International Journal of Multiphysics
Volume 18, No. 2, 2024
ISSN: 1750-9548

Robustness of Civil Aviation Air Cargo Network Based on Scara Robot Dynamics Model

Lin Li[1,*], Ya Zhang[1]
[1]Aviation and Tourism Management Faculty, Chongqing Aerospace Polytechnic, Chongqing, China, 400021
Correspondence should be addressed to Lin Li; lilin@cqht.edu.cn

Abstract
As an integral part of the civil aviation network, the freight network is an indispensable and important channel in the logistics and transportation. As the construction of the cargo network continues to increase, the environment has become more complex. The challenges posed by its risks place higher demands on the robustness of the freight network. The improvement of network robustness, the establishment of preventive measures, and the stabilization of transportation network are the basis for health management and construction of aviation network. Therefore, in this paper, the robustness of the civil aviation air cargo network was deeply studied by combining the SCARA robot dynamics model. On the basis of the general situation of the development of the freight network, a basic understanding of the complex characteristics of the network structure was obtained. Then the robustness analysis provided support for the subsequent network optimization, and a robust controller was constructed using the dynamic model. Finally, the network state changes under random attack and selection attack were observed through simulation experiments. The simulation data has showed that the degree of change in the outer freight network after re-identification and optimization is very significant. The growth rates of the number of routes, average degree, network efficiency and clustering coefficient were 12.16%, 10.07%, 13.14% and 5.47%, respectively, the average path length also decreased by 4.63% due to the increase of isolated nodes. This shows that the optimal control under the SCARA robot dynamics model improves the overall robustness of the civil aviation air cargo network, which has important practical value for planning and improving the structure of the air cargo network, maintaining stable cargo transportation capacity, and improving logistics efficiency.
Keywords: Network Robustness, SCARA Robot Dynamics Model, Air Cargo, Civil Aviation

Introduction

With the continuous expansion of the transportation industry and the rapid development of e-commerce, the status of civil aviation air freight in logistics and transportation is becoming more and more important. The cargo network can not only meet the growing demand for air transport, but also promote the in-depth development of civil aviation companies in the market, which plays an important role in the development of the huge development potential of air cargo. However, with the continuous construction of the transportation network, the radiation range of the air cargo network is becoming wider and wider, and the structure is becoming more and more complex, and the corresponding risks also follow. It has seriously hindered the safe operation and healthy development of the freight system. Therefore, it is very urgent to improve the robustness of the civil aviation air cargo network and improve the network performance and operation status. At present, with the mature development of robot technology, the industrial robot market is constantly being developed. In practical applications, in addition to ensuring production efficiency, there are also other requirements for the accuracy of the robot. Among them, the SCARA robot can not only meet the high-efficiency requirements, but also have the advantages of flexibility, speed, and high repeatability. Therefore, it has developed in many fields of production. For example, it can be seen in professional fields such as medicine, computer control, and satellite navigation. On its basis, a dynamic model is established, which can effectively avoid external interference factors and reduce the uncertainty in the operation of the air cargo network. It is of great significance to ensure the normal and healthy development of cargo transportation.

Air cargo occupies an important position in the transportation industry, and its network robustness research has always attracted the attention of many scholars. Malighetti P conducted an analysis of the robustness of the Asian aviation network and its configuration through graphical analysis and complex network metrics [1]. In order to improve the decision support capability of freight planning, Peng P evaluated the robustness of the global freight network in the latest automatic identification system data [2]. Gong Q identified the key drivers of China's civil aviation air cargo international trade through an augmented gravity model, and investigated its air freight network robustness using complex network analysis methods [3]. Chao C C, based on the air cargo LCL model, studied the impact of cargo network robustness and other factors on airline revenue, and effectively combined the types of air cargo to improve airline revenue [4]. Fu C divided the aviation network structure into self-healing structure and coupling structure, and abstractly analyzed and modeled the three growth mechanisms of aviation network robustness [5]. Donnet T identified and explained different governance models of the global aviation network from a resource perspective, and analyzed its network robustness and resources [6]. The development of civil aviation air cargo puts forward higher requirements for network robustness. Previous studies have not conducted in-depth research on control performance, and there are still some limitations in actual operation. The SCARA robot dynamics model can play a unique dynamic advantage in it.

As an important product of the intelligent era, the SCARA robot dynamics model has extremely high research value. Anh H proposed a novel adaptive dynamics model control system for a highly nonlinear SCARA serial robot using PAM actuators, and demonstrated its performance advantages through experiments [7]. Izadbakhsh A used a SCARA dynamic model driven by a permanent magnet DC motor to reduce tracking errors and improve the stability of the network [8]. Popov V proposed a dynamic model for controlling a SCARA robot using body poses and in this way created a more efficient interface with the controlled robot [9]. In order to reduce the end position error when the robot performs repetitive motion tasks, Zhang T obtained the dynamic model of the SCARA robot through the Lagrangian equation, and designed an iterative algorithm for controlling the torque [10]. Luan F built the SCARA robot dynamics model by defining a set of auxiliary variables to avoid the use of joint acceleration signals due to slow convergence [11]. Liu H proposed an accurate and efficient SCARA robot kinematics calibration model for serial robot kinematics calibration of any combination of revolute and prismatic joints [12]. At present, the application direction of SCARA robot dynamics model in research is continuously expanded. However, the research on combining it with the construction of civil aviation air cargo network is not in-depth. In order to improve the robustness of the air cargo network, it is urgent to study the robustness of the civil aviation air cargo network based on the SCARA robot dynamics model.

Based on the SCARA robot dynamics model, this paper deeply studied the robustness of the civil aviation air cargo network and conducted simulation experiments. Experimental data showed that with the increase of node removal rate, the average path of the freight network was continuing to increase. When the node removal rate reached 35%, the average path length growth rate under random attack was 3.8%, and the growth rate under selective attack was 9.1%. In the core layer network optimization, the average path length under the dynamic model method was reduced by 3.44% and the average degree was increased by 7.76%. The clustering coefficient increased by 5.13%, and the route also increased by 8.11%. However, under the traditional method, the route and average degree only increased by 2.17% and 2.03%, the average path length decreased by 1.01%, and the network efficiency and clustering coefficient changed by only 4.49% and 2.62%. In the outer network optimization, the variation degree of the number of routes, average degree and network efficiency under the control method in this paper reached 12.16%, 10.07% and 13.14% respectively. Its average path length was reduced by 4.63%, and the clustering coefficient was improved by 5.47%. It can be seen that the freight network under the dynamic model control method was more robust.

Air Cargo Network Robustness

Overview of the Development of Civil Aviation Air Cargo Network

The air cargo network is mainly composed of air cargo airports and cargo routes [13]. A functioning freight network can not only transport goods efficiently and conveniently, but also bring huge economic benefits. Under the background of consumption transformation and industrial structure upgrading, the rapid growth of e-commerce and express delivery industry has promoted the vigorous development of air cargo industry, which enables air cargo to better meet the cargo transportation needs of cargo owners. From the perspective of the capacity structure, air cargo is mostly transported by passenger aircraft in the form of cargo carried in the belly hold. Except for the decline in 2020 due to the impact of the epidemic, the overall trend of its cargo transportation volume is developing well, as shown in Table 1.

Table 1. 2017-2021 civil aviation air cargo traffic

Particular year	**Volume of transport(10,000 tons)**	**Growth rate(％)**
2017	708	4.8
2018	741	4.6
2019	764	3.1
2020	682	-10.7
2021	713	4.5

Air cargo has a good development momentum, but there is also the problem of poor anti-risk ability. The network is easily interfered by a variety of factors, including weather, airport facilities and equipment failures, terrorist attacks, etc., and the airport after the interference is in a state of failure. The air route connected to the airport cannot operate normally, and the cargo cannot be transported. At the same time, it affects the normal operation of many adjacent airports, which causes a large amount of cargo in the cargo system to accumulate in the airport cargo area, reducing the efficiency and quality of cargo transportation.

With the development of science and technology and the needs of society, the current air transportation network has developed from the round-trip and intercommunication of each node between independent cities to the overall high degree of sharing. It forms a complex network structure integrating openness, economy and society. The manifestations of its complex features are also diverse. This article summarizes it into four major aspects.

(1) Structural complexity

There are various cargo nodes with different functions and different levels in the air cargo network [14]. This enables a large-scale, statistical network representation of the air cargo network. Hierarchical development is also a feature of the air cargo network. Cargo nodes and systems with different functions make the overall air cargo network show structural complexity, as shown in Figure 1.

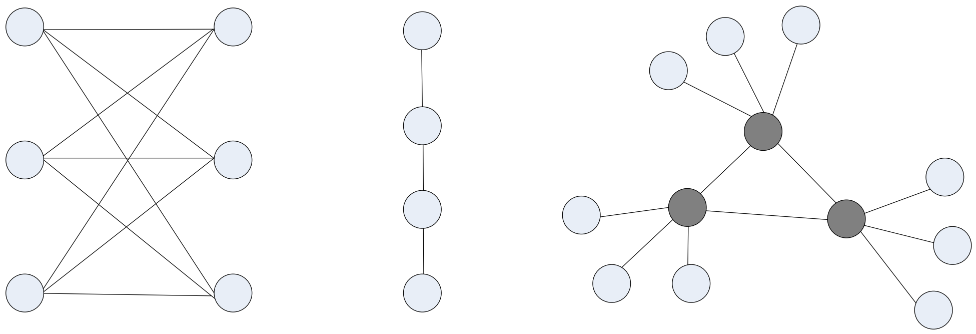

Figure 1. Network structure form legend

(2) Node complexity

The cargo functions carried by each node city in the air cargo network are different. The importance of the freight system varies from node to node, for example, belonging to different agencies or city groups, forming subgroups of various air freight systems that are differentiated and interconnected, with different freight volumes and different freight plans. This is manifested in the node complexity of the air cargo system, and the simple node topology model is shown in Figure 2.

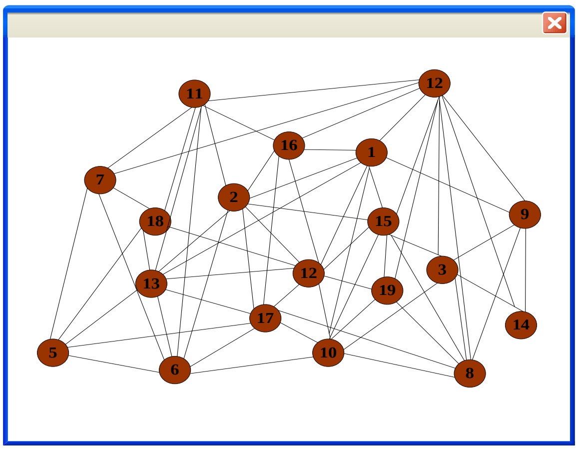

Figure 2. Node simple topology model

(3) Evolutionary complexity

In the development process of the air cargo network, the linear increase of new nodes must be accompanied by the geometric multiple increase of routes, which makes the scale and density of the air cargo system expand rapidly. Whether it is the interconnection between local areas or the connection across areas, the development of the system presents dynamic complexity. It seems very random and disordered, but after careful analysis, it is found that the development of air cargo system has certain complex network characteristics.

(4) Operational complexity

The operational status of each node in the air cargo network is uncertain. It may be due to internal system failure or external interference, the occurrence of large and small accidents is unavoidable, which first evolves into partial air cargo function failure. If the danger spreads along the complex network, it is more likely to cause the whole system to fail, which makes the freight balance, a state determined by the network security, showing dynamic complexity.

Due to the nonlinear superposition of the manifestations of these complex factors, the air cargo network with complex characteristics has become increasingly difficult to control.

Network Robustness

The robustness of the freight network is an important part of analyzing whether the network can operate normally. How to analyze, optimize and improve the network has become an important work goal of many researchers. Robustness analysis of air cargo system network structure is mainly based on changing network nodes and introducing emergencies. For example, a navigable city is paralyzed due to human or non-human factors, the network is overwhelmed due to the huge freight volume, and so on. These contingencies determine to some extent the overall performance of the transportation network.

When the element components that make up the network are accidentally attacked, the network state changes accordingly. The functional rupture of the network is caused, which can be seen intuitively from the network structure diagram, as shown in Figure 3.

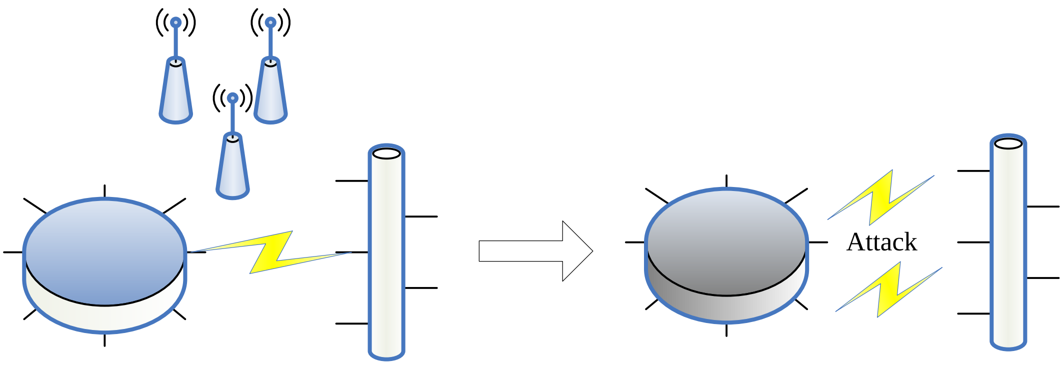

Figure 3. Comparison of network nodes before and after attack

From Figure 3, it can be seen intuitively that the state of the system network changes due to the failure, and the affected nodes exit the normal operating system. In real life, the situation that the air cargo network is interfered and destroyed and affects its operation status is divided into random attack and selective attack.

(1) Random attack

Factors such as the operating conditions of internal and external facilities and weather in the air cargo system can easily affect the normal operation of the system, which in turn affects the normal transportation of the entire cargo network. The random damage caused by such non-subjective factors to the network is called a random attack, such as bad weather, etc. This kind of fault is generally less harmful, and many important nodes escaped this wave of obstacles because they were not affected. The network of systems can also recover quickly due to its lesser impact [15].

(2) Select attack

In addition to weather, facilities and equipment, air cargo can also be disturbed by subjective factors. Such attacks usually target critical nodes with high importance as the preferred targets. The more important the node is, the weaker the freight network's ability to complete cargo transportation after being attacked. This attack method is a selective attack. Because it is too late to prepare, it is suddenly affected. Moreover, it is often a global obstacle that occurs when important nodes are affected, as shown in Figure 4.

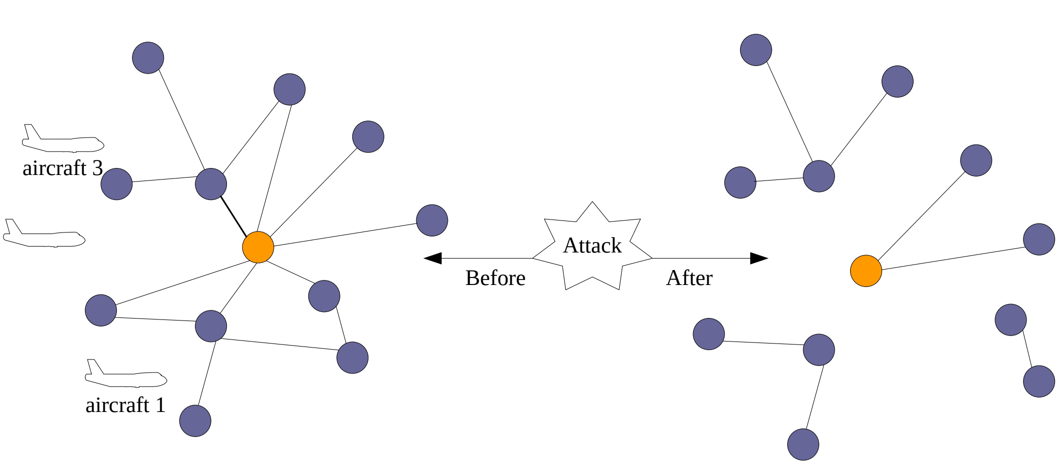

Figure 4. Global barrier legend

The air cargo network is scale-free and layered. In scale-free networks, there are often a few nodes that play an important role. Attacks on these key nodes seriously affect the robustness of the network.

Network Robustness Based on Scara Robot Dynamics Model

From the research on the complex characteristics and robustness of the civil aviation air cargo network, it can be seen that in the actual operation process, the development of civil aviation air cargo is indeed facing many difficulties and challenges. In order to ensure the safety of freight and the operation of stable network, this paper studies it on the basis of establishing the dynamic model of SCARA robot.

In order to achieve high accuracy and a highly robust freight network, accurate dynamic models need to be established. The robot dynamics modeling methods mainly include Lagrange method, Newton-Euler method, Gauss method, etc. In order to better stimulate all the dynamic characteristics of the robot, the optimal excitation trajectory should be designed according to certain constraints and optimization methods. The identification results largely depend on the design of the identification trajectory. The estimated parameters obtained from the identification need to be tested with other trajectories. Comparing the theoretical torque obtained by the dynamic equation with the estimated torque obtained from the identification parameters, the correctness of the parameter identification is verified, and the dynamic model of the robot in actual work is obtained, which lays the groundwork for the subsequent design of the network robust controller.

According to the dynamic model with n links, the dynamic equation of the SCARA robot is established as [16]:

$$\tau = H(q)\ddot{q} + C(q,\dot{q})\dot{q} + G(q) \quad (1)$$

Among them [17]:

$$H(q) = [h_{ij}], h_{ij} = \sum_{i=max(j,k)}^{n} tr\left(\frac{\partial^0 T_i}{\partial q_j} I_i \frac{\partial^0 (T_i)^T}{\partial q_k}\right) \quad (2)$$

$$C(q,\dot{q})=[c_{ij}],c_{ij}=\sum_{k=1}^{n}\frac{1}{2}\left(\frac{\partial h_{ij}}{\partial q_k}+\frac{\partial h_{ik}}{\partial q_j}-\frac{\partial h_{jk}}{\partial q_j}\right)\dot{q}_k \quad (3)$$

$$G(q)=[g_1,g_2,g_3]^T,g_i=-\sum_{j=1}^{n}m_j\bar{g}^T\frac{\partial^0T_i}{\partial q_j}\tilde{r}_{Cj} \quad (4)$$

When the model error is within a certain range during transportation, the tracking trajectory of the air cargo network robust controller designed based on the SCARA robot dynamics model can be controlled within a certain range and is bounded. When it is not affected by the error, it can ensure that the trajectory is completely tracked, that is, the trajectory error is zero.

The parameters are set as shown in Table 2.

Table 2. Interpretation of each parameter of equation 2

Scoping	Sequence	Parameter	Paraphrase
Ideal trajectory	1	$q_d(t)$	Location
	2	$\dot{q}_d(t)$	Speed
	3	$\ddot{q}_{d(t)}$	Acceleration
Actual trajectory	1	$q(t)$	Location
	2	$\dot{q}(t)$	Speed
	3	$\ddot{q}(t)$	Acceleration

Then the position error and velocity error are expressed as:

$$\begin{cases}e(t)=q(t)-q_d(t)\\ \dot{e}(t)=\dot{q}(t)-\dot{q}_d(t)\end{cases} \quad (5)$$

Due to the need to establish control equations with position error and velocity error as state variables, control variables $e(t)$ and $\dot{e}(t)$ are introduced in the design of the controller. From the inverse solution of the dynamic equation, when the trajectory of the node coordinates q of the civil aviation cargo network is known, the moment τ that should be applied can be solved according to the dynamic equation. Based on this consideration, an auxiliary control signal u is added to the original kinetic equation as nonlinear compensation. The joint torque is obtained as [18]:

$$\tau=u+H(q)\ddot{q}_d+C(q,\dot{q})\dot{q}_d \quad (6)$$

Equation (6) is substituted into the kinetic equation to obtain [19]:

$$H(q)\ddot{e}+C(q,\dot{q})\dot{e}+\Delta(q,\dot{q})=u \quad (7)$$

Auxiliary signals are defined as:

$$\eta=\dot{e}+\alpha e \quad (8)$$

Among them, α is an arbitrary constant and $\alpha>0$. The auxiliary signal is substituted into the equation to get:

$$H(q)\dot{\eta}=H(q)\alpha\dot{e}-C(q,\dot{q})\eta+C(q,\dot{q})\alpha e-\Delta+u \quad (9)$$

Taking $\omega(q,\dot{q},e,\dot{e})=H(q)\alpha\dot{e}+C(q,\dot{q})\alpha e$, Equation (9) can be expressed as:

$$H(q)\dot{\eta}=-C(q,\dot{q})\eta+\omega-\Delta+u \quad (10)$$

Assuming that there is a positive definite function $\rho(e,\dot{e})$, for any $\Delta(q,\dot{q})$, then [20]:

$$\|\Delta(q,\dot{q})\|\le\rho(e,\dot{e}) \quad (11)$$

Therefore, according to the dynamic model and specific requirements of this paper, the feedback control law is designed as:

$$u=-K\eta-\omega-v \quad (12)$$

Among them:

$$\begin{cases} v = \frac{\eta\rho^2(e,\dot{e})}{\|\eta\|\rho(e,\dot{e})+\varepsilon}, \varepsilon > 0 \\ K = \begin{Bmatrix} k_1 & 0 \\ 0 & k_2 \end{Bmatrix} k_1 > 0, k_2 > 0 \end{cases} \quad (13)$$

Then for any initial tracking error $e(0)$, $e(t)$ is uniformly bounded. Among them, there are constants A, B, C such that for any satisfying $\Delta(q,\dot{q})$ in Equation (11), then:

$$\|e(t)\| \leq A(\|e(0)\|)^{-at} + Be^{-\frac{\lambda}{2}t} + C, \forall t \quad (14)$$

If the above design results are accurate, it can be shown that when the controller gains k_1, k_2 and parameter α, ε are taken as appropriate values, the trajectory error $e(t)$ of the freight network node is controlled within a range. At the same time, if the controller gain is adjusted, the convergence speed of the error can also be controlled. When the freight system has an uncertainty error of $\Delta(q,\dot{q})$, the controller can effectively improve the path length, which greatly improves the performance of trajectory tracking, so as to meet the efficiency requirements of network operation.

Robustness Simulation Experiment

In order to test the effect of the robust controller under the dynamic model of this paper in the civil aviation air cargo network, this paper uses TOPSIS modeling to conduct simulation experiments. Taking the civil aviation air cargo network node in a certain place as the basic data set, the fault interference is set, and this is used as the attack basis to conduct random attack and selection attack simulation. The changes of the average path length of the freight network and the network efficiency index after the network is attacked are analyzed. Then, the control method designed in this paper and the traditional method are used to optimize the network after fault disturbance. The robustness changes of the core layer network and the outer layer network are compared and analyzed. In order to have a deeper understanding of the structural characteristics of the air cargo network in this region, this paper understands the average clustering coefficient of all airport nodes with degree values in the network, as shown in Table 3.

Table 3. Average clustering coefficient of network nodes

$\boldsymbol{k}$	$\boldsymbol{C(k)}$	$\boldsymbol{k}$	$\boldsymbol{C(k)}$
14	0.36	8	0.53
13	0.41	5	0.67
12	0.37	4	0.79
11	0.39	3	0.74
10	0.47	2	0.62

From Table 3, the current air cargo industry in this area is still showing a development trend. However, there is a certain hierarchical structure, and a hub-and-spoke air cargo network structure centered on the airport with a large degree value has been initially formed. It can be seen that this article uses this area as an experimental data set to be representative.

(1) Fault interference

In the simulation process of fault interference, the random attack is set to select nodes equal to the number of all nodes in the entire network to attack in different networks, and the number of attacks increases gradually. In order to effectively compare the two, in the selection attack setting, the number of nodes selected each time must match the number of nodes in the random attack. Figure 5 shows the change in the average path length of the freight network and the change in network efficiency under the two fault disturbances.

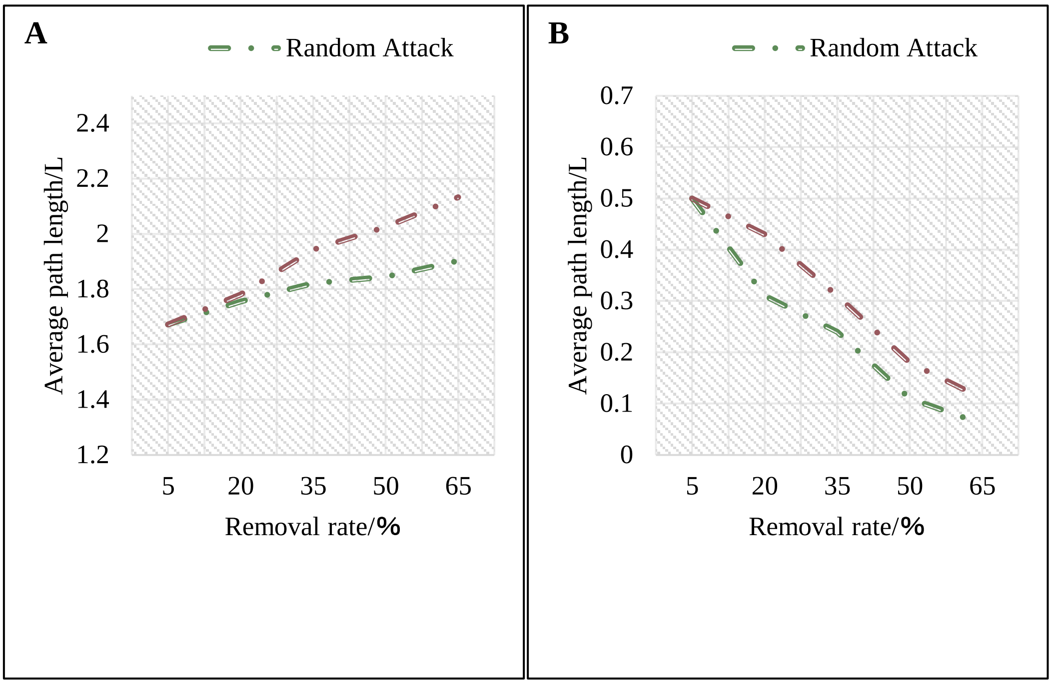

Figure 5. Variation of network robustness under different fault disturbances

Figure 5A shows the average path length variation.
Figure 5B shows network efficiency changes.
It can be clearly seen from Figure 5 that compared to random attacks, selected attacks have a greater impact on the air cargo network. No matter the average path length or network efficiency, the variation range is larger, showing strong vulnerability. In the two attack modes in Figure 5A, as the node removal rate increases, the more routes are broken in the network, and the average path of the entire network increases accordingly. It can be seen from the data that when the node removal rate reaches 35%, the average path length of the local freight network increases by 3.8% in random attack mode and 9.1% in selected attack mode. As can be seen from Figure 5A, the curve declines relatively quickly in the selective attack mode, and its decline rate reaches a maximum of 14.62%. It shows that when the airport node with high degree value in the network is attacked, the local network becomes more vulnerable, and the degree of vulnerability gradually increases with the number of nodes removed, which makes the robustness of the network worse. In the random attack mode, the change of the average path length is not very large, and the impact on the network is small. In Figure 5B, the global initial value of network efficiency is 0.5. As the removal rate of nodes increases, the network efficiency plummets, and when the removal rate reaches 20%, the network begins to disintegrate substantially. In general, after suffering an attack of the same scale, the network efficiency under selective attack is always smaller than that under random attack, and the reduction speed is faster than that under random attack. Therefore, the robustness of the network under random attack is better than that under selective attack.

(2) Robustness changes

This paper uses a robust control method based on the SCARA robot dynamics model as well as traditional methods to optimize the freight core network and outer network. The key nodes of the optimized freight network are re-identified, and selected attacks and random attacks are carried out. The number of routes, average degree, average path length, network efficiency, and clustering coefficient of the freight network in its initial and optimized states are recorded. The initial network state is shown in Table 4. Figure 6 and Figure 7 show the degree of change between the core layer and the outer layer after optimization.

Table 4. Initial state of the network

Sequence	Network parameters	Initial state
1	Number of routes	1634
2	Average degree	15.11
3	Average path length	2.04
4	Network efficiency	0.37
5	Clustering coefficient	0.612

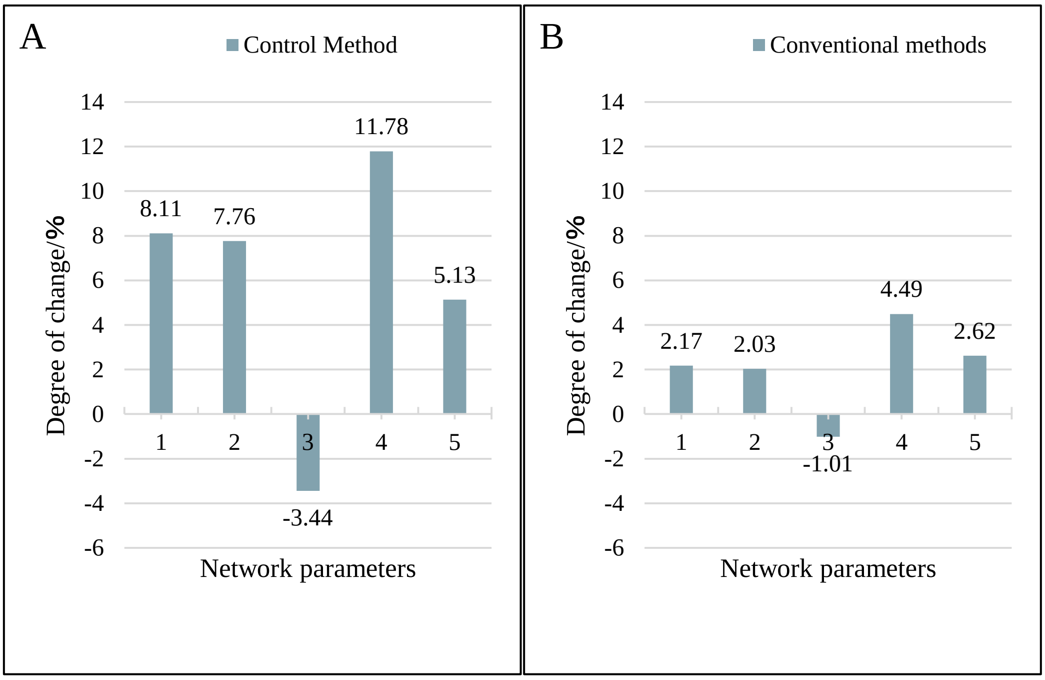

Figure 6. Changes in the core layer of the freight network

Figure 6A shows the degree of change under the control method.

Figure 6B shows the degree of change under the conventional method.

The core layer network is the core part of the entire freight network. It mainly includes the basic route nodes and key route nodes in the entire network structure, and its network operation status has a significant impact on the progress of the entire freight system. From Figure 6, the network robustness under the two optimization methods exhibits varying degrees of change. Compared with the traditional method, the network state under the control method in this paper has obvious advantages. In the data in Figure 6A, after the optimization of the dynamic model controller, the average path length of the core layer network is reduced by 3.44% when the number of nodes remains the same. That is to say, only one transfer is needed on average, and the goods can be transported between any airports. The average degree increases by 7.76%, that is, there are feasible freight routes between each node and the rest nodes on average. The clustering coefficient increases by 5.13%, the connection between network nodes is more closely, and the network efficiency increases by 11.78% compared with the past. On the whole, after adding 8.11% routes, the structure of the air cargo network has been optimized. However, under the traditional method in Figure 6B, the route and average degree only increases by 2.17% and 2.03%, and the average route decreases by 1.01%, and the robustness change is not obvious. The improvement of network efficiency and clustering coefficient is far less than that of the control method under the dynamic model in this paper.

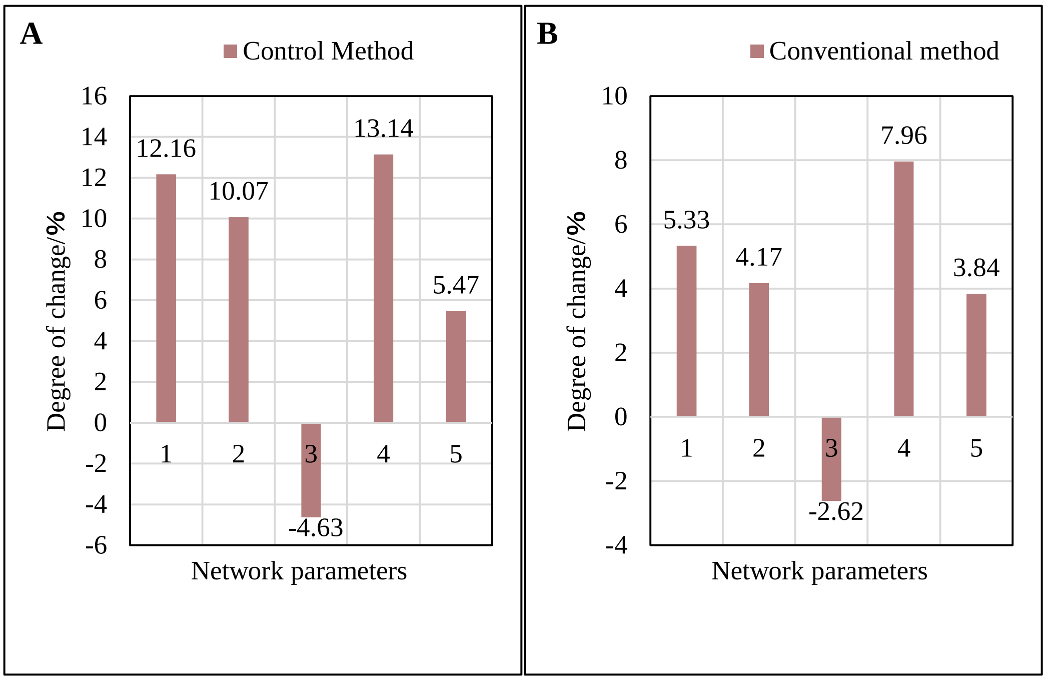

Figure 7. Changes in the outer layers of the freight network

Figure 7A shows the degree of change under the control method.
Figure 7B shows the degree of change under the conventional method.
The outer layer network is an extension of the core layer network. Its robustness is also of great significance to ensure the safe and efficient operation of air cargo transportation. It can play the role of shunting when the core layer network nodes are subjected to selected attacks and random attacks, which becomes a temporary transfer field, so that the network is not paralyzed, and can minimize various losses after node removal. In Figure 7A, the changes in the number of routes, average degree and network efficiency after the control of the SCARA robot dynamics model are very significant. Its growth rates are 12.16%, 10.07% and 13.14%. Even after being attacked, airports that have lost their connection with the network and established isolated nodes can maintain their connection with the network through new routes to realize cargo transportation. Due to the increase of isolated nodes, the average path length is reduced by 4.63%, and the clustering coefficient is improved by 5.47%. Under the dynamic model, the trajectory error is greatly reduced, thus meeting the robustness requirement for the operation of the freight network. In the traditional method in Figure 7B, except for the obvious improvement of network efficiency, the degree of change of other parameters is not obvious. The growth rates of the number

of routes, average degree and clustering coefficient are only 5.33%, 4.17% and 3.84%, respectively, and the decrease in path length is only 2.26%, which shows that the control method in this paper is more feasible.

Conclusion

The civil aviation air cargo network is an important hub in the transportation system. Driven by the market economy, the scale of the freight industry is expanding, and the network structure tends to be complex, which also poses a daunting challenge to the robustness of the network. In this paper, combined with the dynamic model of SCARA robot, aiming at its unstable characteristics, a controller is designed to effectively control the running state of the freight network. The network under selective attack and random attack had been optimized. The average degree and clustering coefficient of nodes has improved, the average path length has reduced to a certain extent, and high network efficiency and robustness have been guaranteed. While the research in this paper has achieved certain results, there are also some problems. In the research on the robustness of the air cargo network, this paper only considers the impact of two forms of attacks on the air cargo network from the network itself. However, in reality, factors such as geographical environment and economic needs all affect the network. In terms of experimental data collection, this paper only selects the cargo route data of a certain region, and does not consider the route data of other regions. In order to enrich the content of the researched air cargo network and provide more valuable research in this field in terms of depth and breadth, in the follow-up research, it is necessary to further improve the robustness of the air cargo network from the perspective of these issues.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflicts of interest.

Funding Statement

This study didn't receive any funding in any form.

Reference

[1] Malighetti P , Martini G , Redondi R . “Air transport networks of global integrators in the more liberalized Asian air cargo industry,” Transport Policy, vol.80, no.C, pp.12-23, 2019.
[2] Peng P , Cheng S , Chen J . “A fine-grained perspective on the robustness of global cargo ship transportation networks,” Journal of Geographical ences, vol.28, no.7, pp.881-889, 2018.
[3] Gong Q , Wang K , Fan X . “International trade drivers and freight network analysis - The case of the Chinese air cargo sector,” Journal of Transport Geography, vol.71, no.JUL., pp.253-262, 2017.
[4] Chao C C , Li R G. “Effects of cargo types and load efficiency on airline cargo revenues,” Journal of Air Transport Management, vol.61, no.Jun., pp.26-33, 2017.
[5] Fu C , Wang Y , Li C . “Self-healing characteristics of aviation network under different growth mechanisms,” Beijing Hangkong Hangtian Daxue Xuebao/Journal of Beijing University of Aeronautics and Astronautics, vol.44, no.6, pp.1221-1229, 2018.
[6] Donnet T , Ryley T , Lohmann G . “Developing a Queensland (Australia) aviation network strategy: Lessons from three international contexts,” Journal of Air Transport Management, vol.73, no.OCT., pp.1-14, 2018.

[7] Anh H , Son N N , Nam N T. "Adaptive Evolutionary Neural Control of Perturbed Nonlinear Serial PAM Robot," Neurocomputing, vol.267, no.dec.6, pp.525-544, 2017.

[8] Izadbakhsh A , Khorashadizadeh S. "Neural control of robot manipulators considering motor voltage saturation: performance evaluation and experimental validation," COMPEL: The International Journal for Computation and Mathematics in Electrical and Electronic Engineering, vol.40, no.1, pp.27-29, 2021.

[9] Popov V , Ahmed S , Shakev N . "Gesture-based Interface for Real-time Control of a Mitsubishi SCARA Robot Manipulator - ScienceDirect," IFAC-PapersOnLine, vol.52, no.25, pp.180-185, 2019.

[10] Zhang T , Changda L I , Qin B . "Adaptive Iterative Learning Control of Trajectory Tracking of SCARA Robots," Zhongguo Jixie Gongcheng/China Mechanical Engineering, vol.29, no.14, pp.1724-1729, 2018.

[11] Luan F , Na J , Huang Y . "Adaptive neural network control for robotic manipulators with guaranteed finite-time convergence," Neurocomputing, vol.337, no.APR.14, pp.153-164, 2019.

[12] Liu H , Zhu W , Dong H . "An improved kinematic model for serial robot calibration based on local POE formula using position measurement," Industrial Robot, vol.45, no.5, pp.573-584, 2018.

[13] Khan H , Kim H H , Abbasi S J . "Real-Time Inverse Kinematics Using Dual Particle Swarm Optimization DPSO of 6-DOF Robot for Nuclear Plant Dismantling," IFAC-PapersOnLine, vol.53, no.2, pp.9885-9890, 2020.

[14] Jia G , Cheng F , Yang J . "Intelligent checking model of Chinese radiotelephony read-backs in civil aviation air traffic control," Chinese Journal of Aeronautics, vol.31, no.12, pp.2280-2289, 2018.

[15] Oaki J. "Physical Parameter Estimation for Feedforward and Feedback Control of a Robot Arm with Elastic Joints - ScienceDirect," IFAC-PapersOnLine, vol.51, no.15, pp.425-430, 2018.

[16] Leottau D L, Ruiz-Del-Solar J , R Babuška. "Decentralized Reinforcement Learning of Robot Behaviors," Artificial Intelligence, vol.256, no.MAR., pp.130-159, 2018.

[17] Belzile B , Eskandary P K , Angeles J. "Workspace Determination and Feedback Control of a Pick-and-Place Parallel Robot: Analysis and Experiments," IEEE Robotics and Automation Letters, vol.5, no.1, pp.40-47, 2020.

[18] Lin Y M , Lin H S , Lin P C. "Model-based dynamic gait generation for a leg-wheel transformable robot," IEEE Robotics & Automation Letters, vol.2, no.2, pp.804-810, 2017.

[19] Agarwal N, Shrivastava, N Pradhan, M K. "Hybrid ANFIS-Rao algorithm for surface roughness modelling and optimization in electrical discharge machining," Advances in Production Engineering & Management, Vol.16, No.2, pp.145-160, 2021.

[20] Sari T, Gules H K, Yigitol B. "Awareness and readiness of Industry 4.0: The case of Turkish manufacturing industry," Advances in Production Engineering & Management, Vol.15, No.1, pp.57-68, 2020.