Appendixes

Appendix Formula

Link effectiveness capability

Assuming a network denoted as $G(V, E)$, wherein, for any pair of nodes v_i and v_j , there exists a node v_i with n neighboring edges connect to node v_j . The data traffic acquired by node v_i is represented by $Input\_flow(v_i)$, while $Output\_flow(v_i, j)$ signifies the data traffic emanating from node v_i through its j-th neighbor edge. Consequently, the effectiveness of the j-th neighbor edge, denoted as v_i , in the network can be expressed as follows:

$$LEC(e) = \delta(v_i, j) = \frac{Input\_flow(v_i) - Output\_flow(v_i, j)}{Output\_flow(v_i, j)} \quad (7)$$

Equation7 encapsulates the efficacy of the link denoted as e .e is the j-th link of node v_i .

Node effectiveness definition

In the preceding section, we have calculated the effectiveness of the link. From the perspective of traffic, given the inherent interdependence between the link and the node, the traffic flowing through the link ultimately converges at the node. so the effectiveness of the link serves as a basis for calculating the effectiveness of the node. Consequently, the node effectiveness for node v_i can be conceptualized as the expected value derived from the effectiveness of all neighboring edges. Mathematically, the node effectiveness is defined as follows:

$$NEC(v_i) = E\left(\sum_{j=1}^{n} \delta(v_i, j)\right) \quad (8)$$

where n represents the count of links directly connected to the node v_i, and $E()$ signifies the expectation function.

Link Importance Capability

Suppose the network G is a connected graph with V vertices and E edges, where nodes are reliable, and the probabilities of edge failures are independent in the network $G(V, E)$. Comparing subgraphs generated by deleting and contracting links, assuming the probability of failure for each edge is P, $0 < \mathrm{P} < 1$. The probability that all target nodes are connected by a failure-free link can be represented as a polynomial function of P:

$$\mathrm{R}(G) = \sum_{k=1}^{E_G} a_k \mathrm{P}^{E_G - k}(1 - \mathrm{P})^k \quad (9)$$

here, E_G is the number of communication links in the set of communication links of the network topology graph G, and k denotes the number of communication links in non-failure states. a_k represents the number of connected subgraphs consisting of k non-failure state communication links, where subgraph O has exactly k edges.

Let $\left(G - e_j\right)$ represent the network topology subgraph of network graph G after the deletion of communication links e_j, similarly, let $\left(G * e_j\right)$ be the topology subgraph of network graph G after the contraction of the communication link e_j. When evaluating the importance of edges in network graph G, the edge e_j that minimizes the reliability of $\left(G - e_j\right)$ from a deletion perspective is considered the most important. Conversely, from a contraction perspective, the edge e_j that maximizes the reliability of $\left(G * e_j\right)$ is deemed the most important. Therefore, an edge e_j is considered most important if it satisfies both conditions. According to the reliability polynomial method, when any two links $e'e''$ satisfy both conditions

$$\begin{cases} \mathrm{R}(G - e'') \geq \mathrm{R}(G - e') \\ \mathrm{R}(G * e'') \leq \mathrm{R}(G * e') \end{cases} \quad (10)$$

e' is judged to be more important than e'', denoted as $LIC(e') \geq LIC(e'')$. Similarly, when any two links $e'e''$ satisfy both conditions

$$\begin{cases} \mathrm{R}(G - e'') \geq \mathrm{R}(G - e') \\ \mathrm{R}(G * e'') \geq \mathrm{R}(G * e') \end{cases} \tag{11}$$

their importance is considered the same, denoted as $LIC(e') = LIC(e'')$. The ranking of the importance of each link and the corresponding score can be obtained based on these criteria. The importance of the j-th communication link is calculated as given in equation.

$$LIC(e_j) = R\left(G - e_j\right) + R\left(G * e_j\right) \tag{12}$$

where it is required that the above two conditions are satisfied for all P. Consequently, the evaluation results derived from the reliability polynomial are linked not to the reliability of the links but to the topology of the network. Simultaneously, the reliability polynomial method yields more accurate results compared to the minimum road set-cut set method.

Node Importance Capability

To comprehensively gauge the importance of a node amidst evolving network dynamics, we adopt a dual perspective by assessing node importance at both global and local levels. Specifically, the feature vector centrality of the network is employed to characterize the global significance of a node within the network topology. Simultaneously, the measurement of local importance is achieved through evaluating the similarity between a node and its neighboring nodes, providing a measurement understanding of a network node's significance within its immediate context.

In a network denoted as $G(V, E)$, the eigenvector centrality of a given node v_i is defined as the sum of the centralities of its neighboring nodes. Mathematically, this is expressed as:

$$c_e(v_i) = \sum_{j=1}^{N} A_{j,i} c_e\left(v_j\right) \tag{13}$$

here, N represents the number of nodes in the set of nodes for the network topology graph G, and the connectivity of node v_i and v_J is denoted by $A_{j,i}$.

In this study, the similarity of node v_i is defined as the expectation of the similarity between node v_i and its neighbor node v_j. The formula for node similarity $S(v_i)$ is expressed as:

$$S(v_i) = E\left(\sum_{j=1}^{N} A_{j,i} S\left(v_i, v_j\right)\right) \tag{14}$$

Where $S\left(v_i, v_j\right)$ is the similarity between node v_i and node v_j, and is defined by:

$$S\left(v_i, v_j\right) = \sum_{z \in \left(\Gamma_{v_i} \cap \Gamma_{v_j}\right)} \frac{1}{k_z} \left| \frac{\Gamma_{v_i} \cap \Gamma_{v_j}}{\Gamma_{v_i} \cup \Gamma_{v_j}} \right| \tag{15}$$

here, Γ_{v_i} and Γ_{v_j} represent the sets of neighboring node v_i and node v_j, respectively. $\Gamma_{v_i} \cap \Gamma_{v_j}$ denotes the number of node v_i and node v_j by common neighboring node z. Node $z \in \left(\Gamma_{v_i} \cap \Gamma_{v_j}\right)$, k_z are degrees of node z.

We start from the network resource allocation to give meaning to the nodes, considering the process of resource transfer between node v_i and v_j through common neighbors, the importance of node v_i is determined by a combination of its eigenvector centrality and node similarity. The formula for determining the importance of node v_i is given as:

$$NIC(v_i) = \frac{c_e(v_i) = \sum_{j=1}^{N} A_{j,i} c_e\left(v_j\right)}{S(v_i) = E\left(\sum_{j=1}^{N} A_{j,i} S\left(v_i, v_j\right)\right)} \tag{16}$$

Network reliability capability

This paper advocates employing the relative size of the maximum connectivity subgraph as a metric to evaluate network reliability. Following the fundamental principles of graph theory, a network graph G is deemed connected if there exists a path between any two nodes, thereby ensuring connectivity across the network. Where the initial network, upon an attack-induced node failure, fractures into distinct yet individually connected subgraphs. These subgraphs may exhibit internal connectivity but remain disconnected from each other, and the maximally connected subgraph, containing the most nodes, assumes prominence. Consequently, the network reliability is expressed as :

$$NRC = E\left(\frac{V_{sub}}{V_{ori}}, \frac{E_{sub}}{E_{ori}}\right) \tag{17}$$

Network Integrated Performance

We introduce the concept of Network Integrated Performance (NIP) to comprehensively assess the effectiveness, importance, and reliability of the network. This involves the analysis of link effectiveness, node effectiveness, link importance, node importance, and network reliability at each moment. Mathematically, this is expressed as follows:

$$NIP_T = F\left(NEC_T, NIC_T, LEC_T, LIC_T, NRC_T, w_T\right) \tag{18}$$

where, LEC denotes link effectiveness capability, NEC is node effectiveness capability, LIC represents link importance capability, NIC stands for node importance capability, and NRC signifies network reliability capability. The parameter w denotes the weight assigned to each capability, which is calculated by the entropy method, not defined by oneself, which will be more objective. The complexity of our adopted TOPSIS ensemble method is approximately $O\left(mn + mlog\left(m\right)\right)$, with n indicating the number of indicators and m the number of nodes.

Appendix Experimentation

In order to verify the robustness of the proposed algorithm in different network environments, we re injected the IoT traffic obtained from the LOT-23 project into a new topology uninet network. This IoT network traffic was captured in the Stratosphere Laboratory of the AIC group at CTU University FEL in the Czech Republic, and different types of traffic were replayed in different network topologies to make the experiment more reliable. The experimental results obtained are as follows:

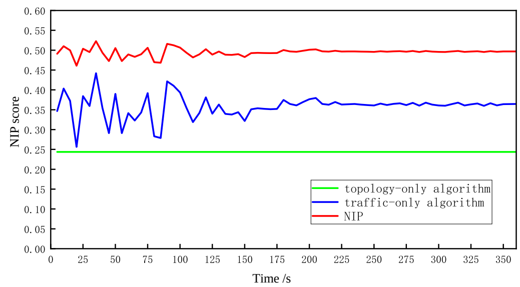

Fig. 4 NIP evaluation results of different algorithms

As shown in Fig. 4, the red curve represents the NIP evaluation algorithm, and the green curve represents the performance values of the network evaluation algorithm that only considers topological information. The blue curve represents the performance value of the network evaluation algorithm when only considering the impact of traffic. The trend of the red curve is more in line with expectations. Similarly, it can be calculated that the variance of the red curve is 6.37x10-5, with a standard deviation of 0.0079; The variance of the green curve is 0.00057, and the standard deviation is 0.0239, so the stability of the NIP algorithm is better than that of the green evaluation algorithm that only evaluates traffic information.

Overall, the performance of NIP algorithm is superior to the other two algorithms. Therefore, only by comprehensively considering both traffic and topology, and evaluating the attribute values of the network from multiple dimensions, can accurate evaluation be achieved.