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Exploring the topology of the maritime transport network in a large-scale archipelago: A complex network approach

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Abstract

In this study, we use a complex network analysis approach to investigate the topological structure of container shipping networks in the Indonesia archipelago to understand the network topology. Containerized cargo is responsible for more than half of the inter-island trade volume, making it one critical freight transport mode in the Indonesia archipelago. We summarize the network topological structure by measures such as degree distribution, average path length, and average clustering coefficient. Based on the initial result, we find that the degree distribution of the container shipping network in archipelago fits a hybrid distribution. The distribution proves the studied network is not scale-free. With regards to the network structure, the archipelago's shipping network exhibits a short path length and a low value of the clustering coefficient, potentially rejecting the small-world structure hypothesis. These initial findings provide evidence that the maritime shipping network in a large-scale archipelago shows a distinctive pattern compared to other maritime shipping networks in the existing literature.

Keywords: maritime shipping network, complex network, large-scale archipelago, network topology, Indonesia

1. Introduction

The maritime transport network is the backbone of both international and domestic seaborne trade, which shapes global economic growth. According to the statistics from the United Nations (2018), global seaborne trade continuously expands at 4 percent annually with total trade volumes reaching 10.7 billion tons in 2018. Overall, seaborne transportation carries 70 percent of the value and around 80 percent of the global trade volume. Container shipping has a significant role in shaping the network, as 70% of total seaborne trade volume is being moved in containers. From this perspective, Hu & Zhu (2009) argues that container shipping networks are the backbone of maritime transport for freight movement, thus improving its quality can remove global and regional trade barriers to accelerate economic growth (Veenstra, 2015).

Container shipping networks consist of various elements that form a complex transport network system. Multiple elements contribute to defining the container shipping network: seaports as nodes, container shipping services as links, the volume of goods transferred as flows, and the organization of container transport chains as interconnected shipping corridors (Rodrigue, 2020). The complexity of networks, which provide inevitable challenges for transport authorities to design them efficiently, contributes to increasingly long time delays and high maritime logistics costs in container shipping line

operations (Yercan & Yildiz, 2012).

As the increasing demand of container shipping creates a growth in the network load, scholars and transport analysts should find a way to obtain an accurate overview of the network complexity, which later allows them to address specific transport-policy problems in the network. Watts & Strogatz (1998) suggest the identification of network topology as a starting point to understand a complex real-world network. A notable work by Strogatz (2001) found that different network topology could affect particular network functions and performance, which implies the importance of network topology identification in transport systems.

Previous studies showed great efforts have been devoted to empirically find containership network topology in the maritime transportation system. Peng et al. (2018), Li et al. (2015), Ducruet & Notteboom (2012), Kaluza et al. (2010), and Hu & Zhu (2009) unveiled the topology of global containership network to achieve an understanding of global trade patterns and ports hierarchical structure worldwide. The works by Liu, Wang, & Zhang (2018) and Fraser et al. (2016) analyzed the network topology of regional containership networks in Asia and Southern Africa to analyze the topological evolution and its functional position in the global maritime network. On a national level, we found that the topological analysis of container shipping networks is dominated by studies on maritime transport in China (Changhai, Shenping, Fancun, & Shaoyong, 2020; B. Hu & Zong, 2013).

This article investigates for the first time, according to the best of our knowledge, a national-level topological analysis in a large-scale archipelago. In this study, we used empirical data from Indonesia which is a large-size archipelago with six main islands and 17,508 small-islands divided into 34 administrative provinces. Indonesia is heavily dependent on maritime transport network since up to 89% of its domestic trade is carried out by seaborne transportation (Hanafi, 2018). Besides, Indonesia has more than 10,043 national vessels, 1,415 routes, and 191 connected ports that form the complex containership network, of which a simplified illustration is shown in Figure 1.

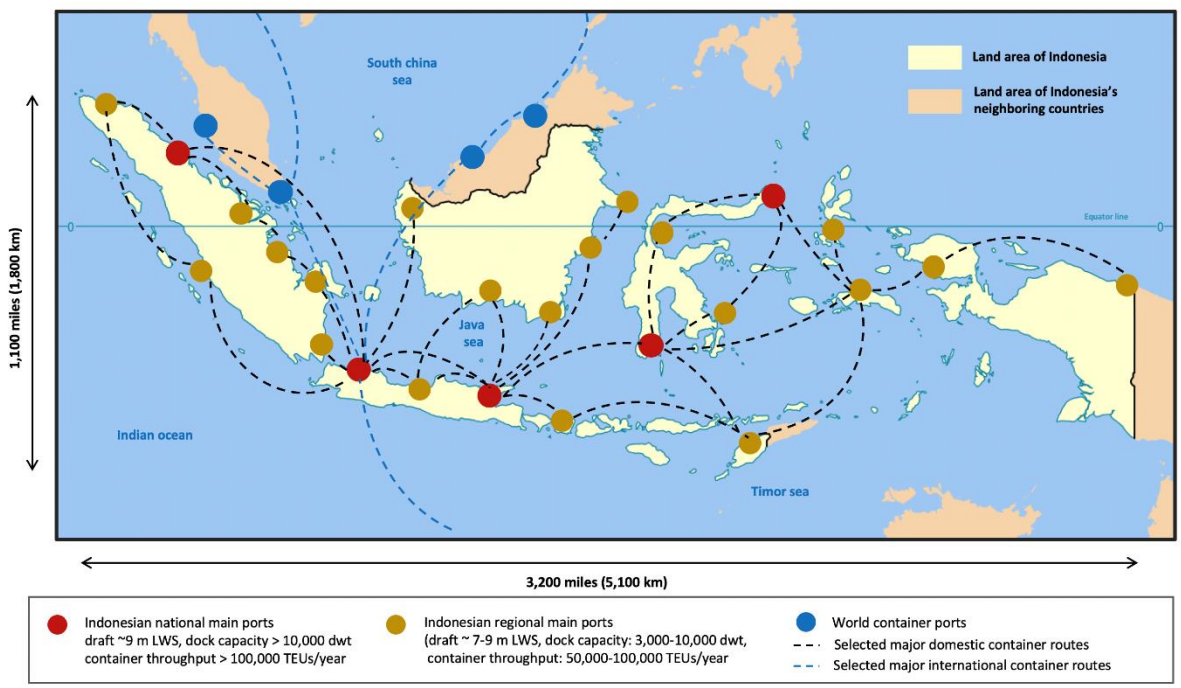

Figure 1. A simplified illustration of the Indonesia container shipping network. Note this illustrates less than 5% of total routes in reality

This study aims to unveil the network topology of a large-scale archipelago country. A comprehensive topological analysis of a large-scale archipelago using complex network analysis is presented to enrich the existing literature, which mainly focuses on global or multi-national scale network analysis. We expect that the result of our study could provide insight for related transport authorities to identify what kind of network topology exists in a large-scale archipelago maritime network and use the given information to address more specific transport-policy problems.

2. Literature review

Network topological analysis has emerged as a research topic in maritime transport since the advances in network theory and computational capabilities in the mid-2000s. The advances of network theory allow scholars and transport analysts to measure some basic topological properties, such as the average path length, clustering coefficient, and degree distribution of a

complex network (Newman, 2003). As the further step of basic properties analysis, scholars are interested in comparing the topological properties with theoretical models that can be useful to identify the real-world network structure.

Some theoretical models in network theory, such as random, scale-free, small-world, and broad-scale models, were found to be particularly relevant in explaining the topological properties of transport system structure. In random networks, a new link between any pair of nodes occurs randomly with an equal probability (Erdös & Rényi, 1959). A scale-free network has a degree distribution that follows a power law, which implies the high-degree nodes in a network connect preferentially with other nodes with high-degree properties (Barabási & Albert, 1999). Small-world networks are densely connected in local regions, generally exhibiting a small path length and high clustering coefficient value (Watts & Strogatz, 1998). Last, broad-scale networks are characterized by the power-law degree distribution covering some limited nodes, followed by a sharp cutoff for the others (Amaral, Scala, Barthelemy, & Stanley, 2000).

Previous research often mentioned that scale-free and small-world models are fit to describe real-world maritime networks. Peng et al. (2018) stated that the scale-free characteristics exist in the global container shipping network, supporting the works by Li et al. (2015) and Ducruet & Notteboom (2012). Liu et al. (2018) described the maritime network communities in Asia, Europe, North America, and Africa belong to a scale-free network class, while South America and Oceania networks belong to small-world networks. Another topological study in East-west container shipping corridor, which connects North America, Europe, and East Asia, confirms that the studied network is scale-free (Tran & Haasis, 2014). Scale-free properties also can be found in the China shipping network (Hu & Zong, 2013). The work by Tsiotas & Polyzos (2015), who analyzed the topology of the Greek maritime network (GMN), is the only study on archipelago maritime networks using a complex network approach and it confirms that the Greek maritime network exhibits scale-free properties.

In this study, we focus on network analysis of Indonesia as an opportunity to capture and understand the maritime network characteristics in a large-scale archipelago. As a large-scale archipelago country, Indonesia's total area is about 9.8 million square kilometers, of which 1.9 million square kilometers consist of land areas that scattered into more than 17,508 islands, and the rest are sea territory. As a consequence of its heavily fragmented land, Indonesia has considerable challenges of removing trade barriers between islands. Hence, the container shipping network plays critical roles as a primary freight transport mode to facilitate inter-regional trade, in which absence of transportation could isolate particular islands in the network (Tu, Adiputranto, Fu, & Li, 2018).

Given the scarcity of studies on maritime network topology in large-scale archipelagos, our main contributions are to provide an in-depth analysis to find its network topological patterns. Afterward, we compare its network properties with several network models in complex network theory to identify the similarities and differences to our network. Different from an earlier topological analysis of the archipelago network (Tsiotas & Polyzos, 2015) that utilized official statistics record to model the network topology, we extracted and analyzed the trajectories of individual containerships from the automatic identification system (AIS) data. Hence, we could identify Indonesia's containerships sailing schedules with a more accurate description of movements and therefore provide a better preparation for describing its complexity. The analysis based on the real containership trajectories is thus more informative to unveil the maritime network structure and to provide insightful knowledge for national policy decisions in transportation systems concerning the efficiency, stability, and growth of inter-regional trade.

3. Materials and Methods

We constructed the Indonesia container shipping network as a connected graph adopting the notations used in graph theory (Diestel, 2017) and analyzed its topological properties with complex network analysis (Newman, 2003). In this study, a complex container shipping network is a graph $G = (V, E)$ with a set of vertices (V) and edges (E). A vertex or node represents a container seaport where containerships are taking stops to load or unload its cargo, while an edge represents a connection that containerships travel directly between a pair of seaports. This section provides the details of how we collect data to construct the network model. In addition, we explain the analysis and introduce the quantitative indicators for measuring the network structure.

3.1. Data sources

Topological analysis of maritime network in archipelago required detailed knowledge of ship movements, which consist of ships' departure and arrival times at their port of calls. Since 2001, ports and vessels have installed the AIS equipment that provides the capability of real-time vessel movement tracking. The main aim of this technology installation is to avoid collisions between vessels and aid ports with improving their security. However, this technology opens the opportunity to advance maritime transport research by providing precise arrival and departure records for each registered ship.

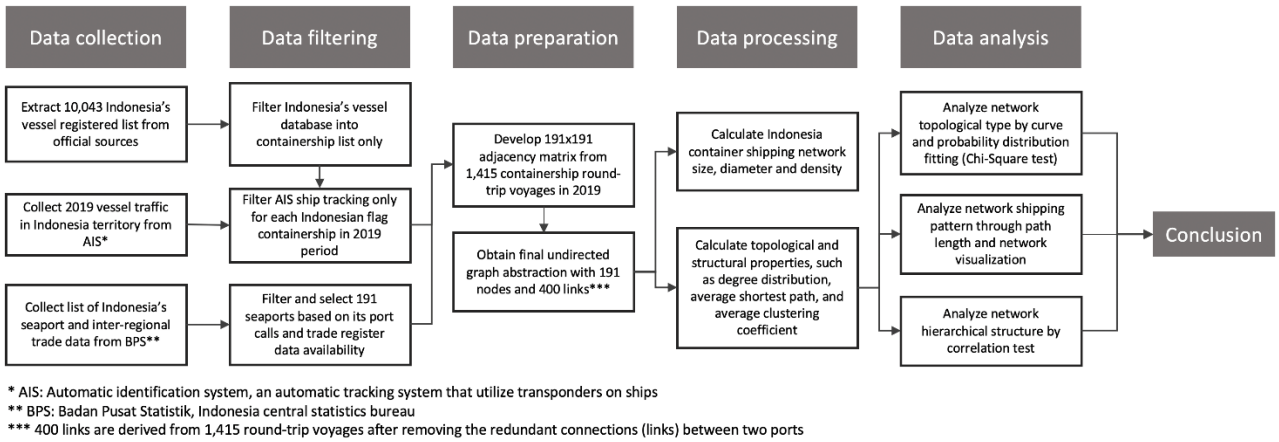

Figure 2. Workflow of the complex network analysis conducted in this study

In this study, we analyzed Indonesia's container shipping network based on Sea/Net, an online ship tracking system available online from Clarksons Research (www.clarksons.net), that records the departure and arrival time of the vessels in 2019. In addition, we also referred to data records from Indonesia government, such as Indonesia sea transportation statistics and inter-regional trade data (BPS, 2019b, 2019a), and a list of registered vessels from the Ministry of Transportation to crosscheck the validity of data we obtained from AIS.

We restricted our study to analyze the containerships under the Indonesian flag with a capacity between 100-6,000 twenty-foot equivalent units (TEUs) that make up 78% of the total capacity for cargo ship transport in Indonesia. From this filtering, we selected all 512 container vessels, taken as representatives of Indonesian container traffic, serving 191 ports within the network where AIS data are available. For each containership, we analyzed the trajectory from AIS records and found there were 1,415 round trip journeys linking 400 distinct pairs of ports. For each link from port i to j in the network, we assigned a weight w_{ij} equal to the sum of the containership capacity that has traveled on the link measured in TEUs. If the containership is sailing more than once from port i to j, its capacity contributes multiple times to w_{ij}. Note that we combined trajectories of three different types of containership services: domestic commercial, public service obligation, and international commercial service that connect Indonesia ports with other countries to obtain a high-level description of complete container shipping networks in a large-scale archipelago.

3.2. Complex network analysis approach

Complex network analysis is an approach to describe the network's topological structure by using global-level metrics and comparing its properties with general theoretical models (i.e., small-world and scale-free networks). In this paper, we use the definition of network topology as the arrangement and connectivity of network elements, consisting of nodes and links that provide an abstract representations of a complex transportation system (Zhang, Miller-Hooks, & Denny, 2015). The conceptual detail of complex network analysis procedure in this study is shown in Figure 2.

In this subsection, we present several essential indices that we used to quantify the network properties and the reasoning why we choose those metrics as the network assessment indicators. In general, we selected the metrics because of its powerful features to point out the network topology, yet relatively easy to compute. A study by Wang et al. (2011) showed how these metrics are helpful as a testbed when comparing a real-world model to a theoretical one; Therefore, the result can be used to uncover what type of topology a network has.

3.2.1. *Degree, average degree and degree distribution*

In complex network theory, a degree k_i represents the number of direct connections that a node i has with other nodes in the network. It is defined based on the sum of the values in either its respective row or column in the adjacency matrix. Note that when there is an edge from node i to j, the element a_{ij} in the matrix is expressed in:

$$k_i = \sum_{j \in V} a_{ij} \tag{1}$$

The degrees are straightforward indicators to distinguish the centrality level of a node, which becomes a fundamental concept for topological analysis as demonstrated in social networks (Freeman, 1977, 1978). Generally, the most central nodes must be the ports that provide a high number of direct shipping services to the other ports.

In the network-level assessment, we adopt the average degree $\langle k \rangle$ to express the average number of direct connections with neighbors that a node has in

the network, which can be expressed as:

$$\langle k \rangle = \frac{1}{n} \cdot \sum_{i=1}^{n} k_i \quad (2)$$

Following the degree and average degree calculation, we also enumerate the degree distribution to discover the degree heterogeneity of ports. Barabasi and Albert (1999) define degree distribution *P(k)* as a mathematical function expressing the occurrence probability of nodes in connection to a certain degree (n_k). Degree distribution is essential properties to unveil which theoretical models the real-network belongs to. For instance, the degree distribution of network with scale-free features should follow a power law, while the degree distribution in a classic random network exhibits Poisson distribution.

3.2.2. *Average path length*

The average path length $\langle L \rangle$ metric describes the mean value of all node-pairs shortest path in the network (Watts & Strogatz, 1998). This measure corresponds to the average path length of all available port pairs connection in the Indonesia container shipping network. This metrics is essential to investigate the efficiency of freight transport on the network by quantifying its scale of distance that this network could serve, written as:

$$\langle L \rangle = \frac{1}{n(n-1)/2} \cdot \sum_{i>j} d_{ij} \quad (3)$$

Where d_{ij} is the sum of steps along the shortest paths from all existing pairs of nodes. The analysis could be extended to find network diameter d, where d is the maximum value of all d_{ij}.

3.2.3. *Clustering coefficient*

The clustering coefficient of node i, C_i expresses the number of triangles shaped by the node. This coefficient implies the portion of actual links between the nodes within its neighborhood divided by the maximum possible edges between them (Latapy, 2008; Watts & Strogatz, 1998), written as:

$$C_i = \frac{E_i}{k_i(k_i-1)/2} \quad (4)$$

In the context of maritime shipping networks, the clustering coefficient is a fundamental metric to quantify the local connectivity around a port as it points out the intensity of triangles around a node. A higher C_i value means that the port has more connections within its neighbors, which means that the nodes are more likely to reach one another within short transfers. For network-level measurement, we use the average clustering coefficient $\langle C \rangle$, which expresses the average value of all individual C_i's, presented as:

$$\langle C \rangle = \frac{1}{n} \cdot \sum_{v_i \in V} C_i \quad (5)$$

4. Results and Discussion

4.1. Descriptive analysis of the network

In general, the Indonesia container shipping network consists of 191 commercial ports where 400 pairs of ports are connected with containership services. Table 1 summarizes the overview of the Indonesia container shipping network, including its network size and some basic topological properties.

The shipping network has a maximum node degree $k_{max}(G)$ = 91 that belongs to the Port of Tanjung Perak in Surabaya, making it the most central port in Indonesia's domestic seaborne trade. Another high degree node is the Port of Tanjung Priok in Jakarta with a degree value of 84. This port is a central transshipment hub for international trade. The minimum degree found in this network is $k_{min}(G)$ = 1, implying the existence of lateral ports in remote regions, which has a single direct link to another port. This single link can be considered as a critical link, in which the absence of it could isolate the node from trade connection to other regions.

Table 1. Topological properties of the Indonesia container shipping network

Metric	Indonesia container network (2019)
Network Size	
No. nodes (n)	13
No. edges (m)	400
Max. degree (k_{max})	91 (Port of Surabaya)
Min. degree (k_{min})	1
Average degree $\langle k \rangle$	2.094
Graph density	0.068
Topological properties	
Average clustering coefficient $\langle C \rangle$	0.193
Average path length $\langle L \rangle$	2.943
Modularity	0.314
Degree distribution $P(k)$ fit	Exponentially truncated power-law
Degree distribution class	Broad-scale network

The average node degree $\langle k \rangle$ of the Indonesia container shipping network is 2.094, which means the average number of direct links between a pair of ports is approximately 2 for each node in the network. In comparison with the network's highest degree value ($k_{max} = 91$), the low average degree score provides evidence of extreme degree heterogeneity in the network. This low score of average degree contributes to a low graph density score of 0.068. This finding means the extremely low proportion of all possible connections in the network. The rest of Table 1 shows the quantitative topological properties, which we

discuss in more detail in the following subsection.

4.2. Topological analysis of the network

This subsection mainly discusses the topological properties of the Indonesia shipping network to recognize its pattern and draw a conclusion about its structure. The type of network topology is derived from its degree distribution $P(k)$, average path length $\langle L \rangle$ and average cluster coefficient $\langle C \rangle$.

4.2.1. Broad-scale network characteristics

The degree distribution is an important metric in network analysis once we have obtained a degree for all nodes because it is useful to understand how these measures are distributed across the network. In the context of maritime shipping networks, the degree distribution allows us to determine whether our network contains hub and lateral ports, thus providing understanding in the potential influence that this port structure has on the maritime network function and performance. Once identified, the degree distribution can be compared to theoretical network models available in the literature to find out its theoretical explanation about network growth mechanism processes that have shaped the existing network topology.

At first, the degree distribution of Indonesia container shipping network exhibits a right-skewed degree distribution and seems to follow the power-law distribution $P(k) \sim k^{-\gamma}$, as shown in Figure 3, with power-law parameter $\gamma = 1.055$ and coefficient of determination $R^2 = 0.894$. Note that we cannot directly conclude that the network is scale-free, as the network should retain the power-law parameter to $2 < \gamma < 3$ (Barabási, 2009; Barabási & Albert, 1999; Broido & Clauset, 2019). To obtain further evidence of power-law fitness, we plot the corresponding cumulative distribution functions on logarithmic scales. As shown in Figure 4, the degree distribution of the Indonesia container shipping network does not appear as a straight line on logarithmic axes, while true scale-free networks demonstrate consistent scaling behavior across all scales.

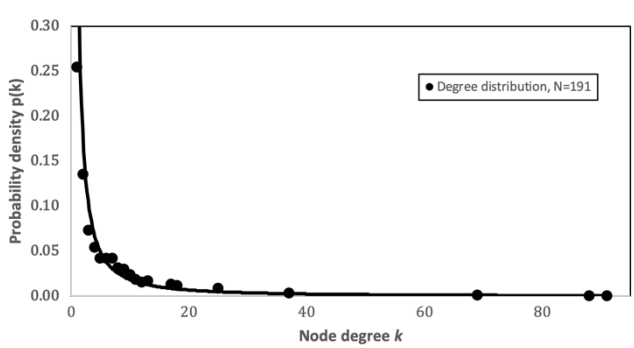

Figure 3. Degree distribution in the Indonesia container shipping network is right-skewed, with the 'thin' tail of distribution corresponding to a very low probability of finding high degree nodes in the network.

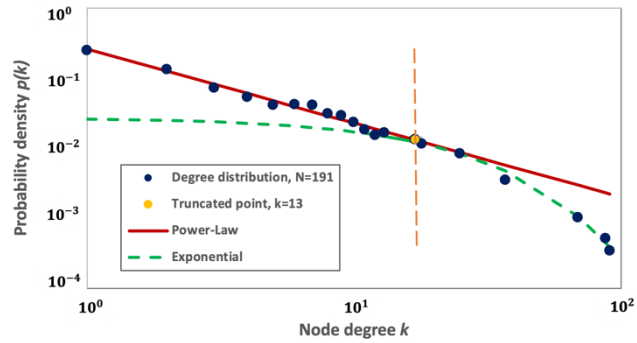

Figure 4. Degree distribution in the Indonesia container shipping network plotted on logarithmic axes appears as power-law fit over a limited range of degree, before showing an exponential decay above the cutoff value.

Table 2. Result of Chi-Square goodness of fit test for the degree distribution of container shipping networks in Indonesia

Distribution	$P(k)$	$k \leq 13$	$k > 13$
		p-value	p-value
Power-law	$P(k) = 0.4648k^{-1.398}$	0.875	0.001
Exponential	$P(k) = 0.0569e^{-0.059k}$	0.000	0.843

In addition, we conducted the Chi-Square goodness of fit test to compare the observed degree distribution with the expected theoretical distribution, as the determination of power-law characteristics through curve fitting has been criticized (Broido & Clauset, 2019; Newman, 2003). The statistical test result, as shown in Table 2, points out that for the degree below around 13 $(k \leq 13)$, the power law distribution is a good fit on the network with $\gamma = 1.398$ and a p-value of 0.875, which means we cannot reject the null hypothesis. However, for the degree distribution above around 13 $(k > 13)$, the $P(k)$ better fits the exponential than power law distribution with p-values of 0.843 and 0.001 respectively. This finding provides us with insight that the Indonesia container shipping network follows an exponentially truncated power-law degree distribution, which is different to right-skewed degree distributions in scale-free networks. Rather than scale-free, we conclude that the maritime shipping network in the archipelago belongs to a broad-scale network.

This finding is interesting because it points out that the maritime structure in a large-scale archipelago is different from the global-scale maritime networks which are often scale-free (Hu & Zong, 2013; Peng et al., 2018). In the international and global maritime networks, the volume of trade flows is often higher and growing faster than the trade flow of national network. This fact encourages strategic international ports in each country to evolve sometimes faster than the economic growth rates of their countries to induce economies of scale in global trade markets.

In contrast, the evolution of national maritime networks seems to be more endogenously ruled, depends on the agenda of national transportation and economic policies. The policies reflect the strategy of national transport authorities to deal with external constraints in expanding national maritime networks. Intuitively, transport authorities prioritize the development of existing strategic international seaports to maximize the network economies of scale in the international market rather than developing new regional domestic hubs in the underdeveloped area, which also forces the authorities to spend budget on physical infrastructure in hinterland's transport and industrial development. Hence, we can find in the world maritime network that the probability of finding a node with a high degree is higher compared to the maritime networks in the archipelago.

Comparing our broad-scale network findings to those reported for another topological analysis in the GMN archipelago (Tsiotas & Polyzos, 2015), the latter shows interesting similarities in its topological properties with the result we found. For instance, GMN has $\gamma = 1.745$ and the power-law fitting curve does not follow a perfect straight line in a logarithmic scale plot. By obeying the strict rules of scale-free properties as explained in Broido & Clauset (2019) and through the network analysis procedure we did, we conjecture that the degree distribution of GMN can be broad-scale rather than scale-free.

Last, our findings confirm a recent study that concludes scale-free structures are rare in real-world networks (Broido & Clauset, 2019). This finding implication reinforces the need for a new network formation model that can generate a broad-scale structure for the maritime network model in the archipelago with similar degree distribution and its topological properties.

4.2.2. *Small-world properties*

According to Watts and Strogatz (1998), small-world networks are a class of networks that are "highly clustered, like regular lattices, yet have small characteristic path lengths, like random graphs." In general, the characteristics of real-world networks that exhibit this network class has efficient information transfer between their nodes and has strong connections in its network communities. The standard quantitative measures are calculating average path length and average clustering coefficient to unveil the small-world properties in the network.

We calculated the average path length of the Indonesia container shipping network based on Equation (3). The average path length $\langle L \rangle$ of the Indonesia container shipping network is 2.9, or nearly 3. This number describes the travel of container cargo within a given network by 2-4 steps, which below the largest small-world 'six degrees of separation' between any Indonesia's port origins and destinations. We generated a random network with the same size and found the average shortest path of our network is larger than a random network $\langle L_{rand} \rangle = 2.2126$. However, the ratio between $\langle L \rangle$ and $\langle L_{rand} \rangle$ indicates a value close to one, implies $\langle L \rangle \approx \langle L_{rand} \rangle$. This means the network has a small number of average shortest path similar to the properties of the random graph as expected in small-world networks.

The average clustering coefficient $\langle C \rangle$ of the Indonesia container shipping network is close to 0.2. This value is much larger compared to the average clustering coefficient value from the same size random network $\langle C_{rand} \rangle = 0.078$. However, Telesford et al. (2011) argues that comparing network clustering coefficient to that random network can result in anomalous findings and that networks once thought to exhibit small-world network properties might be not, because almost all of the real-world networks have higher value of $\langle C \rangle$ when comparing to the similar size of $\langle C_{rand} \rangle$ although that networks have a very low clustering score.

We adopted the suggestion proposed by Telesford et al. (2011) to compare the value of $\langle C \rangle$ with the similar size of the lattice network. The clustering coefficient of similar lattice network to our size is $\langle C_{latt} \rangle = 0.72$. We found the $\langle C \rangle$ value of the Indonesian network relatively small compared to $\langle C_{latt} \rangle$. This implies the weak cohesiveness on the network resulting in the low presence of modular structures. Additional interpretation can involve the notion of network community structure resilience. For instance, the value of $\langle C \rangle \approx \langle C_{latt} \rangle$ implies a well-interconnected community: when a port X is connected to ports Y and Z, it is highly possible that there is also a link from Y to Z. In contrast, $\langle C \rangle \ll \langle C_{latt} \rangle$ indicates a higher risk of local trip isolation in case of disruptions, as the ports in communities are disconnected. According to the original description of small-world network characteristics pointed out by Watts and Strogatz (1998), the real-networks are considered small-world if the value of $\langle L \rangle \approx \langle L_{rand} \rangle$ and $\langle C \rangle \approx \langle C_{latt} \rangle$. Based on this finding, we conclude that the container shipping network in Indonesia does not fully exhibit small-world properties, since the values we found are $\langle L \rangle \approx \langle L_{rand} \rangle$ and $\langle C \rangle \ll \langle C_{latt} \rangle$.

This finding suggests future research on network topological analysis to compare $\langle C \rangle$ with $\langle C_{latt} \rangle$, instead of $\langle C_{rand} \rangle$. It is also worth to re-assess some previous claim on small-world network properties in the maritime transport network to avoid misclassification of the system that is not presenting short path length and high clustering coefficient into small-world networks class.

5. Conclusions

In this study, we analyzed the topological properties of the container shipping network in Indonesia, which represents the characteristics of a large-scale archipelago nation. We modeled the Indonesia container shipping network as a non-directed graph,

consisting of 191 nodes and 400 links, by using AIS data and complex network analysis to identify the network topology. Indonesia, the largest archipelagic state in the world, has a complex national container shipping network. Its unique geographical properties which make Indonesia highly dependent on maritime transport mode makes the investigation and documentation of its topological properties useful as a preparation for policy making.

Our first finding is the absence of a scale-free structure in the Indonesia shipping network, which is contrary to popular belief that scale-free structure is prevalent in the maritime shipping networks, including the archipelago, as we have seen in section 2. We found that the degree distribution of the network exhibits exponentially truncated power-law, which makes the network broad-scale rather than scale-free.

Second, we found that the network neither fully fits into the small-world networks category. The supporting evidence of small-world characteristics in our network is the short path length, which is below six steps and approximately similar to the value generated from the identical size of a random network. In contrast, the value of the average clustering coefficient restricts the network to be classified into small-world because the score is too low compared to the lattice graph with a similar size, which is not expected to exist in small-world networks.

For the modeling and simulation practitioner of the large-scale archipelago shipping network, identifying the network topology as demonstrated by this study could give some benefits. First, the network topology can be useful in the conceptual model evaluation process. The modeling and simulation approach employs the conceptual model as a foundation for modeling and simulation design. Modelers can adopt this type of topology as the system definition or basic network configuration for which the modeling and simulation application will be built. In this end, the empirical network topology could be used as the benchmark to verify and validate the model to increase its credibility.

Second, identifying the shipping network topology in the archipelago can encourage transportation modeling and simulation practitioners to investigate the role of this topology to the particular network performance. For instance, one can assess the influence of this type of topology and how it affects the connectivity vulnerability when disruption happens, such as unexpected events that subtract specific nodes or links. The result obtained from this kind of simulations can provide insight for network transportation planning, whether to retain or transform the topology into another one that can more fit to achieve specific policy objectives.

The limitation of our study lies in the data completeness, especially the data obtained from AIS. AIS devices have not been installed in all containerships in Indonesia, although all major Indonesia ports and the majority of containerships are included in this study. In detail, there are 67 other Indonesia's pioneer containerships, which 32 ships are state-owned and 35 ships are private, which excluded from the analysis because of the limitation of the AIS tracking feature in those ships. Future research can address other container and cargo ships not registered by AIS, especially for shipping network in remote regions of Indonesia to obtain a complete high-level understanding of the maritime transport network in a large-scale archipelago.

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