Network Repair Strategy Based on the Failure of Airline

Zhang Yuxiang [a], Wu Minggong [b], Wang Xiaorong [c], Wen Xiangxi [d]

College of Air Traffic Control and Navigation, Air Force Engineering University,Xian, 710051, China

[a]email: 18691307145@163.com, [b]email:wuminggong@sohu.com, [c]email: 532472153@qq.com, [a]email: wxxajy@163.com

Abstract. Contraposing to the network repair problem of airline network after edge failure, an optimization model was proposed based on network repair study and hub airline network theory. The model regarded the best performance under certain cost as the objective function. And it satisfied different requirements by giving different weights. The model considered the cost caused by distance and congestion. The network efficiency was selected as measurement for performance. The model was solved by improved particle swarm optimization. At last, taking the airline between Hang zhou and Xian yang as an example, a simulation was conducted to verify the model. The experimental result shows that capacity decision coefficient can control the cost well caused by congestion through changing the node capacity, which can affect the allocation method of traffic and has an influential effect on network survivability. What's more, the model can well adjust the balance between cost and network performance. The model has a good application prospect.

1 Introduction

In recent years, our air transport industry develops rapidly, and airline network expands continuously, which provides a strong impetus for the economic development of our country. However, in this process some contradictions become more and more sharp. At present, it occurred from time to time that the military training or bad weather interrupted route operation, which led to serious economic loss for airlines and negative impact on military department. Therefore, it has important practical significance to improve network survivability through repairing failure route.

There are mainly two kinds of study on improving network survivability. One is the network survivability optimization research in advance, which can be divided into three categories: Topology optimization, link capacity optimization and routing strategy optimization. The optimization model generally considered the cost and survivability as optimization factors, and they optimize the network before operation. And the effect of those researches is limited due to the network development status and cost restrictions. What's more, the optimization is mainly based on the typical network, with a little research on the actual networks, and the research on the aviation network even less. So the network repair strategy research becomes another important way to improve the network survivability.HU Bin proposed three repair strategies under different attack strategies based on node failure[1]. But his restoration strategy focuses on theory, and does not put forward the actual repair method. As well, it does not have timeliness. For the computer network repair, various routing models and optimization algorithms were proposed. There are also studies on load traffic. Cheng Jie put forward the repair model with the effect of cascading failure based on edge failure [2]. Liu Ming proposed an optimal path selection model based on incomplete information under load congestion [3]. But compared to these networks, airline network has its own characteristics: network traffic travel direct, if an airport occurs to paralysis, the flights related to the airport will be cancelled , and there is no backup routing or no cascading failure; if the route is invalid, the redistribution is restricted by the number of transit times; airport congestion would happen, and the cost caused by congestion is different; because of the space trait of the airline network, distance would cause cost. These characteristics lead to the current network repair optimization model not being a good solution to this problem, although they provide ideas. Dang

Yaru put forward that the repair method by adding a backup node and the use of ground transportation [4]. Although the model has certain feasibility, there are still large practical limits on the backup node and the use of ground traffic.

Therefore, in accordance with the study of repair strategies, combined with the characteristics of the airline network, this paper proposed a new repair model by considering repair cost and network performance to improve network survivability.

2 Model analysis and establishment

2.1 problem description and analysis

The essence of traffic redistribution is to make a scientific and reasonable plan for the traffic on the original route, and to meet the demand of the passenger flow, which containing these problems: multiple dispatch or single airport distribution, choose which airport to transit; if multiple airport transit, how to reasonably distribute the flow. The research of hub route network provides scientific theory reference for the selection of airport [5-6]. These literatures try to spend the least cost to construct the network with different transit strategy and capacity constraint. Its objective of the optimization is cost minimization, not the network survivability. And these studies do not take cost of node congestion into account. But they still analyze the practical constraints which need to be considered in the optimization, which has a good reference value for this paper.

In the model construction, two factors need to be considered: cost and network performance. The relationship between weight change and cost is mainly reflected in the following aspects: cost will increase due to the increase of distance when transiting; due to airport capacity constraints, too concentrated traffic in a certain airport will lead to cost increasing by congestion. What's moreThe change of weight distribution leads to the change of network efficiency, and the efficiency of network has a strong sensitivity to the weight distribution [7]. Therefore, the weighted network efficiency is used as a measure of network performance index in this paper. In order to simplify the model, according to the actual situation of our country, the paper makes the following assumptions:

(a) flight traffic flows between the two airports are basically the same, so the network can be regarded as an undirected network, and the route flow is the sum of the two directions;

(b) the hub network in our country at present has not officially formed, so it take non-strict connection mode, any airport can be selected to transit;

(c) due to the special nature of the passenger transport, any O-D flow transport path only needs one transit;

(d) Airport congestion and discount factor has the intrinsic link, so this paper only considers the congestion effect.

2.2 Cost influencing factors

In this paper, we mainly consider the distance cost and node congestion cost. The first one is the distance cost. Suppose the unit cost of a flight unit distance is f_0, then the distance cost is defined as:

$$f = \sum_{k \in P} w_k f_0 x_k \quad (1)$$

Where w_k is the traffic flow through the node, x_k is the distance of transferred path, P is a set of nodes for transfer.

The second one is congestion cost. In the study of cascading failure in complex networks, the relation between node capacity and the network load is usually considered as a linear function.so the paper assumes that the node capacity is linearly related to the strength of node degree [8], which is:

$$C_i = (1 + \alpha) S_i \qquad （2）$$

Where C_i is node capacity, S_i is node strength, which is the sum of edge weights directly connected to the nodes, α is capacity limitation coefficient., which is given as $\alpha = 1/k_i^\omega$ （$\alpha \in (0,1)$）, where k_i is node degree, ω（$\omega \in [0, +\infty)$)is capacity control coefficient. Generally speaking, the more busy the airport, the smaller the capacity of the airport. And the ω can play

such a regulatory role. Since there are capacity constraints, there is the use of the efficiency problem. In the literature [9], the relationship between the link cost and the utilization rate is given. As the link utilization and the utilization ratio of the nodes are similar, the paper given the node congestion cost as following:

$$\rho(a) = h * \begin{cases} u(a), & 0 \le u(a) < 1/3 \\ 3u(a) - 2/3, & 1/3 \le u(a) < 2/3 \\ 10u(a) - 16/3, & 2/3 \le u(a) < 9/10 \\ 70u(a) - 178/3, & 9/10 \le u(a) \le 1 \end{cases} \quad (3)$$

Where h is congestion cost control coefficient, which gives weight to control congestion cost in appropriate range, and $u(a)$ is route utilization, defined as:

$$u(a) = w_k / (S_i / \alpha) \quad (4)$$

Formula (3) gives a relationship between utilization and cost, but it do not directly relate to the actual cost. Therefore in this paper, the node congestion cost is added to the route cost, and the total cost of the network is:

$$F = \sum_{k \in P} w_k f_0 x_k (1 + \rho_k) / F_{max} \quad (5)$$

Where F_{max} is maximum possible value for cost, that is the maximum cost of distribution without considering the network performance optimization, so as to ensure the impact of the cost control in the range [0,1] by dividing it.

2.3 network performance

In airline network, if the speed of transmission between any two nodes is faster, it means that business contacts more convenient and the network performance is better, which can use traffic density to reflect the characteristics between two nodes. The airline network is a similarity weight network. The network efficiency calculation method based on the similarity weight network is given in the literature [10]:

$$E = \frac{1}{n(n-1)} \sum \frac{d_{ij}^*}{d_{max}} \quad (7)$$

Where d_{ij}^* is the shortest path between node v_j and node v_j, d_{max} is the maximum path among all node pairs in a network. $\eta_E \in [0,1]$, and the greater the η_E, the better the efficiency of the whole network.

2.4 Model building

In the previous studies, the optimal value of the objective function is obtained in a condition that the other target value is determined, which reduces the practicability and flexibility of the model. Therefore, in order to overcome these shortcomings, this paper balances the relationship between the two aspects by giving the cost and network efficiency weight respectively, gives The following optimization model:

$$\min[(1-\beta)F - \beta E] \quad (8)$$

$$s.t. \sum_{k \in N} X_{ik} = \sum_{k \in N} X_{kj} = W_0 \quad (9)$$

$$X_{ik} = X_{kj}, \quad k \notin i, j \quad (10)$$

$$S_k \le C_k, \quad k \notin i, j \quad (11)$$

$$W_{kl} \in Z^+, \quad k, l \in N \quad (12)$$

Where $N = \{1, 2, 3 \cdots, n\}$ is the number of airports for transit, i is the departure city number, j is destination city number, k is transit city number, W_0 is the traffic on the failed route. Formula (8) indicates that the optimal relation between cost and network performance. Formula (9), (10) indicates the distribution contains all traffic of the failure route, and it must obey the flow conservation. Formula (11) guaranteed capacity constraints, and formula (12) is to ensure that the allocation of flight is an integer..

3 Algorithm analysis

The established model is a nonlinear integer programming problem. Particle swarm optimization algorithm has the advantages of relatively simple iterative process and fast convergence speed. At present, it is widely used in the field of nonlinear and integer programming [10]. The algorithm is used to solve the problem of traffic redistribution. The methods of dealing with constraints are as follows:

(1) Through two aspects to ensure the sum of the flow is a fixed value. One is to increase the penalty function, so the objective function is changed into:

$$\min[(1-\beta)F/F_{\max}-\beta E+\lambda(sum(p)-y)^2]　（11）$$

Where p is feasible solution, λ is penalty coefficient. The other is to distribute the total flow according to the size of the particle size.

(2) Capacity constraints are guaranteed by constantly selecting, changing over large or small position values [10]. If the position of the particle is less than zero, then we deal like this:

$$\begin{cases} p(i,j)=0 \\ v(i,j)=-v(i,j) \end{cases}　（12）$$

Instead if the position of the particle is larger than the constrained value, then :

$$\begin{cases} p(i,j)=max \\ v(i,j)=-v(i,j) \end{cases}　（13）$$

4 Case analysis

In order to verify the validity of the model, this paper takes the Hangzhou to Xianyang route (daily flights 24) failure as an example to simulate. The data is mainly from the "From the statistical view of civil aviation" 2013 Edition. According to the established network, there are 22eligible cities, like Beijing, Wuhan, here we use serial number1-22 on behalf, 23 and 24 for Hangzhou and Xianyang respectively.

Parameter setting. The learning factors were both 2, the number of particle population was 50, the number of iterations was 500, and the inertia factor was 0.9, $\lambda=10^8$, $h=1, f_0=1$.

Firstly, analyze the maximum cost of the network without considering the performance of the network ($\beta=0$), which is shown in Fig. 1. Fig. 2 shows the average capacity that node can increase, which can be defined as $\Delta C=\sum S_i/k_i^w/n$. According to the situation of this paper, make $\omega\in[0,2.5]$.
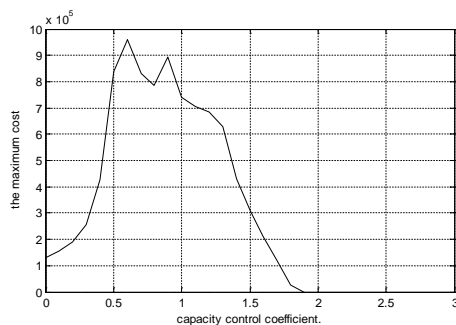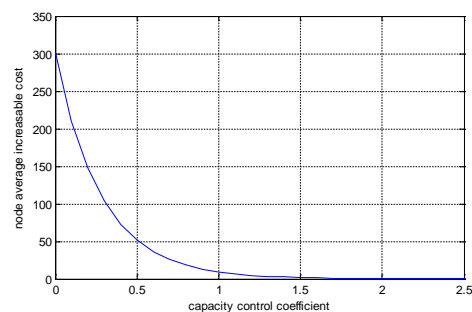

Fig.1 Changing curve of the maximum possible cost

Fig.2 Changing curve of node average increasable cost

From Fig. 1 we can see that the maximum cost of the network has the trend of decreasing first and decreasing later, and there appears abnormal when near the point $\omega=0.8$. Combined with the analysis of Fig. 2, in the first half of the curve, the capacity that node can increase is relatively large so as to allow all traffic transiting from a single node. Therefore the increased cost is mainly caused by congestion in this stage. Near the point $\omega=0.8$, capacity of node does not allow all traffic transiting from the single node, resulting in congestion cost decreasing and distance cost increasing.

The fluctuation is caused by the change between the congestion cost and the distance cost. So it can be seen that the capacity control coefficient has good effect.

Secondly, we investigate the effect of the capacity control coefficient (ω) on the cost and the performance of the network in the optimization model. Fig. 3 and Fig. 4 are the optimal value of network cost and network performance under different ω. From themwe can see the absolute value of the two part is basically in the range of [0, 1], and the difference is not big, belonging to the same order of magnitude. Cost optimization first becomes small and then becomes large with the change of ω. Combined with Fig. 1, the node capacity caused by congestion cost occupies a large proportion. Capacity constraint also plays a role in the optimization of network efficiency: with the increase of the node capacity, the traffic distribution becomes divergent and the network efficiency reduces. Combined with Fig. 3 and 4, we can see that when the node has a larger capacity, the cost of distribution is lower, and the network performance is better. Make $\omega = 0, \beta = 0.5$ and $\omega = 1, \beta = 0.5$. The specific traffic distribution is shown in Table. 1, only giving the node has designed traffic. From Table. 2 we can see that, due to the capacity control coefficient becoming larger, network node capacity reduces, Centralized traffic allocation will result in a sharp increase in costs. So the traffic is distributed dispersedly, and the total cost increases. However, the maximum possible cost increases relatively larger, resulting in a reduction in the cost of Table 1.
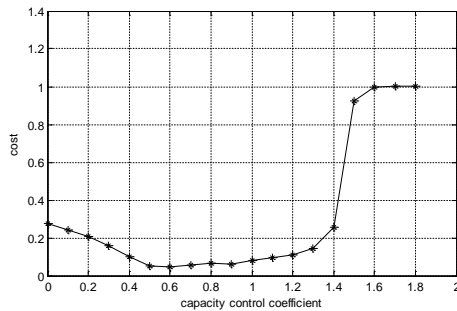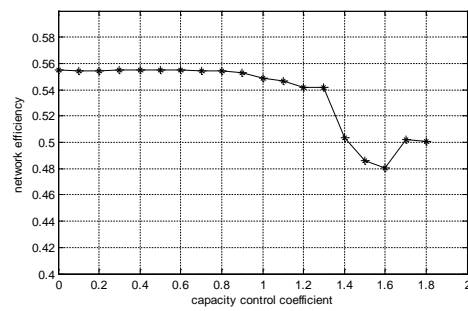

Fig.3 Cost based on capacity control coefficient

Fig.4 Efficiency based on capacity control coefficient

Table 1 Traffic distribution result of different capacity control coefficient

node	1	7	8	13	14	16	17	18	19	21	22	F
ω=0	0	0	0	0	24	0	0	0	0	0	0	0.2776
ω=1	2	2	1	2	2	2	1	1	2	3	4	0.0874

Again, investigate the effect of weight coefficient on network optimization. Make $\beta = [0,1]$. Fig.5 and Fig. 6 show that, as emphasis on the performance of network increases, network efficiency comes better and better; the cost is getting higher and higher. The model can play a better tradeoff between cost and network performance. Make $\omega = 0.8$, $\beta =0, 0.5, 1$,respectively, the results shown in Table 2. With more and more attention on network performance, the distribution of traffic starts to ignore the low cost advantage of "close range and low congestion", but turns to high network performance. Sot the adjustment by weight for the cost and the performance of the network is simpler and more flexible.
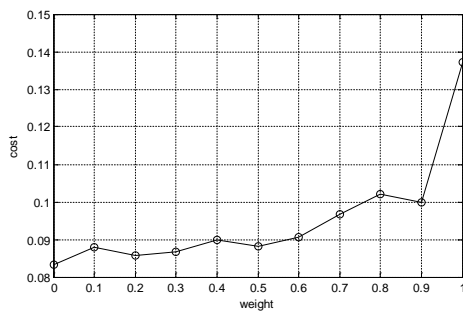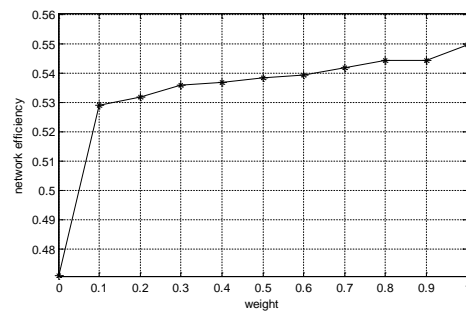

Fig.5 Cost based on weight change

Fig.6 eEficiency based on weight change

Table 2 Traffic distribution result of different weight

node	1	2	4	5	6	7	9	11	12	13	14	16	17	18	19	20	21	22	F	E
β=0	0	0	0	1	1	3	0	2	2	0	6	4	0	0	2	0	0	3	0.0647	0.4990
β=0.5	2	2	0	2	0	2	1	2	0	1	2	2	1	1	2	0	2	2	0.0747	0.5418
β=1	6	0	1	0	0	0	4	3	0	0	0	0	5	0	0	1	3	1	0.1292	0.5535

5 Conclusion

From the results of the simulation, we can draw the following conclusions:(1) capacity control coefficient can effectively regulate the node capacity and well measure the impact of congestion. With the increase of the capacity control coefficient, the distribution cost is mainly affected by the congestion cost, causing the phenomenon of the first increasing and then decreasing. The network traffic distribution cost is low, and the overall network efficiency is high when the network has a large node capacity, which provides a feasible way to optimize the performance of the network. And through the node congestion cost control coefficient, the impact of congestion can be adjusted to improve the flexibility and operability of the model. (2) The optimization bias between the cost and network performance can be controlled by adjusting the weights, so that the model does not need to meet the requirements of the Specific cost constraints, which improves the practical application of the model.(3) The airport capacity plays an important role in improving the survivability of network repair: on one hand, high capacity can reduce cost, improve the network survivability by saving cost indirectly; On other hand it can directly improve network survivability in improving network performance.

Acknowledgement

References

[1]HU Bin, LI Fang. Repair strategies of scale-free networks under multifold attack strategies [J]. Systems Engineer ing and Electronics, 2010, 32（1）：86-89.

[2] KVALBEIN A, HANSEN A F, CICIC T, et al. Fast recovery from link failures using resilient routing layers[C]//Proceedings of the 10th IEEE Symposium on Computers and Communications (ISCC 2005). Cartagena, Spain: IEEE Press, 2006: 554-560.

[3]LIU Ming, XU Yinfeng, DU Yuan jiang, et al. Most shortest vital- path problem with incomplete information on traffic network[J]. Systems Engineering, 2006,24（12）：16-20]

[4]DANG Yaru, LI Xuejiao. Characteristics contrast and invulnerability analysis of seven regional air traffic control complex network[J]. Complex System and Complexity Science, 2015,12（3）:19-26.

[5]Jeng Fung Chen. A hybrid heuristic for the uncapacitated single allocation hub location problem [J]. Omega, 2007(35): 211 – 220.

[6]Alumur S A, Nickel S, Saldanha-da-Gama F. Hub location under uncertainty［J］. Transportation Research Part B,2012, 46(04):529-543．

[7]TIAN L, DI Z R, YAO H. Effect of distribution of weight on the efficiency of weighted networks [J]. Acta Phys. Sin. Vol. 60, No. 2 (2011) 028901]

[8] Y C Lai, A E Motter, T Nishikawa. Attacks and Cascade in complex Networks［J］. Lect Notes Phys, 2004: 650, 299-310．

[9]YUAN Rong-kun, MENG Xiang-ru, LI Ming-xun, et al. Approach of enhancing network survivability by optimizing weights based on particle swarm optimization[J], Journal of Computer Applications, 2012，32(1):127-130.]

[10] TAN Yue, TAN Guan zheng, DENG Shu guang. Hybrid particle swarm optimization with chaotic search for solving integer and mixed integer programming [J]. Journal of Central South University,2014, 21(7):2731-2742.