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Article

Analysis of the Liner Shipping Network Structure of the Asia–Europe Main Trunk Route Using Social Network Analysis

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Abstract: Due to COVID-19, the shipping market has faced uncertainty, and the possibility of changes in port routes has increased. The purpose of this study was to analyze the network of container liner shipping routes between Asia and Europe. In particular, this research focused on a global risky situation—the COVID-19 pandemic. The data examined encompassed Asia–Europe route schedules from January 2018 to October 2021, which exhibited significant fluctuations due to the COVID-19 pandemic originating in 2019. To access this problem, utilizing concepts of centrality from social network analysis (SNA), namely degree centrality and betweenness centrality, this analysis incorporated route capacity as a weighted factor. The findings revealed that the port of Rotterdam held the highest degree of centrality in 2018, 2019, and 2021, while Shanghai claimed the highest degree of centrality in 2020. Singapore exhibited the highest betweenness centrality. Asian ports wielded greater influence during the COVID-19 pandemic compared to European ports. Furthermore, Singapore emerged as a pivotal mediator in the Asia–Europe routes, playing a significant role within the global supply chain. Results showed that the port could be put into an unstable situation. Therefore, the managers of port and shipping companies should be ready to minimize risk. From an academic perspective, it is difficult to integrate and analyze container liner schedules as they are monthly updated. This study therefore analyzed continuous schedules to examine dynamic changes in schedules. By adopting SNA, we presented changes in connectivity over multiple periods. This study addressed questions stakeholders may have had about route changes during the global crisis, contributing to sustainable container transportation. This study provides a general understanding of Asia–Europe container scheduling for decision makers. Using market schedules, this research analyzed the connections, and evaluated and compared each port.

Keywords: container liner shipping; SNA (social network analysis); Asia–Europe ports; container volume; sustainable shipping network

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1. Introduction

Container shipping schedules are determined by the operations departments of shipping companies. The operations departments organize optimal routes by considering the use of ports around the world and providing optimized operational services. Factors considered in organizing liner shipping routes include cargo volume, client type, punctuality, and degree of digitalization [1]. Among these factors, cargo volume projections often serve as a key factor in the decision-making process. This process plays an important role in selecting strategic routes [2]. Under normal market conditions, shipping liner schedules remain relatively stable due to the long-standing business relationships between shipping lines and ports, which are reinforced by the unique facilities and capabilities that each port offers such as terminal capacity, port depth, infrastructure, and hinterland connectivity. However, when markets are characterized by uncertainty, temporary alterations to port calls and even complete route overhauls may occur.

Recent developments in the logistics industry, coupled with various changes in societal factors, have exacerbated port congestion and delayed port calls. Therefore, shipping companies must pivot toward more flexible decision-making strategies, departing from traditional route scheduling methods. Consequently, route changes have become more frequent. In unpredictable situations, city blockades and rapid increases in cargo volume increase the congestion of ports, creating an unavoidable situation where liners must call at other ports. This means that decision makers select another option instead of their priority options that they have planned. Therefore, all activity is moved to alternative ports, and this makes global hub ports lose their throughput or calling vessels. But this is not easy to judge by past events or literature alone, rather, it should be investigated by collecting data, and analyzing and assessing them theoretically.

Meanwhile, shipping companies, akin to other businesses, operate in response to supply and demand dynamics. In typical market conditions, they tend to maintain the status quo in terms of route operations. However, when there is insufficient demand, they scale back capacity at certain ports to prevent a precipitous drop in market prices. This adaptive approach enables them to navigate shifting market conditions by adjusting route capacity rather than completely altering routes. Therefore, it is imperative to conduct analyses that incorporate capacity information in addition to research identifying the connection of routes. This study used social network analysis (SNA) to incorporate capacity data into network analysis. The structure of this study is as follows: after this introductory chapter, Section 2 presents a review of the literature relevant to SNA and port networks. Section 3 outlines the research methodology, while Section 4 delves into the application of degree centrality and betweenness centrality, along with empirical analysis results. Finally, Section 5 provides conclusions and implications.

2. Literature Review

SNA finds diverse applications across various sectors. For example, Buchnea and Elsahn [3] conducted an analysis of international business research, illustrating changes in the Liverpool–New York trade and financial network across different time periods. This is an example of how SNA can visualize network changes. Anugerah et al. [4] explored network relationships among multiple studies employing SNA, examining a total of 2158 articles published from 2001 to 2020. SNA is frequently utilized in management and business studies. Additionally, it has been employed to comprehend social phenomena, such as identifying influential countries in terms of air pollution control technologies [5] and measuring urban resilience [6].

Previous studies have frequently applied SNA techniques such as degree centrality, betweenness centrality, and closeness centrality. Notable examples include studies conducted by Tsai [7], Reagans and Zuckerman [8], and Brown et al. [9] that investigated social partnerships and mutual communication. Many trend analyses have also harnessed these techniques, such as Choi and Yeo's [10] study on trends in inland waterways that utilized degree centrality, betweenness centrality, and closeness centrality. Furthermore, research on trends in public health [11], themes and trends in Korean educational technology research [12], and themes and trends in Australian and New Zealand tourism research [13] have employed SNA.

These aforementioned SNA studies are characterized by non-directional network analysis, as they focus on nodes that do not incorporate directionality information. In this way, network data without directionality are relatively easy to access and network data with directionality are relatively scarce, and even when they exist they are rarely used as analyzable data. However, in logistics markets such as container shipping, there is always a network with directionality, and when conducting network analysis, it is imperative to consider and analyze the directionality. As is the case with many nodes, as long as there exist data that can reflect weights, analysis performed on these data will be accurate and reliable. If the weight information is not reflected, only the number of links connected to the node are calculated, which has limitations compared to measuring the connection relationship with weight information. Moreover, in the case of a container network, data on throughput always exist, hence, identifying centrality only by the number of connections clearly has its own meaning [14]. However, for more advanced research, it is necessary to consider weighted data and analyze them.

In addition to this background, previous studies have not used weight data because of a lack of data or the data do not have any weight information. This research, however, adopted weight data to address the limitations of previous studies.

The relevant ideas are as follows:

First, directional SNA was employed when network relationships flowed in only one direction, necessitating the differentiation of departure and destination points for each relationship. This distinction between inbound and outbound directions allows for a deeper understanding of network characteristics, the significance of specific nodes, and the flow of information.

Directional SNA is applied across various domains, including social network analysis, web network analysis, and traffic network analysis, yielding more accurate results and a deeper understanding of network structures by accounting for directional relationships.

The examination of directionality between nodes has been frequently applied to port-related research. In Bombelli's [15] study, directional network data were analyzed with a specific focus on international courier companies such as FedEx, UPS, and DHL. These logistics companies operating cargoes by airway inherently generate directional data due to the one-way flow of shipments, and the data focus on the impact of COVID-19 and meticulously tracked changes in network centrality during this period, yielding noteworthy findings. For the study, in- and out-degree centrality were employed, as well as betweenness centrality, to discern the significance of nodes within the network. This research provided crucial insights into how the logistics industry evolved in response to COVID-19, offering timely perspectives on the effects of external disruptions on directional network dynamics.

Accordingly, in container liner shipping routes, data on departures and arrivals at ports are inherently directional. Thus, it is imperative to incorporate directionality information into SNA. This study employed an SNA model that considered directional links between nodes.

Second, many previous studies have focused solely on network connections without considering weight data utilized on the routes or network edges. Akhavan et al. [16] attempted to determine the connectivity of cities including 3PL headquarters, ports, and airports. The research, however, did not utilize weight data. It appears as if they did not have any weight information in the data. Jeon et al. [17] conducted SNA without adopting weight data in the research. The research type was research trend analysis. Therefore, it had no directionality and no weight data. Thus, it only handled the connectivity of each node. In this case, the research assumed that nodes had equal weight. Macurová et al. [18] stated that the numbers of flights, passengers, and capacity can be used as weights. However, they utilized the frequency of flights as weight information to determine the connectivity of the European air transport network in their study. From the research, ports could be divided into those that were influenced by COVID-19 and those that were not. The study provided implications to help understand the connectivity of the air transport network and a basis for future research.

As above, if nodes have data or weight information, it would be appropriate to reflect these in the research. Overall, the studies conducted with SNA lack directionality or weight, hence, this study sought to rectify this limitation by incorporating directional data and capacity data into the analysis, thereby enabling a more comprehensive and nuanced evaluation.

3. Methodology

SNA was originally developed to understand social structures. It has been used widely in many fields since it was proposed in 1977 [19]. It analyzes and visualizes social relations with network and graph theories, using nodes within the network, as well as edges or links that connect the nodes. This methodology starts from the basic concept of the network of relations. Therefore, it is necessary to attempt to identify and understand the structure through basic analysis. Adding some advanced analysis at this step can also enable understanding and practical use. This analysis, an advanced analysis reflecting weights, is performed based on degree centrality analysis and betweenness analysis. Park, Park, and leydesdorff [20] adopted degree centrality and betweenness centrality to analyze big data research. Although it is a relatively recent study, the research problem was solved through basic degree centrality and betweenness analysis. This is an example of how social structure can be understood through conceptual analysis, and the study used UCInet software Ver. 6.747. As in the above study, the same software was used in this study. Research methods such as degree centrality and betweenness centrality can be explained as follows:

Degree centrality is a pivotal centrality measure employed in SNA. It quantifies the number of connections that a particular node has with other nodes. In essence, it is calculated by tallying the number of edges (links or relationships) linking a given node. Degree centrality facilitates an understanding of the network structure and evaluates the importance of specific nodes. Nodes with high degree centrality, directly connected to numerous other nodes, possess greater potential to disseminate network information or exert influence effectively. Consequently, nodes with high degree centrality are deemed to hold crucial positions [19].

Degree centrality can be calculated as follows: For an undirected network, it involves counting the number of edges (links or relationships) connected to one node. In a directed network, the in-degree (number of incoming links) and out-degree (number of outgoing links) of a node are calculated separately. While a connection is calculated by weighted information. Below is an adopted equation of this study.

$$C_D^w(i) = \frac{\sum_{j=1}^{n} a_{ij} w_{ij}}{n} - 1,\ i \neq j \tag{1}$$

In this equation, a_{ij} means a connection of node 'i' and node 'j', which means, if there is a connection between node 'i' and node 'j', the value of a_{ij} is calculated as 1; otherwise, it is calculated as 0.

'w_{ij}' means the weight of edges. In a directed network, when node 'i' transfers the specific number of information or throughput to another node 'j', node 'i' is calculated as sum of the specific number in in-degree, while node 'j' is calculated as the sum of the specific number in out-degree. Comprehensively, node 'i' is multiplied by whether it connects to another node or not, and weight [20].

The equation presents a normalized degree centrality. Nominal value cannot reflect a standardized value in different degrees. Therefore, to standardize the value, the equation is adopted [19].

Betweenness centrality measures the number of times a node lies on the shortest path between other nodes in a network. In other words, it measures the degree to which one node serves as a hub for efficient information transfer between other nodes. Betweenness centrality is used to identify nodes that play a significant role in delivering information or exerting influence within the network. Nodes with high betweenness centrality are in a key position in communication or information transfer between other nodes, and also effectively deliver information. These nodes can be regarded as central mediators (hubs) [19].

Betweenness centrality is calculated as follows:

$$C_B(i) = \left(\sum_{j<k}^{n} g_{jk}(i)/g_{jk}\right)\frac{2}{(n-1)(n-2)} \tag{2}$$

Here, 'n' represents the number of nodes in the network. If node 'j' cannot connect to 'k' without the intermediary node 'I', and node 'I' assumes the role of intermediary between node 'j' and 'k', then $g_{jk}(i) = 1$ otherwise $g_{jk}(i) = 0$. To normalize the metric, it is multiplied by $\frac{2}{(n-1)(n-2)}$.

4. Results

This study conducted SNA to examine changes in the Asia–Europe container liner shipping route network and centrality between January 2018 and October 2021. The analysis hinged on data encompassing Asia–Europe route data and liner schedules for voyages between Asia and Europe.

These data are limited to the Asia–Europe route. Therefore, even if the ports are connected to global ports that are not included in the Asia–Europe route, those connections were not counted.

The liner shipping companies have monthly plans to operate container vessels for routes. The adopted data for this study were composed of route data including throughput data, which is recorded by TEU unit by each route. This study uses all the monthly data, including the throughput data, and, furthermore, the monthly data were piled to yearly data by taking the average. Therefore, duplicated ports linking the other ports can be calculated by the sum of the duplicate route.

Table 1 below presents the scope of the analysis undertaken in this study.

Table 1. 2018–2021 statistical data of the connected ports of Asia–Europe.

Category	2018	2019	2020	2021
Average number of routes	19	19	18	19
Average number of ports	51	48	48	50

Table 2 below offers insight into the average degree centrality, categorized by year, for the major ports under examination. Rotterdam exhibited the highest degree centrality in 2018, 2019, and 2021, registering figures of 5923 in 2018 and 6355 in 2019. Rotterdam is a central port and is recorded as the port with the highest throughput in Europe, as well as one of the top 10 ports in the world. Thus, it has the highest degree centrality overall on the Asia–Europe route, and the network is connected to small ports in Europe through Rotterdam. The role of Rotterdam is pivotal as a hub in the Asia–Europe container liner shipping network. These results reflect Rotterdam's critical position in connecting smaller European ports that are not hub ports, but instead are small ports with smaller-scale terminals. These ports have had throughput distributed from Rotterdam. As can be seen in Table 2, Rotterdam's degree centrality dropped after emerging out from the peak of COVID-19. This is the case due to the distribution of throughput into surrounding ports such as Tanger Med and Antwerp. Additionally, it can be inferred that overall connectivity increased for each port.

Container volume in 2019 increased due to COVID-19, which broke out in late 2019 and increased the overall degree centrality. In particular, the degree centrality of Shanghai increased to 7029 in 2020, which caused Rotterdam to drop to second. The COVID-19 pandemic seemed to have increased the container volume of ports in Asia rather than ports in Europe. This led, in particular, to a significant increase in the degree centrality of ports in China where global ports are concentrated. Shanghai, which was ranked second in 2018 and 2019, and first in 2020, dropped to fourth with 5923 in 2021. Both Rotterdam and Shanghai are hub ports, and Shanghai's centrality increased, while Rotterdam's did not. This indicates that not only does Shanghai have a very large throughput, but it also has the capacity to handle the throughput, unlike Rotterdam.

Table 2. Major port ranking of degree centrality based on average per year.

Rank	Port	2018	Port	2019	Port	2020	Port	2021
1	Rotterdam	5923	Rotterdam	6355	Shanghai	7029	Rotterdam	6405
2	Shanghai	5566	Shanghai	6231	Rotterdam	6444	Singapore	6355
3	Yantian	4973	Yantian	5035	Yantian	6366	Yantian	6196
4	Singapore	4732	Ningbo	4899	Singapore	6128	Shanghai	5923
5	Ningbo	4583	Singapore	4724	Ningbo	5294	Ningbo	5140
6	Hamburg	3436	Hamburg	3742	Hamburg	3724	Hamburg	3717
7	TangerMed	2758	TangerMed	3000	TangerMed	3330	TangerMed	3242
8	Felixstowe	2607	Antwerp	2766	Antwerp	2917	Antwerp	3078
9	Antwerp	2549	LeHavre	2360	HongKong	2285	TanjungPelepas	2924
10	HongKong	2313	Qingdao	2122	Felixstowe	2203	Felixstowe	2229

On the other hand, the degree centrality of the port of Singapore increased, which shows that the prolonged COVID-19 pandemic reduced the influence of Shanghai in the Europe–Asia route, and Singapore as the port of call served as a hub, resulting in the increase.

The ports in Europe that showed the next highest degree centrality after Rotterdam were Hamburg and Antwerp. These are ports in Germany and Belgium that play a key role in transporting cargo inland. They also have many inland barges operating through the terminal [21]. Overall, ports in Europe showed lower centrality compared to ports in Asia.

Tables 3 and 4 below show the ports eliminated and added in each period from November 2019 to April 2020 in Rotterdam and Shanghai.

Table 3. Rotterdam port network changes (November 2019 to April 2020).

In-Direction		Out-Direction	
Eliminated	**Added**	**Eliminated**	**Added**
Tangier	Algeciras	Tangier	Algeciras
Wilhelmshaven	-	Jebel Ali	Singapore
-	-	Piraeus	Antwerp
-	-	Dunkirk	-

Table 4. Shanghai port network changes (November 2019 to April 2020).

In-Direction		Out-Direction	
Eliminated	**Added**	**Eliminated**	**Added**
HongKong		HongKong	Busan
Qingdao			-

In the Rotterdam port network, Tangier and Wilhelmshaven were eliminated from the in-direction route, while Algeciras was added. In the out-direction, Tangier, Jebel Ali, Piraeus, and Dunkirk were eliminated, with Algeciras, Singapore, and Antwerp being introduced.

As for Shanghai, Hongkong and Qingdao were eliminated from the in-direction, while Busan was added to the out-direction. This addition was prompted by a rapid surge in container volume demand at the port of Busan. Shanghai, in particular, achieved the highest degree centrality in 2020, despite no increase in the number of ports connected in its network. This is the effect of the increased container volume handled at ports connected in the existing network.

5. Betweenness Centrality Analysis

Table 5 presents the betweenness centrality of the top 10 ports. The port showing the highest betweenness centrality between 2018 and 2021 is Singapore. It is a major port of call on global routes and also has the highest centrality on the Asia–Europe route. The betweenness centrality appeared to have increased significantly in 2020, especially due to the COVID-19 pandemic. The metric rose from 0.407 in 2018 and 0.354 in 2019 to 0.431 in 2020. Subsequently, betweenness centrality reached 0.437 in 2021, maintaining its elevated status. Singapore is a gateway port in the Asia–Europe network, as shown in Figures 1 and 2. Singapore has an important role in the network, and its role did not change even during the COVID-19 pandemic. Although it may be affected by the increase or decrease in cargo volume, it can be seen that it has always had the upper hand in terms of connectivity as a result of betweenness centrality. Additionally, it can be seen in Table 5 that connectivity decreased from 2018 to 2019, however, the returning centrality values in the years after indicate that Singapore still had the ability to maintain its network. Rotterdam secured the second highest betweenness centrality, followed by Yantian and Shanghai. The intermediary role in the Asia–Europe route is focused on Singapore, which was not much affected, even in a global crisis. This is because Singapore plays a major role in the Asia–Europe route with its geographical location as a transshipment port.

Table 5. Major port ranking of betweenness centrality based on average per year.

Rank	Port	2018	Port	2019	Port	2020	Port	2021
1	Singapore	0.407	Singapore	0.354	Singapore	0.431	Singapore	0.437
2	Rotterdam	0.270	Rotterdam	0.270	Rotterdam	0.273	Rotterdam	0.232
3	Yantian	0.136	Yantian	0.141	Yantian	0.147	Yantian	0.207
4	Shanghai	0.132	Shanghai	0.137	Bremerhaven	0.132	Ningbo	0.143
5	Ningbo	0.091	Ningbo	0.127	Shanghai	0.131	Shanghai	0.125
6	Bremerhaven	0.090	Bremerhaven	0.126	Ningbo	0.126	Bremerhaven	0.119
7	TanjungPelepas	0.087	LeHavre	0.081	LeHavre	0.062	TangerMed	0.107
8	Colombo	0.084	TanjungPelepas	0.080	TanjungPelepas	0.061	Antwerp	0.069
9	LeHavre	0.071	Colombo	0.065	TangerMed	0.059	TanjungPelepas	0.065
10	Felixstowe	0.069	Qingdao	0.053	Antwerp	0.049	LeHavre	0.056

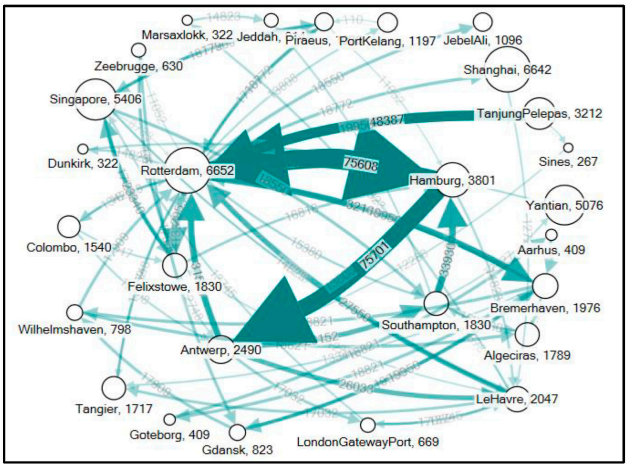

Figure 1. January 2020 port network.

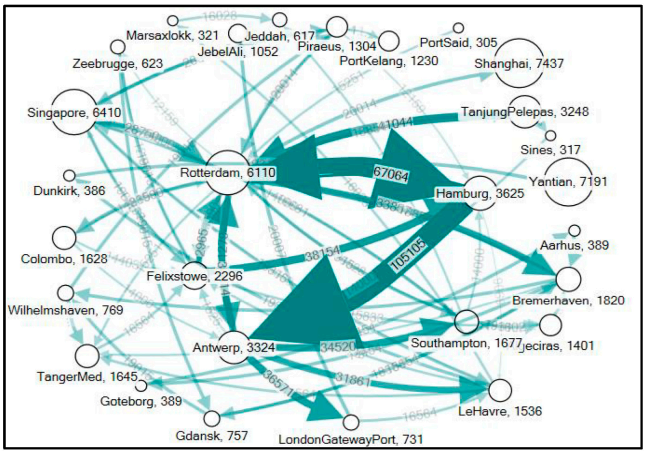

Figure 2. December 2020 port network.

Figures 1 and 2 below illustrate the network graphs of the ports in January and December 2020. The size of the nodes represents centrality, and the numbers on the nodes represent centrality scores. The thickness and transparency of the arrows represent the weight (capacity in the route), and the numbers on the arrows represent the weighted scores.

These graphs highlight that most connections remained intact. However, the degree centrality of a few European ports appeared to decline, with Rotterdam decreasing from 6652 to 6110, and Hamburg from 3801 to 3625. Conversely, Asian ports exhibited an increase in degree centrality, with Singapore rising from 5406 to 6401, Yantian from 5076 to 7191, and Shanghai from 6642 to 7437. This demonstrates a decline in the significance of European ports in the aftermath of COVID-19, while the centrality of Asian ports surged. This implies that, during social challenges such as COVID-19, the centrality of Asian ports experiences a more pronounced increase in comparison to European ports, enabling them to effectively navigate the global crisis.

6. Conclusions

The purpose of this study was to analyze the network of Asia–Europe container liner shipping routes. To facilitate this analysis, data spanning from 2018 to 2021 pertaining to the Asia–Europe container liner shipping routes operated by shipping companies were used. Degree centrality and betweenness centrality, key concepts in SNA, were utilized in the analysis, with the incorporation of route capacity as a weight.

The outcomes of the analysis can be succinctly summarized as follows:

First, Rotterdam is the linchpin of the Asia–Europe port network. It consistently held the top position in degree centrality, except for in 2020 when the profound impact of COVID-19 was felt. Rotterdam's unique status as the sole large European port ranking within the top 10 global ports in container volume underscored its pivotal role in the Asia–Europe route. Rotterdam serves as a hub port that shares container volume with neighboring ports.

Second, the significance of Shanghai appeared to amplify during global crises like COVID-19. The port of Shanghai was ranked first in terms of degree centrality in 2020, when COVID-19 had the greatest impact, and value for degree centrality was even greater than Rotterdam, indicating a significant increase in its role. The reason for this can be found from the scale and role of network. The port of Shanghai has its own ability to digest container volume as it has large terminals and management capability. Therefore, during the COVID-19 pandemic, Shanghai was able to maintain degree centrality. Furthermore, the decrease in centrality in 2021 was caused by the diminishing impact of the COVID-19 outbreak as all ports entered normal operating ranges and regained their original centrality. Thus, considering the relativity of centrality, this result is reasonable.

Third, Singapore has an absolute advantage as a port of call on the Asia–Europe route. It maintains high betweenness centrality, as well as an influence as a port of call even in a global crisis. This is due to the natural locational advantage of Singapore, as well as its competency as a transshipment port.

This study offers several implications below.

Shipping companies can use the above results for future strategic analysis material. In the event of a global crisis, cargo volume increases explosively and changes tend to occur as a result of the crisis, as opposed to from efforts to preserve the initial ports' routes. Reasons for this change include delays in ship docking, a reduction in port processing speed, and a reduction in work speed at facilities around the port. Risk factors such as additional allocation of ships due to an increase in cargo volume and the reduction in work force from infectious diseases may occur. Therefore, shipping companies need to carefully plan and implement alternatives to minimum manpower operations.

Port authorities can use these data as part of future emergency planning. It was observed that the rise and fall of connectivity was clearly visible in the COVID-19 Pandemic situation. Shipping networks have a tendency to maintain routes, except in the emergence of exceptional situations like a global crisis. Therefore, if the port call route is changed, it is highly likely that the changed route will be maintained for a while. This may result in a weakening of the port's competitiveness. Therefore, preparations must be made to maintain the same service quality to avoid losing trust in the port and its operation in the above uncertain situations and emergency situations.

Additionally, this study can be used from a long-term perspective. Since a port's connectivity is related to the port's revenue and quality of service in any situation, a decrease in connectivity can be seen as being related to a decline in the quality of revenue and services. It was mentioned above that the reason for the decline in port connectivity is related to the size and handling capacity of the port. Therefore, in preparation for such uncertain situations, it is necessary to discuss the expansion of facilities and reorganization of systems to be able to cope with situations that may arise in the future.

This study bears significant industrial implications by aiding port officials and decision-makers involved in route planning to understand networks and formulate strategic responses. Additionally, it facilitates the assessment of competitive rankings among ports. While previous studies only considered the analysis of port connections, this study has academic implications in that it conducted more elaborate research by conducting a network analysis of port capacity. Hence, this research adopted traditional social network analysis to aid the basic understanding of results, and added weighted data for advanced study. It can assist not only researchers but also workers in the field. Future research endeavors should expand upon these findings by incorporating diverse datasets, such as data concerning the number of ships arriving and departing ports, and infrastructure data, to enrich the analysis further.

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References

1. Notteboom, T.E. Container shipping and ports: An overview. *Rev. Netw. Econ.* **2004**, *3*, 2. [CrossRef]
2. Kuhlemann, S.; Ksciuk, J.; Tierney, K.; Koberstein, A. The stochastic liner shipping fleet repositioning problem with uncertain container demands and travel times. *EURO J. Transp. Logist.* **2021**, *10*, 100052. [CrossRef]
3. Buchnea, E.; Elsahn, Z. Historical social network analysis: Advancing new directions for international business research. *Int. Bus. Rev.* **2022**, *31*, 101990. [CrossRef]

4. Anugerah, A.R.; Muttaqin, P.S.; Trinarningsih, W. Social network analysis in business and management research: A bibliometric analysis of the research trend and performance from 2001 to 2020. *Heliyon* **2022**, *8*, e09270. [CrossRef]
5. Liu, S.; Chevallier, J.; Xiao, Q. Identifying influential countries in air pollution control technologies: A social network analysis approach. *J. Clean. Prod.* **2023**, *389*, 136018. [CrossRef]
6. Yao, Y.; Guo, Z.; Huang, X.; Ren, S.; Hu, Y.; Dong, A.; Guan, Q. Gauging urban resilience in the United States during the COVID-19 pandemic via social network analysis. *Cities* **2023**, *138*, 104361. [CrossRef] [PubMed]
7. Tsai, W. Social structure of 'coopetition' within a multiunit organization: Coordination. competition, and intraorganizational knowledge sharing. *Organ. Sci.* **2002**, *13*, 179–190. [CrossRef]
8. Reagans, R.; Zuckerman, E.W. Networks. diversity, and productivity: The social Capital of corporate R&D teams. *Organ. Sci.* **2001**, *12*, 502–517. [CrossRef]
9. Brown, J.; Broderick, A.J.; Lee, N. Word of mouth communication within online communities: Conceptualizing the online social network. *J. Interact. Mark.* **2007**, *21*, 2–20. [CrossRef]
10. Choi, Y.S.; Yeo, G.T. An analysis of research trends of inland waterway utilizing social network analysis. *Asian J. Shipp. Logist.* **2023**, *39*, 52–59. [CrossRef]
11. Shen, B.; Guan, T.; Ma, J.; Yang, L.; Liu, Y. Social network research hotspots and trends in public health: A bibliometric and visual analysis. *Public Health Pract.* **2021**, *2*, 100155. [CrossRef] [PubMed]
12. Choi, J.; Woonsun, K. Themes and trends in Korean educational technology research: A social network analysis of keywords. *Procedia-Soc. Behav. Sci.* **2014**, *131*, 171–176. [CrossRef]
13. Benckendorff, P. Themes and trends in Australian and New Zealand tourism research: A social network analysis of citations in two leading journals (1994–2007). *J. Hosp. Tour. Manag.* **2009**, *16*, 1–15. [CrossRef]
14. Opsahl, T.; Agneessens, F. Skvoretz Node centrality in weighted networks: Generalizing degree and shortest paths. *Soc. Netw.* **2010**, *32*, 245–251. [CrossRef]
15. Bombelli, A. Integrators' global networks: A topology analysis with insights into the effect of the COVID-19 pandemic. *J. Transp. Geogr.* **2020**, *87*, 102815. [CrossRef]
16. Akhavan, M.; Ghiara, H.; Mariotti, I.; Sillig, C. Logistics global network connectivity and its determinants. A European City network analysis. *J. Transp. Geogr.* **2020**, *82*, 102624. [CrossRef]
17. Jeon, J.W.; Wang, Y.; Yeo, G.T. SNA approach for analyzing the research trend of international port competition. *Asian J. Shipp. Logist.* **2016**, *32*, 165–172. [CrossRef]
18. Macurová, M.; Vittek, P.; Pecherková, P. Connectivity of the European air transport network during the Covid-19 pandemic. *Transp. Res. Procedia* **2022**, *65*, 208–215. [CrossRef]
19. Freeman, L.C. A set of measures of centrality based on betweenness. *Sociometry* **1977**, *40*, 35–41. [CrossRef]
20. Park, H.W.; Leydesdorff, L. Decomposing social and semantic networks in emerging "big data" research. *J. Informetr.* **2013**, *7*, 756–765. [CrossRef]
21. Caris, A.; Macharis, C.; Janssens, G.K. Network analysis of container barge transport in the port of Antwerp by means of simulation. *J. Transp. Geogr.* **2011**, *19*, 125–133. [CrossRef]

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