Heliyon 8 (2022) e11474

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

CelPress

An effective distance-based centrality approach for exploring the centrality of maritime shipping network



Zengjie Kuang^a, Chanjuan Liu^{a,*}, Jinran Wu^b, You-Gan Wang^c

^a School of Business Administration and Customs, Shanghai Customs College, Shanghai 201204, China

^b School of Mathematical Sciences, Faculty of Science, Queensland University of Technology, Brisbane, QLD 4001, Australia

^c The Institute for Learning Sciences and Teacher Education, Australian Catholic University, Brisbane 4000, Australia

ARTICLE INFO

Keywords: Shipping network Weighted network centrality Effective distance Maritime silk road

ABSTRACT

Centrality has always been used in transportation networks to estimate the status and importance of a node in the networks, especially in the shipping networks. However, most of the studies only take the shipping network as an unweighted network or only considering the tie weights in the weighted networks, ignoring the truth that both the number of ties and tie weights contribute to the centrality in weighted shipping networks. Therefore, we proposed a new method combining both the number of ties and tie weights to assess the node centrality based on effective distance by integrating the studies of Opsahl et al., (2010) and Du et al., (2015). An empirical analysis of shipping network at the country level for the 21st-centrtury Maritime Silk Road (MSR) was performed. The result of correlation analysis between country's degree centrality and the Liner Shipping Connectivity Index (LSCI) published by the United Nations Conference on Trade and Development (UNCTAD) proved the superiority of our method compared to the traditional centrality metrics. In weighted networks, both the number of ties the tie weights should be considered by adjusting the parameters. The method proposed in this study can also be used to nodes' status and importance estimation of various networks in other fields.

1. Introduction

The concept of centrality has been widely used in various fields and disciplines to assess the status and importance of a node in a network. For example, viral and disease transmission mechanisms (Madar et al., 2004; Keeling and Eames, 2005; Meyers et al., 2005), internet and email network (Newman et al., 2002; Yang and Yang, 2014), communication system (Burgess, 1969; Cohen, 2010), and transportation networks (Burghouwt, 2007; Zhang et al., 2016; Lowry, 2014). In recent years, it has been a popular research topic in maritime transportation as well (Ducruet and Notteboom, 2012; Cheung et al., 2020; Hu et al., 2020a, 2020b).

The global container liner shipping network is a huge complex system consisting of numerous terminals, ports, countries, regions, and routes, which makes it easier to abstract into a network. Therefore, the complex network analysis theory can well be applied to the shipping network (Schinas and Von Westarp, 2017), especially the centrality metrics can be used to estimate the status and importance of a port or a country in the shipping network (Wang and Cullinane, 2016; Ducruet et al., 2010).

However, existing studies about shipping networks mostly take ports as nodes (Wang and Cullinane, 2016; Ducruet et al., 2018), and few studies have focused on the centrality of the shipping network at the country level. Although within the same region, two ports belonging to different countries may serve the same hinterland, such as the ports of Antwerp and Rotterdam in Europe. However, from the perspective of geopolitics and global trade, the jurisdiction of ports belongs to different countries. Therefore, it is more beneficial for managers to formulate policies related to the investment and development of shipping infrastructure and maritime trade from a national perspective by building a global shipping network with countries as nodes and analyzing the positions of different countries in the shipping network. In addition, there is a long-standing premise in maritime economics that countries are strongly integrated into the global maritime transportation network have enhanced access to global markets and trade opportunities. Therefore, Xu et al. (2020) pointed that metadata, such as nationality of ports should be considered in centrality measures of shipping network studies.

What's more, these studies either regard the shipping network as an unweighted network (Ducruet et al., 2010; Lu et al., 2018a, 2018b) or

https://doi.org/10.1016/j.heliyon.2022.e11474

Received 4 July 2022; Received in revised form 17 September 2022; Accepted 2 November 2022



^{*} Corresponding author. E-mail address: liuchanjuan@shcc.edu.cn (C. Liu).

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Table 1. Degree	centrality	of the	node under	different	values	of α .
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Scenarios	Node degree centrality
$\alpha = 0$	The value equals to degree centrality computed in basic binary networks.
0 < lpha < 1	The total node strength is fixed, the degree centrality of a node increases as the total strength is distributed over more connections.
$\alpha = 1$	The value equals the node strength computed in general weighted networks.
lpha > 1	The total node strength is fixed, increasing the number of connections over which the strength is distributed decreases the value of the measure in favor of a greater concentration of node strength on only a few nodes

Fable 2. Closeness	and betweenness	centrality under	different scenarios of α .

Scenarios	Node closeness and betweenness centrality
$\alpha = 0$	The proposed measure produces the same outcome as the binary distance measure.
0 < lpha < 1	The distance of the shortest path between pairs of nodes increases as more intermediary nodes are involved.
$\alpha = 1$	The outcome is the same as the one obtained with Dijkstra's algorithm.
$\alpha > 1$	The additional intermediary nodes are relatively unimportant compared to the strength of the connections and paths; such that more intermediaries are favored.

only consider the tie weights in the weighted network (Wang and Cullinane, 2008), ignoring the truth that both the number of ties and tie weights contribute to the centrality of nodes in weighted shipping networks (Opsahl et al., 2010). In addition, the traditional calculation of the closeness and betweenness centrality of shipping network is only based on the geodesic distance between two ports or areas, or the actual geographical distance. Nevertheless, in a real network, the weights between nodes have specific meanings, e.g., travel cost, trade volume, shipping time, shipping frequency and so on. Geodesic distance alone cannot fully measure the distance between two nodes in a network. Therefore, the trade-off between the number of ties and tie weights in shipping network, and the fact that the geodesic distance between two nodes is not always the shortest distance between them are the motivations for this study. The contributions of this study are threefold: First, we developed a new centrality measure considering both the number of ties and tie weights in weighted shipping networks based on effective distance. Second, we measured the status and importance of the countries along the 21st-centrtury Maritime Silk Road (MSR) in the shipping network. Third, we used the correlation between the Liner Shipping Connectivity Index (LSCI) and the centrality of shipping countries in the maritime network to verify the effectiveness of the centrality index proposed in this article. The results suggested the effectiveness of our method and the superior performance over the traditional centrality metrics in node importance estimation in shipping networks.

The remaining contents of the paper are organized as follows: Section 2 reviews the related literatures. Section 3 depicts the methodology employed in this work. Section 4 introduces the sample network constructed in this paper. Section 5 presents an empirical application to the sample network consisting of 36 maritime countries along MSR. Final remarks and conclusions are presented in Section 6.

2. Literature review

The concept of centrality first comes from the study of social networks and it was used to analyze the central position of individuals in human communication network (Bavelas, 1948). Since the idea of centrality is proposed, many scholars have conducted in-depth researches and continuous expansion about it (Borgatti, 2005; Burgess, 1969; Freeman, 1979; Rogers, 1974; Shaw, 1954). However, there is certainly no unanimity on exactly what centrality is, and very little agreement on the proper procedure for its measurement until Freeman (1979) gave specific definitions and forms for three different measures of node centrality: degree, closeness, and betweenness. Even so, Freeman's centrality measures are only applicable to the binary networks. In the real network, since each edge has its specific connotation, it is improper to study the centrality of nodes by just treating it as a binary network (Opsahl and Panzarasa, 2009). Therefore, related literatures attempted to extend Freeman's measures (Freeman, 1979) to weighted networks (Barrat et al., 2004; Brandes, 2001; Newman, 2001; Qiao et al., 2018). For example, Barrat et al. (2004) redefined the degree in weighted networks as the sum of weights attached to the ties connected to a node. For the definition of the closeness and betweenness, the most critical issue is to determine the



Figure 1. Topological structure of the shipping network at the country level in Maritime Silk Road (MSR).

Region	country	C_{D-out}^{wlpha}					
		$\alpha = 0$	$\alpha = 0.5$	$\alpha = 1$	$\alpha = 1.5$		
East Asia	China	0.9286	1.0000	1.0000	1.0000		
West Asia	Egypt	0.8214	0.5344	0.3253	0.1972		
	UAE	0.7857	0.3941	0.1862	0.0875		
	Saudi Arabia	0.7500	0.3452	0.1501	0.0648		
	Greece	0.7143	0.1929	0.0503	0.0130		
	Turkey	0.7143	0.3160	0.1322	0.0549		
	Oman	0.6429	0.2040	0.0622	0.0188		
	Lebanon	0.5714	0.1947	0.0635	0.0205		
	Israel	0.4643	0.0604	0.0080	0.0011		
	Bahrain	0.4286	0.0727	0.0116	0.0018		
	Jordan	0.3929	0.0630	0.0103	0.0017		
	Iran	0.3214	0.0577	0.0096	0.0016		
	Kuwait	0.2500	0.0525	0.0100	0.0019		
	Yemen	0.2143	0.0123	0.0007	0.0000		
	Cyprus	0.1786	0.0248	0.0033	0.0004		
	Qatar	0.0357	0.0161	0.0044	0.0011		
South Asia	Sri Lanka	0.6429	0.2409	0.0860	0.0304		
	India	0.6071	0.3264	0.1645	0.0822		
	Pakistan	0.5357	0.1525	0.0420	0.0115		
	Maldives	0.1071	0.0362	0.0096	0.0024		
ASEAN	Singapore	1.0000	0.5354	0.2701	0.1359		
	Malaysia	1.0000	0.6272	0.3693	0.2170		
	Indonesia	0.7857	0.4232	0.2143	0.1080		
	Thailand	0.5714	0.1586	0.0427	0.0114		
	Vietnam	0.5714	0.2688	0.1192	0.0523		
	Philippines	0.5000	0.1656	0.0527	0.0165		
	Cambodia	0.2143	0.0435	0.0093	0.0019		
	Myanmar	0.1786	0.0403	0.0081	0.0016		
	Brunei	0.0357	0.0074	0.0013	0.0002		
CEE	Romania	0.4643	0.0971	0.0202	0.0042		
	Slovenia	0.4643	0.0721	0.0114	0.0018		
	Croatia	0.2500	0.0511	0.0095	0.0017		
	Bulgaria	0.1786	0.0248	0.0033	0.0004		
	Albania	0.0000	0.0000	0.0000	0.0000		
CIS	Ukraine	0.3929	0.0858	0.0187	0.0040		
	Georgia	0.1071	0.0200	0.0033	0.0005		

 Table 3. Out-degree centrality of 36 countries with different values of tuning parameter.

 Table 4. In-degree centrality of 36 countries with different values of tuning parameter.

Region	country	C_{D-in}^{wlpha}					
		$\alpha = 0$	$\alpha = 0.5$	$\alpha = 1$	$\alpha = 1.5$		
East Asia	China	0.9630	1.0000	1.0000	1.0000		
West Asia	Egypt	0.8519	0.7597	0.6496	0.5545		
	UAE	0.7407	0.4253	0.2348	0.1289		
	Saudi Arabia	0.7778	0.3934	0.1926	0.0938		
	Greece	0.7407	0.2775	0.1015	0.0369		
	Turkey	0.7407	0.3860	0.1940	0.0970		
	Oman	0.7778	0.2330	0.0689	0.0203		
	Lebanon	0.5926	0.2141	0.0749	0.0260		
	Israel	0.3333	0.0546	0.0090	0.0015		
	Bahrain	0.3333	0.0518	0.0081	0.0013		
	Jordan	0.3704	0.0673	0.0122	0.0022		
	Iran	0.2963	0.0545	0.0100	0.0018		
	Kuwait	0.1481	0.0388	0.0093	0.0022		
	Yemen	0.1481	0.0069	0.0001	0.0000		
	Cyprus	0.1481	0.0256	0.0043	0.0008		
	Qatar	0.0370	0.0132	0.0033	0.0008		
South Asia	Sri Lanka	0.7778	0.3122	0.1223	0.0476		
	India	0.5926	0.3447	0.1901	0.1040		
	Pakistan	0.4444	0.1464	0.0463	0.0145		
	Maldives	0.0741	0.0229	0.0058	0.0014		
ASEAN	Singapore	0.9259	0.6495	0.4409	0.2987		
	Malaysia	1.0000	0.8164	0.6457	0.5102		
	Indonesia	0.7778	0.5053	0.3153	0.1960		
	Thailand	0.5185	0.1868	0.0648	0.0222		
	Vietnam	0.2963	0.2227	0.1465	0.0946		
	Philippines	0.5185	0.1930	0.0690	0.0244		
	Cambodia	0.1852	0.0432	0.0095	0.0021		
	Myanmar	0.2222	0.0421	0.0078	0.0015		
	Brunei	0.0370	0.0094	0.0020	0.0004		
CEE	Romania	0.4815	0.1200	0.0294	0.0072		
	Slovenia	0.5185	0.1038	0.0208	0.0042		
	Croatia	0.5185	0.0786	0.0121	0.0019		
	Bulgaria	0.1111	0.0207	0.0037	0.0007		
	Albania	0.0000	0.0000	0.0000	0.0000		
CIS	Ukraine	0.4444	0.1053	0.0245	0.0057		
	Georgia	0.1111	0.0194	0.0033	0.0006		

shortest distance. In a binary network, the shortest path is found by minimizing the number of intermediary nodes, and its length is defined as the minimum number of ties linking the two nodes, either directly or indirectly (Opsahl et al., 2010). Newman (2001) proposed to inverse the tie weights as the length between nodes in weighted network, because most weighted networks are operationalization of tie strength rather than the cost of them.

In maritime studies, researchers usually used centrality measurements to assess the status of a port in shipping network. The studies of maritime network centrality can also be classified into two types:

- a. Unweighted shipping network. Earlier, due to the limitation of data sources, most of the studies have taken the shipping network as a binary case to study its topological structure such as the small world and scale-free nature of the network (Ducruet et al., 2010; Laxe et al., 2012; Kang and Woo, 2017; Song et al., 2019; Wu et al., 2019; Wan et al., 2021).
- b. Weighted shipping network. With the development of the studies on the centrality of weighted network, some scholars have begun to study the weighted shipping network in recent years as well. In particular, scholars have begun to redefine the closeness and

betweenness centrality in weighted maritime networks (Wang and Cullinane, 2016; Jeon et al., 2019; Xu et al., 2015; Liu et al., 2018).

Although scholars have conducted in-depth research on the centrality of shipping networks, the following problems still exist. Firstly, most of the studies on the centrality of weighted maritime networks either consider only the number of ties or consider only the tie strength (Wang and Cullinane, 2008). But in fact, both the number of ties and tie strength will affect the centrality of network (Opsahl et al., 2010). Secondly, existing studies upon centrality of shipping network are just based on the geodesic distance between two ports or areas ignoring the actual distance between nodes in shipping network, which may lead to the inappropriate conclusions in the directed and weighted shipping network. Thirdly, most studies on the centrality of shipping networks take ports as nodes in the network, although Xu et al. (2020) pointed out the importance of considering the nationality of ports in the centrality measures. However, only the betweenness centrality was proposed by Xu et al. (2020) for the global shipping country network. More centrality measures, such as degree centrality and closeness centrality need to be proposed and improved for the study of the shipping country networks. To address these two problems, we proposed a new method integrating both the



Figure 2. Out-degree of the countries under different values of α (A) Out-degree of the countries when $\alpha = 0$ (B) Out-degree of the countries when $\alpha = 0.5$ (C) Out-degree of the countries when $\alpha = 1.5$.



Figure 3. In-degree of the countries under different values of α (A) In-degree of the countries when $\alpha = 0$ (B) In-degree of the countries when $\alpha = 1.5$ (C) In-degree of the countries when $\alpha = 1.5$.

studies about centrality of Opsahl et al. (2010)andDu et al. (2015) to improve the existing centrality metrics in shipping network. The proposed method not only considers the number of ties and the tie weights of links in the weighted network at the same time, but also uses the concept

of effective distance in the centrality calculation process. Furthermore, we used the proposed method to the shipping network at the country level for the 21st-centrury MSR to assess the status, importance, and connectivity of the countries in the MSR shipping network.



Figure 4. Ego networks of Russia (A), India (B). The width of a tie corresponds to the shipping frequency sent from the focal node to their contacts.

Table 5. Closeness centrality based on effective distance (EDCC) of 36 countries with different values of tuning parameter.

Region	country	C ^{wa} _{EDCC}					
		$\alpha = 0$	$\alpha = 0.5$	$\alpha = 1$	$\alpha = 1.5$		
East Asia	China	0.9138	0.9914	0.9635	0.6467		
West Asia	Egypt	0.7985	0.9062	1.0000	0.9274		
	UAE	0.7985	0.8737	0.8748	0.8347		
	Saudi Arabia	0.7633	0.8630	0.9430	0.8778		
	Greece	0.6973	0.7522	0.6958	0.6962		
	Turkey	0.6973	0.7954	0.9178	0.9884		
	Oman	0.6364	0.7140	0.7916	0.8151		
	Lebanon	0.6078	0.6943	0.7795	0.8293		
	Israel	0.5280	0.5870	0.6466	0.8021		
	Bahrain	0.5033	0.6102	0.7962	1.0000		
	Jordan	0.4343	0.4336	0.3890	0.4943		
	Iran	0.3720	0.4067	0.4088	0.6035		
	Kuwait	0.2805	0.3151	0.3176	0.6285		
	Yemen	0.2638	0.3454	0.3776	0.6351		
	Cyprus	0.2165	0.2476	0.3009	0.6935		
	Qatar	0.1205	0.2043	0.2570	0.6099		
South Asia	Sri Lanka	0.6364	0.6107	0.3605	0.3082		
	India	0.5802	0.6285	0.6390	0.7115		
	Pakistan	0.5280	0.5184	0.3972	0.4889		
	Maldives	0.2165	0.2023	0.0245	0.0000		
ASEAN	Singapore	1.0000	0.9978	0.7842	0.3189		
	Malaysia	1.0000	1.0000	0.8051	0.3962		
	Indonesia	0.7296	0.6725	0.3404	0.2227		
	Thailand	0.5033	0.4767	0.2615	0.1315		
	Vietnam	0.5536	0.5714	0.4232	0.3424		
	Philippines	0.4565	0.5178	0.4850	0.4219		
	Cambodia	0.2476	0.2003	0.0000	0.0162		
	Myanmar	0.2476	0.2438	0.0634	0.0247		
	Brunei	0.1872	0.2560	0.1647	0.1145		
CEE	Romania	0.4565	0.5251	0.5861	0.7553		
	Slovenia	0.5033	0.6121	0.7935	0.9572		
	Croatia	0.3921	0.4610	0.5484	0.7255		
	Bulgaria	0.1872	0.2530	0.3721	0.7718		
	Albania	0.0000	0.0000	0.0064	0.4669		
CIS	Ukraine	0.3921	0.4576	0.5285	0.7074		
	Georgia	0.1461	0.1848	0.2462	0.6826		

3. Methodology

3.1. Degree centrality

Degree measures the involvement of the node in the network as described by Freeman (1979). With the development of complex network

theory, degree has been extended to the sum of weights when analyzing weighted networks (Opsahl et al., 2008, 2010). However, Opsahl et al. (2010) pointed out that both the number of ties and tie weights should be incorporated in node centrality, since both of them can be indicators of the level of involvement of a node in the network. Therefore, Opsahl et al. (2010) proposed to use a tuning parameter, α , to determine the relative importance of the number of ties compared to tie weights. The out-degree (C_{D-out}^{wa}) and in-degree (C_{D-in}^{wa}) can be illustrated as Eq. (1) and Eq. (2) respectively.

$$C_{D-out}^{wa}(i) = k_i^{out} \times \left(\frac{s_i^{out}}{k_i^{out}}\right)^a \tag{1}$$

and

$$\mathcal{L}_{D-in}^{w\alpha}(i) = k_i^{in} \times \left(\frac{s_i^{in}}{k_i^{in}}\right)^{\alpha}$$
(2)

where *w* is the weighted adjacency matrix, k^{out} represents the number of ties that originate from a node, k^{in} is the number of ties that are directed towards a node, s^{out} and s^{in} can be defined as the total weight attached to the outgoing and incoming ties, respectively (Barrat et al., 2004; Newman, 2001).

Actually, both the number of ties and tie weights contribute to the centrality in weighted shipping networks. Therefore, in this study we used two measures proposed by Opsahl et al. (2010) to assess a node's activity and popularity considering both the number of ties and tie weights in shipping networks. The degree centrality of the node under different values of α are shown in Table 1.

3.2. Closeness and betweenness centrality

3.2.1. Effective distance

The effective distance is proposed by Brockmann and Helbing (2013), which is firstly used to study the geographic spread of emergent infectious diseases. In a real network, although it is logically and physically reasonable to calculate the distance by the number of edges passed or the actual geographical position, there are deficiencies in the real network that interacts with information flow. For example, in a shipping network that regards maritime countries as nodes, the distance between China and Singapore is much greater than the distance from China to Myanmar based on the actual geographical location. However, based on the idea of the effective distance, we conclude that the shipping distance from China to Singapore is less than the shipping distance from China to Myanmar because the number of liner routes, the number of ships, and the frequency of navigation from China to Singapore are much greater than that from China to Myanmar.

It is assumed that node *i* connects to node *j* with edges in a directional weighted network, and the effective length from node *i* to node *j* is d_{ij}^e (Eq. (3)), which is defined as:



Figure 5. Comparison of Opsahl's closeness and closeness centrality based on effective distance (EDCC) (A) when $\alpha = 0$ (B) when $\alpha = 1$.



Figure 6. Top ten maritime countries owning high closeness under different methods (A) The results of Opsahl's closeness method (B) The results of EDCC.

Region	country	$C_{EDBC}^{w\alpha}$	C_{EDBC}^{wa}					
		$\alpha = 0$	$\alpha = 0.5$	$\alpha = 1$	$\alpha = 1.5$			
East Asia	China	0.6880	0.9651	0.9056	1.0000			
West Asia	Egypt	0.4096	0.5421	0.6185	0.7211			
	UAE	0.5737	0.7659	0.7303	0.7353			
	Saudi Arabia	0.3969	0.3285	0.3410	0.4390			
	Greece	0.5300	0.0801	0.0347	0.0143			
	Turkey	0.5387	0.9035	0.9441	0.9540			
	Oman	0.3220	0.0000	0.0000	0.0000			
	Lebanon	0.1557	0.0000	0.0116	0.0048			
	Israel	0.0607	0.0000	0.0116	0.0428			
	Bahrain	0.2121	0.0000	0.0000	0.0048			
	Jordan	0.0279	0.0000	0.0000	0.0000			
	Iran	0.0347	0.0000	0.0000	0.0000			
	Kuwait	0.0493	0.0000	0.0000	0.0000			
	Yemen	0.0000	0.0000	0.0000	0.0000			
	Cyprus	0.0019	0.0123	0.0116	0.0095			
	Qatar	0.0000	0.0000	0.0000	0.0000			
South Asia	Sri Lanka	0.2894	0.0246	0.0405	0.0380			
	India	0.1139	0.0000	0.0000	0.0475			
	Pakistan	0.0611	0.0000	0.0000	0.0000			
	Maldives	0.0000	0.0000	0.0000	0.0000			
ASEAN	Singapore	0.8718	0.0862	0.1040	0.0428			
	Malaysia	1.0000	1.0000	1.0000	0.7924			
	Indonesia	0.4182	0.0000	0.0000	0.0000			
	Thailand	0.1583	0.0123	0.0116	0.0285			
	Vietnam	0.1564	0.0554	0.0636	0.1094			
	Philippines	0.1057	0.0616	0.0694	0.0428			
	Cambodia	0.0000	0.0000	0.0000	0.0000			
	Myanmar	0.0000	0.0000	0.0000	0.0000			
	Brunei	0.0000	0.0000	0.0000	0.0000			
CEE	Romania	0.1840	0.0000	0.0000	0.0000			
	Slovenia	0.3950	0.0554	0.1156	0.0618			
	Croatia	0.2898	0.3737	0.2871	0.2647			
	Bulgaria	0.0111	0.0000	0.0000	0.0048			
	Albania	0.0000	0.0000	0.0000	0.0000			
CIS	Ukraine	0.1433	0.0000	0.0000	0.0000			
	Georgia	0.0000	0.0000	0.0000	0.0000			

 Table 6. Betweenness centrality based on effective distance (EDBC) of 36 countries with different values of tuning parameter.

$$d_{ij}^e = \left(1 - \ln R_{ij}\right) \ge 1,\tag{3}$$

$$R_{ij} = \frac{F_{ij}}{F_i},\tag{4}$$

and

$$F_i = \sum_j F_{ij} \tag{5}$$

where, F_{ij} is the flow from node *i* to node *j* in the network; F_i is the sum of all traffic flowing from node *i* (Eq. (5)); R_{ij} quantifies the fraction of the flow with destination *j* emanating from node *i* (Eq. (4)). Therefore, a quasidistance is defined by Eq. (3), which is generally asymmetric ($d_{ij}^e \neq d_{ij}^e$).

Based on effective length d_{ij}^e , the effective distance D_{ij} is defined from an arbitrary reference node *i* to another node *j* in the network by the length of the shortest path from *i* to *j*. Similarly, the effective distance D_{ij} is asymmetric as well ($D_{ij} \neq D_{ji}$).

3.2.2. Closeness and betweenness centrality based on effective distance

Based on the above definition about distance between two nodes, Du et al. (2015) proposed a new closeness centrality based on effective distance (EDCC) in complex networks. The effectiveness and advantages of EDCC has been proved on four real networks (Du et al., 2015). Here, we further expanded it into betweenness centrality based on effective distance (EDBC) and combining the method proposed by Opsahl et al. (2010) to give new closeness and betweenness centrality measures considering both the number of ties and tie weights based on effective distance.

The EDCC and EDBC proposed in this study are defined respectively as Eq. (6) and Eq. (7).

$$G_{EDCC}^{wa}(i) = \left[\sum_{j}^{N} D^{wa}(i,j)\right]^{-1},$$
(6)

$$C_{EDBC}^{w\alpha}(i) = \frac{D_{jk}^{w\alpha}(i)}{D_{jk}^{w\alpha}},\tag{7}$$

and

$$D^{wa}(i,j) = \min\left(\left(d^e_{ih}\right)^a + \ldots + \left(d^e_{hj}\right)^a\right) \tag{8}$$

where $D_{jk}^{w\alpha}$ is the sum of all shortest paths between nodes *j* and *k* based on the effective distance, and $D_{jk}^{w\alpha}(i)$ is the number of these shortest paths



Figure 7. Comparison of Opsahl's betweenness and betweenness centrality based on effective distance (EDBC) (A) when $\alpha = 0$ (B) when $\alpha = 1$.



Figure 8. Top ten maritime countries owning high betweenness under different methods (A) The results of Opsahl's betweenness method (B) The results of EDBC.

that go through the node *i* (Eq. (8)). The positive tuning parameter α is set according to the different scenarios in Table 2.

4. Data collection

After tracking the world's top 20 liner shipping companies sailing schedules from January 1, 2015 to January 1, 2016, we got a total of 777 ports route data. Among them, 202 ports involved in the MSR were selected, and assigned them to 36 countries. To study the position and importance of the countries along MSR, we construct a shipping network at the country level with 36 countries as nodes (Figure 1).

Due to the lack of availability of actual container traffic statistics when compiling such a dataset, edges between all pairs of countries within the sample network are weighted by the monthly shipping transportation frequency deployed by the top 20 liner shipping companies.

5. Empirical application and analysis of the results

In this section, three centrality measures proposed in this paper are used to assess the node centrality of countries along the MSR. In order to identify the relative importance of the number of ties and tie weights, the tuning parameter $\alpha \in \{0, 0.5, 1, 1.5\}$ is set according to Tables 1 and 2. Wang and Cullinane (2016) has demonstrated the effectiveness of this approach in maritime networks. All results have been normalized using the min–max normalization to make the values between 0 and 1 (and ensure the consistency).

5.1. Degree centrality of maritime countries

Table 3 shows the out-degree of 36 maritime countries against different values of α . China, Egypt, Malaysia, Indonesia, and Singapore are always the top five countries of out-degree centrality, regardless of the values of α (Figure 2 (A-D)). However, the specific rankings and out-degree scores of these five countries change under different values of α . Both Malaysia and Singapore possessed the highest score when $\alpha = 0$, namely, in the binary case, which implied that they possessed the highest number of connections with other countries in MSR.

When the shipping frequency was considered, China performed as the most active country with $\alpha = 0.5, 1, 1.5$. This is mainly attributed to the fact that China is a major exporter of global trade. Moreover, the centrality of Malaysia and Singapore was slightly reduced when shipping frequency is considered. Malaysia maintained a relatively stable position, ranking the second, and Singapore ranked the fourth when $\alpha = 1$ or $\alpha =$

Table	7.	Correlations	between	country's	degree	centrality	corresponding	to
differe	nt v	values of α an	d Liner Sl	nipping Co	nnectivi	ity Index (I	LSCI).	

α	The correlation coefficient				
	Out-degree and LSCI	In-degree and LSCI			
0	0.93019	0.87515			
0.1	0.92451	0.90579			
0.2	0.92760	0.89627			
0.3	0.92297	0.91480			
0.4	0.92168	0.92149			
0.5	0.91911	0.92149			
0.6	0.91808	0.92278			
0.7	0.91447	0.92304			
0.8	0.91164	0.92072			
0.9	0.89961	0.91712			
1	0.88621	0.91171			
1.1	0.87303	0.91223			
1.2	0.86641	0.90631			
1.3	0.86409	0.90605			
1.4	0.85792	0.90142			
1.5	0.85534	0.89858			

1.5. However, the centrality of Egypt increased from forth in binary network to the third when frequency was considered. This might be due to the Suez Canal in Egypt, which communicates between the Mediterranean Sea and the Red Sea, providing the closest shipping routes from Europe to the Indian Ocean and land near the Western Pacific. It is one of the most frequently used shipping routes in the world.

From the perspective of geography regions according to Table 3, Egypt, Sri Lanka, Singapore (Malaysia), Romania (Slovenia) and Ukraine ranked as the most central countries within their corresponding regions when $\alpha = 0$. However, when shipping frequency was considered, India possessed higher centrality than Sri Lanka in South Asia, and Malaysia possesses higher centrality than Singapore in ASEAN. These results highlight the importance of shipping frequency to a country's out-degree. Moreover, Malaysia and Singapore exhibit strong competitiveness in both the regional and the whole shipping network of MSR.

Figure 3 (A–D) shows the in-degree centrality of 36 maritime countries against different assumptions for the tuning parameter, and the specific score of each country is given in Table 4.

Malaysia still possessed the highest score of in-degree when $\alpha = 0$ (Figure 3 (A)). This reflects that Malaysia is the most attractive maritime countries and the hub of shipping network for MSR in terms of the binary case. China ranked second, and followed by Singapore, getting a score of 0.9630 and 0.9259 respectively. The high value of in-degree centrality for these countries represents the attraction of countries in MSR. However, when shipping frequency is taken into account, China is the most attractive country when $\alpha \in \{0.5, 1, 1.5\}$ (Figure 3 (B-D)). Similar results can be observed when accounting for the out-degree centrality. Furthermore, the in-degree centrality of Egypt increased, and which maintains a relatively stable position, ranking the second when $\alpha \in \{1, 1.5\}$.

From the perspective of geography regions according to Table 4, Egypt, Sri Lanka, Malaysia, Slovenia (Croatia) and Ukraine rank as the most central within their corresponding regions when $\alpha = 0$. Nevertheless, when shipping frequency was considered, India possessed the higher in-degree centrality than Sri Lanka in South Asia. Malaysia still possessed higher centrality than Singapore in ASEAN.

In addition, most countries maintained a relatively stable ranking across the different values of α . However, a few individuals present significantly different results. In particular, the ranks of Greece and India changed greatly when different α was used in out-degree centrality. Greece ranked eighth when $\alpha = 0$ for it connects to 22 countries as illustrated in the left panel (A) of Figure 4, but fifth in the weighted network

when the shipping frequency was considered. On the contrary, India ranked twelfth when $\alpha = 0$ for it only connects to 19 countries as illustrated in the right panel (B) of Figure 4, but seventh in the weighted network. This is because the mean number of shipping frequency or mean value of the container throughput Greece sent to others is relatively low as compared to countries with the same total amount of shipping frequency.

5.2. Closeness centrality of maritime countries

Table 5 shows the EDCC of maritime countries against different assumptions for the tuning parameter α . When $\alpha = 0$, both Malaysia and Singapore ranked first in binary case, since both the ports of Singapore and Klang in Malaysia are international trunk hub ports in Southeast Asia, and they are the keys of shipping routes linking the Pacific and Indian Oceans. However, when shipping frequency is considered, Egypt raised from the fourth ($\alpha = 0$) to the first place ($\alpha = 1$). Meanwhile, China ranked in the second place in the case of $\alpha = 1$. It is worth noting that with the increase of tuning parameter α , the centrality of Singapore decreased from the first ($\alpha = 0$), to the tenth ($\alpha = 1$), which denotes that Singapore may not be able to reach other countries quickly by sea in a weighted network though it only needs to pass fewer countries to connect with other countries.

Furthermore, the EDCC calculated in this paper is compared with the results calculated according to the method proposed by Opsahl et al. (2010). When $\alpha = 0$, namely in the binary network, as illustrated in Figure 5 (A), the closeness centrality of each country in MSR calculated by the two methods are basically the same.

However, as we can see in Figure 5 (B), the closeness centrality calculated by the two methods are very different for most nodes when $\alpha = 1$, namely, in the weighted network. Opsahl et al. (2010) used the inverted tie weights as shortest path between two nodes to calculate the closeness centrality. However, in the actual global shipping network, when the shipping frequency or throughput between maritime countries (ports) is regarded as the weights of the edges, the distance between countries (ports) may not be inversely proportional to the weights. Therefore, applying the effective distance to calculate the closeness centrality can better reflect the node's accessibility to reach others in the network. Besides, Figure 5 (B) shows that Albania, Jordan, Myanmar, Sri Lanka, and Yemen have the most significantly different values of closeness under two methods. Although they own high closeness according to Opsahl's method, their EDCC is quite low.

The geography distribution of the top ten maritime countries that can reach other countries quickly (own high closeness centrality) under different methods when $\alpha = 1$ is illustrated in Figure 6. In countries/regions with frequent and direct shipping services, efficient and well-connected container ports are key to reducing trade costs. However, it must be noted that these countries/regions with higher centrality will also have higher carbon emissions and environmental pollution, such as shipping countries/regions with dark blue color in Figure 6 (A-B).

5.3. Betweenness centrality of maritime countries

Betweenness centrality often represents the potential for being an intermediary country. This means that the container ports in these countries are usually the transshipment ports of the entire shipping network.

Table 6 presents the EDBC of maritime countries against different assumptions for the tuning parameter α . In the binary case, Malaysia is the most central countries in MSR and followed by Singapore. When shipping frequency is considered in the weighted network, Malaysia still ranked first no matter $\alpha = 0.5$ or $\alpha = 1$. Notably, the betweenness centrality of Singapore decreased with the increasing of the tuning parameter α . It dropped from the second ($\alpha = 0$) to the eighth ($\alpha = 0.5$), and to the ninth ($\alpha = 1$), which is like the results of closeness centrality.







Figure 9. (A) The effects of α on closeness centrality (B) The effects of α on betweenness centrality.

It is worth noting that the EDBC of some ports are 0 in Table 6. According to the definition of EDBC in Eq. (7), if none of the shortest paths between *j* and *k* based on the effective distance pass through node *i*, then it means that the $D_{ik}^{wa}(i)$ in Eq. (7) is 0, and the EDBC of node *i* is 0. For example, the EDBC of Qatar is zero where a = 0, mainly because the shortest route between any two countries among the other 35 countries does not pass Qatar. It also means that Qatar's ports cannot become transit ports in the MSR shipping network. Furthermore, the EDBC calculated in this paper was compared with the results calculated according to the method proposed by Opsahl et al. (2010). When $\alpha = 0$, namely in the binary network, the betweenness centrality of each country in MSR calculated by the two methods are basically the same (Figure 7 (A)).

However, when $\alpha = 1$, namely, in the weighted network, the betweenness centrality calculated by the two methods are very different for most nodes (Figure 7 (B)). Bahrain, Greece, Indonesia, Jordan, and Turkey have the most significantly different values of betweenness under two methods. Although Turkey possessed a high EDBC value, its betweenness centrality according to Opsahl's method was very low. However, Bahrain, Greece, Indonesia, and Jordan experience a totally opposite results to Turkey, and they owned a high betweenness according to Opsahl's method and low in EDBC. The geography distribution of the top ten maritime countries that have potential to become intermediary countries in MSR under different methods when $\alpha = 1$ is illustrated in Figure 8 (A-B).

5.4. The effect of the tuning parameter α on centrality

5.4.1. Comparison between degree centrality and LSCI index

Liner Shipping Connectivity Index (LSCI) indicates a country's position within global liner shipping networks. It is calculated from the number of ship calls, their container carrying capacity, the number of services and companies, the size of the largest ship, and the number of other countries connected through direct liner shipping services. The calculation process of LSCI is similar to the definition of degree centrality in shipping country network. The LSCI released by UNCTAD is currently recognized as one of the most commonly used benchmarks to measure a country's degree of linkage in global trade (Reza et al., 2015; Xu et al., 2020). To some extent, the degree centrality of countries in the shipping network has the same function as LSCI. Therefore, the LSCI can be used to verify the validity of the degree centrality proposed in this study.

We analyzed the correlation between the degree centrality corresponding to different values of α and LSCI. In general, the correlation between out-degree centrality and LSCI decreases with the increase of α , while the correlation between in-degree centrality and LSCI increases first and then decreases with the increase of α . When $\alpha = 0$, the correlation between out-degree centrality and LSCI is the highest. However, when $\alpha = 0.7$, the correlation between in-degree centrality and LSCI is highest (Table 7). This proves the necessity of introducing the tuning parameter α in the calculation of the degree centrality of the shipping network.

5.4.2. The effects of α on closeness and betweenness centrality

Unfortunately, for betweenness centrality and closeness centrality, we cannot use LSCI as a benchmark for verification like degree centrality. However, in order to illustrate the effectiveness of the centrality metrics proposed in this study, we also analyzed the influence of different values of α on EDCC and EDBC.

Compared with EDBC (Figure 9 (B)), changes in the tuning parameter α had a greater impact on EDCC (Figure 9 (A)) for most of the countries in MSR shipping network. It is difficult for us to give a "most plausible" value of α for the entire network. However, we can get the values of EDCC and EDBC at different values of α for each country. Furthermore, according to the decision-making needs of managers, the centrality value in different situations could be selected as a reference for the importance of shipping countries in the shipping network.

6. Discussion and conclusions

This paper addressed the centrality of shipping network at the country level for MSR. A weighted network was constructed by considering the maritime countries as the nodes and the shipping frequency between countries as weights. Based on the approach for node centrality in weighted networks proposed by Opsahl et al. (2010), which considered both the number of connections and the strength of connections, a new method based on the effective distance was proposed to calculate the closeness and betweenness centrality of shipping network at the country level. The importance of countries along the MSR was studied according to the centrality based on the effective distance.

In terms of degree centrality, the out-degree of Malaysia and Singapore ranked the first in the binary network ($\alpha = 0$). However, when the shipping frequency was considered, China ranked first regardless of the value of α . Moreover, with respect to the shipping frequency, the degree centrality of Malaysia is larger than that of Singapore, no matter in out-degree or in-degree. Malaysia is the most central country in MSR, though the port of Singapore is more active and attractive than any port in Malaysia. Besides, most countries maintain a relatively stable ranking across different tuning parameters of α . Nonetheless, several individuals present significantly different results. For example, the ranking of Greece and India in terms of out-degree centrality was changed significantly in

different α values. Because the mean number of shipping frequency or mean value of the container throughput that sent to others from Greece is relatively low as compared to the same total amount of shipping frequency (container throughput), and the number of ties it connected to others is high. This result confirms that the necessity of combining number of ties and tie strength to the calculating of node centrality in shipping network.

In terms of the closeness and betweenness centrality, when $\alpha = 0$, namely in the binary case, Malaysia was the most central country in shipping country network along MSR. This implies that Malaysia has high accessibility to reach other maritime countries via direct and indirect shipping connections and the potential to become an intermediary between countries in MSR. This also illustrates the correctness of China's investment decision-making in the construction of Melaka Gateway in Malaysia. In addition, the Melaka Gateway, which is under construction in Malaysia, and is expected to be completed in 2025, may surpass the port of Singapore becoming the largest port on the Strait of Malacca, and further strengthen Malaysia's central position in MSR shipping network.

When shipping frequency was considered, the closeness centrality of Egypt ranked first, mainly because Egypt is located in the traffic hub of Europe, Asia, and Africa continent. Furthermore, the Suez Canal in Egypt connects the Mediterranean Sea and the Red Sea. It is one of the most frequently used routes in the world.

Although in the binary network, the closeness centrality of Singapore and Malaysia ranked first, the closeness centrality of Singapore dropped down to tenth when $\alpha = 1$. This indicates that Singapore may not be able to reach other countries quickly by sea in a weighted network though it only needs to pass fewer countries to connect with other countries. Besides, Albania, Jordan, Myanmar, Sri Lanka, and Yemen get the most significantly different values of closeness under two methods. Although they own high closeness according to Opsahl et al. (2010) method, their EDCC is quite low.

In conclusion, the position and importance of some countries in the Maritime Silk Road shipping network may be underestimated when using traditional centrality measures. For example, the position of Malaysia, Turkey, Greece, and Bahrain in MSR. In addition, Lebanon (in-degree and out-degree), Croatia and Slovenia (EDBC), and Georgia, Bahrain, and Pakistan (EDCC), have very important positions in the Maritime Silk Road shipping network and should further actively integrate into the Belt and Road Initiative.

Furthermore, the correlation analysis between the country's LSCI and degree centrality indicates the necessity of introducing the tuning parameter α in the calculation of the degree centrality of the shipping network. The effect of the tuning parameter α on centrality was particularly pronounced on closeness centrality, compared to betweenness centrality.

Finally, because of the limitation of data availability, this paper used the shipping frequencies between nodes and the number of ties as the weight to construct the weighted shipping network. In future research, if we can use the cargo flow data between different nodes or throughput as the weight to construct the weighted shipping network, we might receive more direct and reliable results.

Declarations

Author contribution statement

Zengjie Kuang: Conceived and designed the experiments; analyzed and interpreted the data, Wrote the paper.

Chanjuan Liu: Contributed reagents, materials, analysis tools or data; performed the experiments, analyzed and interpreted the data; wrote the paper.

Jinran Wu, You-Gan Wang: Performed the experiments; wrote the paper.

Funding statement

Chanjuan Liu was supported by the Ministry of education of Humanities and Social Science project (22YJC630083) and 2021 General project of Shanghai Philosophy and Social Science Planning (2021BJB006).

Data availability statement

Data will be made available on request.

Declaration of interest's statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

Acknowledgements

All authors would like to thank Professor Zhi-Hua Hu with the Logistics Research Center, Shanghai Maritime University for providing the data used in this paper.

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