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Examining the spatiotemporal changing pattern of freight maritime transport networks in Indonesia during COVID-19 outbreaks

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ABSTRACT

The COVID-19 pandemic in Indonesia has led to a significant change in human mobility. It is also considered the most serious threat to the inter-island trade network since the economic crisis in 1998. Leveraging two-year historical port call data (covering 6,000 records in total) of Indonesian domestic cargo vessels from the Automatic Identification System (AIS), this study examines the spatiotemporal changes of maritime freight transport network connectivity and cargo shipping capacity during the COVID-19 outbreaks period. We constructed two directed graphs, one in 2019 and another in the 2020 period, based on 1,283 Indonesian domestic cargo ship trajectories that connect 25 main Indonesian ports through 370 links. This study calculated and compared the four metrics of complex network analysis, including assortative coefficient, average degree, betweenness centrality, and clustering coefficient, to figure out the shipping network pattern changes. The result shows that the network connectivity and its shipping capacity changed in 2020, although the national port call trend is not significantly different from 2019. Based on our observation, we notice that the network is shifting from a "main hub-and-spoke connection," which dominantly involves western Indonesia hub-ports structure, towards a "multi hub-and-spoke connection," which increases the ports centrality position in eastern Indonesia. We also analyzed the change of cargo shipping capacity in each link to reflect how shipping liner companies respond to the pandemics. The insights generated in this study are hoping to contribute toward more rapid, effective, and comprehensive responses to this unprecedented disruption.

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CCS CONCEPTS

• **Networks** → Network performance evaluation; Network performance analysis; Network properties; Network dynamics.

KEYWORDS

maritime transport network, shipping network, covid-19 pandemic, complex network analysis, freight transportation

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1 INTRODUCTION

The recent coronavirus (COVID-19/SARS-CoV-2) that originates from Wuhan in December 2019 is considered a serious threat to the global trade network since the financial crisis of 2008. According to UNCTAD [1], the COVID-19 pandemic drove significant international trade declines in 2020. The value of merchandise trade worldwide is estimated to have declined by 5.6% in 2020 compared to the previous year. This number shows the highest fall in global trade since 2009, when trade dropped by 22%. The estimated decline in service trade is much more significant, with services likely to fall by 15.4% in 2020 compared with 2019. This condition would be the most significant decline in service trade since 1990, following the 2008 global economic crisis where the services trade decreased by 9.5%. The COVID-19 pandemic resulted in an economic downturn for all OECD countries and most developing economies [2].

Indonesia is one of the countries that not immune from the effect of COVID-19 outbreaks. As of February 25, 2020, Indonesia's number of COVID-19 confirmed cases had surpassed over 1.3 million, with the death toll exceeding 35.254. The COVID-19 outbreak has raised an unprecedented challenge for the Government of Indonesia. Aside from medical measures, non-medical interventions like large-scale social restrictions (PSBB) and micro-scale restrictions imposed on public activities (PPKM) have been widely implemented throughout the nation to reduce virus contagion [3, 4]. PSBB are large-scale national restrictions, including closing public places, schools, inter-provincial travel restrictions, and reducing public transport utility that local governments implement with the Ministry of Health's formal approval. At the same time, PPKM is a measure that focuses on lowering public activities in the Java dan Bali regions. The extensive restriction indicating at least more than 200 million people had been urged to avoid unnecessary trips, maintain social distancing, and stay-at-home as long as possible. These initiatives with the pandemic spread caused significant changes in Indonesian citizen mobility [5] and consumer patterns to essential goods [6].

One of the production sectors directly exposed to the COVID-19 pandemic and its adaptation measures is the transport sector. According to the Indonesian Central Agency on Statistics, the total domestic and international passenger of air transportation dropped by 85,18% and 95,35% in April 2020 (year on year/YoY), respectively. A similar pattern also occurred in passenger railway and sea transportation, which dropped 53,55% and 70,82% (YoY). An increasing number of studies investigated the effects of COVID-19 outbreaks on the Indonesian public transport service, which regarded it as the central transmission of the virus. Ariyani et al. [7] found that the switching of transportation users' reference to use public urban transportation into private transportation modes in Jakarta Greater area had been significantly associated with the government social restriction measures. Restu et al. [8], Soelasih [9] and Ratnawati [10] investigated to what extent the change of human mobility pattern during COVID-19 affected the air transportation industry in Indonesia. Sari and Rudeviyani [11] observed the influence of the extensive social restriction measures on the user's decision to choose railway transportation as their daily transport mode.

Although studies mentioned above have reported the pandemic impacts on Indonesia's transport sectors, rare studies have solely focused on freight transportation. The study of how the pandemic impacts freight transport is essential because the non-pharmaceutical measures to contain COVID-19 spread, like PSBB and PPKM, resulted in a significant fall in non-essential product demand and supply. The declining demand is mainly caused by the consumer behaviour shifting that spends less due to limited retail activities. Simultaneously, the limited supply resulted from limited manufacturing or service activities due to strict social distancing [12]. The highly uncertain environment caused by COVID-19 outbreaks distorted the inter-island trade due to the suppression of demand and supply across the nation triggered by PSBB and PPKM [13]. These conditions make the new imbalance trade between regions and potentially increase the national logistics cost because many vessels travel back with less or empty cargo. We notice that freight transportation is directly exposed due to the COVID-19 contagion yet inadequately investigated in Indonesia.

The purpose of this work is to assess for the first time, according to the best of the authors' knowledge, the consequence of the COVID-19 epidemic on Indonesia's freight transportation flow, specifically on its maritime transportation networks. We defined maritime transport networks as seaside traffic of freight transportation that connects ports by its shipping services, according to the elaboration by Rodrigue [14]. The main question we want to answer is how Indonesia's domestic maritime shipping network changes spatiotemporally during the COVID-19 pandemic time frame. Indonesia is a large archipelago nation with six main islands and 17,508 small-island splits into 34 administrative provinces, making the network very complicated. Indonesia is highly reliant on its maritime transport network since up to 89% of its domestic freight trade is carried out by seaborne transportation [15]. The in-depth analysis of Spatio-temporal changes in maritime shipping networks could be helpful for transport authorities to identify and maintain the critical inter-island connectivity to avoid the spike of national logistics cost caused by COVID-19 measures. To answer the question, we construct the network based on 1,283 Indonesian domestic cargo ship trajectories that connect 25 main Indonesian ports retrieved from the Automatic Identification System (AIS) in the 2019 and 2020 periods. We chose 25 main Indonesian ports as they represent more than 50% of national inter-island cargo traffic. In total, our dataset covered more than 1,283 cargo vessel voyages from those two years. We analyze the maritime transport network changes by comparing it between the pre-pandemics period in 2019 and the during-pandemics period in 2020 through complex network analysis.

2 LITERATURE REVIEW

Sufficient studies on maritime transport network analysis to evaluate worldwide and inter-regional cargo trade patterns have already been well-documented in the last decades [16]. Maritime transport networks play a crucial role in exchanging goods worldwide, with 80 per cent of all international trade volume and 70 per cent of trade value are carried through the sea [1]. Graph theory and complex network analysis are the most used methods to analyze the maritime transport network. At the same time, AIS and statistics records become primary sources to construct the network based on the vessel movements [16].

Previous studies used complex network analysis to determine how the worldwide maritime shipping network was built and evolved [17–20]. Most findings are consistent in explaining how the worldwide maritime network was built over time. The preferential attachment model is majorly fit to describe worldwide and some maritime network groups in Europe, North America, Asia, and Africa [21]. Preferential attachment means that the more central a port position is, the more likely it will receive new connections [22]. In real-world maritime shipping networks, ports with a higher connection with other ports have a higher ability to grab new links assigned to the network. These identified networks commonly lie in the category of scale-free networks, meaning that they exhibit a power-law (or scale-free) degree distribution [23]. However, the opposite result of how the real-world maritime network was built also exists. For instance, Liu et al. [24] exhibit the small-world network in South America and Oceania, while Destyanto et al. [25] show the absence of power-law degree distribution in a large-scale archipelago container transport network. The recent findings support Broido and Clauset's [26] work, claiming that scale-free networks are infrequent in real-world networks.

Besides analyzing how the maritime shipping network was evolved, some studies focus on examining to what extent maritime disruptions affect the structural changes of maritime transport networks [21, 27–29]. These studies emerge since the maritime disruption intensity and frequency are steadily increasing worldwide [30]. Previous studies mainly investigate how the maritime transport network adapts due to purposeful (e.g., terrorisms, sabotages, politics) and non-purposeful events (e.g., natural disasters, financial crisis, human errors, or operational accidents). For instance, Wu et al. [31] found that the network's shipping time will rise by over 25% if the Suez Canal is disturbed. Rousset and Ducruet [28] found that various maritime events, such as earthquakes, hurricanes, and terrorism, caused a short term decrease in the vessel traffic, depending on the type of vessels (container, bulk, passenger, or general cargo), as container flows are the most susceptible to those disturbances. Previous studies focused on investigating disruptions characterized by frequently occurred events that directly impact the maritime infrastructure or vessel traffic flow. This situation leads to the absence of considering pandemics as a specific case of maritime disruptions before COVID-19 outbreaks [32, 33].

Since the beginning of the COVID-19 pandemic cases expansion in early 2020, cargo flow through seaborne transportation has drastically reduced due to restricted human activities. Vidya & Prabheesh [34] found that the trading density among 15 leading countries has decreased considerably by almost 50% and found only China that has not changed drastically in the trade network position. This effect encourages the scholar to put the COVID-19 pandemic as a specific case of maritime disruptions. For instance, Notteboom et al. [2] compared the changes of worldwide container shipping network connectivity and worldwide ports centrality between COVID-19 and the 2008-2009 global recession period. Notteboom et al. [2] found that the ports, terminal operators, and shipping lines have all exhibited an increased short-term resilience, partly supported by the adaptation in the aftermath of the 2008/2009 economic meltdown when facing the COVID-19 pandemics. However, one should investigate the long-term impacts of COVID-19 because the pandemic has a long-term disruption existence, and the effect scaling is unpredictable.

In this study, we focus on assessing the impact of COVID-19 on the maritime shipping network in a large-scale archipelago with Indonesia as a central case study. As a large-scale archipelago country, Indonesia has a total area of 1.9 million square kilometers consisting of land areas scattered into more than 17,508 islands, and the rest are sea territory. Indonesia has 250 million populations affected by PSBB and PPKM measures to contain the coronavirus spread. Due to COVID-19 outbreaks, the maritime transport network plays a critical role as a primary transport mode to facilitate inter-island products trade. The absence of shipping services could increase the logistic cost and accessibility of essential goods [35]. The maritime network in the archipelago and worldwide has significant differences. The main commercial ports in Indonesia are commonly operated by state-owned enterprises, subjected to intense cooperation in reducing national logistic costs and increasing national shipping network connectivity. The aforementioned characteristic contrasts with the global maritime transportation networks, in which the nodes represent the hub ports that serve mainly the national hinterland, which is subject to fierce competition for transshipment flows [2].

Given the scarcity of studies on how COVID-19 affects maritime transport networks in a large-scale archipelago, our main contribution is to provide an in-depth analysis to observe the maritime network connectivity changes in Indonesia. Examining how the pandemic affects the Indonesian maritime transport networks is in imperative need for several reasons. First, Indonesia is an archipelago nation that heavily relies on a maritime transport network as the only bridge to connect an island with another [36]. Note that not all Indonesian regions, especially the small and underpopulated islands, have airport facilities. The observation of how the freight maritime shipping network changes due to COVID-19 can provide insight for policymakers to avoid the spike of national logistics cost across the nation caused by the absence of shipping services in particular regions. Second, the analysis of how shipping network changes can also help policymakers identify adaptive reactions that the shipping liners have used to respond to the pandemic period. The insights may create opportunities, especially in policy guidance, to speed up the supply chain recovery to accelerate economic growth. We expect our findings can be insightful for Indonesia's transport authorities when formulating specific freight transport policies to enhance the resilience of maritime freight shipping networks.

3 RESEARCH DESIGN

To generate insight into how COVID-19 changes the maritime shipping connectivity, we formed the Indonesia maritime shipping network as a connected graph that adopts the notations used in graph theory [37]. Then we analyzed its topological properties with complex network analysis. In this study, Indonesia maritime freight shipping network is defined as a graph $G = (V, E)$ with a set of vertices (V) and edges (E). Vertices or nodes represent a port, while edges indicate a cargo shipping connection between a pair of ports.

As the first step in constructing the directed graph, we prepared an adjacency matrix with $V = 25$ main Indonesian ports, according to the port hierarchy classification by the Indonesian central bureau of statistics (BPS). We extracted and calculated vessel traffic volume to a matrix (A). The value of the adjacency matrix A_{ij} denotes the total times a vessel traveled from i to j, while the value A_{ji} implies the sum of voyages from nodes j to i. An edge exists along the line between the two nodes i and j if its value is more than 0. For each edge that existed in the network from port i to j, we assigned a weight w_{ij} equal to how many vessels have traveled from port i to j. If the cargo vessels are traveling more than once from port i to j, its frequency contributes multiple times to w_{ij}. We also visualize each link shipping capacity by multiplying vessel traveling frequency and deadweight tonnes (DWT). Then, the shipping capacity is showing by a colormap in the graph. This section details how we collect data to construct the network model. We also explain the quantitative metrics we used to conduct the maritime shipping network analysis.

3.1 Data sources

The precise analysis of maritime shipping traffic demands the accurate trajectory of ship movements, consisting of ships' departure and arrival times at their port of call. Since 2001, ports and vessels have installed the Automatic Identification System (AIS) equipment that provides real-time vessel movement tracking capability. We utilize AIS as the primary source to obtain ship movement data because the data are objective, accurate, reliable, and collected continuously throughout ports worldwide. The AIS data for this study was obtained from MarineTraffic (http://marinetraffic.com), an online ship tracking data provider.

In total, our dataset covers cargo shipping services of 1,283 cargo vessels linking 25 main Indonesian ports. Our dataset covers 769 general cargo, 222 containerships, 111 dry bulk, and 181 liquid bulk vessels movement from January 2019 to December 2020. Note that we exclude all passenger ships in this study. We extracted the port call records for each vessel from AIS for two periods, the whole full year of 2019 representing the pre-COVID19 period and 2020 representing the network performance under COVID-19 outbreaks. Those records contain the departure and arrival time log of Indonesian cargo vessels in 2019 and 2020. For each cargo vessel, we analyzed the historical trajectory from AIS records. In total, we obtained more than 6,000 port call entries that connect 370 port pairs in the 2019 - 2020 period. We also referred to data records from the Indonesian government official, such as Indonesia sea transportation statistics and inter-regional trade data in 2019. We also referred to a list of registered vessels from the Ministry of Transportation to crosscheck the data we obtained for AIS. However, we have not yet retrieved the official statistics data for 2020, which means we only rely on AIS data for that period.

3.2 Complex network analysis approach

Our analysis investigates the structural change of the Indonesian maritime shipping network using a complex network science approach. According to Newman [38], complex network analysis is an approach to analyze network complexity in the form of mathematical graph theory, which is one of the essential pillars of discrete mathematics. Complex network analysis is a suitable approach to describe the network structure and see the relationship between different elements in terms of nodes and edges [38]. Table 1 presents several essential metrics we used to quantify network connectivity features before and after the COVID-19 pandemic outbreak in this study.

There are several reasons why we chose the selected metrics, as shown in table 1. First, we selected the metrics because of their accurate features to point out the connectivity of the network elements, which become the primary purpose of this analysis. Second, those metrics have been successfully implemented to describe a large-scale real-world transportation network interconnectedness, as shown by Kaluza et al. [18] and Notteboom et al. [2] work. Third, the algorithm to execute the calculation for each metrics is publicly available, make it relatively quick to obtain. We did all metrics calculations and network visualizations by using the NetworkX package in the Python programming language. We present the result of the analysis and discuss the empirical finding in the following section.

4 RESULT AND EMPIRICAL FINDINGS

In this section, we investigate the impact of COVID-19 on the inter-island maritime transport network in Indonesia. The network size of this study is consists of 25 nodes and 370 links. We took two periods for comparison in 2019 and 2020 cargo vessel traffic we obtain from AIS. To further investigate the time series of changes in the Indonesian maritime transport network, Figure 1 reports the number of cargo vessel port calls in Indonesia for the last two years.

The port call showed slightly positive growth despite common seasonal and weekly variations until week-9 or early March. The significant reduction in early March 2020 is mainly caused by the reduced port calls in the leading international hub-port in Indonesia, such as Port of Jakarta, which suffered 5.13% or 53,000 TEUs throughput loss caused by the severe lockdown effect in China. Since the first half of April (week-13) 2020, the number of cargo vessel calls has been significantly dropped, with some typical weekly and national holiday variations. Towards the middle of May (after Eid Al-Fitr), it seems like the trend has been relatively stable again, following the port call trend in 2019 with a less negative percentage gap. In summary, these analyses show that the period of March until May 2020 caused significant port calls disruptions, driven by the decline of international shipping traffic that implements strict lockdown policies. For the rest of the year in 2020, there are no significant differences with the port call trends than in 2019. However, it is worth noting that although the trends did not change substantially, the number of port calls is not grow yet until the end of 2020.

Table 2 shows the percentage change of quantitative metrics used between the 2019 and 2020 periods. The betweenness centrality measures the fraction of the shortest path on which the port is positioned. Intuitively, the larger the betweenness centrality of a node has, the more likely shipping liners will travel through the node in their most efficient routes. We can see that the average betweenness in the networks increased significantly throughout the pandemics, which means that several ports rise as a transit for the shipping services to adapt to this pandemic efficiently. The assortative coefficient represents a node preference to attach to another node similar in some way (usually degree centrality). Here, we report the assortative coefficient change on Indonesia's maritime shipping network. A zero coefficient identifies the network as non-assortative, while positive values imply that it is more assortative. Based on our calculation, we found that the assortativity of the network increased. In addition, the average clustering coefficient or transitivity increased. The higher the coefficient means the higher probability that the adjacent nodes of a port are also connected. We analyze empirical shipping network patterns through network visualization on two selected years (2019 and 2020) to confirm these quantitative findings.

Figure 2 (a) and 2 (b) shows that the network structure changes from a classic "hub-and-spoke" structure to a more hybrid and steers towards a "multi-hub or hub-hub" connection system in the network. This finding explains the increase of average betweenness centrality in the network. Several ports, such as Port of Samarinda, Bitung, and Sorong, rise as a new transit hub and establishes more frequent connections in the network with other emerging hub ports as described by a significant increase of assortativity coefficient. This initial finding might be explained how the commercial shipping service companies adapt to COVID-19 pandemics and decide to serve short distance and more localized shipping services. Figure 2 (c) confirms that the commercial shipping services reduce the frequency of long-distance direct shipping service from Indonesia's western to Indonesia's eastern part. Figure 3 shows a significant

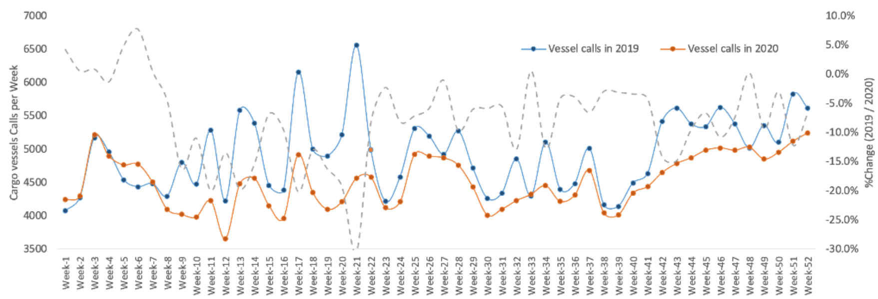

Figure 1: The trend of the cargo vessel calls per week in Indonesia during the 2019 and 2020 period

Table 1: Metrics used in this study to analyze the maritime network change due to the COVID-19 pandemic

Features	Metrics	Description	Symbol & Equation	Interpretation
Network structure connectivity	Average network degree	Mean value of the node degrees k (i), with i ∈ V(G)	$k = \frac{1}{n}\sum_{i=1}^{n} k(i)$	The average degree <k> expresses the average number of direct connections with neighbors that a node (a port in this case) has in the network
	Average betweenness	Mean value of the node betweenness centrality $C_B(i)$, with i ∈ V(G).	$C_B = \frac{1}{n}\sum_{i=1}^{n} C_B(i)$	The larger the betweenness centrality, the more like vessels use another port as a cargo transfer hub.
	Assortativity coefficient	Assortativiy measures the similarity of connections in the graph concerning the node degree	$\tau = \frac{M^{-1}\sum_i j_i k_i [M^{-1}\sum_i \frac{1}{2}(j_i+k_i)]^2}{M^{-1}\sum_i \frac{1}{2}(j_i^2+k_i^2)-[M^{-1}\sum_i \frac{1}{2}(j_i+k_i)]^2}$	The coefficient value of 1 shows a perfectly assortative network (more hub-hub or spoke-spoke connections) and 0 for a randomly mixed network.
	Average clustering coefficient	The clustering coefficient of node i, C_i expresses the number of triangles shaped by the node. The average clustering coefficient C_i represents the average value of all individuals C_i.	$C = \frac{1}{n} \cdot \sum_{v_i \in V} C_i$	A higher C_i value means the higher probability that the adjacent connection of a port is also connected.

decline in the capacity of long-distance direct shipping services from the western to the eastern part of Indonesia to transport cargo.

5 DISCUSSION AND CONCLUSION

Our study provides an initial step of empirical analysis on the impact of the COVID-19 pandemic on maritime freight transportation networks in a large-scale archipelago through a complex network perspective. We use a database with 6,000 port call history records of 1,285 Indonesian cargo ships from January 2019 to December 2020 from AIS to construct the maritime network. In this section, we summarize the significant findings of our study for a discussion.

Table 2: The comparison of the selected maritime transport network in Indonesia between 2019 and 2020

Indonesian maritime shipping network interconnectedness in 2019 and 2020				
Year/Metrics	Average network degree	Average betweenness	Assortativity coefficient	Average clustering coefficient
2019	4.091	0.085	0.081	0.275
2020	3.121	0.193	0.215	0.397
%Change	-31.7%	127%	165%	44%

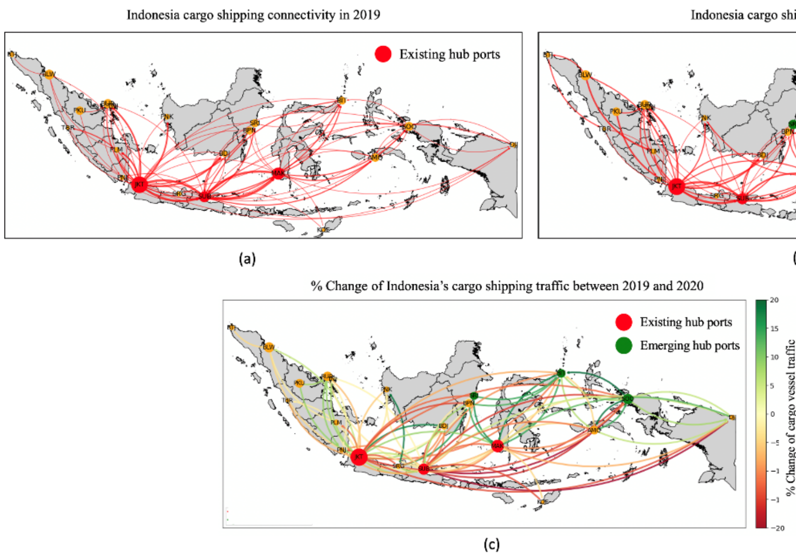

Figure 2: (a) and (b) show Indonesia's maritime freight transport network on two selected years before and during the COVID-19 pandemic. The weighted links represent the number of cargo vessels. (c) shows the percentage change of cargo vessel traffic between 2019 and 2020.

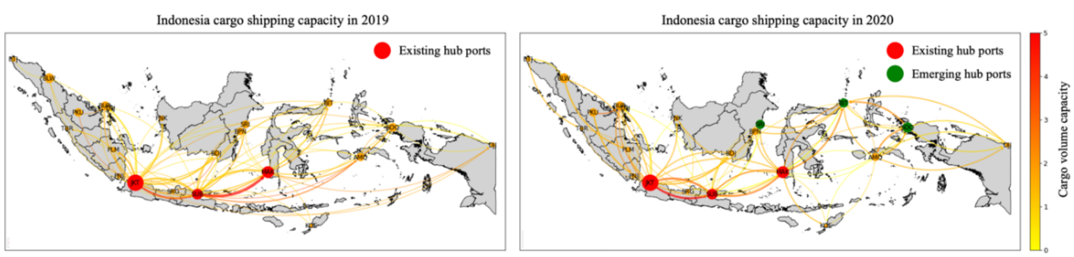

Figure 3: The percentage change of cargo shipping service capacity (vessel frequency times vessel DWT) in pre-and during COVID-19 pandemics

First, we observed from the Indonesian maritime shipping network that although there is no significant change in the national port calls history trend between 2019 and 2020, surprisingly, the freight network connectivity has been largely changed. The empirical finding based on four commonly-used connectivity metrics confirms this structural change of the network. Based on this finding, we suggest the impact of COVID-19 is not only be measured by using aggregate port calls indicator. Although the port calls can be used as a network performance indicator, stakeholders should further investigate the COVID-19 distributional effect to avoid a misleading conclusion.

Second, we found that the network structure changes from a classic "hub-and-spoke" structure to a more hybrid and steers towards a "multi-hub or hub-hub" connection system in the network, as shown in Figure 2 (a) and 2 (b). Those figures describe that commercial shipping services shift to serve more localized routes with shorter distances, especially in Indonesia's middle and eastern parts. Consequently, several ports in the central and east areas, such as

Samarinda, Bitung, and Sorong, emerge as a new regional hub in the network. The increasing value of assortativity coefficient, average betweenness centrality, and clustering coefficient support those findings.

Third, we also analyze the change of cargo shipping capacity between 25 Indonesian main cargo ports using historical data from AIS. Our finding shows that shipping volume capacities significantly reduced between central hub ports in the western region and the eastern region ports of Indonesia. The reason might be that during this COVID-19 pandemic, the imbalance of trade flow between the western and eastern part of Indonesia becomes higher as the consequences of international trade restrictions and strict PSBB-PPKM policy in Java island, which is the epicenter of the COVID-19 contagion in Indonesia. This condition makes several existing long-distance shipping routes are unprofitable and unattractive enough for commercial shipping services in Indonesia. Based on this finding, it is most likely that the most eastern part of Indonesia potentially suffer from higher logistics costs because the shipping capacity that connects the region directly with the western part of Indonesia is reduced significantly. This finding could become an early sign for Indonesian maritime transport authorities to strengthen the maritime connection and shipping capacity to transport cargo for Indonesia's eastern part to enhance the maritime network resilience during this pandemic period.

Although we believe this work can be an initial step towards a better understanding of the effect of COVID-19 on maritime network structure and its shipping capacity changes, it is challenging to state a single reason for this structural shifting. One possible explanation might be related to the shipping liner business adaptive strategy that should respond to change in inter-island trade due to different degrees of social restriction policies between regions. This phenomenon should be analyzed and explained further in future research using topological network analysis presented by Destyanto et al. [25]. Further studies can provide a comprehensive investigation between the change of maritime shipping network structure and various independent variables, including socio-demographics, land use, cargo vessel features in the regions, port characteristics, and the total cases of COVID-19 infections.

We recognize several limitations in this study. First, the study only includes the 25 main ports in Indonesia. Considering there are more than 400 seaports across the nation, it would be interesting to analyze the changes when including remote region ports. Second, we aggregate the analysis by accumulating all types of cargo vessels when constructing the network. It would be insightful for policy-making and business practitioners to analyze how the COVID-19 pandemics change the network structure based on the different cargo types, such as container, bulk, break-bulk, or liquid. Last, our research findings are regional-specific since we focus only on Indonesia as a case study. The verification for multiple cases is required to test the generalizability of the research findings.

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