstraction, mission-link evaluation, dynamic evolution, or failure propagation mechanisms. The problem of how to design interlayer dependency edges from a joint structural-functional perspective remains insufficiently investigated.

C. Research Gap and Motivation

The above studies indicate that coupling design is critical for the robustness of interdependent networks and that C2Ns require mission-oriented modeling and evaluation. However, three limitations remain in existing interlayer coupling studies.

First, many coupling strategies rely on degree-related indicators, which mainly describe local connectivity and cannot fully capture the indirect influence of nodes in global information transmission. Second, shortest-path-based indicators such as betweenness centrality may be insufficient for C2Ns, because information transmission in C2Ns may follow multiple redundant, non-shortest, or dynamically selected paths.

Third, topology-driven coupling strategies do not explicitly evaluate whether cross-layer nodes are functionally compatible in terms of sensing, command support, and firepower coordination.

These limitations motivate the proposed PRO strategy. By introducing walk-betweenness-based dependency strength, PRO characterizes node importance from the perspective of multipath information transmission. By introducing operational attribute matching, PRO further evaluates the functional compatibility of heterogeneous cross-layer nodes. Therefore, the proposed strategy provides a joint structural-functional coupling framework for survivability-oriented interlayer dependency design in two-layer interdependent C2Ns.

III. Abstraction of Two-Layer Interdependent C2N Modeling

A. Characterization of C2N

With the continuous evolution of combat modes and battlefield environments, the relationships among various combat units within C2Ns have become increasingly complex and diverse. Therefore, C2Ns are characterized by node heterogeneity, interlaced links, and multi-network interdependence. To simplify model analysis, we adopted the two-layer interdependent C2N model abstracted in Ref. [16]. The model was constructed as follows: 1) The firepower and sensing subnetworks were independently constructed using an attribute synergy strategy. 2) The aforementioned subnetworks were then connected using a detect–strike integration edge strategy to form the upper-layer firepower–sensing fusion network; 3) An improved tree-like network structure was used to construct the command and control subnetwork, forming the lower-layer network; 4) An interlayer coupling strategy was employed to connect the upper and lower layers, resulting in a complete two-layer interdependent C2N. The specific structure of the two-layer interdependent C2N is shown in Fig. 1. In this structure, the upper layer is the firepower–sensing fusion network, formed by integrating the sensing and firepower subnetworks; the lower layer is the command-and-control subnetwork. Intra-layer edges represent synergistic relationships within a subnetwork, while interlayer edges represent dependency relationships between subnetworks.

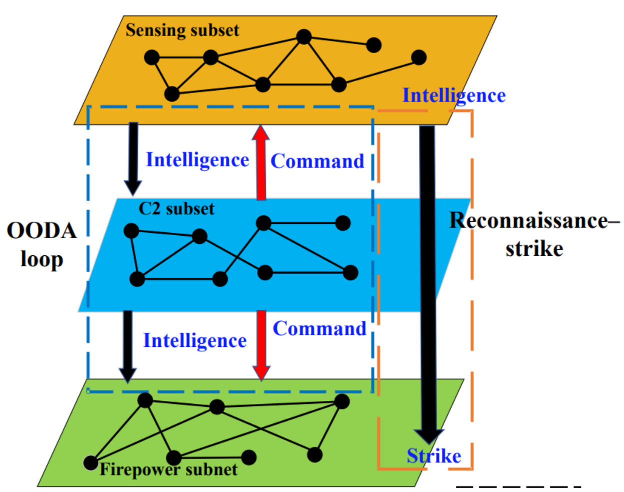

Fig. 1. Structure of the two-layer interdependent C2N.

This model can be represented by the adjacency matrix as follows:

$$W = \begin{bmatrix} W_{sf} & W_{sf-c} \\ W_{c-sf} & W_c \end{bmatrix} \quad (1)$$

where, W_{sf} is the upper-layer firepower–sensing fusion network; W_c is the lower-layer command and control subnetwork; W_{sf-c} and W_{c-sf} are the interdependent coupling networks between the two subnetworks.

B. Node Abstraction

Combat units in the C2N are abstracted as sensing nodes V_s, command and control nodes V_c, and firepower nodes V_f. Considering the operational attribute characteristics of each type of node, they are modeled as follows:

$$V(i) = \langle ID_V, T_V, H_V, Attribute_V, DependentNode_v \rangle \quad (2)$$

where, ID_V is the unique network sequence identifier of the node; T_V indicates the node type, including sensing, command and control, and firepower; H_V is the node's hierarchical level, with lower values indicating higher levels; $Attribute_V$ is the normalized attribute vector of the node, modeled as a scenario-based role-related descriptor. For sensing nodes, it mainly characterizes detection-related capability; for command-and-control nodes, it mainly characterizes communication and command-support capability; and for firepower nodes, it mainly characterizes strike-related capability. $DependentNode_v$ is the node(s) on which node i is dependent. To clarify the source and semantic meaning of the operational attributes used in this study, the attribute categories and representative components of sensing, command-and-control, and firepower nodes are summarized in Table I.

TABLE I. Operational Attribute Categories and Semantic Meanings of Heterogeneous Nodes in the C2N

Node type	Attribute semantic meaning	Representative attribute components
Sensing node	Detection-related capability	Detection range, detection accuracy, reconnaissance timeliness
Command-and-control node	Communication and command-support capability	Bandwidth, signal-to-noise ratio, hierarchical level
Firepower node	Strike-related capability	Strike range, firepower intensity, response timeliness

C. Link Abstraction

Combat units within the C2N exchange and process different types of information via wired, wireless, and other communication means. Edges can be represented as

$$E(m) = \left\langle ID_{E(m)}, type_{E(m)}, DependentAttribute_{E(m)} \right\rangle \quad (3)$$

where, $ID_{E(m)}$ is the identifier of an interlayer edge; $type_{E(m)}$ is the edge type, including intra-layer synergistic and interlayer dependent edges; $DependentAttribute_{E(m)}$ is the dependency strength of a dependent edge.

IV. INTERLAYER COUPLING STRATEGY FOR TWO-LAYER INTERDEPENDENT C2NS

A. Node Walk Betweenness

C2Ns employ diverse communication methods, and information dissemination follows multipath transmission patterns. Taking into account the weights of different path lengths and based on the concept of betweenness, we introduced the notion of walk betweenness to characterize the frequency with which a node acts as an intermediary across all possible walk paths. Walk betweenness accounts for path length weighting. The core idea is to count the number of times a node appears in walks from every source to the destination, using a decay factor to handle the issue of infinite paths.

The walk betweenness of node v_i is defined as the proportion of the information volume ultimately received by that node in the total information volume of the network when each node in the network sequentially acts as a unique source to send an initial message (total information normalized to 1), and the message propagates according to a hierarchical walk rule. The calculation procedure is as follows:

Step 1: Initialize the information volume of each node in the C2N to I_0. Assume that in each information walk iteration, only one node sends information while others receive it. The initial information volume of a node is

$$H_0 = [I_0, I_0, \cdots, I_0]_N \tag{4}$$

where, N is the total number of nodes.

Step 2: During the walk process, the information volume of node v_j is evenly distributed to its neighboring nodes, and its own information volume is reset to zero. If the degree of node v_j is k_j, then after n iterations, the information volume received by a directly connected node v_i is

$$H_n(v_i) = H_{n-1}(v_j)/I_0 g k_j \tag{5}$$

where, $i \neq j$ and $H_{n-1}(v_j)$ are the information volume possessed by node v_j after the (n-1)th iteration. The total number of iterations does not exceed the network hierarchy level D, i.e., $n = 0,1 \cdots, D$.

Step 3: Let G denote the set of all nodes directly connected to node v_i. After n iterations of information walks, traversing G yields the information volume of node v_i:

$$H_n(v_i) = \sum \frac{H_{n-1}(v_j)}{I_0 k_j} g a_{ij} \tag{6}$$

where, a_{ij} is the connection between nodes i and j, $n = 0,1 \cdots, D$, $v_j \in A$.

Step 4: After D rounds of information propagation, the total information volume accumulated by each node in the network is computed, yielding the walk betweenness for each node. The resulting set of walk betweenness values is

$$H_G = [H(1), H(2), \cdots, H(N)] \tag{7}$$

B. Dependency Strength Based on Node Walk Betweenness

Dependent edges reflect the relationship of information exchange between subnetworks. The more frequent the exchange, the closer the dependency and the greater the mutual influence between networks. Dependency strength is commonly used to quantify the degree of such interdependence. The strength of dependency not only reflects the extent of mutual influence and control between networks but also affects the propagation speed of cascading failures within interdependent networks.

Most existing studies define dependency strength based on node degrees. However, this only captures local connectivity and ignores indirect influence, thus failing to measure the intermediary role of nodes in the global network. A few studies use betweenness centrality, assuming that information is transmitted only along shortest paths, thereby overlooking the diversity and randomness of path selection during information transmission. By simulating the random walk process, walk betweenness more accurately characterizes functional dependencies and path diversity among nodes. Accordingly, we defined a new metric for dependency strength based on walk betweenness, as follows:

$$DS(A_i, B_j) = b_i b_j + \alpha \tag{8}$$

where, $b_i = H_A(i)$ is the walk betweenness of node i in subnetwork A and $b_j = H_B(j)$ is the walk betweenness of node j in subnetwork B. The parameter α ($0 < \alpha < 1$) is an adjustment coefficient introduced to avoid cases where edge nodes may have a walk betweenness of zero.

C. Node Operational Attribute Matching

Sensing nodes refer to combat units equipped with early warning, detection, reconnaissance, and surveillance capabilities, such as early warning radars and reconnaissance radars. Command-and-control nodes are responsible for intelligence fusion, command dissemination, information coordination, and decision support, such as command organizations and intelligence processing agencies. Firepower nodes refer to combat units capable of interception, attack, and destruction. Because these three types of nodes play different roles in the command-and-control process, their operational attributes are heterogeneous. Therefore, quantifying node operational attributes and analyzing attribute matching provides a basis for constructing functionally coordinated interlayer dependency relationships.

In this study, node operational attributes are modeled as scenario-based normalized descriptors constructed according to node roles, hierarchical characteristics, and combat-task semantics in the considered air-defense command-and-control scenario. These attributes are not intended to reproduce exact equipment specifications; instead, they provide a unified and comparable description of heterogeneous node characteristics for interlayer matching analysis. Specifically, for sensing nodes, the attribute vector mainly characterizes detection-related capability; for command-and-control nodes, it mainly characterizes communication and command-support capability; and for firepower nodes, it mainly characterizes strike-related capability.

In the upper-layer network, a node's operational capability depends not only on its intrinsic capability but also on its ability to cooperate with neighboring nodes. Therefore, the operational capability of a node in the upper-layer network is defined as

$$COM_A(i) = \sum_{i=1}^{n} \omega_i att_i + \sum_{k \in z_i} c_{ik} \tag{9}$$

where, $\sum_{i=1}^{n} \omega_i att_i$ is the weighted sum of node i's operational attributes, quantifying its intrinsic operational capability as an independent combat unit, and $c_{ij} = \sqrt{\sum_{z=1}^{n} (att_z^i - att_z^j)^2}$ is the cooperation factor between node i and its neighboring nodes, indicating the degree of difference between the node and its neighboring nodes in terms of attribute vectors. This factor helps compensate for individual capability gaps and reflects the cooperative capability of node i in the upper-layer network. In the simulation, the components of the attribute vector within the same node category are normalized and assigned equal weights.

In the lower-layer network, nodes mainly function as command-and-control units. Their role is not direct combat execution, but command dissemination, information transmission, and operational support. Therefore, the capability of a lower-layer node is characterized in terms of command-support capability rather than direct combat capability. Considering that the communication capability of a network node is determined by its inherent hardware characteristics and is positively correlated with its hierarchical level [18], the capability of a lower-layer command-and-control node is defined as:

$$C\_COM_B(i) = \frac{CP(i) g H_i(i)}{CP_{\max} g H_{\max}} \tag{10}$$

where, $CP(i) = B(i)\log_2(1 + SNR(i))$ represents the Shannon channel capacity of node i, indicating its physical-layer information throughput capability; $H(i)$ denotes the hierarchical level of node i; both $B(i)$ and $SNR(i)$ are elements of the node's attribute vector attribute_$V(i)$.

By integrating the node operational attributes of both upper and lower networks, the interlayer node operational attribute matching is computed as follows:

$$MS_{ij} = \frac{\frac{M_{ij}}{AT_{ij}}}{\sum_{j \in B} M_{ij}/AT_{ij}} \tag{11}$$

where, $M_{ij} = \frac{1}{1+|COM_A(i) - COM_B(j)|}$ is the matching index between nodes i and j; $AT_{ij} = \frac{L_{ij}}{\max_{i,j} L_{ij}}$ is the normalized path length between nodes i and j. A larger matching value indicates that the two nodes are more compatible in terms of operational role and transmission convenience and are therefore more suitable for establishing an interlayer dependency relationship.

D. Interlayer Coupling Strategy Based on Dependency Strength and Operational Attribute Matching

In contrast to intra-layer edge strategies, interlayer edge strategies must account for both the dependency strength between nodes and their operational attribute matching. Dependency strength describes the inter-node relationship from the perspective of multipath information transmission, while attribute matching quantifies node compatibility based on operational attributes. To this end, we proposed an interlayer coupling strategy for two-layer interdependent C2Ns that integrates dependency strength and operational attribute matching. In addition, to prevent load imbalance and reduce the risk of cascading failures, an adjustment coefficient was introduced. This ensures that sensing nodes preferentially connect to upper-layer nodes in the command-and-control subnetwork, while firepower nodes preferentially connect to lower-layer nodes in the same subnetwork. The edge connection probability for the interlayer coupling strategy is calculated as

$$p_{ij} = \begin{cases} \frac{DS_{ij}MS_{ij}}{\sum_{j \in N_c} DS_{ij}MS_{ij}}, type(A_i) \in T_s \\ \frac{DS_{ij}MS_{ij}H(j)}{\sum_{j \in N_c} DS_{ij}MS_{ij}H(j)} type(A_i) \in T_f \end{cases} \tag{12}$$

where, i is a node in the upper-layer network; j is a node in the lower-layer network; N_c is the set of command-and-control nodes; $H(j)$ is the hierarchical level of node j; T_s and T_f are the sets of sensing and firepower nodes, respectively. The procedure for calculating the edge connection probability under the proposed interlayer coupling strategy is as follows (Algorithm 1):

Algorithm 1: Coupling strategy

Input: Network *A*, network *B*, attribute vectors of nodes: attribute_*V(A)*, attribute_*V(B)*

Output: Coupled network *(A, B)*

Step 1: Initialize nodes in network *A* and form queue Q_A.

Step 2: Initialize nodes in network *B* and form queue Q_B.

Step 3: Calculate the walk betweenness for each node using Eq. (4)-(6).

Step 4: Sequentially select from Q_A the nodes that have not yet formed coupling edges, denoted as node *i*. Once Q_A is fully traversed, proceed to Step 10.

Step 5: Use Eq. (8) and Eq. (11) to compute the dependency strength and attribute matching between node *i* and all nodes in Q_B.

Step 6: Determine the type of node *i*, compute its dependency probabilities with nodes in Q_B using Eq. (12), and select a dependent node *j* via the roulette selection method.

Step 7: Identify the neighboring nodes of *i* and *j*, denoted as Q_i and Q_j, respectively.

Step 8: Remove node *j* from queue Q_B. If Q_B is empty, return to Step 2.

Step 9: Treat queues Q_i and Q_j as local neighborhoods and repeat Steps 5–6. Continue this process until all Q_i pairs are traversed, then return to Step 4.

Step 10: End.

Time Complexity: $O(mn)$, where m and n are the total number of nodes in the upper and lower layers of the two-layer structure, respectively.

The above complexity analysis shows that the computational burden of the proposed method mainly arises from path-related structural evaluation and interlayer attribute matching. As the network scale increases, the structural computation becomes the dominant cost, which makes the current implementation more suitable for offline architecture optimization and periodic survivability assessment than for strict real-time operational scenarios. Nevertheless, the proposed framework remains extensible to larger-scale command-and-control networks. Its scalability can be further improved through candidate-pair pruning, caching, or local updating of structural information, and parallel implementation of the evaluation process.

V. Simulation Analysis

To validate the effectiveness of the proposed strategy, we conducted simulation experiments, covering parameter analysis, interlayer coupling strategy analysis, and network model analysis. Based on an air defense command and control system, the initial parameter values were as follows: the total number of nodes is 580, including 160 command and control nodes (n_c = 160), 150 sensing nodes (n_s = 150), and 270 firepower nodes (n_f = 270); the command span was set as $k = 3$ and the command hierarchy as $h = 4$. For all simulations, the components of each node's attribute vector were normalized and assigned equal weights within the same node category to control the number of free parameters and ensure a fair comparison among different coupling strategies.

Two attack strategies, namely deliberate attack and random attack, were adopted. Unless otherwise specified, each reported result was obtained from 200 independent simulation runs. For each metric, the mean value across runs is reported, and the shaded region in the corresponding figures represents the 95% confidence interval. In this way, the robustness of the observed performance differences can be evaluated not only in terms of average behavior but also in terms of statistical variability across repeated simulations.

A. Analysis of Dependency Strength Adjustment Parameter α

To determine a suitable value for the dependency strength adjustment parameter α, we conducted simulation experiments to assess network performance as α varies. Given the large scale of the network (580 nodes in total), a significant number of nodes must be removed to clearly observe changes in node survival rate. Fig. 2 shows the variation in node survival rate with α after removing 100–150 nodes under deliberate attack. Fig. 3 shows the same under random attack with 300–350 nodes removed. From Fig. 2 and 3, clearly, the node survival rate peaks at α = 0.3. Therefore, this value is used in all subsequent experiments.

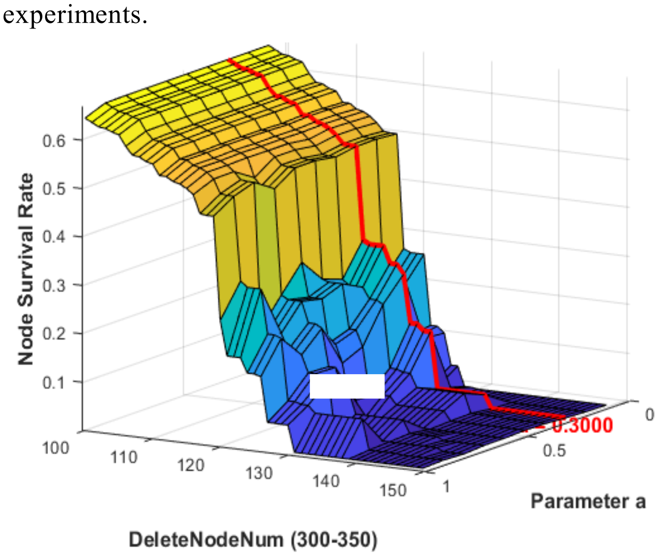

Fig. 2. Node survival rates under different α values (deliberate attack).

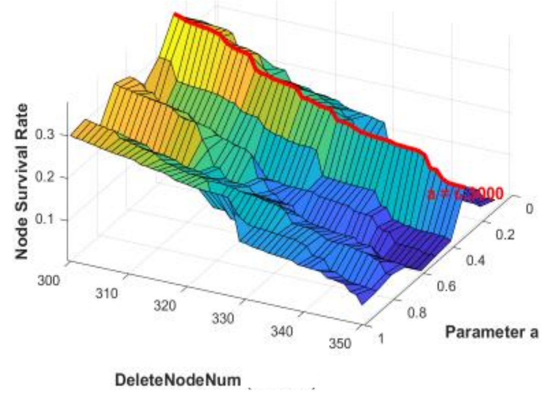

Fig. 3. Node survival rates under different α values (random attack).

B. Analysis of Interlayer Coupling Strategies

To validate the rationality of the proposed interlayer coupling strategy, we conducted comparative simulations focusing on different dependency strengths, node operational attribute matching levels, and interlayer coupling connection strategies.

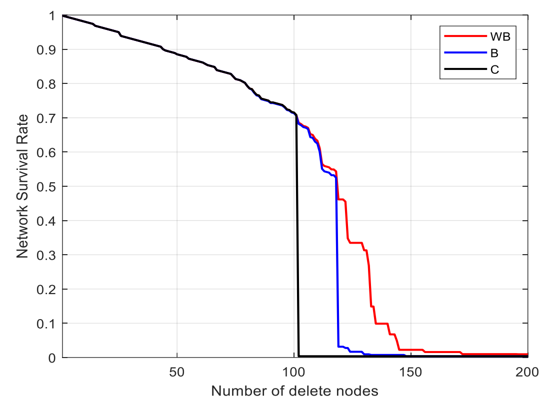

Fig. 4. Node survival rates under different dependency strengths (deliberate attack).

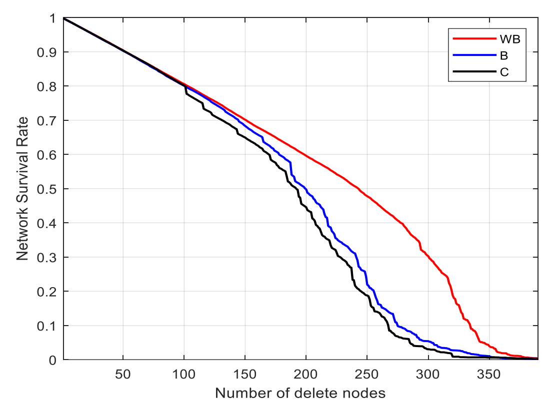

Fig. 5. Node survival rates under different dependency strengths (random attack).

1) Comparative analysis of different dependency strengths: Three types of dependency strengths were selected for comparison: walk betweenness (WB), betweenness centrality (B), and closeness centrality (C). Fig. 4 and Fig. 5 show the node survival rates under deliberate and random attacks, respectively, for these three strategies. Under deliberate attack (Fig. 4), the node survival rates of all three methods were initially similar. However, after removing 100 nodes, an inflection point appeared, indicating the onset of large-scale cascading failures. For networks constructed using betweenness and closeness centrality, node survival rapidly dropped to zero. In contrast, the dependency strength based on WB proposed in this study delayed cascading failures. Its survival rates did not drop to zero until 150 nodes were removed. Under random attack (Fig. 5), the proposed method clearly outperformed the other two. This advantage is attributed to the use of WB, which accounts for multipath information transmission and dynamic network behavior, thereby mitigating abrupt performance degradation.

2) Comparative analysis of different node matching degrees: Three scenarios were compared: operational attribute matching (AM) proposed in this study, matching based on the node's hierarchical level (LM), and random matching (RM). Fig. 6 and 7 illustrate the node survival rates under deliberate and random attacks, respectively, for these three matching strategies. Under both attack strategies, the proposed matching degree achieved the highest node survival rate and the best network survivability. This is because considering node matching degree helps avoid unbalanced dependency edges formed between nodes with significantly different combat capabilities, thereby suppressing cascading failures.

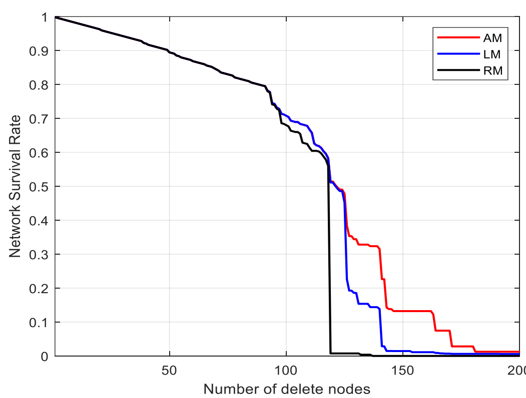

Fig. 6. Node survival rates under different node matching degrees (deliberate attack).

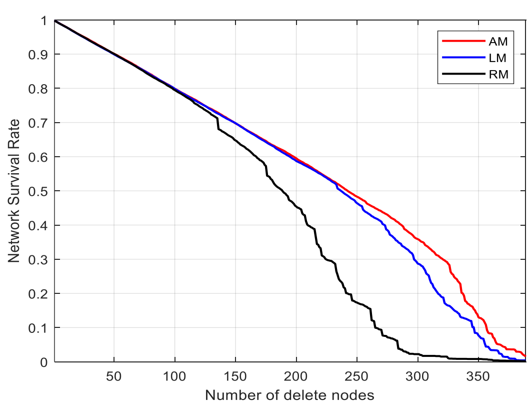

Fig. 7. Node survival rates under different node matching degrees (random attack).

3) Comparative analysis of different interlayer coupling strategies

a) Node survival rate analysis: Eight interlayer coupling strategies were evaluated: the proposed strategy (PRO), the strategy from Ref. [16] (DB), random (RL), neighbor NPC, degree-assortative coupling (BAL), degree-disassortative coupling (BDL), betweenness-assortative coupling (DAL), and betweenness-disassortative coupling (DDL). Fig. 8 and 9 show the node survival rates under deliberate and random attacks, respectively. As can be seen in the figures, under both attack strategies, the proposed PRO strategy achieved the highest node survival rate and better network survivability. This is because WB captures the global influence of a node under multipath and random walk conditions, rather than relying solely on the shortest path. The importance of key nodes is distributed across more paths instead of being concentrated in a few dominant nodes. Therefore, even after partial node failures, the network can still maintain functionality through non-shortest paths, thereby delaying the sharp decline in node survival rate.

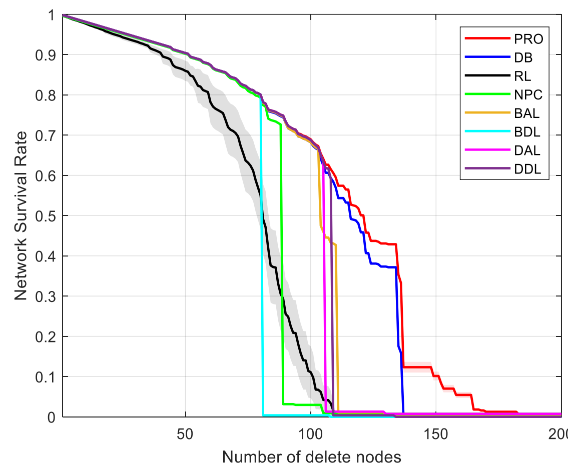

Fig. 8. Node survival rates under different interlayer coupling strategies (deliberate attack).

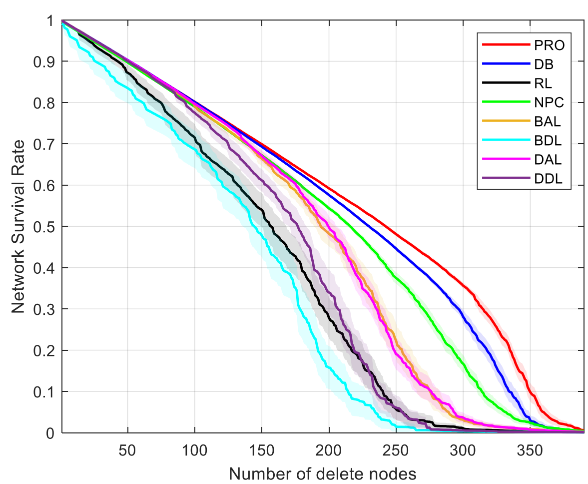

Fig. 9. Node survival rates under different interlayer coupling strategies (random attack).

b) OODA-Oriented functional chain retention analysis: To further evaluate whether the proposed strategy can preserve the functional stability of the command-and-control process, an OODA-oriented functional chain retention ratio is introduced. This metric is used to measure the extent to which the network can still maintain effective sensing–command–firepower coordination after node failures and cascading effects.

Specifically, an effective OODA-oriented functional chain is considered to exist if a surviving sensing node can still coordinate with a surviving command-and-control node, and the latter can further support a surviving firepower node through the remaining intra-layer and interlayer connections. Then, the OODA-oriented functional chain retention ratio is defined as the ratio between the number of effective functional chains after attack and that in the initial network.

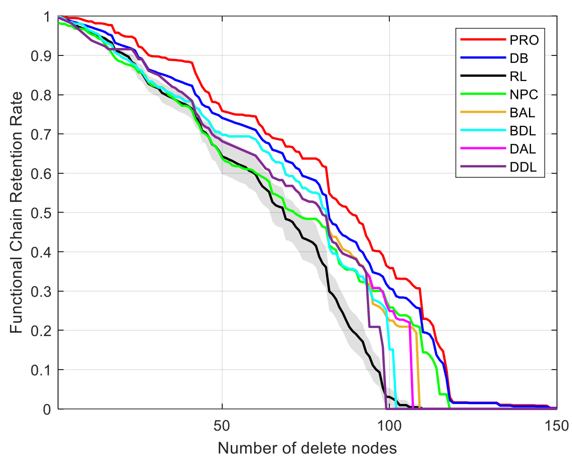

Fig. 10. OODA-oriented functional chain retention ratios under different coupling strategies (deliberate attack).

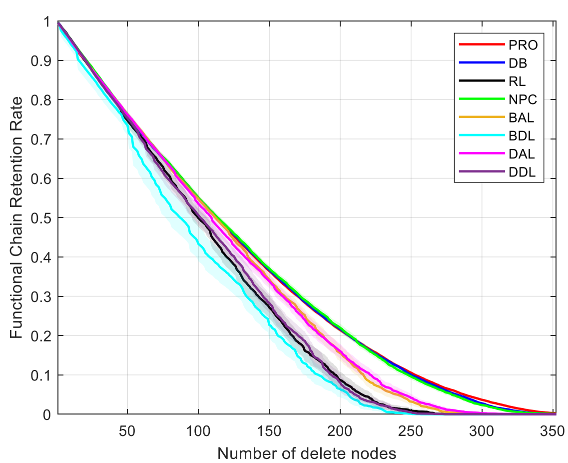

Fig. 11. OODA-oriented functional chain retention ratios under different coupling strategies with 95% confidence intervals (random attack).

Fig. 10 and Fig. 11 show the OODA-oriented functional chain retention ratios under deliberate and random attacks, respectively. As can be seen from the figures, under both attack strategies, the PRO strategy maintained the highest functional chain retention ratio and exhibited the slowest degradation trend among all compared methods. This indicates that the proposed strategy is more effective in preserving the sensing–command–firepower coordination required by the command-and-control process, rather than merely retaining a larger number of surviving nodes.

Compared with the baseline strategies, the advantage of PRO in this metric can be attributed to two aspects. First, the walk-betweenness-based dependency strength better captures multipath information transmission characteristics, thereby reducing the vulnerability caused by over-reliance on shortest-path-dominated key nodes. Second, the operational attribute matching mechanism reduces functionally mismatched interlayer couplings, which helps preserve semantically compatible sensing–command–firepower chains under attacks. Therefore, the superiority of PRO is reflected not only in structural robustness but also in functional robustness related to OODA-oriented command-and-control stability.

c) Combat link efficiency analysis: The same eight strategies were used to compare combat link efficiency. Fig. 12 and Fig. 13 show the degradation rate of combat link efficiency under deliberate and random attacks, respectively. As seen in the figures, under both attack strategies, the PRO strategy displayed the best combat link efficiency, with lower degradation rates of combat link efficiency than other models. This is because the proposed strategy considers node operational attributes, which reduces functional mismatches between interlayer-coupled nodes and improves overall network operational effectiveness. These results further validate the rationality of the proposed model.

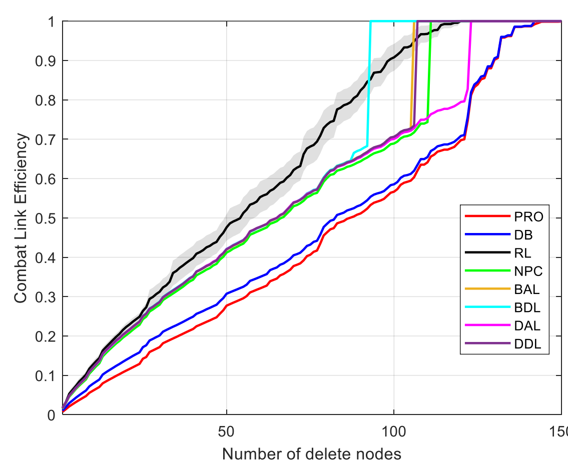

Fig. 12. Combat link efficiency degradation rate under different coupling strategies (deliberate attack).

d) Comprehensive analysis: Tables II and III summarize the average node survival rate, OODA-oriented functional chain retention ratio, and combat link efficiency degradation rate of different interlayer coupling strategies under deliberate and random attacks, respectively. All reported values are the mean results over 200 independent simulation runs, while the corresponding line figures present the 95% confidence intervals as shaded bands. Degree-disassortative coupling and betweenness-disassortative coupling strategies were excluded because of their significantly inferior overall performance.

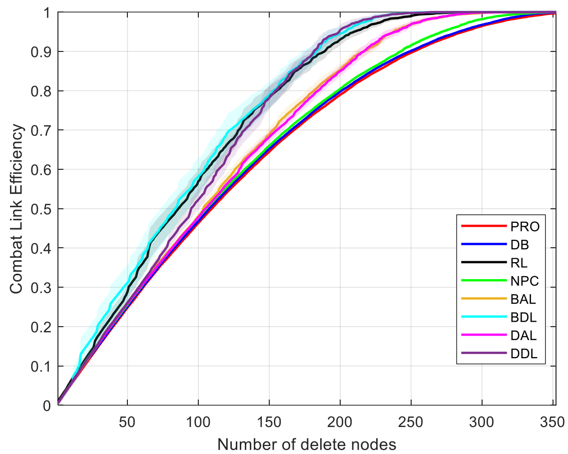

Fig. 13. Combat link efficiency degradation rate under different coupling strategies (random attack).

The results show that the PRO strategy achieves the best overall performance under both attack modes. Under deliberate attack, PRO attains the highest node survival rate and the lowest combat link efficiency degradation rate, while maintaining a competitive functional chain retention ratio close to that of the best-performing baseline. Under random attack, PRO performs best among all compared strategies in all three metrics.

Compared with the baseline random strategy (RL), PRO improves node survival rate by 24.82% and 50.00% under deliberate and random attacks, respectively. Meanwhile, the OODA-oriented functional chain retention ratio is improved by 13.38% and 19.40%, and the combat link efficiency degradation rate is reduced by 6.37% and 3.53%, respectively. These results indicate that the superiority of PRO is consistently reflected in structural robustness, functional chain preservation, and performance maintenance.

TABLE II. COMPARISON OF NETWORK PERFORMANCE UNDER DIFFERENT COUPLING STRATEGIES (DELIBERATE ATTACK)

	Average node survival rate (%)	Average functional chain retention ratio (%)	Average combat link efficiency degradation rate (%)
PRO	58.79	19.58	71.23
DB	56.39	20.76	71.67
NPC	54.61	17.58	73.26
BAL	51.24	18.15	74.21
DAL	48.12	17.90	75.17
RL	47.10	17.27	76.08

The advantage of PRO mainly stems from two aspects. First, walk betweenness characterizes node importance from the perspective of multipath information transmission, thereby alleviating the excessive reliance on shortest-path-dominated structural indicators in conventional coupling methods. Second, the operational attribute matching mechanism improves functional compatibility between cross-layer nodes, which helps preserve sensing–command–firepower coordination and suppress the propagation of cascading failures.

TABLE III. COMPARISON OF NETWORK PERFORMANCE UNDER DIFFERENT COUPLING STRATEGIES (RANDOM ATTACK)

	Average Node survival rate (%)	Average functional chain retention ratio (%)	Average combat link efficiency degradation rate (%)
PRO	56.55	32.07	87.10
DB	53.74	31.91	87.22
NPC	49.98	32.00	89.05
BAL	44.79	29.58	89.36
DAL	43.85	29.54	89.55
RL	37.70	26.86	90.29

C. Network Model Analysis

To further evaluate the advantages and disadvantages of the proposed edge connection strategy, we constructed six network models (Table IV). Among them, M1, M2, M4, and M5 adopt the attribute synergy strategy for constructing the upper-layer subnetworks (sensing subnetwork and firepower subnetwork), while M3 and M6 apply the scale-free edge connection strategy. In the detect–strike integration phase, M1 and M4 employ the node efficiency prioritization strategy, whereas M2, M3, M5, and M6 adopt the degree prioritization strategy. All models use an improved tree-like network model for the intra-layer lower-layer subnetwork (command and control subnetwork). Based on these models, two categories of experiments were designed: (i) To compare the performance of the proposed strategy with that of the method in Ref. [16] under the same subnet construction configurations, with comparison groups including M1 vs. M4, M2 vs. M5, and M3 vs. M6; (ii) To evaluate the applicability of the proposed strategy under different subnet construction models, with comparison groups including M1, M2, and M3.

TABLE IV. CONSTRUCTION STRATEGIES FOR NETWORK MODELS

Model	Intra-layer Upper Network Linking Strategy		Intra-layer Lower Network Linking Strategy	Inter-layer Coupling Strategy
	Perception–Firepower Subnet Linking Strategy	Integrated Reconnaissance–Strike Operation Mode Linking Strategy		
M1 (Pro Model)	Attribute-prioritized	Node-efficiency-prioritized	Improved tree topology	Proposed method
M2	Attribute-prioritized	Degree-prioritized	Improved tree topology	Proposed method
M3	Scale-free	Degree-prioritized	Improved tree topology	Proposed method
M4	Attribute-prioritized	Node-efficiency-prioritized	Improved tree topology	Method of Ref. [16]
M5	Attribute-prioritized	Degree-prioritized	Improved tree topology	Method of Ref. [16]
M6	Scale-free	Degree-prioritized	Improved tree topology	Method of Ref. [16]

1) Node survival rate analysis: Under random attack (Fig. 15), all models had survival rate curves that were nearly linear with similar slopes in the early stages. In the later stages, under the same intra-layer connection strategy, the proposed strategy slightly outperformed the method in Ref. [16], with only minor differences between the curves. This suggests that during random node removal, even with different coupling strategies, each model can rely on the inherent scale-free redundancy of the network to maintain connectivity in the early phase.

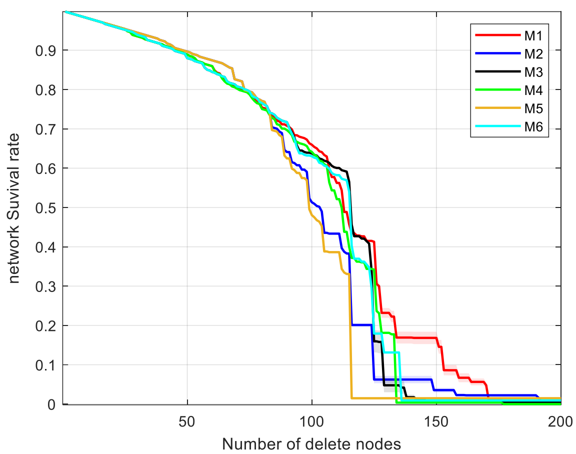

Fig. 14. Node survival rates of different network models (deliberate attack).

Under deliberate attack (Fig. 14), inflection points appeared in the node survival rate curves during the mid-to-late phases. A steep “step-wise decline” occurred after every few dozen node removals, corresponding to the cascading failure effect in interdependent networks. Under deliberate attack, M3 and M6 were the first to collapse. Their survival rates dropped sharply when 120 nodes were removed. M2 and M5 followed, collapsing when 150 nodes were deleted. M4 failed around 160 node removals. M1 had the highest stability: it survived until 180 nodes were removed. Thus, the proposed strategy performed best under conditions of attribute synergy and node efficiency prioritization, but was slightly less effective in scale-free configurations. As the proposed strategy introduces operational AM, it effectively optimizes node selection based on node operational attributes. However, when subnets are constructed using scale-free connections, this introduces interference to the strategy. In contrast, scale-free subnetworks inherently reduce overall network survivability. Comparisons among M1 vs. M4, M2 vs. M5, and M3 vs. M6 demonstrated that the proposed strategy consistently outperformed the method in Ref. [16] under various subnet modeling conditions, highlighting its robustness and general applicability.

2) OODA-Oriented functional chain retention analysis: To further examine whether the proposed strategy can maintain functional stability under different network structures, the OODA-oriented functional chain retention ratios of different network models were compared. Fig. 16 and Fig. 17 show the corresponding results under deliberate and random attacks, respectively.

As can be seen from the figures, although the overall degradation patterns vary across network models, the PRO strategy consistently maintains a higher OODA-oriented functional chain retention ratio than the compared methods in most cases. This indicates that the proposed strategy is able to preserve sensing–command–firepower coordination more effectively under different structural configurations, rather than exhibiting advantages only in a specific network instance.

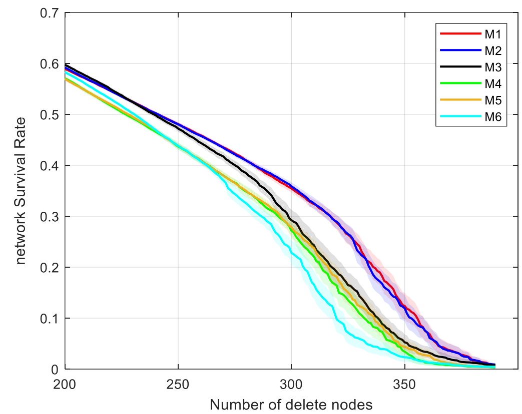

Fig. 15. Node survival rates of different network models (random attack).

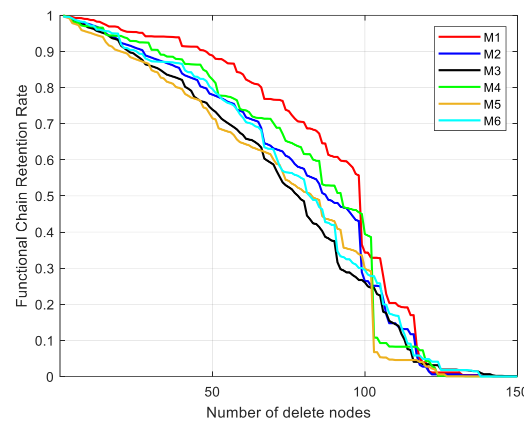

Fig. 16. OODA-oriented functional chain retention ratios under different network models (deliberate attack).

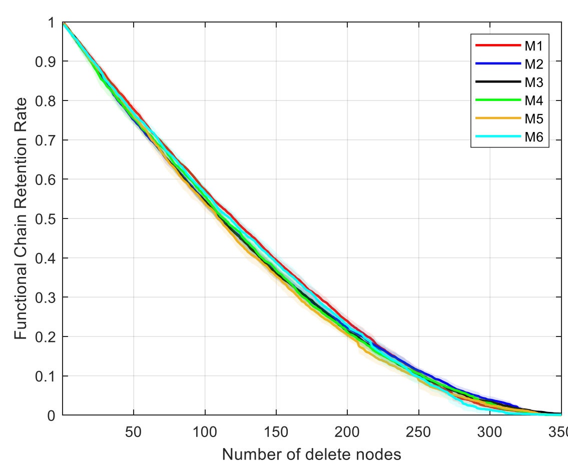

Fig. 17. OODA-oriented functional chain retention ratios under different network models (random attack).

3) Combat link efficiency analysis: Under both random and deliberate attacks (Fig. 18 and Fig. 19), M1 consistently maintained the lowest degradation rate of combat link efficiency. As the number of removed nodes increased, the proposed model demonstrated a clear advantage in terms of the degradation rate of combat link efficiency, compared to the other three models. This is attributed to the fact that the proposed strategy more effectively selects nodes with matched combat capabilities across the two subnetworks, particularly within the attribute-synergy subnetwork, thereby reducing combat capability imbalances between nodes and enhancing overall network robustness.

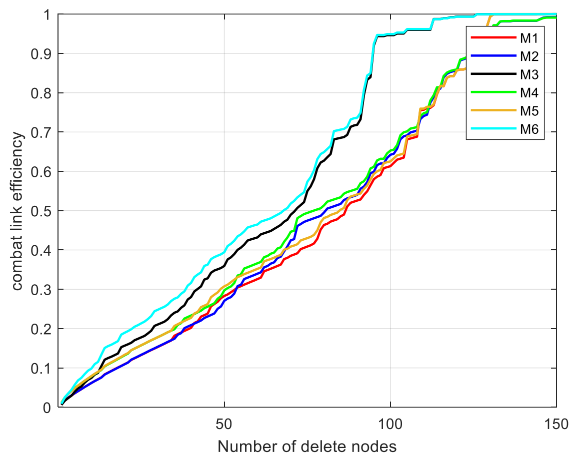

Fig. 18. Combat link efficiency degradation rate of different network models (deliberate attack).

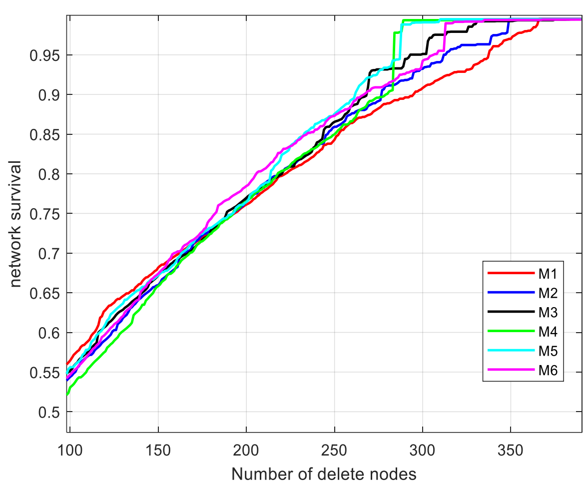

Fig. 19. Combat link efficiency degradation rate of different network models (random attack).

VI. Discussion

The simulation results demonstrate that the advantage of PRO is not limited to a single metric or a specific attack mode. Compared with topology-driven coupling strategies, PRO achieves better overall performance in node survival rate, OODA-oriented functional chain retention ratio, and combat link efficiency degradation rate. This indicates that the proposed strategy improves both the structural survivability of interdependent C2Ns and the functional stability of sensing–command–firepower coordination under cascading failures.

The performance improvement mainly comes from the joint consideration of multipath structural importance and operational compatibility. The walk-betweenness-based dependency strength captures the intermediary role of nodes from the perspective of multipath information transmission, rather than relying only on local degree or shortest-path-based indicators. Therefore, it helps avoid excessive concentration of dependency risks on a small number of structurally dominant nodes. Meanwhile, the operational attribute matching mechanism improves the functional rationality of interlayer dependency edges. Since sensing, command-and-control, and firepower nodes perform different roles in the OODA process, functionally compatible cross-layer coupling is important for maintaining effective operational chains after node failures.

From a system-engineering perspective, the results suggest that interlayer dependency design in C2Ns should jointly consider structural importance and role-related operational compatibility. The proposed strategy is particularly suitable for C2N architecture planning, survivability-oriented network design, and periodic robustness assessment before deployment or reconfiguration. Although the computation of walk betweenness and attribute matching introduces additional cost, the framework can be further accelerated through candidate-pair pruning, caching or local updating of structural indicators, and parallel implementation of the matching process.

VII. Future Directions

Future work will further extend the proposed framework from three aspects. First, more realistic C2N data and equipment-level operational parameters can be incorporated to improve the fidelity of node attribute modeling, including sensing, communication, command-support, and firepower-related characteristics. Second, the current interlayer coupling design can be extended to dynamic and adaptive scenarios, where communication quality, node status, task priorities, and command relationships may change over time. Third, the computational efficiency of the proposed framework can be further improved for larger-scale C2Ns through candidate-pair pruning, incremental updating of structural indicators, distributed computation, and parallel matching algorithms. These extensions would further enhance the scalability and applicability of PRO in larger-scale and more dynamic command-and-control network scenarios.

VIII. Conclusion

This study proposed PRO, an interlayer coupling strategy for two-layer interdependent C2Ns based on node walk betweenness and operational attributes. The proposed strategy integrates walk-betweenness-based dependency strength with operational attribute matching, thereby supporting survivability-oriented interlayer dependency design from a joint structural–functional perspective.

Simulation experiments on an air-defense command-and-control scenario were conducted under deliberate and random attacks. The results show that PRO achieves better overall performance than the compared baseline strategies in terms of node survival rate, OODA-oriented functional chain retention ratio, and combat link efficiency degradation rate. These findings indicate that the proposed strategy can effectively mitigate cascading failure risks while preserving sensing–command–firepower coordination.

The main contribution of this work lies in providing a structural–functional coupling framework for interdependent C2Ns. Unlike topology-only coupling strategies, PRO jointly considers multipath information transmission and operational compatibility, which provides a more mission-oriented basis for interlayer dependency design in command-and-control networks.

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