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Impact of COVID-19 on China’s international liner shipping network based on AIS data

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\begin{abstract}
As an essential sub-network of the global liner shipping network, China’s international liner shipping network was the earliest to be affected by the COVID-19 and also had a significant impact on the global shipping network. This paper uses Automatic Identification System (AIS) data to analyze the impact of COVID-19 on the typical route networks and major ports of China’s international liner shipping. On this basis, the changes in network efficiency and connectivity under the failure of important nodes are simulated. The research finds that, during the epidemic period, the scale of China’s international liner shipping network increased, with more routes gathering at fewer hub ports. Still, the overall connectivity and connection strength declined. Meanwhile, the epidemic caused fluctuations in container volume and the mismatch of ship cargo capacity supply, in which China-U.S. routes was the most prominent. From the view of node, the competitiveness of China’s mainland ports was significantly promoted during the epidemic. In addition, ports such as Busan, Singapore, and Hong Kong substantially impacted China’s international liner shipping network. The current study might be helpful for the industry management departments and related companies to prepare contingency plans, thus enhancing the resilience of the logistics chain and ensuring the stability of the global supply chain.
\end{abstract}

1. Introduction

At the end of 2019, the coronavirus disease (COVID-19) broke out and quickly swept the world. On March 31, 2020, the World Health Organization (WHO) listed COVID-19 as a pandemic. The unexpectedly rapid spread of the epidemic on a global scale has almost completely made the multiple sectors of economic activities paralysis in most nations, and the world economy has been severely hit. As a derivative industry born to meet freight demand, the shipping industry’s prosperity or depression is determined mainly by the macroeconomic environment and the overall market demand. Therefore, the shipping network has suffered a major blow, which especially impacted on the security and stability of the global supply chain system. The specific performance includes shipping capacity reduction, port congestion, container turnover rate decline, freight soaring and container shortage. By December 2020, the global schedule reliability of shipping has hit the lowest point 44.6% since 2011.\textsuperscript{1}

Marine container transport revolves around liner shipping, which is carried out by container ships sailing on fixed routes. In the context of globalization of supply chains, ports as nodes and shipping services as links play a significant role in global supply chains. The outbreak of COVID-19 has greatly exposed the container market to a lack of resilience in response to emergencies (Chen et al., 2022). Thus, the original operation and scheduling mode of port and shipping enterprises has been difficult to keep up with the volatile market. At the same time, the shipper was forced to accept the high freight and the transaction risk brought by the uncertain shipping time. The epidemic would not disappear in a short time and might even resurge over time. It is therefore necessary to prepare for the coming “new normal”. Some researchers have conducted the impact of the epidemic on the transport

\textsuperscript{1} Data Source: Sea-Intelligence Maritime Analysis.
sector and response measures. However, there is still a lack of scientifi-
cally sound recommendations that are suitable for making policy de-
cisions for container shipping networks to respond to current COVID-19
and future pandemics.

With the gradual integration of China into the global production
system in recent years, China’s international liner shipping network has
developed rapidly and become one of the most important sub-networks
of the global liner shipping network. China’s freight market is closely
connected to the international shipping market, and China’s interna-
tional liner shipping network was the earliest part to be affected by
COVID-19, thus had a significant impact on the global liner shipping
network. Before the epidemic, Chinese container shipping share of
global container shipping capacity has increased to 28%. 2 The container
throughput of China’s ports reached 261 million TEU, 3 with 7 ports
ranking top 10 in the world. 4 Of the 6162 operating container ships
worldwide, 2600 ships called at Chinese ports, accounting for 42.4%.
Besides, 87.7% of the large container ships (above 12000 TEU) called at
Chinese ports. 5 After the epidemic outbreak, China’s international liner
shipping network was hit seriously by the impact of the epidemic
superimposed “Spring Festival factors”. However, due to the effective
control of the epidemic, China’s container shipping market took the lead
in warming up, driving the rebound of the global container shipping
market. The analysis of the specific impact of COVID-19 on China’s in-
ternational liner shipping network is conducive to an accurate under-
standing of the transmission mechanism of the epidemic. It may provide
a reference for relevant departments and enterprises to formulate the
contingency epidemic plan, and is of great significance to improve the
operation efficiency security of global supply chain.

The current study uses Automatic Identification System (AIS) ship
trajectory data to make a preliminary attempt at exploring the changes
of China’s International Liner Shipping Network under the impact of the
epidemic by applying complex network methods. The spread of COVID-
19 threatens disrupted the smooth flow of materials and products along
international supply chains, with severe consequences for global logistics.
This paper evaluates the impact of the epidemic on the liner shipping
network by studying the changes of network indicators such as ship
capacity and network node degree, thus finding out its changing trend and
vulnerable links. Then the important hub nodes in the network are
selected to calculate the damage of the failure node to the efficiency and
connectivity of the liner shipping network. Finally, suggestions are
provided for ports and shipping companies on how to deal with the
impact of the epidemic and help maintain the security of the global
supply chain.

The rest of this paper is organized as follows. Section 2 is the liter-
ature review. Section 3 introduces the data and the research method.
Section 4 presents the analysis results combining the index calculation.
Section 5 presents the simulation of the failure node. Section 6 sum-
marizes the paper and puts forward the relevant suggestions.

2. Literature review

2.1. Container shipping network

At present, most of the related literatures on the characteristic
analysis and evolution of liner shipping network are concentrated in the
topological structure characteristics of shipping networks, network ef-
ficiency evaluation, the evolution of ports and networks, network risk
assessment and other fields.

Scholars who researched network topological structure first proved
liner shipping network is a complex network, like Tian et al. (2007), and
then analyzed it based on the complex network theory. For example, Xu
et al. (2007) built the ship-transport network of China based on complex
network, and discussed the properties of this network, such as degree
distribution, degree correlations, clustering, shortest path length, and
betweenness centrality. Hu and Zhu (2009) and Ducruet and Zaidi
(2012) analyzed and optimized the topological structure of the global
shipping network by collecting route data of liner companies. Ducruet
and Notteboom (2012) applied a topological decomposition method to
the global shipping network, and investigated the reasons for the
emergence of port systems. Gastner and Ducruet (2015) studied the port
degree and the distribution of berthing ships in the global cargo ship
network in different years, and found a tendency towards a more
centric distribution in port traffic. Xu et al. (2020) established a global
liner shipping network through the liner route data, and found it
is an economic small-world network with a low wiring cost and high
transportation efficiency.

Through the study of the topological structure, the mystery of the
liner shipping network has been gradually unveiled. On this basis, some
scholars have gone a step further and researched other attributes in the
shipping network Yao et al. (2014). Due to the better evaluation of
network efficiency, the connectivity of network and port has been paid
more attention. Using the data of commodity flows and container liner
route, Wilmsmeier et al. (2006), Wang et al. (2016), and Dadashpoor
and Arasteh (2020) analyzed the port connectivity and network effi-
ciency in the shipping network, and explores the influencing factors.
Kaluzo et al. (2010) divided the world shipping network into three sub-
networks: bulk dry carriers, container ships and oil tankers, and
researched the community structure and port distribution characteris-
tics of the network from these three perspectives. Jiang et al. (2015)
developed a container shipping network based on the route data of
the liner companies, and suggested an improved port connectivity model.
Through the index of degree, closeness and betweenness centrality of
the complex network, Wang and Cullinane (2016) discussed the port con-
nectivity, and analyzed the influence of the relative importance of
available shipping capacity and foreland market coverage on the
connectivity of the port. Cheung et al. (2020) further studied the
connectivity of container shipping networks, and proposed an algorithm
to optimize the connectivity of shipping networks.

Undoubtedly, in addition to the current efficiency evaluation
research, the evolution of ports and networks also plays a crucial role in
understanding the shipping network. So Kim (2016), Dang and Yeo
(2017) and Kavirathna et al. (2018) researched the port competitiveness
and its dynamic change process and analyzed its influencing factors and
future trends. Under the influence of sustainable development, Zhao
et al. (2021) explored the status of ports in the Maritime Silk Road
network, and forecasted the evolution of major ports in the network
based on complex network methods. Xu et al. (2015) studied the
changes of the seventeen regions in the global shipping network
regarding their vulnerability and dominance by analyzing the changing
positions of world regions during the period from 2001 to 2012, and
investigated the evolution of regional inequality in the global shipping
network.

A small number of scholars focus on network risk assessment. The
failure node model in the complex network can reasonably simulate
some port operation breakdown impact on network efficiency (Montes
et al., 2012). For example, Berle et al. (2011) presented a structured
Formal Vulnerability Assessment methodology to assess the risks faced
by the maritime transportation system. Calatauyud et al. (2017) explored
the risks of international trade due to the multiple complex structure of
liner shipping networks, and analyzed the impact of port failure based
on the simulation of attacks on ports in the shipping network. Viljoen

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1 Data Source: Clarkson database (http://www.clarksons.net.cn/portal).
2 Data Source: Ministry of Transport of China.
3 Data Source: Hong Kong Shipping Statistics (Fourth Quarter 2020)
https://www.censtatd.gov.hk/ct/Engindexb inspiration.html?rcode =
B102008&rcode = 230).
4 Data Source: (1) Data on the number of ships in operation worldwide comes
from the Clarkson database (http://www.clarksons.net.cn/portal); (2) Data on
the number of ships calling at Chinese ports comes from the China International
Liner Shipping Network database constructed in this paper.
and Joubert (2016) analyzed the vulnerability of the global container shipping network’s flexibility and robustness to changes in service configuration from a complex network perspective.

In summary, the existing literatures have carried out a wealth of research on the liner shipping network. However, these researches pay more attention to the liner shipping network on the global scale, and less research the liner shipping network in China or other regions, which cannot reflect the actual characteristics of specific regional liner shipping networks. Meanwhile, the data used in most studies is port throughput, or shipping company’s liner schedules. This kind of data is “planned” information rather than actual occurrence. In addition, the liner schedule is adjusted every month, which cannot reflect the real situation at different points in time.

2.2. AIS data application

In recent years, Automatic Identification System (AIS) data has been applied in many research fields. The existing AIS literatures focused on ship collisions and shipping safety, as well as prediction of destinations and Estimated Time of Arrival (ETA), ship route discovery and extraction, anomaly detection, feature extraction, etc. (He et al. 2017; Gao and Shi 2019). Many scholars have studied ship collisions and navigation safety based on AIS data (Wang et al., 2020; Zhang et al. 2019). Zaman et al. (2015) generated the value of risk from AIS data and developed a risk-based collision model for Tanker Ship in the Malacca Straits. Zhang et al. (2016) proposed a model to detect the possible occurrence of ship collision by AIS data, and the model can rank ship-shipping encounters of conflict severity levels. Liu et al. (2019) proposed a novel framework of regional collision risk identification and identified the collision risk of each vessel from the perspective of vessel pairs.

In the aspect of predicting the destination and ETA, scholars used AIS data to get similar trajectory or historical trajectory and established data-driven model to predict them. Zhang et al. (2020) built a random forest model based on AIS data to measure and utilize the similarity between the shipping routes and historical trajectories to predict the destination. El Mekkaoui et al. (2020) outlined three data sources that can serve ETA prediction and developed a neural network model that used AIS data to predict the arrival time of ships to their destinations. Park et al. (2021) proposed an AIS data-driven methodology for the estimation of vessel ETA at ports.

In addition, the unique trajectory information of AIS data can also be used to discover popular routes. Lei et al. (2016) proposed a framework of maritime traffic routes discovery based on AIS data to generate pattern-aware routes, which achieved an effective understanding of maritime traffic awareness. Wang et al. (2017) applied a modified hierarchical clustering algorithm to discover popular routes by using AIS data. Yan et al. (2020) built a maritime route extraction method based on ship history AIS data, which transformed the ship trajectory into a ship trip semantic object to realize the extraction and expression of the shipping routes.

AIS data can also be used for anomaly detection. It can detect the abnormal behavior and potential illegal behavior of the ship and provide real-time alerts. Kontopoulos et al. (2019) proposed a modified density-based clustering algorithm to identify anomalies in vessels’ trajectories based on AIS data. Rong et al. (2020) presented a data mining approach for probabilistic characterization of maritime traffic and anomaly detection using trajectory compression and clustering algorithms. The approach can identify relevant waypoints along the route where significant changes in the ship navigation behaviors are observed. Nguyen et al. (2021) built a new model for maritime anomaly detection from AIS data streams, which exploited neural network schemes to learn the probabilistic representation of AIS tracks and a contrario detection to detect abnormal events.

With the rise of big data, AIS data is gradually used to study the container shipping network. Jiang et al. (2019) constructed a container shipping network and analyzed its topological structure characteristics by means of AIS data. Peng et al. (2019) proposed a modified linear threshold model based on big AIS data, and examined the influential ports in the global oil traffic network. Our team has begun to explore related aspects. Based on ship AIS data, Jin et al. (2021) analyzed the network characteristics, port importance, network evolution and vulnerability of China’s international liner shipping network.

To sum up, this article explores the use of AIS ship trajectory data to build a complex network model of China’s foreign trade container routes. On this basis, we analyze the characteristics and changes of China’s liner shipping network under the influence of COVID-19 and conduct network connectivity simulation analysis to assess the vulnerability of China’s liner shipping network.

3. Data and research method

3.1. Data collection and processing

Automatic Identification System (AIS) is a digital navigation aid system, mainly composed of shore-based, satellite-based and ship-based facilities and shipboard equipment. AIS data is extracted from the actual navigation process of the ship and contains a lot of ship information, including ship name, IMO number, time, longitude, latitude, speed over water, course to ground, etc. There are more than 5,000 container ships worldwide and AIS signals are updated every 6 s at the shortest interval, so the original data volume is enormous. AIS data has both time and space attributes, which can accurately locate the ship’s navigation position. Compared with the shipping company’s liner schedules, AIS data has the advantage of being more accurate and comprehensive.

At present, almost all ocean-going container ships have installed ship AIS equipment. To obtain the above spatial-temporal information, the original AIS data provided by the supplier is processed in several steps, including data purification, port segmentation, node extraction and sequence reorganization, etc. First, the data purification mainly includes the following aspects: Elimination of noise information such as flying spot jumping off the trajectory, correction of abnormal information (e.g. different position information of the same IMO ship in a certain period of time), supplement of missing information, and identification of non-business docking points (e.g. anchorage, shipyard, etc.). Then, one ship’s docking track could be identified using electronic fence and other technologies combined with the real-time speed information. The earliest port of call within the period is taken as the starting node and the last port of call is taken as the end of the track, as shown in Fig. 1. On this basis, a complete shipping trajectory of a ship in a certain period is extracted. At the same time, the AIS data was associated with the Clarkson’s ship database through the ship’s call sign to establish China’s international liner shipping network database covering static data such as the container load capacity of container ships.

This research selects the trajectory information of all container ships going to and from China and establishes China’s international liner shipping network. After that, the AIS data from January to September 2020 is used to analyze the impact of COVID-19, and the data of the same period in 2019 without the epidemic impact is taken as the control group. According to statistics, in the first three quarters of 2020, a total of 2598 container ships were operating in China’s international liner shipping network.6 Besides, the network involves 55 ports in mainland China. In order to analyze the scope and extent of this impact more deeply and completely, this paper studies the efficiency and port level changes of sub-networks of China-Europe, China-U.S. and China-Southeast Asia based on the whole network.

In addition, we add the container traffic volume data to support the conclusions drawn by the AIS ship data, mainly the monthly throughput of the China-Europe routes, China-U.S. routes and China-Southeast Asia

6 Data Source: China International Liner Shipping Network database constructed in this paper.
routes of ports in mainland China. Thus, the impact of COVID-19 on the Chinese shipping market would be fully revealed from both the ship (supply) and the source of goods (demand).

3.2. Liner shipping complex network

In this paper, China's international liner shipping network is abstracted as a complex network of graph \( G(V, E) \). The ports in the shipping network are regarded as the nodes \( V \) in the complex network. The shipping lines between ports are regarded as the edges \( E \) in the complex network. In this research, the following indexes are mainly used to measure nodes importance and network efficiency:

- **Degree, in-degree, out-degree, weighted degree.** The degree is the number of all edges connected with the port, which reflects the external connectivity of the port. In the undirected graph, the port degree is calculated as follows:

\[
k_i = \sum_{j=1}^{N} x_{ij}
\]

where \( i \) and \( j \) belong to the nodes set \( V \), \( i \) is the target port, \( i, j \) are the ports different from port \( i \) in the network, \( k_i \) is the degree of port \( i \) in the undirected graph, \( N \) is the total number of ports in the network, and \( x_{ij} \) represents whether there is a connection between port \( i \) and \( j \). \( x_{ij} = 1 \) and \( x_{ij} = 0 \) represent existence and nonexistence, respectively.

When considering the directionality of the shipping network, the degree can be divided into in-degree and out-degree. Extending the degree index to the weighted network, then the weighted degree reflecting the strength of the node can be obtained. The weighted degree is another essential index to evaluate the importance of the port.

In this paper, the liner cargo capacity is taken as the weight of the edge. The weight \( u_{ij} \) is expressed as the cumulative cargo capacity between port \( i \) and port \( j \). For example, if a ship moved from port \( i \) to port \( j \), or from port \( j \) to port \( i \), the weight \( u_{ij} \) is added to the container capacity of the ship. Thus, the weighted degree \( s_i \) is calculated as:

\[
s_i = \sum_{j=1}^{N} u_{ij} x_{ij}
\]

The average weighted degree \( S \) is the average value of all ports' weighted degree in the network.

\[
S = \frac{1}{N} \sum_{i=1}^{N} s_i
\]

3.2.1. Betweenness centrality

Betweenness centrality is the proportion of a port that appears on the shortest path of other ports in the network. The calculation formula is as follows:

\[
B_i = \sum_{j=1}^{N} \sum_{k=1,k\neq i}^{N} \frac{g_k(i)}{g_k}
\]

where \( B_i \) is the betweenness centrality of port \( i \), \( j \) and \( k \) are any two other ports in the network, \( g_k \) is the number of the shortest path between \( j \) and \( k \), \( g_k(i) \) is the number of times that port \( i \) appears on the shortest path between \( j \) and \( k \).

3.2.2. Average path length

Before calculating the average path length of the network, we need to find the distance between the ports. The distance between two ports refers to the minimum number of routes directly or indirectly connecting them. It is defined as follows:

\[
d_{ij} = \begin{cases} 
1, & \text{if port } i \text{ and port } j \text{ can be connected by } l \text{ routes} \\
0, & \text{other cases}
\end{cases}
\]

\[
d_{ij} = \min \left(1 \cdot d_{ij}^{1}, 2 \cdot d_{ij}^{2}, \ldots, L \cdot d_{ij}^{L}\right)
\]

where \( d_{ij}^{l} \) is whether port \( i \) and port \( j \) can be connected by \( l \) routes, \( L \) is the maximum value of \( l \) when \( d_{ij}^{l} = 1 \), \( d_{ij} \) is the distance between port \( i \) and port \( j \).

The average path length of the network is the average distance between all ports in the shipping network. The formula is as follows:

\[
d = \frac{1}{N(N-1)} \sum_{i=1}^{N} \sum_{j=1,j\neq i}^{N} d_{ij}
\]

3.2.3. Diameter

Diameter is the largest graph distance between any two ports in the network. It can be calculated as follows:

\[
D = \max_{1 \leq i,j \leq N} d_{ij}
\]

where \( D \) is the diameter of the network.

3.2.4. Network efficiency

Network efficiency is the average efficiency of all ports in the network. It can reflect the shipping difficulty in the international container shipping network. Network efficiency is defined as the average value of reciprocal of the distance between all ports in the network.

\[
E = \frac{1}{N(N-1)} \sum_{i=1}^{N} \sum_{j=1,j\neq i}^{N} \frac{1}{d_{ij}}
\]

where \( E \) is network efficiency, \( N \) is the total number of ports in the shipping network, \( d_{ij} \) is the distance between port \( i \) and port \( j \).
3.2.5. Clustering coefficient, average clustering coefficient

Suppose that a node has \( k \) edges, so its degree is \( k \). Then the maximum possible number of edges between the nodes connected by the \( k \) edges is \( k(k - 1)/2 \). The clustering coefficient of this node is the ratio of the actual number of edges divided by the maximum possible number of edges. It can be calculated as follows:

\[
C_i = \frac{2a_i}{k_i(k_i - 1)}
\]  

(10)

where \( C_i \) is the clustering coefficient of port \( i \), \( k_i \) is the degree of port \( i \), and \( a_i \) is the actual number of edges between the nodes connected by the \( k_i \) edges.

The average clustering coefficient \( C \) is average value of all nodes’ clustering coefficients in network. When the network is a fully connected network, the average clustering coefficient is 1.

\[
C = \frac{1}{N} \sum_{i=1}^{N} C_i
\]  

(11)

4. COVID-19 impact analysis

From the perspective of the whole network, the impact of COVID-19 has not stopped the expansion. The number of network nodes in the first three quarters of 2020 is 752, increasing by 64 over the same period in 2019. The number of edges is 8093, which is 479 more than that of 2019. The growth rates of nodes and edges are 9.3% and 6.3%, respectively. But at the same time, the connectivity of the network is declining. Moreover, the network’s average degree and average weighted degree of considering ship container capacity decreased by 2.8% and 20.9%, respectively. This phenomenon shows that while the connectivity declined slightly, the ship capacity has experienced a large-scale curtailment. However, the average clustering coefficient of the network is increased by 4.2%, indicating that the network is more agglomerated and clustered. The network diameter and average path length do not change, indicating that the overall accessibility of the network remains stable (see Fig. 2).

As for the typical routes, the scales of the three sub-networks (China-Europe, China-U.S. and China-Southeast Asia route network) all declined to varying degrees, but the connectivity strength of China-Europe route network and China-U.S. route network has increased. In the first three quarters of 2020, the number of edges of the two sub-networks increased by 4.9% and 7.5%, and the average degree increased by 5.4% and 10.8%, respectively. Meanwhile, the diameter of China-U.S. route network decreased by 2, showing that the number of edge ports in the network are decreasing. The diameter of China-Southeast Asia route network increased by 4, indicating that although the number of nodes and edges decreases, new branch routes appear in the network, and the network scope is extended (see Table 1).

4.1. Impact on liner shipping network

In order to analyze the impact of the epidemic on the transport network more effectively, we investigate the changes in the transport network before and after the epidemic from the aspects of both supply and demand. According to the statistics of container import-export volume and AIS data, in the first three quarters of 2020, the demand and supply of China’s international liner shipping network dropped by 3.7% and 11.7%, respectively. Through the analysis of the entire transport network and typical routes, the following conclusions can be drawn.

First of all, although supply and demand declined simultaneously, it can be seen from the monthly fluctuations that the oscillation in capacity and demand under the impact of the epidemic were misaligned. Fig. 3 shows that before the COVID-19, the growth curves of supply and demand were basically the same, showing a U-shaped curve with low front and high back. After the epidemic, significant fluctuations occurred in the former three quarters, and the capacity allocation of the entire transport network showed a W-shaped curve. Especially, the capacity declined in March, May, and June, in which the demand rebounded rapidly. The mismatch between supply and demand was one of the main reasons for the severe fluctuations in the container shipping market in 2020.

Secondly, the fluctuation range between peaks and valleys has been enlarged. Generally, there are two kinds of main seasonal fluctuations in China’s container market, consisting of the slack season due to the Spring Festival in China (from January to February) and the peak season due to Christmas in western countries (from July to August). The impact of the epidemic in 2020 had exceeded the seasonal factors mentioned above and the freight volume increased by 68.9% from the slack month (February) to the peak month (September), much larger than that (30.8%) in the same period in 2019.

Thirdly, demand for China-U.S. route network rebounded firmly, while fluctuations on China-Europe routes and China-Southeast Asia routes were tiny relatively. Since February 2020, the container freight volume of China-U.S. routes has rapidly rebounded from 1.14 million TEU to 2.40 million TEU, with an increase of 110.6%. In contrast, China-Europe routes and China-Southeast Asia routes have relatively tiny fluctuations in demand. It is also the reason behind the frequent occurrence of terminal congestion and ships’ queuing problems in U.S. ports (especially U.S. West Coast ports mainly for Chinese routes) in the latter half of 2020.

4.2. Impact on main ports

Before the epidemic, typical global hub ports such as Busan and Singapore played an important role in China’s international liner shipping network through the analysis of the entire shipping network and typical shipping routes, as shown in Fig. 4(a). Meanwhile, although container throughput of Chinese mainland ports took a lead on the global level, their ranking in China’s international liner shipping network was lower. On the one hand, it was caused by the choice of transit bases due to the different preferences of liner companies for port services and business environment. On the other hand, it is also the service level of Chinese ports that limited their own development. After the COVID-19, the competitiveness of China mainland container ports has been significantly improved, as shown in Fig. 4(b). Among the Chinese ports, Ningbo-Zhoushan Port made the most obvious improvement with an increase of 33.3% from 114 to 152 in in-degree. Its betweenness centrality increased from the eighth to the third place as well. In addition, Xiamen Port and Dalian Port have also been developed. In terms of different shipping networks (Fig. 4(c)-(h)), the connectivity and hub degree of Chinese ports on China-Europe routes and China-U.S. routes have been greatly improved, but they basically maintained the pre-epidemic level on China-Southeast Asia routes.

One of the main reasons for the improvement of China’s port status is the backflow of transshipment containers brought by China’s effective epidemic control. After the outbreak of COVID-19, countries have adopted various isolation measures for ships and crew arriving at ports and carried out stricter declaration, quarantine and disinfection procedures for cargo on board. These measures ensure the health and safety of the port, but at the same time have a tremendous negative impact on the port business environment. Among the shipping transport services of different goods, the cold-chain logistics during the epidemic period is a very representative example. In the stage of basically zero growth of the Chinese mainland epidemic, most sporadic outbreaks came from overseas input, one of which was frozen food transported to the port from

\footnote{Chinese mainland container ports: The promotion of competitiveness is mainly reflected in the eight trunk ports, namely Dalian, Tianjin, Qingdao, Shanghai, Ningbo-Zhoushan, Xiamen, Shenzhen and Guangzhou.}
abroad. As a result, the quarantine declaration procedures for ships carrying frozen fresh goods have become more stringent. Because of the complicated epidemic conditions and prevention policies of different countries, some ports have been updating and implementing restrictive measures to prevent and control the continued spread of COVID-19. Given that the overall situation of China’s epidemic prevention and control is relatively stable, China’s ports have created a steady shipping service environment, so more ships operating in China’s international liner shipping network choose China’s ports for transit.

5. Liner shipping network vulnerability assessment

The vulnerability of shipping network refers to the extent to which the connectivity and efficiency are disturbed when external factors impact the network. This section takes the 2019 shipping network as the normal state without the impact of epidemic situation, and then selects the typical ports of each route for node failure simulation analysis. According to the calculation results of port connectivity and hub degree in the last section, six non-Chinese-mainland ports, Busan, Singapore, Hong Kong, Antwerp, Said and Los Angeles, are selected as typical ports for analysis (see Fig. 5). Then we can accurately evaluate the overall impact on China’s international liner shipping network when the important nodes are paralyzed or the major routes are disrupted. It is of practical value for the risk of early warning of China’s container shipping network under the influence of the epidemic. In addition, the shortest path, network efficiency and other indicators are all calculated based on the set of Chinese-foreign port point pairs, rather than all port point pairs in the global shipping network. With such more targeted calculation and analysis, it is conducive to get the specific impact of a certain node failure on China’s liner shipping network.

5. Liner shipping network vulnerability assessment

Table 1

Main characteristic indexes of a typical liner shipping network.

|                | Entire Network | China-Europe | China-U.S. | China-Southeast Asia |
|----------------|----------------|--------------|------------|----------------------|
|                | Q1th-Q3rd of 2019 | Q1th-Q3rd of 2020 | Q1th-Q3rd of 2019 | Q1th-Q3rd of 2020 | Q1th-Q3rd of 2019 | Q1th-Q3rd of 2020 | Q1th-Q3rd of 2019 | Q1th-Q3rd of 2020 |
| node number    | 688            | 752          | 451        | 449                  | 411              | 399             | 448              | 435             |
| edge number    | 7614           | 8093         | 3232       | 3391                 | 2949             | 3171            | 2194             | 3167            |
| average degree | 11.067         | 10.762       | 7.166      | 7.552                | 7.175            | 7.947           | 7.129            | 7.280           |
| average weighted degree | 1328248 | 1050431     | 835558    | 648043               | 657965           | 59613           | 282381           | 244290          |
| network diameter | 10        | 10           | 9          | 9                    | 11               | 9              | 11               | 15              |
| average clustering coefficient | 0.431 | 0.449        | 0.388      | 0.383                | 0.393            | 0.401           | 0.383            | 0.392           |
| average path length | 3.286 | 3.282        | 3.468      | 3.337                | 3.529            | 3.244           | 3.727            | 3.722           |

Fig. 2. The entire international liner shipping network of China before and after the COVID-19

*Note: The area of the circle in the topological diagram indicates the size of betweenness centrality.

Generally speaking, the failure of Busan, Singapore and Hong Kong might have a greater impact on China’s international liner shipping network, while the effect of Antwerp and Port Side might be relatively smaller. However, the influence of the same port on different routes shows great differences.

(1) The failure of Busan Port appears to have the most significant impact on the China-U.S. route network. For the China-U.S. route network, the paralysis of Busan Port would lead to an increase of 6.5% in the average shortest path of container shipping from China to the United States, a decrease of 7.0% in the network efficiency, and an increase of 8 isolated nodes. In the China-Europe route network, the impact of Busan Port failure is also considerable for the export container flow, with the average shortest path increases by 4.2% and the network efficiency decreases by 2.8%, while the influence on import cargo is less obvious. Besides, the influence of Busan Port is relatively less prominent for the Sino-Southeast Asia routes.

(2) Singapore Port is of vital importance in China-Southeast Asia route network and China-Europe route network. If Singapore Port closed, the average shortest path of return cargo on China-Southeast Asia routes would increase by 3.4%, and the network efficiency would decrease by 2.8%. It can be found that the change range of network efficiency caused by the failure of Singapore port is greater than that of the shortest path and the number of isolated nodes, and a similar situation also occurs on other routes. One reason might be that although Singapore has a strong hub degree, its neighboring ports, such as Tanjung Pelepas and Tanjung Priok, all play the role of transshipment. Therefore, there are alternative ports when the operation of Singapore port
Fig. 3. Changes in container freight volume and capacity before and after the COVID-19.
is blocked, and the interference effect on the shipping network is limited.

(3) Hong Kong mainly affects China-Europe route network and China-Southeast Asia route network, with significantly greater impact on return routes than that on departure routes. The failure of Hong Kong Port would lead to an increase of 3.4% in the average shortest path for China to import containers from Europe. The proportion of isolated nodes would reach 1.10%. At the same time, the average shortest path of reverse export goods would increase by 2.8%, and the proportion of isolated nodes would reach 0.58%. The data shows that Hong Kong is a crucial container import and export transshipment hub for China. Due to the convenience of customs clearance and other advantages, a considerable number of containers are declared through Hong Kong Port and then transported to mainland China.

(4) Antwerp plays an essential role as a transshipment hub in China-Europe route network. In the case of failure of the Antwerp Port, the average shortest path of containers exported from China and imported from Europe would increase by 1.7% and 2.5%, respectively, and the network efficiency would decrease by 2.1% and 2.3%, respectively. Additionally, since some vessels operating on China-Southeast Asia routes also participate in the maritime transportation between Southeast Asia and Europe this year, Antwerp also shows its influence on China-Southeast Asia route network.

(5) Said Port is the gateway to the Mediterranean Sea, mainly affecting the operation efficiency of China-Europe route network. When Said Port is simulated to be closed, the average shortest path of containers exported from China and imported from Europe would increase by 1.4 and 2.2, respectively, and the network efficiency would decrease by 0.2% and 0.9%, respectively. Moreover, there is an increase of 1 and 3 isolated nodes respectively under this simulation scenario.

(6) The port of Los Angeles is one of the most important destinations in China-U.S. shipping network, as well as the hub gateway in the western United States. If Los Angeles Port was shut down, the network efficiency for exports and imports between China and the U.S. would decrease by 2.7% and 2.0%, respectively. However, compared with larger transshipment hubs such as Busan and Singapore, which are located on the main shipping routes, the impact of Los Angeles is more reflected along the West Coast of the United States. Thus, from the perspective of the whole network, the impact of Los Angeles Port is relatively limited.

6. Conclusion and discussion

This paper uses AIS data to analyze the impact of the COVID-19 on China’s foreign trade container route network and main nodes, and simulates the changes of network efficiency and connectivity under the situation of important node failure in the network. In the first three quarters of 2020, the demand and supply in the network decreased by 3.7% and 11.7%, respectively, and the supply recovery generally lagged behind the demand recovery. This is also one of the main reasons for the drastic fluctuation of the container shipping market in 2020. From the perspective of the network, during the epidemic period, the scale of China’s international liner transport network increased, with more routes gathering at fewer ports. However, the overall connectivity and connection strength declined. From the perspective of nodes, on the one hand, before the COVID-19, although the container throughput of ports in China was leading in the world, the connectivity and hubness in the container network were not robust. Ports such as Busan and Singapore play an important role in the network. On the other hand, due to the backflow of transfer container sources, the competitiveness of container ports in Chinese mainland has been significantly improved after the outbreak. Finally, by simulating the impact of important port failure on the efficiency and connectivity of China’s foreign trade container network, we conclude that Busan port has the heaviest and widest network impact. Singapore and Hong Kong ports have strong influence in Europe and Southeast Asia. More specifically, Singapore port has a greater impact on export goods while Hong Kong port has a more significant impact on import network. The influence of Antwerp port and Port Said is relatively small, mainly reflected in the China-Europe routes.

COVID-19 has exposed the existing problems, that is, the container transport industry management departments, as well as the market main bodies (mainly port and shipping enterprises) lack effective plans and
countermeasures to deal with emergencies. First, under the influence of such emergencies, all parties are advised to strengthen the investigation and prediction of demand to provide a matching level of transport capacity. Second, for port enterprises, the impact of COVID-19 is not entirely negative. It can strengthen the linkage with liner companies and enhance the port competitiveness, thus turning crisis into opportunity. Third, the traffic management department should make contingency plans and capacity adjustment strategy in advance for important international logistics channels and hub ports, and increase alternative routes and ports to enhance network resilience. Finally, there are still many issues worthy of further exploration for the current research. For example, the hubness of some ports like Ningbo-Zhoushan port has been greatly improved during the outbreak. An in-depth discussion on the causes of this phenomenon and the implementation of port strategies might provide a reference for other ports to maintain competitive during the outbreak. In addition, focusing on the hot issue of “empty container shortage”, we can overlay the container source transport data on the existing AIS ship network to analyze the impact of the epidemic on the imbalance between import and export figures and the container source turnover efficiency.

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Supplementary data

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References

Berle, Ø., Ashjenslett, B.E., Rice, J.B., 2011. Formal vulnerability assessment of a maritime transportation system. Reliab. Eng. Syst. Saf. 96 (6), 696-705.
Calatayud, A., Mangan, J., Palacin, R., 2017. Vulnerability of international freight flows to shipping network disruptions: a multiplex network perspective. Transport. Res. E Logist. Transport. Rev. 108, 195-208.
Cheung, K.F., Bell, M.G., Pan, J.J., Perera, S., 2020. An eigenvector centrality analysis of world container shipping network connectivity. Transport. Res. E Logist. Transport. Rev. 140, 101991.
Chen, C., Feng, T., Gu, X., Yao, B., 2022. Investigating the effectiveness of COVID-19 pandemic countermeasures on the use of public transport: a case study of The Netherlands. Transport Pol. 117, 98-107.
Dadashpoor, H., Arasteh, M., 2020. Core-port connectivity: towards shaping a national hinterland in a West Asia country. Transport Pol. 80, 57-68.
Dang, V.L., Yeo, G.T., 2017. A competitive strategic position analysis of major container ports in Southeast Asia. Asian J. Shipp. Logist 33 (1), 19-25.
Ducruet, C., Notteboom, T., 2012. The worldwide maritime network of container shipping: spatial structure and regional dynamics. Global Network 12 (3), 395-423.
Ducruet, C., Zaidi, F., 2012. Maritime constellations: a complex network approach to shipping and ports. Marit. Pol. Manag. 39 (2), 151-168.
El Mekkaoui, S., Benabdou, L., Berrada, A., 2020. Predicting ships estimated time of arrival based on AIS data. In: Proceedings of the 13th International Conference on Intelligent Systems: Theories and Applications, pp. 1-6.
Gao, M., Shi, G.Y., 2019. Ship spatiotemporal key feature point online extraction based on AIS multi-sensor data using an improved sliding window algorithm. Sensors 19 (12), 2706.
Gastner, M., Ducruet, C., 2015. The distribution functions of vessel calls and port connectivity in the global cargo ship network. In: Spatial Structures and Time Dynamics. Maritime Networks, pp. 242–261.

He, W., Li, Z., Malekian, R., Liu, X., Duan, Z., 2017. An internet of things approach for extracting featured data using AIS database: an application based on the viewpoint of connected ships. Symmetry 9 (9), 186.

Hu, Y., Zhu, B., 2009. Empirical analysis of the worldwide maritime transportation network. Phys. Stat. Mech. Appl. 388 (10), 2061–2071.

Jiang, J., Lee, L.H., Chew, E.P., Gan, C.C., 2015. Port connectivity study: an analysis framework from a global container liner shipping network perspective. Transport. Res. E Logist. Transport. Rev. 73, 47–64.

Jiang, L., Jia, Y., Zhang, C., Wang, W., Feng, X., 2019. Analysis of topology and routing strategy of container shipping network on “Maritime Silk Road”. Sustain. Comput.: Inf. Syst. 21, 72–79.

Jin, L., Chen, Z., Wang, X., Yao, H., Liu, C., Yu, B., 2021. China’s International Liner Shipping Network Evolution and Vulnerability Based on Automatic Identification System (AIS) Data. No. TRBAM-21-04428.

Kaluza, P., Kalksch, A., Gastner, M.T., Blasius, B., 2010. The complex network of global cargo ship movements. J. R. Soc. Interface 7 (48), 1093-1103.

Kavirathna, C.A., Kawasaki, T., Hanako, S., 2018. Transshipment hub port competitiveness of the Port of Colombo against the major Southeast Asian hub ports. Asian J. Shipp. Logist 34 (2), 71–82.

Kim, A.R., 2016. A study on competitiveness analysis of ports in Korea and China by Entropy weight TOPSIS. Asian J. Shipp. Logist 32 (4), 187–194.

Kontopoulos, I., Varlamis, I., Tsperes, K., 2019. Uncovering hidden concepts from AIS data: a network abstraction of maritime traffic for anomaly detection. In: International Workshop on Multiple-Aspect Analysis of Semantic Trajectories. Springer, Cham, pp. 6–20.

Lei, P.R., Tsai, T.H., Peng, W.C., 2016. Discovering Maritime Traffic Route from AIS Network. 2016 18th Asia-Pacific Network Operations and Management Symposium (APNOMS). IEEE, pp. 1–6.

Liu, Z., Wu, Z., Zheng, Z., 2019. A novel framework for regional collision risk identification based on AIS data[J]. Appl. Ocean Res. 89, 261–272.

Montes, C.P., Seoane, M.I.F., Laze, F.G., 2012. General cargo and containership emergent routes: a complex networks description. Transport Pol. 24, 126–140.

Nguyen, D., Vadaine, R., Hajduch, G., Garello, R., Fablet, R., 2021. GeoTrackNet–A maritime anomaly detector using probabilistic neural network representation of AIS tracks and A contrario detection. IEEE Trans. Intell. Transport. Syst. https://doi.org/10.1109/ITITS.2021.3055614.

Park, K., Sim, S., Bae, H., 2021. Vessel estimated time of arrival prediction system based on a path-finding algorithm. Marit. Transport Res. 2, 100012.

Peng, P., Poon, J.P., Yang, Y., Lu, F., Cheng, S., 2019. Global oil traffic network and diffusion of influence among ports using real time data. Energy 172, 333–342.

Rong, H., Teixeira, A.P., Soares, C.G., 2020. Data mining approach to shipping route characterization and anomaly detection based on AIS data. Ocean Eng. 198, 106936.

Tian, W., Deng, G.S., Wu, F.J., 2007. Analysis of network effect in port and shipping system characterized by scale-free network. In: International Conference on Intelligent Systems and Knowledge Engineering. Atlantis Press.

Vijayakumar, N.M., Joubert, J.W., 2016. The vulnerability of the global container shipping network to targeted link disruption. Phys. Stat. Mech. Appl. 462, 396–409.

Wang, G.W., Zeng, Q., Li, K., Yang, J., 2016. Port connectivity in a logistic network: the case of Bohai Bay, China. Transport. Res. E Logist. Transport. Rev. 95, 341–354.

Wang, L., Li, Y., Wan, Z., Yang, Z., Wang., Quan, K., Fu, L., 2020. Use of AIS data for performance evaluation of ship traffic with speed control. Ocean Eng. 204, 107250.

Wang, Y., Cullineane, K., 2016. Determinants of port centrality in maritime container transportation. Transport. Res. E Logist. Transport. Rev. 95, 326–340.

Wang, S., Gao, S., Yang, W., 2017. Ship route extraction and clustering analysis based on automatic identification system data. In: Eighth International Conference on Intelligent Control and Information Processing (ICICIP). IEEE, pp. 33–38, 2017.

Wilmsmeier, G., Hoffmann, J., Sanchez, R.J., 2006. The impact of port characteristics on international maritime transport costs. Res. Transport. Econ. 16, 117–140.

Xu, M., Li, Z., Shi, Y., Zhang, X., Jiang, S., 2015. Evolution of regional inequality in the global shipping network. J. Transport Geogr. 44, 1–12.

Xu, M., Pan, Q., Muscoloni, A., Xia, H., Cannistraci, C.V., 2020. Modular gateway-ness connectivity and structural core organization in maritime network science. Nat. Commun. 11 (1), 1–15.

Xu, X., Hu, J., Li, F., 2007. Empirical analysis of the ship-transport network of China. Chaos: Interdiscipl. J. Nonlinear Sci. 17 (2), 023129.

Yan, Z., Xiao, Y., Cheng, L., He, R., Ruan, X., Zhou, X., Li, M., Bin, R., 2020. Exploring AIS data for intelligent maritime routes extraction. Appl. Ocean Res. 101, 102271.

Yao, B.Z., Hu, P., Lu, X.H., Gao, J.J., Zhang, M.H., 2014. Transit network design based on travel time reliability. Transport. Res. Part C 43, 233–248.

Zaman, M.B., Kobayashi, E., Wakabayashi, N., Maizun, A., 2015. Development of risk-based collision (RBC) model for tanker ship using AIS data in the Malacca Straits. Proc. Earth Planet. Sci. 14, 128–135.

Zhang, C., Bin, J., Wang, W., Peng, X., Wang, R., Halldearn, R., Liu, Z., 2020. AIS data driven general vessel destination prediction: a random forest based approach. Transport. Res. C Emerg. Technol. 118, 102729.

Zhang, L., Meng, Q., Fwa, T.F., 2019. Big AIS data based spatial-temporal analyses of ship traffic in Singapore port waters. Transport. Res. E Logist. Transport. Rev. 129, 287–304.

Zhang, W., Goerlandt, F., Kujala, P., Wang, Y., 2016. An advanced method for detecting possible near miss ship collisions from AIS data. Ocean Eng. 124, 141–156.

Zhao, C., Wang, Y., Gong, Y., Brown, S., Li, R., 2021. The evolution of the port network of the Maritime Silk Road: from a sustainable development perspective. Mar. Pol. 126, 104426.