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A Port Importance Evaluation Method Based on the Projection Pursuit Model in Shipping Networks

Junfeng Zhu, Wei Liu and Yanbin Yang *

College of Transport and Communications, Shanghai Maritime University, Shanghai 201306, China; 201940610004@stu.shmtu.edu.cn (J.Z.); weiliu@shmtu.edu.cn (W.L.)
* Correspondence: yanbinyang321@163.com

Abstract: Shipping networks face natural or man-made port emergencies, and the failure of a port affects the network's connectivity and efficiency. It is very necessary to give priority to the selection of ports that should be maintained or ensure service capacity in case of port failure. The importance evaluation of ports is of great significance to improve the efficiency of maritime transport. In view of this, this paper proposed a port importance evaluation method in shipping networks integrating the centrality index and vulnerability index. The indexes are, respectively, degree centrality, weighted degree centrality, betweenness centrality, closeness centrality, change rate of network efficiency, and connectivity. The weight of each index is calculated by the projection pursuit model. The results show that the proposed method integrates the different performances of each index. The importance of Singapore port, Colombo port, and Port Klang rank as the top three. They are the hub ports of the main lines of Asia, Europe, and Africa and occupy extremely important core positions in the network. Finally, the ports are classified based on importance value, and the shipping network after the failure of some ports is compared. This research can provide a scientific basis for ensuring the efficiency, connectivity, and stability of shipping networks.

Keywords: port importance evaluation; shipping network; centrality; vulnerability; projection pursuit model

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1. Introduction

Since the 21st century, the degree of economic globalization and regional integration has been deepening. An important feature of economic globalization is the rapid development of international trade. More than 80% of the goods transported in international trade are transported by sea, accounting for 70% of the total international trade [1]. In October 2013, China put forward the concept of the Maritime Silk Road (MSR) for the first time, and proposed strengthening connectivity construction to achieve common development and prosperity. As strategic infrastructure and important fulcrum points, ports increasingly become the nerve center of the global integrated transport network and the core of resource allocation in the international market [2].

At present, trade between ports along the MSR has become increasingly frequent, and a relatively complete route network has been basically formed. However, due to the complexity of the countries and regions along the MSR, there are political, environmental, religious, cultural, economic, and other problems. And natural disasters such as earthquakes, tsunamis, typhoons, etc., sometimes pose a fatal threat to the ports, thus affecting normal operations [3]. If core ports are unable to realize their own port functions due to certain emergencies, the network efficiency of the container transport network will be reduced, affecting the trade exchanges between countries and regions along the MSR [4].

The role played by ports has changed from traditional regional gateways to locations of important value-added and complex logical-related activities [5]. Therefore, studies on the importance of ports have attracted wide attention from countries all over the world.

The different positions and topologies of port nodes in the network result in their different importance [6]. For example, Ducruet et al., 2010, used betweenness centrality to study the changes in the location of hub ports in Northeast Asia and revealed the changing trend of shipping routes in this region [7]. Li et al., 2015, divided the global shipping network into 25 regions from a geographical perspective and analyzed the status of each shipping region in global shipping based on the proposed multi-center index [8]. Wan et al., 2021, proposed a measurement method for port importance. Their study not only considered the network centrality index, but also integrated the economic index [9]. Yang et al., 2022, proposed a method to analyze the importance of ports along the MSR by considering both local propagation and global centrality. The SIS model and the Kendall correlation coefficient were used to verify the superiority of their method [10].

Indexes based on centrality have been widely used to evaluate and determine the importance of ports, but the use of centrality measures alone only reflects one aspect of the role of ports in shipping networks, and vulnerability indexes also reflect the impact of ports on the network in different aspects. In order to evaluate the importance of ports more comprehensively, this paper synthesizes the centrality index and vulnerability index, using the projection pursuit model to calculate the weight. Then the importance of ports along the MSR is evaluated. These research results can provide useful insights for identifying influential ports in the shipping network. The obtained ranking of port importance also provides a theoretical basis for the selection of ports that should be prioritized for maintaining or guaranteeing service capability under actual emergencies, which is of great significance for ensuring the connectivity, stability, and reliability of the network and promoting trade cooperation among countries along the MSR.

The paper is structured as follows. Section 2 provides a review of related literature. Section 3 introduces the research methods, including the indexes and the projection pursuit model. In Section 4, we construct the MSR shipping network and combine the centrality indexes and vulnerability indexes to calculate the importance of all ports. Finally, the conclusions are provided in Section 5.

2. Literature Review

A shipping network can be abstracted into a complex network composed of ports, routes, ships, and other major elements [11]. Based on complex network theory, current research transforms the real maritime system into an abstract complex network and analyzes the topology structure of the network, including node degree, clustering coefficient, average path length, and node strength. These topologies help us better understand the maritime network. The degree distribution reveals the scale-free characteristics of the maritime network [12]. A few ports have high node degree, and the rest have low node degree, which follows the power-law distribution. The smaller average shortest path length and larger agglomeration coefficient also illustrate the small-world characteristics and accessibility of the maritime transport network [13].

Centrality is an important reflection of the position of port nodes in the network and plays an important role in revealing the spatial structure characteristics of the shipping network. Tovar et al., 2015, analyzed the connectivity of ports in the Canary Islands by selecting the degree, betweenness, and port accessibility index [14]. Based on the core area of the MSR shipping network in the 21st century, Li et al., 2018, selected 34 major container ports in the target area and analyzed the central position of ports in the MSR container shipping network based on five indicators. The results show that Hong Kong port, Shenzhen port, Dalian port, Singapore port and Shanghai port occupy relatively more important hubs in the network [15]. Wang et al., 2016, expanded the application of three basic centrality measures (degree centrality, betweenness centrality, and closeness centrality) in the directional weighted container shipping network. The factors of cargo flow and transportation capacity are considered, which better reflect the characteristics of the actual situation [16].

In addition, researchers have also found some rules in combination with the space–time characteristics of the centrality index. Xu et al., 2015, studied the centrality characteristics of the global shipping network from 2001 to 2012, and analyzed the uneven evolution process of the region [17]. This evolution process also proved that the shipping network has heterogeneity in space and structure [18]. At the same time, due to the different economic backgrounds of each region, the evolution process of the global shipping network is also unstable [19]. Ducruet and Notteboom, 2012, analyzed the global liner transport network in 1996 and 2006, and studied the relative position of ports in the global network through centrality indexes [20].

The concept of vulnerability was first proposed in the field of natural disasters and is used to indicate the possibility and degree of damage to the system when it is affected by adverse factors such as disasters. The study of maritime network vulnerability mainly refers to the impact degree of network connectivity when the network is attacked or partially failed, focusing on the impact on the whole system when some nodes, paths, and other elements fail or are disturbed [21]. From the perspective of quantitative indexes, Wang et al., 2016, proposed a quantitative method to study the change rate of network vulnerability. The quantitative indexes include the change rate of characteristic values such as network average degree, network clustering coefficient, proportion of network isolated nodes, network average distance, and network efficiency [22]. Viljoen and Joubert, 2016, sorted the edges according to their importance and deleted edges in the network according to their order, and studied the impact of edge failure on the topology vulnerability of the global container shipping network. Measures include link betweenness and link salience [23]. Guo et al., 2017, analyzed the vulnerability of the China–Japan–South Korea shipping network based on average degree, clustering coefficient, and distance value by using the blocking flow theory, hub port interruption and deletion, and other methods [24]. Yu et al., 2020, proposed a quantitative method of network survivability to assess vulnerability [25]. Xu et al., 2022, proposed a new global liner transport network cascading model, taking into account the dynamic process of container flow redistribution between ports, and evaluated the vulnerability of network to the cascade failure caused by port congestion propagation [26]. Wen et al., 2022, used three centrality measures considering different network topological information to identify the importance of ports. The three centrality measures include neighborhood-based centrality, gravity-based centrality, and iterative refinement centrality, and an index is proposed based on importance to analyze the vulnerability of the network [27].

3. Research Method

3.1. Index

The indexes involved in the proposed method include centrality indexes and vulnerability indexes. The vulnerability indexes are the change rate of network indexes when the port fails. The specific introduction and formula are as follows [22,28,29].

(1) Degree Centrality (DC)

The degree centrality of node i is measured by the number of nodes connected by edges. The greater the degree centrality of node, the more important the node is. The calculation formula is

$$DC_i = \frac{\sum\limits_{j \in V} a_{ij}}{N-1} \tag{1}$$

where $V = \{v_1, v_2, \cdots, v_N\}$ is the node set, N is the total number of nodes, and a_{ij} is the value in the adjacency matrix in the unweighted network.

(2) Weighted Degree Centrality (WDC)

The weight centrality of node i is measured by the edge weight of the node, and the calculation formula is

$$WDC_i = \frac{\sum_{j \in V} b_{ij}}{\sum_{i \in V} \sum_{j \in V} b_{ij}} \tag{2}$$

where b_{ij} is the value in the adjacency matrix in the weighted network, and the weight is the number of connected edges.

(3) Betweenness Centrality (BC)

The betweenness centrality of node i is measured by the ratio of the shortest path number of any two nodes passing through node i in the network to the shortest path number between the two nodes. The greater the betweenness centrality of nodes, the more important the nodes are. The calculation formula is

$$BC_i = \frac{2}{(N-1)(N-2)} \sum_{i \neq s \neq t} \frac{g(s,t|i)}{g(s,t)} \tag{3}$$

where $g(s,t)$ represents the number of shortest paths of any two nodes s and t in the network, and $g(s,t|i)$ represents the number of shortest paths of nodes s and t through i in the network.

(4)Closeness Centrality (CC)

The closeness centrality of node i is measured by the reciprocal of the average distance between the node and other nodes. The greater the closeness centrality of the node, the easier the node information is to spread, and the more important the node is. The calculation formula is

$$CC_i = \frac{1}{d_i} = \frac{N-1}{\sum_{j \neq i} d_{ij}} \tag{4}$$

where d_{ij} is the shortest path length between port i and j.

(5) Change rate of Network Efficiency (CRNE)

Network efficiency is usually used to reflect the connectivity difficulty between ports in the whole network. The transport efficiency between any two port nodes i and j can be expressed by the reciprocal of the shortest path length. The average value of network efficiency between all port pairs is the efficiency value of the whole network, and the calculation formula is

$$NE = \frac{1}{N(N-1)} \sum_{i \neq j} \frac{1}{d_{ij}} \tag{5}$$

Then, the index of the change rate of network efficiency is

$$CRNE_i = \frac{NE - NE_i}{NE} \tag{6}$$

where NE represents the initial network efficiency, NE_i represents the network efficiency after the failure of port i, and $CRNE_i$ represents the change rate of network efficiency after the failure of port i.

(6) Change rate of network connectivity (CRNC)

The port scale of the maximum connected subgraph reflects the network connectivity after port i fails. The ratio of the number of ports in the maximum connected subgraph to the initial number of ports in the network is used to measure the overall connectivity of the network. The calculation formula is

$$NC = \frac{n_{\max}}{N} \tag{7}$$

where $n_{\max}$ is the number of ports included in the maximum connected subgraph.

Then, the index of the change rate of network connectivity is

$$CRNC_i = \frac{NC - NC_i}{NC} \tag{8}$$

where NC represents the initial network connectivity, NC_i represents the network connectivity after the failure of port i, and $CRNC_i$ represents the change rate of network connectivity after the failure of port i.

3.2. Projection Pursuit Model

The projection pursuit method is a new statistical method for addressing multi-index complex problems. It is a cross between statistics, applied mathematics, and computer technology and offers unique advantages in analyzing and processing data with high dimensionality that is also nonlinear and non-normally distributed [30]. The idea of projection pursuit is to project high-dimensional data onto one-dimensional space, and then find the comprehensive projection eigenvalues of high-dimensional data structures or features in the one-dimensional space, and finally analyze and study the features of high-dimensional data [31]. The one-to-one corresponding functional relationship between the projection eigenvalue and the dependent variable is established, to complete the transformation from high-dimensional data to low-dimensional data. In this process, multiple evaluation indexes are integrated into a comprehensive evaluation index, which is then used for a more reasonable classification and evaluation of samples [32,33].

As a comprehensive evaluation method directly driven by sample data that can be used to deal with multi-index complex problems, this method seeks the best projection direction according to the data characteristics of the sample. The comprehensive evaluation of the research object is realized according to the size of the projection value. The obtained evaluation results are highly consistent with actual data and have strong interdisciplinary universality [34]. Therefore, the projection pursuit model is used for the study of water abundance of mine aquifers with multifactor comprehensive evaluation. Figure 1 shows the flow path of projection pursuit model.

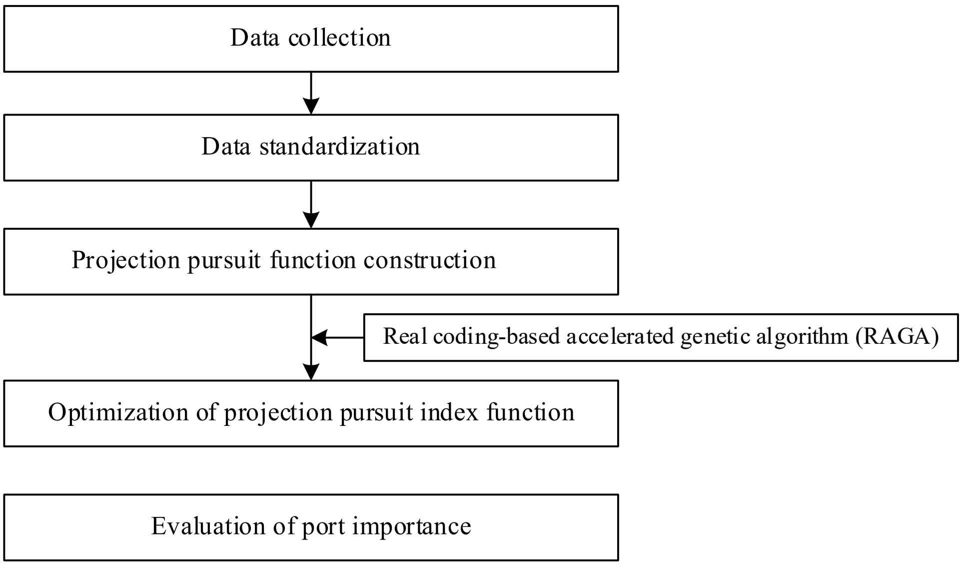

Figure 1. The flow path of projection pursuit model.

(1) Data standardization

In order to eliminate the impact of data dimension and unit between various indexes, it is necessary to standardize the sample data. This paper uses the range method to calculate; the calculation formula is as follows:

$$x(i,j) = [x^*(i,j) - x_{\min(j)}]/[x_{\max(j)} - x_{\min(j)}] \tag{9}$$

where $x^*(i,j)$ is the original value of the j-th index of sample i, $x(i,j)$ is the standardized value of the j-th index of the sample, $x_{\max(j)}$ is the maximum value of the j-th index, and $x_{\min(j)}$ is the minimum value of the j-th index.

(2) Projection pursuit function construction

Assuming that the number of indexes is p, the projection direction vector is $a = \{a(1), a(2), \ldots, a(p)\}$, and the one-dimensional projection of sample i in this direction is $Z(i) = \sum_{j=1}^{p} a(j)x(i,j)$.

And then the projection index function is constructed.

$$Q(a) = S_Z D_Z \tag{10}$$

$$S_Z = \sqrt{\sum_{i=1}^{n} (Z(i) - E(Z)^2/(n-1)} \tag{11}$$

$$D_Z = \sum_{i=1}^{n} \sum_{j=1}^{p} (R - r(i,j))\mu(R - r(i,j)) \tag{12}$$

$$R = 0.1S_Z \tag{13}$$

$$r(i,j) = |Z(i) - Z(j)| \tag{14}$$

$$\mu(R - r(i,j)) = \begin{cases} 1, R \geq r(i,j) \\ 0, R < r(i,j) \end{cases} \tag{15}$$

where S_z and D_z, respectively, represent the standard deviation and local density of the projected eigenvalue $z(i)$, $E(Z)$ is the mean value of $Z(i)$ sequence, $r(i,j)$ is the distance between samples, and R is the window radius of the local density.

(3) Optimization of the projection pursuit index function based on genetic algorithm

When the sample set is given, the projection index function $Q(a)$ is only affected by the projection direction a. The following optimization problems need to be solved to analyze the optimal projection direction.

Objective function:

$$\max Q(a) = S_Z D_Z \tag{16}$$

Constraint condition:

$$s.t. \sum_{j=1}^{p} a^2(j) = 1 \tag{17}$$

This is a nonlinear optimization problem, which is difficult to solve by traditional optimization methods, and it needs to be solved by combining relevant algorithms. In this paper, the real coding-based accelerated genetic algorithm (RAGA) is used to solve the problem of high-dimensional global optimization. This improved genetic algorithm overcomes the shortcomings of binary coding, and can greatly improve the optimization speed, speeding up the convergence speed. The cycle of RAGA can be adjusted gradually, narrowing the interval for searching the optimal value of the optimization variable, and improving the accuracy. The optimization steps of RAGA mainly include the following [33]:

Step 1: Encode the variables to be optimized.

Step 2: Initialize the parent group randomly. Each individual in the parent group represents a chromosome gene code.

Step 3: Calculate the fitness of individuals in the parent group; evaluate and rank the fitness. The higher the fitness, the higher the probability of being selected. The lower the fitness, the lower the probability of being selected.

Step 4: Select individuals encoding chromosome genes according to their fitness.

Step 5: Carry out crossover and mutation operation on the parent group.

Step 6: Optimize and iterate according to the crossover and mutation results of Step 5, so as to generate a new generation of the population.

Step 7: Use the variable change interval generated by the first and second optimization as the initial change interval of the new round of variables, and return to Step 1 to realize the accelerated operation. Until the optimal individual optimization criterion function value is less than the set value, or the number of algorithm runs is equal to the set number, the algorithm ends and the final optimal result is obtained.

4. Importance Evaluation of Ports along the MSR

4.1. Data and Network Construction

The MSR is an open cooperation initiative, with different definitions of its spatial scope. On the whole, its key direction is from China's coastal ports to the South Pacific and Indian Ocean through the South China Sea. According to the key direction of the MSR, the research scope is defined as ports in countries and regions including East Asia, Southeast Asia, South Asia, West Asia, the east coast of Africa, Oceania, the Mediterranean, and Europe. The research scope is as shown in Figure 2.

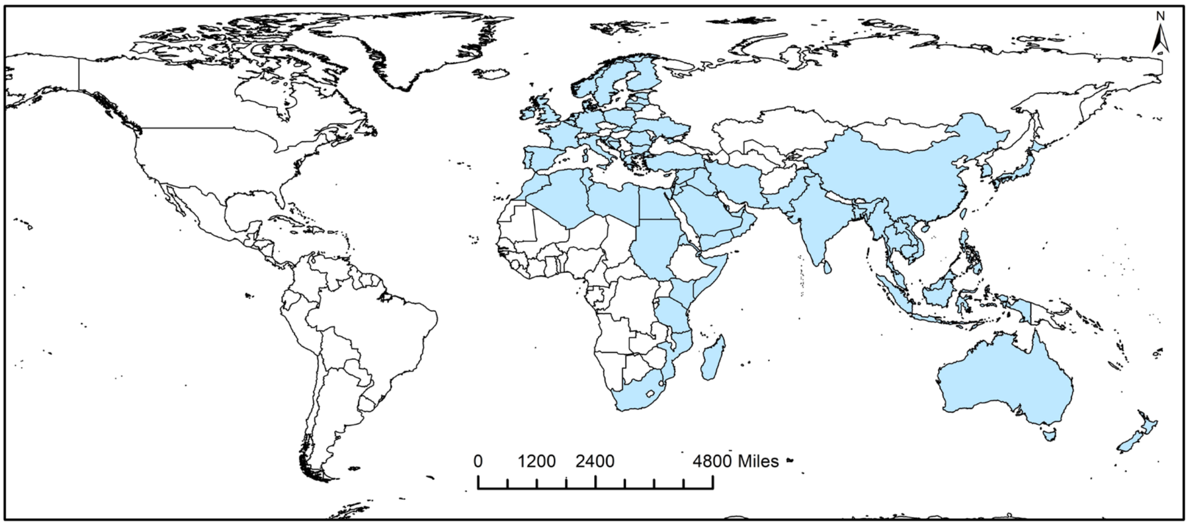

Figure 2. Scope of MSR.

The data come from Container Forecaster in 2019 of Drewry, which includes major container routes and ports. Table 1 shows partial route data; ports are represented by port codes. The original route data used is attached as Supplementary File.

Table 1. Partial route data from Container Forecaster in 2019 of Drewry.

Carrier/Service, 2M (Maersk, MSC)	Service Type	Route
2M—AE7/Condor	ETE	CNTAO, CNNGB, CNSHA, CNYTN, MYTPP, EGSCT, MAPTM, FRLEH, DEHAM, BEANR, GBGTW, FRLEH, MAPTM, OMSLL, AEJEA, CNYTN, CNTAO
2M—AE10/Silk	ETE	CNXGG, KRKWA, CNNGB, CNSHA, CNYTN, MYTPP, PTSIE, DEBRV, PLGDN, DEBRV, NLRTM, MYTPP, CNSHA, CNXGG
2M—AE5/Albatross	ETE	CNDLC, CNXGG, KRPUS, CNNGB, CNSHA, CNYTN, MYTPP, NLRTM, DEBRV, SEGOT, DKAAR, DEBRV, DEWVN, SGSIN, CNSHA, CNDLC
2M—AE2/Swan	ETE	CNTAO, KRPUS, CNNGB, CNYTN, MAPTM, NLRTM, GBFXT, BEANR, NLRTM, ESALG, SGSIN, HKHKG, CNTAO
2M—AE1/Shogun	ETE	CNNGB, CNSHA, CNXMN, HKHKG, CNYTN, MYTPP, LKCMB, GBFXT, NLRTM, DEBRV, NLRTM, MAPTM, OMSLL, LKCMB, CNNGB
2M—AE6/Lion	ETE	CNNGB, CNSHA, CNYTN, MYTPP, ESALG, BEANR, GBFXT, FRLEH, EGSCT, SGSIN, CNNGB
2M—AE7/Condor	ETE	CNTAO, CNNGB, CNSHA, CNYTN, MYTPP, EGSCT, MAPTM, FRLEH, DEHAM, BEANR, GBGTW, FRLEH, MAPTM, OMSLL, AEJEA, CNYTN, CNTAO

After screening, 179 ports are finally obtained. In the Space L model, each port is directly connected according to route, which can directly reflect the spatial characteristics and topological structure of the shipping network. It can facilitate the analysis of key nodes in the network and in the mining of the characteristics of the shipping network. Therefore, this paper uses the Space L model to build the undirected MSR shipping network. Except for the WDC index, other indexes are based on an undirected unweighted network. The edge weight is the number of routes. Figure 3 shows the undirected unweighted MSR shipping network diagram based on Gephi software.

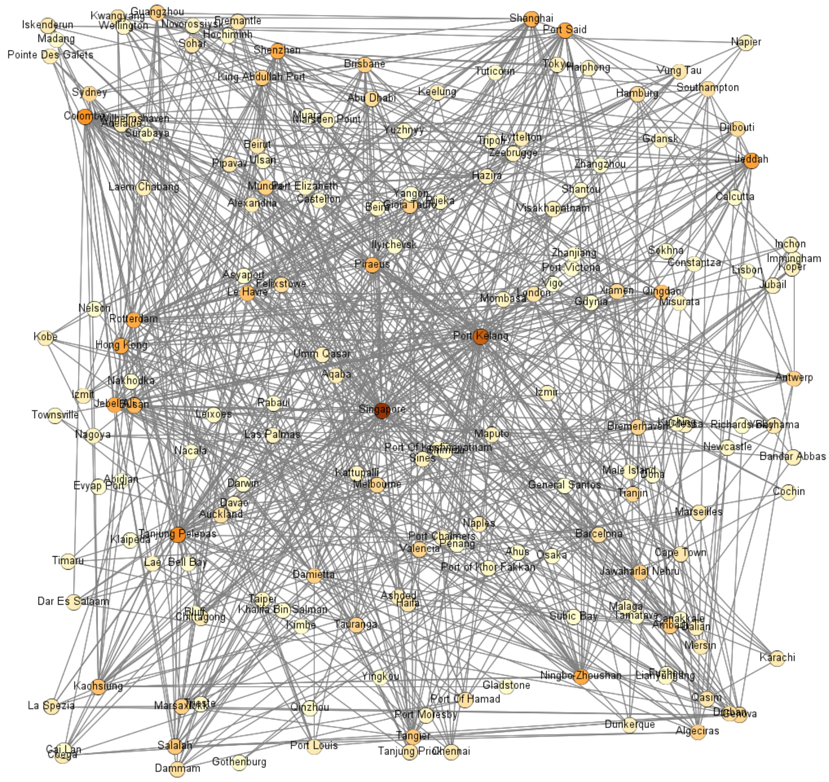

Figure 3. Undirected unweighted MSR shipping network.

4.2. Network Topology Analysis

The average node degree of the MSR shipping network is 7.955, among which 99 port nodes have a degree value less than 5, accounting for 55% of all the nodes, and 16 port nodes have a degree value greater than 20, accounting for 8.9% of all the nodes.

In order to analyze the small-world characteristics of the MSR shipping network, the average path length and aggregation coefficient of the network and a random network of the same size are calculated, respectively, and the results are shown in Table 2.

Table 2. Topological comparison between the MSR shipping network and a random network of the same scale.

Network	Number of Nodes	Average Degree	Average Path Length	Clustering Coefficient
MSR shipping network	179	7.955	2.915	0.4899
Random network	179	7.943	2.721	0.0436

It can be found that the average path length of the random network is 2.721, and the clustering coefficient is 0.0436, while the average path length of the MSR shipping network is 2.915, and the average clustering coefficient is 0.4899. The clustering coefficient of the MSR shipping network is higher than that of the random network. Therefore, it has the characteristics of a small-world network. Moreover, the average route length means that it can be reached after an average of two transshipments from the port of origin to the port of destination. In addition, it is also found that the average path length of the MSR shipping network is slightly higher than that of the random network of the same scale. This is because shipping is limited to a certain extent by factors such as marine geography and channel distribution, and ships cannot sail at will. Most of the cross-regional routes need to pass through certain channels or canals for transportation.

4.3. Importance Evaluation of Ports

Firstly, the centrality index of each port is calculated, including DC, WDC, BC, and CC. Then we calculate the network efficiency and network connectivity of the MSR shipping network when it is not disturbed, and these values are 0.3878 and 1, respectively. Then, we need to simulate the failure of each port one by one. From the perspective of topology, the failed port and its connected edges should be deleted. At this time, each vulnerability quantified index value is calculated by combining the index value of the shipping network in the initial state, namely, CRNE and CRNC. Table 3 shows the index values of the top 20 ports in terms of WDC.

Table 3. The centrality index and vulnerability index of the top 20 ports in terms of WDC.

Port	WDC	DC	BC	CC	CRNE	CRNC
Singapore	0.0390	0.3483	0.2784	0.5651	5.47%	0.56%
Shanghai	0.0266	0.1348	0.0239	0.4310	1.56%	0.56%
Shenzhen	0.0265	0.1461	0.0473	0.4552	1.80%	0.56%
Ningbo-Zhoushan	0.0243	0.1461	0.0427	0.4384	1.80%	0.56%
Port Klang	0.0170	0.2697	0.1816	0.5235	4.45%	0.56%
Colombo	0.0159	0.1854	0.0932	0.4917	2.57%	1.68%
Rotterdam	0.0139	0.1461	0.0647	0.4734	3.01%	1.12%
Jeddah	0.0121	0.1629	0.0645	0.4709	2.17%	0.56%
Jebel Ali	0.0115	0.1461	0.0314	0.4635	1.66%	0.56%
Busan	0.0112	0.1236	0.0318	0.4228	1.66%	0.56%
Tanjung Pelepas	0.0111	0.2022	0.1031	0.5100	3.55%	0.56%
Qingdao	0.0106	0.1124	0.0227	0.4149	1.44%	0.56%
Hong Kong	0.0103	0.1461	0.0362	0.4320	1.92%	0.56%
Hamburg	0.0086	0.0618	0.0073	0.3539	1.18%	0.56%
Antwerp	0.0083	0.0787	0.0158	0.3763	1.33%	0.56%
Xiamen	0.0081	0.0674	0.0015	0.3973	1.28%	0.56%
Port Said	0.0078	0.1517	0.0591	0.4529	1.89%	0.56%
Kaohsiung	0.0072	0.1067	0.0227	0.4352	1.59%	0.56%
Le Havre	0.0071	0.1124	0.0214	0.4300	1.51%	0.56%
Salalah	0.0070	0.0955	0.0069	0.4320	1.40%	0.56%

It can be found that the position of ports along the MSR is different. For example, the WDC value of Shanghai is relatively large, while BC and CC are relatively small. This is because the port bears a large amount of traffic in the network, but its pivotal role is weaker than that of other ports, such as Singapore, Port Klang, Colombo, Shenzhen, etc. Different ports affect different aspects of network vulnerability. From the perspective of CRNC, the failure of each port alone has a small impact on the connectivity of the MSR shipping network. Except for the failure of Colombo and Rotterdam ports alone, which will make some nearby ports become isolated nodes, the failure of other ports alone will not affect the connectivity of the whole shipping network. This is mainly because each port already has shipping contacts with many ports. It does not rely mainly on individual important ports.

The objective function and constraint condition of Formulas (15) and (16) are then constructed. The real coding-based accelerated genetic algorithm (RAGA) is used to solve the optimization problem. The values of the best projection vector are 0.5889, 0.3871, 0.4251, 0.0145, 0.3273, 0.2929, which is the weight of the corresponding index. In the calculation results, Singapore port, Colombo port, and Port Klang are the most important, with values of 1.8843, 1.1160, and 0.9631, respectively. This is mainly because they are the hub ports of the main line of the MSR and occupy very important core positions in the network. Ilyichevsk port and General Santos port are the least important because of their small hinterland location and poor hub function. Due to space limitation, Figure 4 shows only the ports with the top 50 importance values.

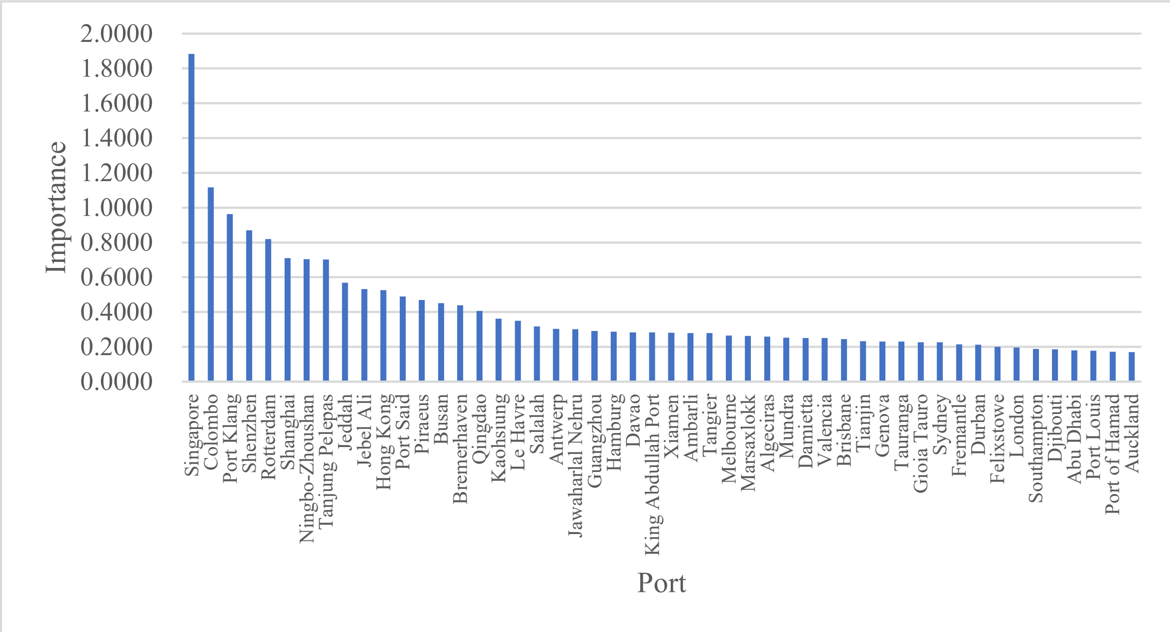

Figure 4. The importance of the top 50 ports.

According to the calculated importance value, the K-means clustering algorithm is used to classify ports. The algorithm flow is as follows. Firstly, K samples are randomly selected in the importance data set as the initial center point of clustering. Then we calculate the Euclidean distance between all other samples and K sample points, compare the K distance values between sample points and K central points, and classify them as the closest center point. Finally, we recalculate the cluster center point and repeat the previous steps until the cluster center point position converges.

The K-means clustering algorithm divides the ports along the MSR into four categories: first-class, second-class, third-class, and fourth-class. The number of ports in each category is 2, 12, 33, and 132, respectively. The ports included in the first three categories are shown in Table 4.

Table 4. Classification results of ports along the MSR based on K-means clustering algorithm.

Category	Port
First-class	Singapore, Colombo
Second-class	Port Klang, Shenzhen, Rotterdam, Shanghai, Ningbo-Zhoushan, Tanjung Pelepas, Jeddah, Jebel Ali, Hong Kong, Port Said, Piraeus, Busan
Third-class	Bremerhaven, Qingdao, Kaohsiung, Le Havre, Salalah, Antwerp, Jawaharlal Nehru, Guangzhou, Hamburg, Davao, King Abdullah Port, Xiamen, Ambarli, Tangier, Melbourne, Marsaxlokk, Algeciras, Mundra, Damietta, Valencia, Brisbane, Tianjin, Genova, Tauranga, Gioia Tauro, Sydney, Fremantle, Durban, Felixstowe, London, Southampton, Djibouti, Abu Dhabi

In order to highlight the important position of key ports in the shipping network, ports of first-class and second-class categories in the classification results are deleted, and a new shipping network is obtained, as shown in Figure 5.

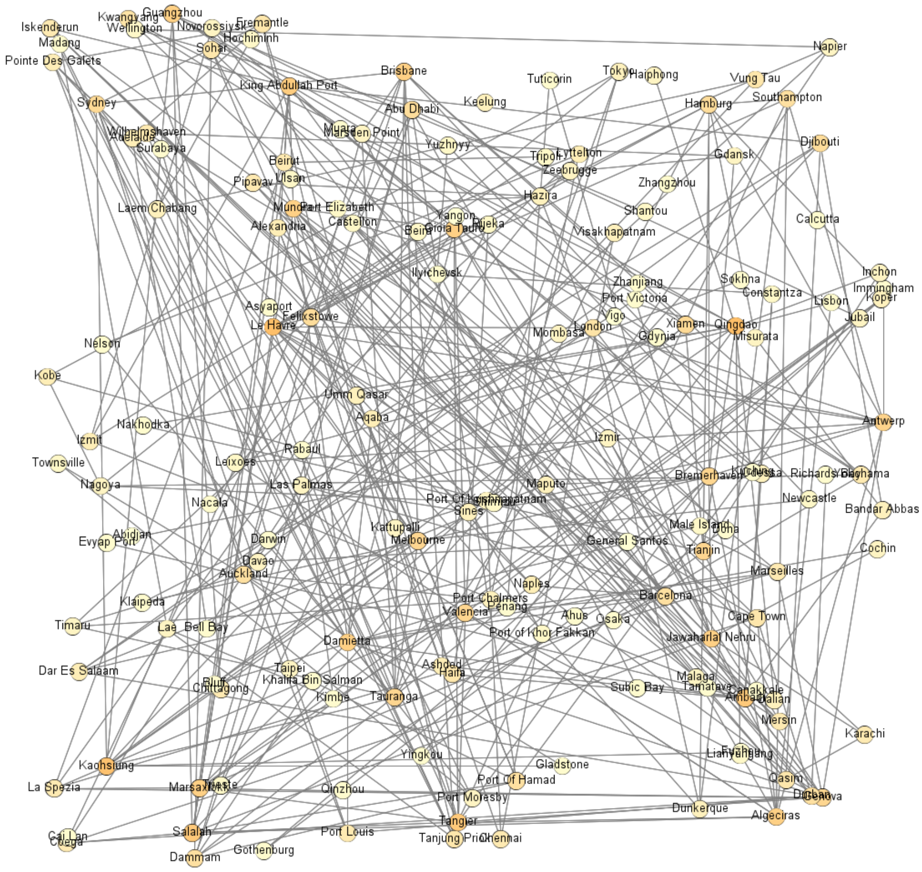

Figure 5. Network diagram after deleting the first-class and second-class ports.

It can be found that these ports occupy a very important position in the MSR shipping network. Deleting these ports destroys the core port group structure of the MSR. At the same time, it shows that the ports of the first-class and second-class categories are at the core of the port group along the MSR. This result is consistent with the actual situation. If these ports are damaged, the accessibility of the MSR shipping network will be seriously affected.

5. Conclusions

This paper proposes a port importance evaluation method based on the centrality index and vulnerability index. The degree centrality, weighted degree centrality, betweenness centrality, closeness centrality, change rate of network efficiency, and change rate of network connectivity are combined comprehensively. The weight of each index is calculated by the projection pursuit model. Finally, the evaluation method is verified in the MSR shipping network.

The method proposed in this paper integrates the different performances of each index. It is more comprehensive in importance evaluation, avoiding the limitations of the individual index. The evaluation results show that the most important ports are concentrated in transport corridors and transit areas. The importance of Singapore, Colombo, and Port Klang rank as the top three. They are the hub ports of the main line of the MSR and occupy extremely important core positions in the network.

The importance evaluation method proposed in this paper comprehensively considers the centrality index and vulnerability index. The research results can provide valuable reference for targeted maintenance of the port, effectively ensuring the transport efficiency of the MSR shipping network. In the future, these evaluation methods can be enriched in combination with actual situations, such as considering the failure probability and self-recovery ability of the port, and providing theoretical solutions for specific decisions.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/jmse11040724/s1.

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