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Identifying vital edges in Chinese air route network via memetic algorithm

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Abstract Due to rapid development in the past decade, air transportation system has attracted considerable research attention from diverse communities. While most of the previous studies focused on airline networks, here we systematically explore the robustness of the Chinese air route network, and identify the vital edges which form the backbone of Chinese air transportation system. Specifically, we employ a memetic algorithm to minimize the network robustness after removing certain edges, and hence the solution of this model is the set of vital edges. Counterintuitively, our results show that the most vital edges are not necessarily the edges of the highest topological importance, for which we provide an extensive explanation from the microscope view. Our findings also offer new insights to understanding and optimizing other real-world network systems.

1. Introduction

With the increasing people and goods transport demand during the accelerating globalization process, the air transportation system plays a more important role than ever before due to its high-speed and high-security advantages. For example, the air transport volume of China grows at an average annual speed of over 10% in the past decades, and now it possesses over one seventh of the total comprehensive transport volume (including roadways, railways, shipping and air transport), which was only 7.9% in 2000. Hence the air transportation system has been drawing much attention from different research communities. One of the most interesting directions is to analyze the structure and function of air transportation systems within the framework of complex network theory.

The air transportation system can be represented as a network, in which nodes denote airport and an edge will be created if there is a direct flight between two airports. In the vast majority of previous literature, the air transport network (ATN) was primarily classified into two scales: worldwide and national.

For the worldwide scale, Amaral et al. firstly found that worldwide ATN is a small-world network with a power-law

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degree distribution, and the highest-degree airport is not necessarily the most central node, prompting them to propose a network model where both geographical and political factors are taken into account.[1,2] Barrat et al. investigated the worldwide ATN from a perspective of complex weighted networks and found the nonlinear positive correlation between flight flow and topology properties.[3,4] They proposed a weighted network model, enlightening the understanding of weighted feature of complex systems. Verma et al. decomposed the worldwide ATN into three distinct layers via k-core decomposition and found that this network is robust to the removal of long distance edges, but fragile to the disconnectivity of short and apparently insignificant edges.[5,6]

For the national scale, ATNs of several major nations, such as US, Brazil, India and China, are extensively studied[3,7–11], and the national ATNs usually exhibit different features from the worldwide ATN. Gautreau et al. studied US ATN during 1990–2000.[3] A remarkable result they presented is that although most statistical properties are stationary, an intense activity takes place at the local level. Fleurquin et al. proposed a delay propagation model via quantifying the network congestion for US ATN, revealing that even under normal operating condition the systemic instability risk is non-negligible.[11] Rocha investigated the Brazilian ATN during 1995–2006, and found that it shrank in topology but grew in traffic volume.[7] Bagler studied the Indian ATN, and found its signature of hierarchy feature.[12] As the most active economy, the Chinese aviation industry ranks second to US in the past decade and keeps a high increase rate. Consequently, Chinese ATN attracts continuous attention in different aspects from topology to dynamics and evolution,[8–10,13,14] one of which is to investigate the backbone of ATN, the air route network (ARN).

ATN is actually a logic network with origin-destination (OD) relationships. In real air traffic operation, a flight does not straightly fly from departure airport to landing airport, but along some air route waypoints. ARN consists of air route waypoints and connections between them. In 2012, Cai et al. firstly investigated the Chinese ARN[15] and found that the degree distribution of Chinese ARN is homogeneous but the traffic flow is rather heterogeneous. Vitali et al. then investigated the horizontal deviation and delays in Italian ARN.[16] The analysis of ARN is quite a novelty in the literature. However, the network robustness, which is an important issue for infrastructure systems[17] and has been extensively studied in ATN,[18,19] is still rare in ARN. In the typical network robustness model, edges are removed by different targeted attack strategies and the size of giant component estimates the robustness of the network.[20] When a small amount of edges are removed, the size of giant component is of a very small change. In this paper, we focus on identifying the vital edges in Chinese ARN by examining the robustness of the new network after removing an edge set via memetic optimization. Remarkably, we find that the most vital edges are not necessarily the edges of the highest topological importance.

The rest of this paper is organized as follows. In the next section, we demonstrate Chinese air route network and its basic properties. Section 3 describes the optimization model and the memetic algorithm. Section 4 presents the simulation results and corresponding analysis. Finally, the paper is concluded in Section 5.

2. Chinese air route network

The latest data of the Chinese air route network are provided by the Air Traffic Management Bureau (ATMB) of China. In the Chinese ARN, airports or air route waypoints are nodes and edges are represented by the air route segments. An air route waypoint is a navigation marker which keeps the pilots informed about the desired track. In the air transportation system, the flights will fly along the air route waypoints, but not directly fly from one airport to another. Fig. 1 is an illustration of ARN, where airlines are depicted by the dotted line and air route segments are denoted by the solid line. Fig. 2 shows the structure of the Chinese ARN, which contains $N = 1499$ nodes and $M = 2242$ edges.

In Ref.[15], the authors found that the topology structure of the Chinese ARN is homogeneous, yet its distribution of flight flow is quite heterogeneous. If we compare the Chinese ATN with the Chinese ARN, we found significant differences. On one hand, the Chinese ATN is a typical small-world with low average shortest path length and large clustering coefficient. On the other hand, the Chinese ARN is not a small-world network due to its low clustering coefficient, large average shortest path length and exponential spatial distance distribution.

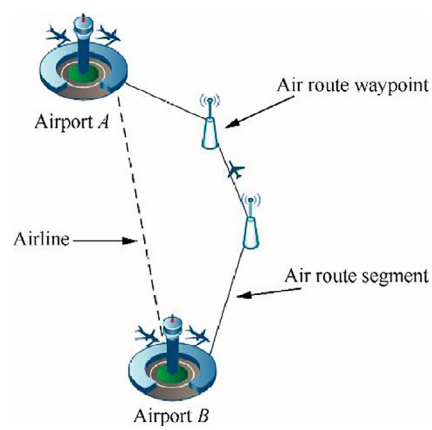

Fig. 1 Illustration of ARN.

Fig. 2 Structure of Chinese ARN (contains $N = 1499$ nodes and $M = 2242$ edges).

3. Model

3.1. Optimization model

The static robustness of complex networks has been extensively studied in the past decades. In Ref.[21], it is quantified by the relative size of the largest connected component $G = N'/N$ where N is the total number of nodes in initial network and N' is the number of nodes in the largest component after attack. The larger value of G represents a more robust network. Based on the largest connected component, Schneider et al. proposed a measure R to evaluate the robustness against targeted attack on nodes.[17]

$$R = \frac{1}{N}\sum_{Q=1}^{N} s(Q) \tag{1}$$

where $s(Q)$ is the fraction of nodes in the largest component after removing Q nodes. For calculating the robustness of a network, we will follow a degree adaptive strategy: the highest degree nodes will be systematically removed one by one. It is a more comprehensive measure of network robustness. Obviously, a network with higher R has a stronger resistance to targeted attacks.

In the Chinese ARN, the closure of air route segment will decrease the connectivity of the whole network. If the vital edges can be recognized, we can prevent the cascading effect induced by the remove of the edges. It is of great significance to identify vital edges that lead to the vulnerability of Chinese ARN. In Ref.[22], Freeman proposed a global metric edge-betweenness to measure the importance of an edge, which can identify influential edges effectively. It is defined as follows:

$$B_E(i) = \sum_{j,k\in\Gamma, j\neq k} \frac{n_{jk}(i)}{n_{jk}} \tag{2}$$

where Γ is the set of nodes, n_{jk} the number of the shortest paths from j to k, and $n_{jk}(i)$ the number of the shortest paths from j to k via edge i.

In this work, we formulate a combinational optimization problem to identify the vital edges within network robust model in the Chinese ARN. The objective is to minimize the network robustness after removing certain edges, i.e. closing certain air route segments. Therefore, these edges play an important role in maintaining network robustness. The optimization model is formulated as follows:

$$\begin{aligned} &\min R(\boldsymbol{x}) \\ &\boldsymbol{x} = [e(1), e(2), \ldots, e(V)] \\ &\text{s.t.} \textstyle\sum_{i=1}^{V} x_i = \text{cost} \end{aligned} \tag{3}$$

where V is the total number of edges in the network and $\boldsymbol{x}$ is a V dimensional binary variable, $e(k) \in \{0, 1\}$ ($e(k)$ represents the kth edge in the network). $e(k) = 1$ represents that the edge $e(k)$ is removed, otherwise it remains in the network. The total number of removed edges is certain and denoted as cost (C). Thus, we can identify critical edges in the network and minimize its robustness.

3.2. Memetic algorithm

For solving this optimization model, we will use the memetic algorithm (MA), a useful tool for dealing with large-scale combinational problem.[23–26] Coming from the concept of meme, MA is defined as a part of local improvement in the process of cultural evolution. It is a hybrid metaheuristic of global search and heuristic local search with three operations: crossover, local search and tournament selection.

(1) Initialization

In MA, the population is composed of P_n individuals. Each individual x represents a scheme of removing edges in the network and was generated randomly.

(2) Crossover

The crossover operator works on two parent individuals and can search in a large area. Suppose that x_{p1} and x_{p2} are two parent individuals, and x_{c1} and x_{c2} are two child individu-

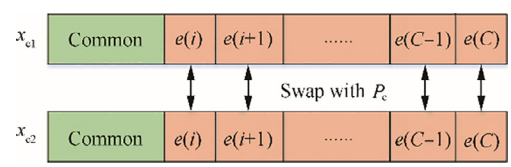

Fig. 3 Illustration of crossover process.

Table 1 Pseudocode of MA.

```
Begin
Initialize Pn individuals with randomly selected existing edges in network.
While g < Pm
  Repeat
    Randomly selected two individual xpi and xpj that have not been selected.
    If rd < Pc (rd is a random number between 0 and 1)
      Assign parent xpi and xpj to child xci and xcj.
      (xci, xcj) ←Crossover (xpi, xpj).
    end if
  Until (all individuals have been selected)
  For i = 1 to 2Pn
    select an individual xl using the roulette wheel selection based on the fitness.
    For each edge eij in individual xl
      if rd < Pl
        mutate with a new randomly selected edge elm but not in xl.
        if μ · |kl − km| − |ki − kj| > 0
          Accept the local search.
        end if
      end if
    end for
  Calculate the robustness of each individual in parent and child.
  Pnext ← 2-tournament selection (Pparent, Pchild);
end while;
End
```

als. First, we assign x_{p1} to x_{c1} and x_{p2} to x_{c2} and obtain the following sets of edges:

$$\begin{cases} E_c = \{e | e \in x_{c1}, e \in x_{c2}\} \\ E_{\overline{c1}} = x_{c1} - E_c \\ E_{\overline{c2}} = x_{c2} - E_c \end{cases} \tag{4}$$

In fact, E_c is the set of common edges of x_{c1} and x_{c2}. $E_{\overline{c1}}$ and $E_{\overline{c2}}$ are the set of edges of the network after removing the common edges of x_{c1} and x_{c2}. That is, $E_{\overline{c1}}$ and $E_{\overline{c2}}$ have the same number of edges but are completely different. Then, for each pair of edges in $E_{\overline{c1}}$ and $E_{\overline{c2}}$, we conduct the following operations with the probability P_c.

$$\begin{cases} x_{c1} = x_{c1} - E_{\overline{c1}}[i] + E_{\overline{c2}}[i] \\ x_{c2} = x_{c2} - E_{\overline{c2}}[i] + E_{\overline{c1}}[i] \end{cases} \tag{5}$$

In summary, only the set of non-common edges that we want to remove will be swapped between x_{c1} and x_{c2} (Fig. 3).

(3) Local search

The local search operator is an important part in MA that can accelerate the convergence speed. Based on previous edge importance evaluations,[27,28] we adopted a local search in the direction of removing more important edges. We first select an individual from parent and child population using the roulette wheel selection based on their fitness. Then for each edge of the selected individual, we conduct a local search with probability P_l. For example, edge e_{ij} (e_{ij} represents the edge between node i and node j) will mutate into a randomly selected existing edge e_{lm} but not in its individual. This mutation will be accepted when the following formula is satisfied:

$$\mu \cdot |k_l - k_m| - |k_i - k_j| > 0 \tag{6}$$

where μ is a formula parameter in the range [0,1] and k_l, k_m, k_i and k_j represent the degree of nodes l, m, i and j respectively.

(4) Tournament selection

In this part, two individuals are respectively chosen from parent population and child population to run a tournament for the tournament selection. The population with the best fitness is selected for the next generation, and the total number of generation is P_m.

To conclude, the pseudocode of MA proposed is presented in Table 1.

Table 2 Parameters of memetic algorithm.

Parameter	P_n	P_c	P_l	μ	P_m
Value	20	0.8	$5/C$	0.7	500

4. Results

In some previous papers, under different kinds of malicious attacks on edges, the strategy based on edge-betweenness is actually a commonly adopted attack strategy.[20,29,30] Here, in order to identify the vital edges, we examine the robustness of the new networks after removing edges via MA, and compare it with the highest edge-betweenness adaptive strategy (B_EAS). As many real-world networks are of scale-free properties, such as air transportation network,[9] World-Wide Web,[31] Internet[32] and social network,[33] the experiments are carried out not only on Chinese ARN but also on Barabási-Albert (BA) scale-free network to demonstrate the universality of

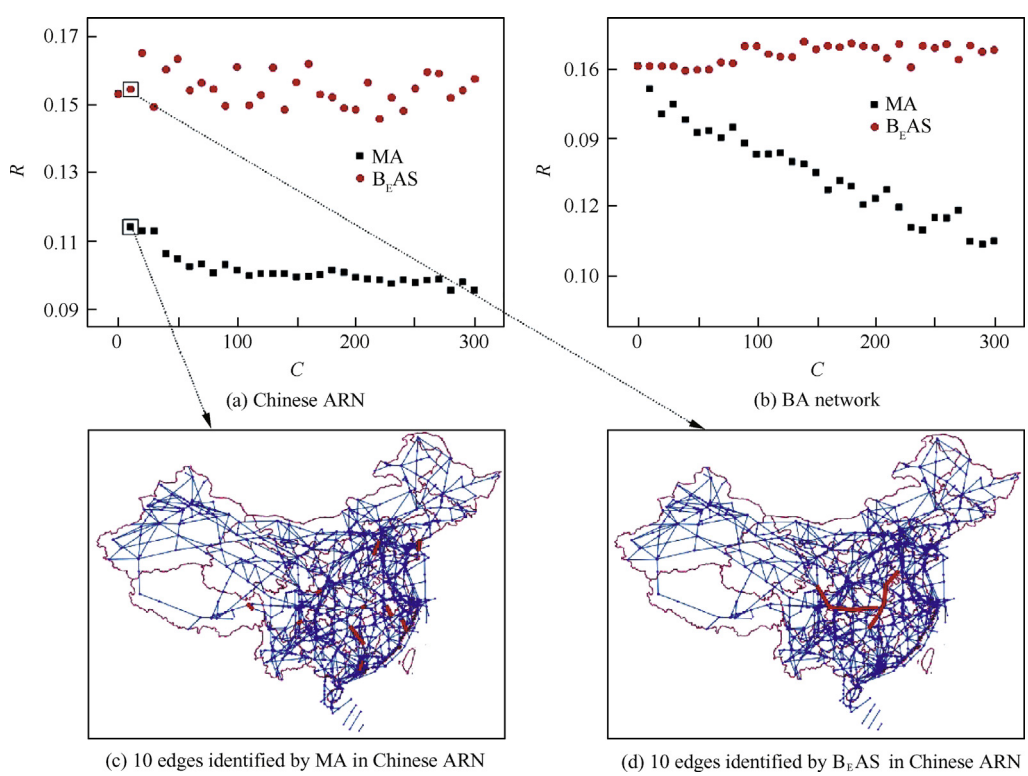

Fig. 4 Robustness R as a function of cost C of removing edges.

our method. The Chinese ARN has 1499 nodes and 2242 edges. The BA scale-free network is generated with m_0 nodes and a new node is added with m edges at each time step, which connect the new node with m different existing nodes. Here, it is set that $m_0 = 2$ and $m = 2$ and the BA network is of 1000 nodes and 2000 edges. The cost denoting total number of removing edges is set from 0 to 300 and the network without edges removed represents the initial network. Table 2 shows the configurations of the memetic algorithm parameters used on the optimization model.

Fig. 4 shows the simulation results of the MA and B_EAS of identifying the vital edges for the BA network and Chinese ARN. Looking at both networks via MA, we can see that the robustness R decreases and the cost C increases when removing edges (Fig. 4(a) and (b)). It can also be noticed that the MA is significantly better than the B_EAS. The difference

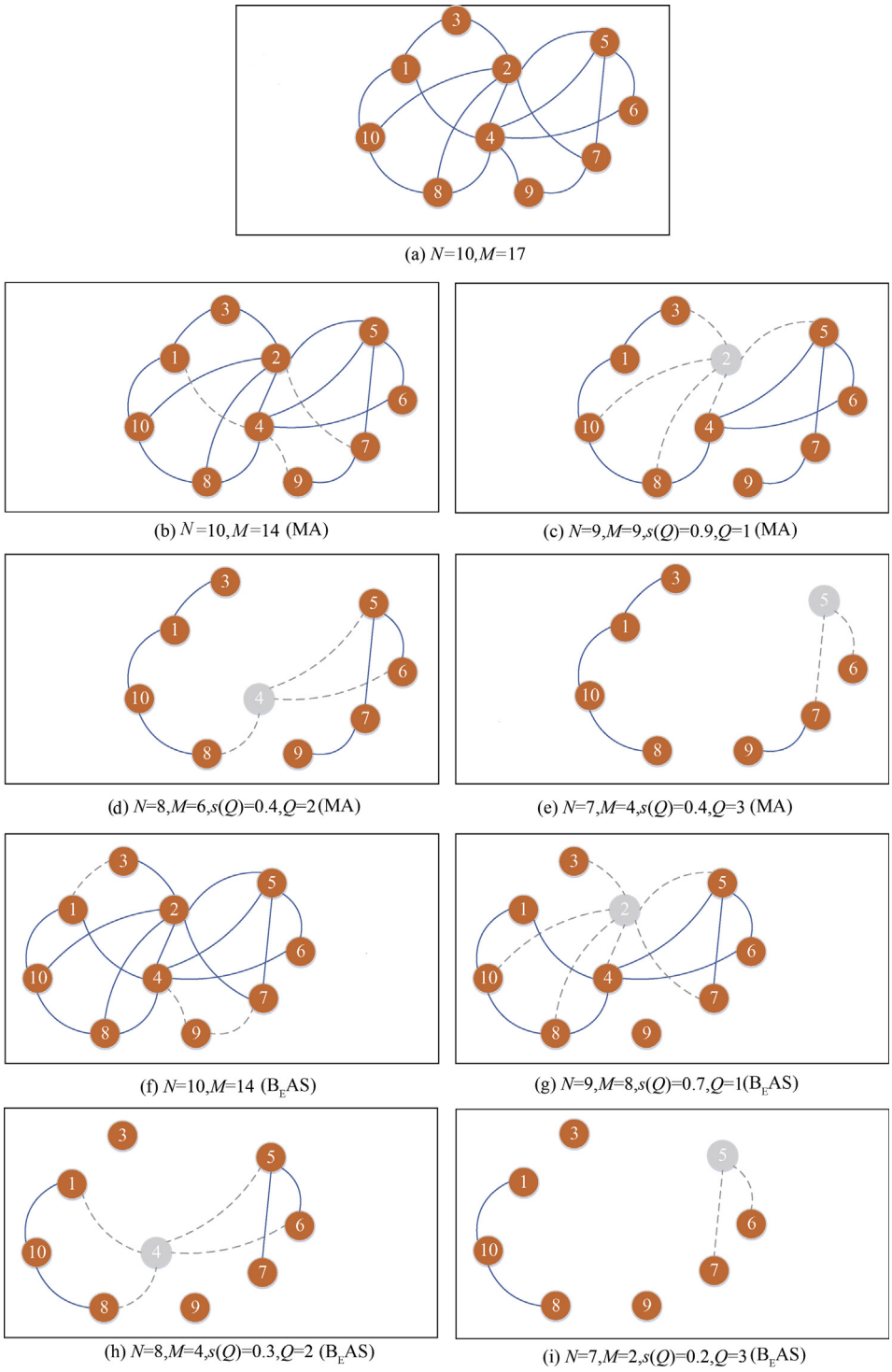

Fig. 5 Illustration of malicious attack process of toy model with 10 nodes via MA and B_EAS.

Table 3 Illustration of vital edges identified by MA and B_EAS.

C	MA	R	B_EAS	R
1	$e_{1,10}$	0.33	$e_{4,9}$	0.35
2	$e_{4,6}, e_{5,6}$	0.32	$e_{4,9}, e_{1,4}$	0.35
3	$e_{1,3}, e_{4,9}, e_{7,9}$	0.29	$e_{4,9}, e_{1,4}, e_{2,7}$	0.37
4	$e_{2,5}, e_{2,7}, e_{7,9}, e_{8,10}$	0.27	$e_{4,9}, e_{1,4}, e_{2,7}, e_{4,6}$	0.36
5	$e_{1,10}, e_{4,9}, e_{5,7}, e_{7,9}, e_{8,10}$	0.24	$e_{4,9}, e_{1,4}, e_{2,7}, e_{4,6}, e_{2,3}$	0.35
6	$e_{1,3}, e_{1,10}, e_{2,3}, e_{2,5}, e_{2,7}, e_{7,9}$	0.24	$e_{4,9}, e_{1,4}, e_{2,7}, e_{4,6}, e_{2,3}, e_{4,8}$	0.34

between the two methods is especially high. It is obvious that the critical edges in the network are not extremely related with the edge-betweenness. Moreover, the memetic algorithm works better in the Chinese ARN and decreases its robustness R faster when a few edges are removed. The reason is that the Chinese ARN is not a small-world network. And the Chinese ARN is vulnerable because of its small clustering coefficient and large average shortest path length. In detail, Fig. 4 (c) and Fig. 4(d) separately show 10 edges identified by the MA and BEAS methods in the Chinese ARN. It is found that all the top 10 highest edge-betweenness edges in the network are located at the middle China, which are almost completely different from the 10 edges identified by MA.

We have seen that the MA works on both Chinese ARN and BA network. In order to reveal the underlying mechanism clearly, we examine a toy model with a network containing 10 nodes and 17 edges (Fig. 5). In Fig. 5, the blue lines are the existing edges and gray dotted lines are edges removed in that step. In the same way, the gray nodes mean that these nodes are removed and yellow nodes still exist. When no edge is removed from the network (Fig. 5(a)), the robustness of the initial network is 0.35. Here, three edges are removed to measure the criticality of these edges using the MA and B_EAS methods. Since edges $e_{1,4}$, $e_{2,7}$ and $e_{4,9}$ have the highest edge - betweenness in the network, they are removed in the B_EAS (Fig. 5(b)) and now we have a new network named A. Similarly, edges $e_{1,3}$, $e_{4,9}$ and $e_{7,9}$ are identified as the most important ones in the MA, and we now have a new network B (Fig. 5(f)). For estimating which group of edges is critical, we compare the robustness of network A and B (Fig. 5(c)–(e)) and Fig. 5(g)–(i)). Table 3 illustrates the corresponding solutions and the robustness of the solution for both methods.

In network A (B_EAS), we first remove node 2 with the highest-degree together with all edges connected with it: $e_{2,3}$, $e_{2,4}$, $e_{2,5}$, $e_{2,8}$ and $e_{2,10}$. $s(Q = 1)$ of the new network is 0.9, which is the fraction of nodes in the giant component after removing 1 node (Fig. 5(c)). However in network B (MA), the value of $s(Q = 1)$ quickly decreases to 0.7 (Fig. 5(g)). Then, after the second nodes are removed, $s(Q = 2)$ in both networks A and B are 0.4 and 0.3 respectively (Fig. 5 (d) and Fig. 5(h)), which is reduced to 0.4 and 0.2 after the third node is removed (Fig. 5(e) and Fig. 5(i)). At the end, all nodes are removed from the network and the robustness of network A and B is 0.37 and 0.29 respectively. Thus, as previous results revealed, the critical edges in the network are not extremely related to the edge-betweenness, which apparently contradicts common intuitions.

Table 3 illustrates the corresponding solutions and the robustness of the solution to both methods of the toy model in Fig. 5. In the network after removing Q nodes and the edges connected with them, N is the number of nodes, M is the number of edges, and $s(Q)$ is the fraction of nodes in the largest component. The results demonstrate that the most vital edges are not necessarily the edge with the highest topological importance. Thus these edges identified by MA are important for the network robustness and should be protected to ensure the survivability of the network.

5. Conclusions

It is of great importance to improve the robustness of real networks. In this paper, we identified the vital edges in Chinese air route network, which lead to fast breakdown after targeted attacks. Our results reveal that the edge-betweenness, an index to measure the importance of edges in short paths, is of little relevance to this problem. Furthermore, we demonstrate that the memetic algorithm is able to pinpoint the edges that have been proven more important than edges of high edge-betweenness. We also confirm these findings in scale-free model networks, hence offering novel insights of edge essentiality in various real networks. Thus, we think the vital edges identified by memetic algorithm should be especially protected to ensure a good performance of a network. In Chinese ARN, this means that air traffic managers should foresee complex solutions when considering the closure of one vital air route segment.

Acknowledgements

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