The vulnerability of the global container shipping network to targeted link disruption.☆

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Abstract

Using complex network theory to describe the relational geography of maritime networks has provided great insights regarding their hierarchy and evolution over the past two decades. Unlike applications in other transport fields, notably air transport, complex network theory has had limited application in studying the vulnerability of maritime networks. This study uses targeted link disruption to investigate the strategy specific vulnerability of the network. Although nodal infrastructure such as ports can render a network vulnerable as a result of labour strikes, trade embargoes or natural disasters, it is the shipping lines connecting the ports that are more probably disrupted, either from within the industry, or outside. In this paper we apply and evaluate two link-based disruption strategies on the global container shipping network, one based on link betweenness, and the other on link salience, to emulate the impact of large-scale service reconfiguration affecting priority links. The results show that the network is by and large robust to such reconfiguration. Meanwhile the flexibility of the network is reduced by both strategies, but to a greater degree by betweenness, resulting in a reduction of transshipment and dynamic rerouting potential amongst the busiest port regions. The results further show that the salience strategy is highly effective in reducing the commonality of shortest path sets, thereby diminishing opportunities for freight consolidation and scale economies.

Keywords: salience, betweenness, vulnerability, maritime, complex networks

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1. Introduction

Since the 1970s, container shipping has been to the maritime industry what the printing press was to literacy [33]. The past two decades have been witness to great and rapid changes in container shipping fuelled on the one hand by changing global trade patterns and on the other by greater industry competition, vessel and equipment advances and port development. Ducruet and Notteboom [20] comment, in their analysis of the container shipping network between 1996 and 2006, that the consequent shifts in port hierarchies and liner service configuration have had a distinct impact in changing the geography of the network. To firmly grasp this dynamic geography requires modelling approaches that move beyond the traditional practice of using traffic intensity,

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economic profitability or proximity to define port hierarchy, port choice and vulnerability. The importance and roles of ports are determined more by their relational position in the network than throughput and should be integral to any approach in studying the network's vulnerability [26].

A number of studies have embraced complex network theory as an appropriate approach to capturing the relational complexity of the maritime network [5, 17–21, 29, 43]. Ducruet et al. [19] compare maritime degree and betweenness centrality with the traditional measure of throughput to show that in the case of Northeast Asian ports, indicators of centrality, connectivity and vulnerability (network dynamics) do far more to describe the role of ports than the traffic statistics previously used to define port hierarchies. In the same year, another study by Ducruet et al. [21] tackled the concept of topology, showing that complex network models, specifically scale-free and small-world topologies, are far more valid representations of port geography and maritime communities than the typical concepts of port systems and geographic proximity. In the words of Caschili and Medda [8], the maritime container network is a "Complex System composed of relatively independent parts that constantly search, learn and adapt to their environment, while their mutual interactions shape obscure but recognizable patterns". It thus deserves a modelling approach like complex network theory that brings to the fore the emergent phenomena resulting from interactions between individuals.

The global air transport network is another example where the application of complex network theory has greatly advanced the understanding of network dynamics and has promoted the study of vulnerability [34–37, 42]. Maritime and air transport networks are parallel in many ways. Functionally, these are two *global* transportation networks where linkages between nodes are primarily determined by competitive, yet internationally regulated, service design. Theoretically, the network representations of these models are similar and, topologically, these networks both present characteristic hub-and-spoke structures (hub networks) which result in very similar complex network characteristics. Most relevant to this study is that both of these networks have a rippling global impact when disrupted. Given its direct impact to human safety and convenience, complex network applications in air transport moved more rapidly beyond static descriptions of network characteristics to the study of network vulnerability. Maritime applications, on the other hand, have focussed mainly on characterising the current network or studying the evolutionary influences that have moulded shipping over the past decades [18]. Maritime vulnerability has not been assessed using complex network metrics until the work of Ducruet [18] investigated the vulnerability of the global container shipping network to the removal of the Panama and Suez Canals. Other contributions to maritime vulnerability often focus on the macro-economic impacts of port shutdowns [48] or the cost, trade or security impacts of international regulation [44] – approaches that either underplay or ignore the influence of and impact on the network as a whole. Global trade depends greatly on the maritime network, therefore a better understanding of its vulnerability is of great value to those who require it (cargo owners, logistics service providers), those who enable and shape it (shipping lines, port authorities) and those who regulate it (policy makers, regulators and governments).

This paper expands the grasp on the vulnerability of the maritime network by using a complex network approach to simulate and assess network disruption in global container shipping. Specifically, we aim to establish how the overall *robustness* and *flexibility* of the network is impacted when a significant number of the network links are removed. Traditionally, vulnerability studies on complex networks concentrate on the removal of nodes but in this case, studying the removal of links would be far more telling. Node removal would imply that an entire port is shut down.

Although this is possible, as recently proven by the explosion that temporarily shut down two container terminals at the port of Tianjin, China [6, 31] and labour-related slowdowns that periodically choked freight flow through US West Coast ports in 2014 and 2015 [16, 40], it is far less prevalent than the changing service configurations that remove and add links on a monthly basis [14–16]. Understanding the network's vulnerability to the ongoing volatility of the market as opposed to its vulnerability to large-scale disasters that affect one or a limited number of ports requires a link-centric disruption approach.

In complex network theory, the concept of disruption was initially divided into random errors and targeted attacks. The former refers to the random removal of nodes or links whereas the latter assumes intelligent design that prioritises the removal of nodes or links to cause the maximal damage [1]. It was found that scale-free networks are far more vulnerable to targeted attack as the hubs (most central nodes) or highways (most influential links) are easily identified and, once removed, affect a great proportion of the network[1, 7, 10, 27]. Therefore, knowing that the global container shipping network is a hub network, which approximates a scale-free network, we use a targeted link disruption approach to study the network's vulnerability. (Note that in this study we refer to *targeted link disruption* and not targeted attack as the latter limits the interpretation to malicious attacks negating the reality of ongoing competitive changes in service configurations.)

Key to targeted link disruption is defining the mechanism whereby the most influential links can be identified for removal. To date, link betweenness has been the most prevalent mechanism, [46]. Counting the number of all shortest paths that a specific link features on, link betweenness intuitively prioritises links in the barycenter of the network. More recently, in the study of the core-periphery structures of complex networks [13, 47, 58], scientists have developed new methods to extract what is termed the *skeleton* of a network [51]. A skeleton is a reduced subset of a network's links that still adequately represents key features. Link *salience*, as introduced by Grady et al. [25], is one metric used by Shekhtman et al. [51] to identify and extract network skeletons. This metric is subtly different from link betweenness in that it counts the number of shortest path *trees* that a link features on, and not the individual shortest paths. As a result, it doesn't necessarily favour the links in the barycenter, but rather those links that are relevant to most nodes in the network. Our study compares two targeted link disruption strategies, one using link betweenness and one using link salience.

A baseline network is created from the Lloyd's List Intelligence data set with ports representing the nodes in the network, and direct container vessel movements between ports representing the directed links. The weight of each link is the aggregate number of twenty-foot equivalent (TEU) container units shipped over the observed period. The two disruption strategies are applied iteratively for ten iterations, after which we evaluate the robustness and flexibility of the resulting networks.

The paper is structured as follows. The next section reviews the literature from four perspectives. The first perspective looks at the recent work on complex networks in the maritime domain, after which we discuss the volatile dynamics of global container shipping in the second perspective. This is useful as it highlights the need to better understand network vulnerability in response to disruptions from within and external to the industry. The third perspective discusses relevant developments in studies regarding the vulnerability of hub networks. Lastly, Section 2 is concluded with a mention of the recent work regarding core-periphery structures which led to the use of link salience as a metric for identifying critical links. Section 3 gives a detailed description of link betweenness and link salience. Section 4 describes the data used for building the complex network, and explains the disruption strategies. The results are presented and discussed in Section 5 before we conclude in Section 6.

2. Related work

We start the review with a more general introduction to complex network theory in the maritime context.

2.1. Applications of complex network theory in the maritime domain

Since 2009 researchers have applied complex network theory concepts to set a new standard for maritime analysis. A network approach views ports as the *nodes* (or *vertices*) of the network while *links* (or *edges*) are established by the movement of vessels between port pairs. The links are defined by the vessel activity and the *weight* of the link is determined by the magnitude of activity (most often measured in combined vessel capacity). Although complex network theory has been applied to other transport networks (road, rail and air) long before 2010, it was the evolvement of commercial ship movement databases, made possible through Automatic Identification System (AIS) technology, that finally made the analysis of the maritime networks an empirical reality [21]. A number of these empirical studies outline the data acquisition and processing methodologies, contributing towards the establishment of a standard methodology [19, 21, 29, 43].

A network view quantifies global maritime shipping in relational terms. The importance of a node can be expressed in terms of many centrality measures. *Degree centrality* measures the number and strength of a node's links to its immediate neighbours; *closeness centrality* expresses the average number of jumps between a node and all other nodes in the network; *eigenvector centrality* looks beyond a node's neighbours to the importance of its neighbours' neighbours; and *betweenness centrality* measures how often one would pass through a node while on the shortest path between two other nodes. Beyond centrality there are measures that characterise the community structure of the network such as connected components and clustering coefficients while motifs describe the nature of directed relationships amongst nodes.

In maritime applications, as in other transportation fields, how the real-life system is translated into a network representation influences the interpretation of the metrics that measure topological characteristics such as centrality, clustering and network diameter. Kurant and Thiran [32] define three representations in their analysis of public bus routes. Quite simply, the bus stations are the nodes, but defining the links is more tricky. In the **space-of-stations** representation two nodes are connected if there is a road linking them directly (i.e. there is no intermediate station). **Space-of-stops** considers two nodes linked if they are *consecutive* stops on a route. Once again it is a direct link with no intermediate stops. **Space-of-changes** considers two nodes linked if the same bus visits both on a route, thus there may or may not be intermediate stops. The latter two of these definitions are relevant to maritime shipping but due to the lack of physical infrastructure constraining the links, the **space-of-stations** representation is irrelevant.

The container shipping industry consists of *shippers* (businesses that own and operate container vessels) that deploy their vessels on regular *services* (a set schedule of sequenced port calls). Shippers may operate services on their own or may collaborate with other shippers in what is called an *alliance*. In a **space-of-stops** representation two ports would be directly linked if they are visited consecutively on a service. Effectively such an approach ignores the fact that two successive port calls are part of a larger service. In a **space-of-changes** representation two ports would be directly linked if they are both visited by the same vessel on a service, regardless of whether there were intermediate port calls. The primary objection to the first representation is that a more realistic representation of container movement must respect the journey of the container itself, which is not independent of a specific service. A counterargument would be that a container's journey seldom exactly aligns with the start and end of one service. The very nature of the network's hub-and-spoke design, the emergence of transshipment and the ability for containers to be loaded and off-loaded at any port call, implies that a container's journey aligns partially with multiple services [18]. To date there is no dataset that reports individual container movements for the global network. Thus, limited to the vessel movements reported by AIS technology reality lies somewhere between the two representations defined above [18].

Early on, two studies investigated the differences in network characteristics brought about by using the two different network representations. Ducruet et al. [21] termed the space-of-stops representation the **graph of direct linkages (GDL)** and the space-of-changes representation the **graph of all linkages (GAL)**. They found that the GDL representation more clearly illustrates the dominance of hub ports over secondary ports, approximating a scale-free network. The GAL network had five to six times greater density, connectivity and lattice degree approximating a small-world type network. This network more clearly illustrates connected maritime regions. These results imply that when studying a shipping line or alliance perspective of the global network, a GAL representation is more appropriate but when focussing on freight movement, GDL is more appropriate as most traffic occurs over short distances. In a similar study Hu and Zhu [28] name L-space as the space-of-stops representation and P-space as the space-of-changes. They present a more detailed study of a greater spread of network metrics but ultimately their findings coincide with those of Ducruet et al. [21]. The majority of complex network studies in the maritime field used the GDL representation, that is, ports are only linked through consecutive port calls.

Applications in the maritime sphere have focussed on exploring, characterising and interpreting the status quo of global networks. Some studies have tracked the network over time to identify the change drivers that have influenced the network and to interpret the causal relationships and practical implications of these drivers.

The formative papers of Ducruet et al. [19, 21] focus only on network concepts relating to degree and centrality, first to study the roles in the network of Northeast Asian ports and then to study the evolution of port roles and the impact of regional integration and the increase in global port competition in the Atlantic between 1996 and 2006. Both studies use a ship movement database from Lloyd's, extracting data relating to fully cellular container ships in 2006 and 1996.

Broadening the focus beyond centrality, Hu and Zhu [28] used data from CI-online for an unspecified time period to study a host of properties from shortest path length, weight distribution and degree distribution (topological features) to clustering and assortativity (hierarchical features) and centrality using two distinct representations (L-space and P-space) as previously discussed. Their networks were built from data from 434 shipping companies covering 878 ports.

Kaluza et al. [29] conducted a study that considered clustering coefficients, shortest paths and community motifs in addition to the concepts of degree and degree-based topology descriptions. Their study used arrival and departure records for 16 000+ cargo ships obtained from Sea-web for the 2007 calendar year and distinguished between dry bulk carriers, container ships and oil tankers. Their work shows that a network-based approach could be far more useful in the study and prediction of bioinvasion through maritime trade than the state-of-practice gravity models. Pais Montes et al. [43] build on these works investigating changes in the container and general cargo markets over three years from 2008 to 2010. Their study also uses ship movements from the

Lloyd's database and compares the two networks in terms of betweenness centrality, average path length, density, average clustering coefficient and degree-based topologies.

Once the initial groundwork of describing maritime networks in complex network terms was laid, researchers started incorporating this approach in multi-disciplinary studies, enhancing the practical impact of the work. An outstanding example of such impact is the Container Port Connectivity Index developed by Bartholdi et al. [5]. This index is a two-metric global port ranking index that uses the concept of eigenvector centrality and the transport economics reflected in United Nations Conference on Trade and Development's long-standing Liner Shipping Connectivity Index, to create a better classification of the roles that global ports play [5, 54]. Focussing more on trade flows, Ducruet [17] adds a commodity perspective to describe the diversity of maritime flows in the global network. The results show a strong influence of commodity types on the specialisation of maritime traffic at ports and on links. This direction of research is a first step in coupling the study of the global maritime network with the trade dynamics it serves.

Applying the complex network approach to understanding regional dynamics, Fraser et al. [22] investigate the peripherality of the Southern African port system to the global container shipping network. Although there has been significant development in port throughput and infrastructure development, they use measures of betweenness centrality and eccentricity, measured during three one-month periods in 1996, 2006 and 2011, to show that Southern Africa has indeed become more peripheral to the global network. In a study of similar purpose, Mohamed-Chérif and Ducruet [39] use global measures of betweenness centrality to complement a very thorough and extensive discussion of the development of the Maghreb port system and its role in the global container shipping network using, once again, 1996 and 2006 data.

To date only one study, that of Ducruet [18], investigated vulnerability by simulating network disruption. The author set out with a very specific research agenda: to determine the vulnerability of the global container shipping network to the removal of two specific nodes, the Panama and Suez canals. Using the same dataset from 1996 and 2006 as in previous studies, results converged to show a decreasing overall dependence on the canals in the light of growing south-south trade with Asia, North America and Europe still remaining the most dependent. According to the classification of Grubesic et al. [26], this study investigated scenario specific vulnerability whereas our study concentrates on strategy specific vulnerability to better understand overall vulnerability to potential flux in service configuration.

2.2. Volatility within global container shipping

The global maritime industry, and the container shipping industry in particular, has become increasingly more volatile in the past decade [14–16]. Drastic change in world trade patterns and uncertain (often overly optimistic) growth forecasts alongside the cut-throat chase for market share amongst shippers have resulted in a mismatch of demand and supply of container capacity. Shippers believe that to be competitive they need to stay ahead of the pack with ever-increasing vessel sizes despite the fact that there is not enough demand for shipping in the market to absorb the capacity. This has been an ongoing trend with no sign of respite in the near future as shippers place more orders for 19 000+ TEU vessels [16]. Drewry Maritime Research [15] believes that "so much water is being added to the bath that it will overflow at some time", and that time is soon. The physical restrictions of these new, larger vessels, the completion of the Panama and Suez Canal expansions and rapid port development in emerging economies are driving a fresh wave of change in service configurations and the competitive landscape.

This overcapacity presents shippers with the dilemma of an even more competitive market where freight rates are used as the primary mechanism to capture demand, squeezing margins from the shipper's books. Cost cutting and efficiency has become an imperative to survival in container shipping, spurring on a number of trends that have a decided impact on the global network. To absorb capacity and ensure a more balanced use of their assets, shippers are deliberately slowing down their vessels so that more vessels can be deployed on one service while maintaining the schedule of port calls. This is called *slow steaming* and while it was considered a drastic intervention a few years ago it is now common practice [14]. The other tool in the shipper's arsenal is the freedom to design their services in the most cost efficient way. Shippers may decide to discontinue a service due to profitability; port calls on a service may be changed in favour of port efficiencies or cargo volumes; or alliances may be formed (disbanded) to consolidate (target) specific market segments. Lately the practice of *void sailings* has also become common, where shippers simply "cancel" a scheduled vessel departure due to unprofitable circumstances [15].

All of these factors represent disruptions from *within* the industry. But outside factors also have the possibility to disrupt business in the maritime arena. Piracy is a growing concern. The risk of piracy around the Horn of Africa reached the point where shippers were willing to change well-established equatorial routes to avoid those waters. Recent security interventions have quelled the attacks in these waters but piracy is as rampant as ever, having shifted its business to the Singapore Strait and Strait of Malacca [30]. It remains to be seen if the threat will grow enough so as to divert vessels from this most prominent shipping highway. Suffice to say the future holds no dwindling of volatility in the global container industry, quite the opposite, in fact.

2.3. Vulnerability in hub networks

Representations of real-world hub networks such as the air transport and the maritime networks can be regarded as a mixture between scale-free and small-world topologies [21, 23, 28, 42]. Although various interpretations of scale-free networks have emerged [42], there is consensus around the foundational definition of Barabási and Albert [2] that scale-free networks have a few super nodes with a very high level of interconnectivity and the rest of the nodes very low interconnectivity so that the degree distribution of the network approximates a power-law function. This heterogenous connectivity renders scale-free networks extremely vulnerable to targeted disturbances [1, 3, 4, 7, 10, 27, 42, 49, 53]. Small-world networks, as originally defined by Watts and Strogatz [57], are large, sparse networks that do not have a particularly dominant node but rather clusters of nodes that are well-connected so that the average path length of the network is short. According to O'Kelly [42] hub network vulnerability lays not only in the hub nodes but also in the links that constitute the backbone of the network – a fact often overlooked in vulnerability studies.

In their study of supply chain networks, Thadakamalla et al. [52] neatly summarise four components of survivability frequently encountered in vulnerability studies. The *robustness* of the network relates to the size of the network's largest connected component (or giant component). If the size of the giant component does not diminish significantly then the overall connectedness is not affected, meaning that the basic functionality can be maintained [1, 7, 10, 23, 27, 49, 53]. A network's *responsiveness* (referred to by some as efficiency) is characterised by its average path length; the lower the length the more efficiently any one node in the network can communicate with another [12, 27, 53]. The *flexibility* of the network depends on the availability of alternative paths and good clustering, reflected by a high clustering coefficient. The fourth component mentioned is *adaptivity*, which is the ability of the network to quickly re-wire itself to re-establish the same level of functionality after attack.

In studying the vulnerability of complex networks, authors experiment with various targeted disruption strategies aimed at either removing nodes or links, although node removal is far more prevalent. A great variety of metrics have been used to identify the most important nodes for removal, but degree and betweenness remain the most prolific concepts [41, 56]. Nie et al. [41] and Lordan et al. [37] show examples of strategies that cleverly combine different metrics to create more effective disruption strategies. Link betweenness is the most commonly used metric when removing links, although Pu and Cui [46] give an example that uses another metric (longest path) to effectively disturb a network. Methods for extracting so-called skeletons from the core-periphery structures of real-world networks are also emerging [51]. There are many established and up-and-coming measures for determining priority nodes or links for targeted disruption, but Ghedini and Ribeiro [23] point out that real-life networks may be on the brink of fragmentation (and thus highly vulnerable) long before the removal of "important" nodes deals the final blow. Often it is the less important nodes that fragment the network, making the point that targeted disruption strategies should take into account the real-life characteristics and functionality of the network when testing vulnerability instead of being preoccupied with statistical properties alone.

Holme et al. [27] and Nie et al. [41] compared adaptive and non-adaptive strategies, proving that by recalculating the chosen metrics (in their cases degree and betweenness centrality), disruption strategies degrade networks far more rapidly. As a result, adaptive strategies are widely applied in vulnerability studies [35, 37, 49, 51, 56].

Dynamic rewiring of networks between disruptions has also been considered, but such studies always assume an overarching design mechanism that can pursue the objective to mitigate the negative impact of disruptions through intentional design [38, 49]. In reality, the maritime network and its response to change is the result of the decisions of many autonomous agents responding in real-time to uncertain and competitive market dynamics. While it may be insightful, from a theoretical point-of-view, to dynamically rewire the maritime network according to the global objective of mitigating damage, it is not useful to this study. Not enough is known about shippers and port authorities and how they make their decisions to quantify realistic rewiring responses at this stage. This is certainly an opportunity for future research.

Our approach uses an adaptive targeted link disruption strategy to investigate the *robustness* and *flexibility* of the global container shipping network. Although link betweenness is an effective metric to identify central links, recent work relating core-periphery structures in complex networks offer new metrics to identify link importance.

2.4. Using core-periphery concepts in vulnerability assessments

Most complex network analyses are on a local level (nodes and edges and their metrics) or on a global level (summary statistics). Studies regarding community detection are defined as intermediate level or meso-scale characteristics and have been very succesful in advancing understanding of complex network phenomena [47, 58]. Another meso-scale feature that has recently received more attention is the core-periphery structure of networks. Many networks exhibit this struture where the core comprises densely interconnected nodes surrounded by a sparser periphery of nodes that are connected to the core but not to each other [13, 47, 51, 58].

While core-periphery structures shed new light on the function of nodes in a network [58], identifying the subset of links, or skeleton, that upholds this structure also sheds new light on the function of links. Shekhtman et al. [51] present a first intersection of studies relating to core-periphery identification and vulnerability by investigating the robustness of network skeletons to three randomised disruption strategies. The authors use two methods to extract the skeleton: the disparity backbone of Serrano et al. [50], which is well-established and tested, and the salience skeleton of Grady et al. [25], which is more recent but holds great promise. In transportation networks skeletons carry the majority of the system's traffic. Based on the response of the two types of skeletons to randomised attack on a number of simulated and real-world networks, using information relating to skeletons could prove useful in targeted link disturbance strategies on transportation networks [51]. These findings led to the application of link salience in this paper.

3. Link betweenness and link salience

Link betweenness determines the fraction of all the shortest paths in the network that passes through a link, therefore favouring links in the barycenter of the network. Link salience is a consensus-based metric that determines the fraction of shortest path sets that a link features in, thereby capturing the general importance of a link to *all* nodes in a network. A link's importance to a specific reference node is determined by whether it features in that node's shortest path set or not. To calculate the salience of a link, consider a weighted network with N nodes. Such a network can be represented by an $N \times N$ weighted matrix, $\boldsymbol{W}$, where each element $w_{ij} \in \boldsymbol{W}$ and $w_{ij} > 0$ quantifies the coupling strength between nodes i and j. In this paper where we consider containerised movement of maritime vessels between ports, w_{ij} denotes the aggregated TEU capacity from port i to port j. We introduce *effective proximity*, denoted by reciprocal coupling $d_{ij} = \frac{1}{w_{ij}}$, as the notion that port pairs with a high level of vessel movement between them can be considered close to one another.

Between any two ports, (n_1, n_K) where n_1 denotes the origin port and n_K the destination port, we can calculate a path P that consists of $K-1$ legs via intermediate nodes n_i. All the nodes in the path should be connected, that is, $w_{n_i,n_{i+1}} > 0$. The shortest path between the two terminal nodes is the one that minimizes the total effective distance $l = \sum_{i=1}^{K-1} d_{n_i,n_{i+1}}$. As noted by Grady et al. [25], the shortest paths in heterogeneous networks with different weights are typically unique.

Each node, in turn, is considered a *reference node*, denoted by r, and the collection of shortest paths from the reference node to all other nodes are calculated. The collection is denoted by $T(r)$ and is represented by an $N \times N$ matrix where each element $t_{ij}(r) = 1$ if the link (i, j) is on at least one shortest path between the reference node r and any of the other nodes in the network, and zero otherwise. Once the set of shortest path matrices for all reference nodes are calculated, they are superposed linearly and the link salience, s_{ij} is calculated using (1).

$$s_{ij} = \frac{1}{N} \sum_{r} t_{ij}(r) \tag{1}$$

More generally we can express the network salience calculation with (2).

$$\boldsymbol{S} = \langle T \rangle = \frac{1}{N} \sum_{r} T(r) \tag{2}$$

The salience value of any link is therefore $0 \leq s_{ij} \leq 1$ and represents the fraction of shortest path matrices that the specific link participates in. A value of $s_{ij} = 0$ indicates that there is consensus, from the perspective of all reference nodes, that the link (i, j) plays no role in connecting them to the rest of the network. Similarly, a value of $s_{ij} = 1$ expresses the consensus that link (i, j) is essential for all reference nodes to be connected to the rest of the network.

Although the difference between salience and betweenness may seem marginal in definition, practically the difference is notable. Grady et al. [25] show that for a number of real-world networks (transportation, biological & ecological and social & economical) the distribution of link salience is bimodal on the interval $[0, 1]$. Links naturally accumulate at the range boundaries with vanishing fractions at intermediate values. This is visualised for our maritime network in the next section (Figure 1b). This implies that the majority of nodes *agree* that a link (i, j) is either non-salient, $s_{ij} \approx 0$, or salient, $s_{ij} \approx 1$. Herein lies the power of link salience, it is a classification that is insensitive to an imposed threshold and therefore is an intrinsic network property of heterogenous networks, making it fundamentally different from weight- or centrality-based measures that have broad distributions.

4. Data and methodology

Since the advent of AIS it has become the state-of-practice in the research of maritime networks to use records of actual vessel movements instead of published service schedules as the latter may not be complete, may not be current and may not reflect delays, vessel re-routing and void sailings. For this study, a database comprising the movements of 5 069 fully cellular container vessels during the 2012 calendar year was obtained from Lloyd's List Intelligence.

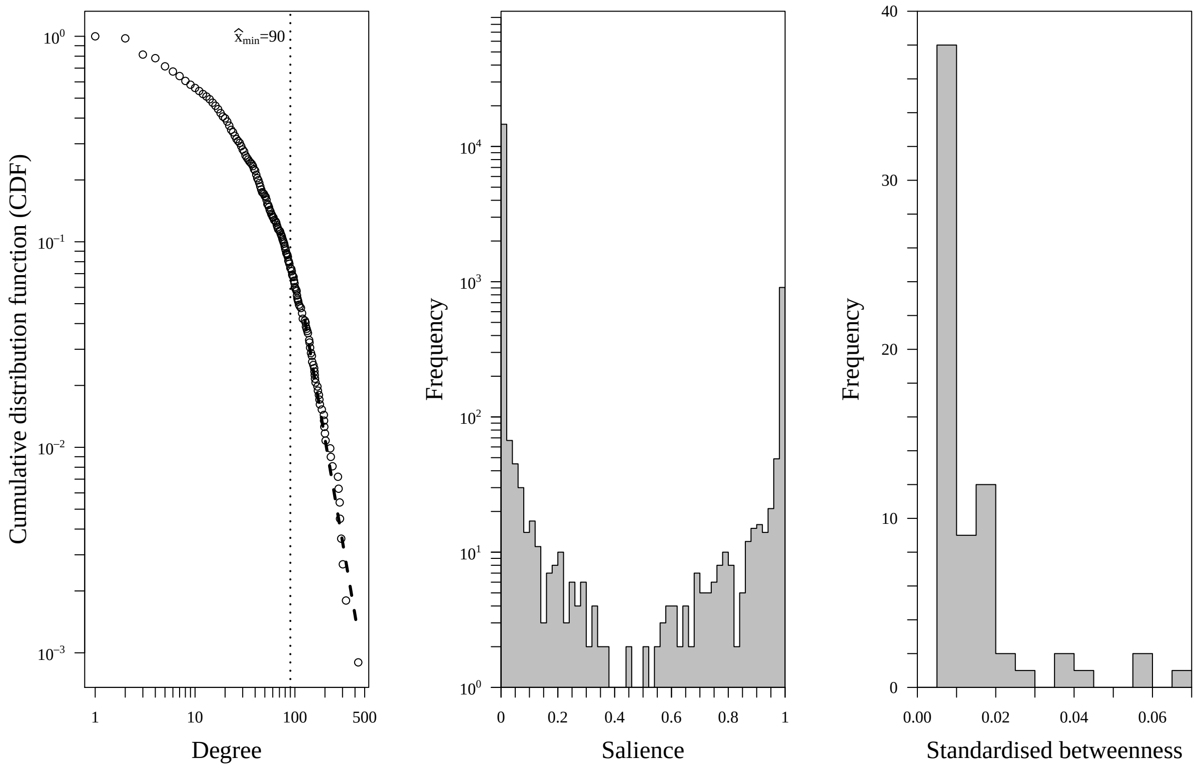
The database consisted of three tables: one detailing 9 000+ locations (including ports, anchorages, canals and straits) and their coordinates; one detailing the characteristics of the fully cellular vessels, most importantly their TEU capacity; and one detailing 520 000+ vessel movements which include port calls, anchorages and instances where vessels passed by locations. Lloyd's compiles the movement database from AIS records and recorded sightings by agents at various locations.

For the purposes of this study only those movements relating to a port call where containers could have potentially been loaded or off-loaded were considered. Furthermore all vessels that have only one record assigned to it do not represent a movement between two ports and were removed.

Two common distortions in AIS data are multiple, subsequent movements recorded at one location and "back-and-forth" movements between two proximate locations that are really due to distortions of the geospatial position system (GPS) signal. After removing subsequent movements at the same location and "back-and-forth" movements between proximate ports that occurred within 24 hours, movement records for 5 001 vessels remained.

Next these records were used to construct a directed, weighted network. The list of unique ports extracted from these 5 001 vessels' activity records are the *nodes* of the network. In keeping with the common representation used by other authors, a *link* exists between two nodes if these nodes are consecutive port calls on a service. The *weight* of a link is the aggregated TEU capacity that traversed that link as recorded in the vessel records. These nodes and links were loaded into a directed network using the Java Universal Network/Graph (JUNG) framework.

The degree distribution of the ports are plotted in Figure 1a. As noted by Clauset et al. [9] there are very few empirical phenomena that obey the theoretical power law $p(x) \propto x^{-\alpha}$ for *all* values of x, but in many cases a power law function can be fitted for values of x beyond a specified minimum. The degree distributions of many empirical scale-free networks can be approximated by a power-law function with scale parameter $2 \leq \alpha \leq 3$ [45]. Using the implementation of Gillespie [24] we estimated the scale parameter to be $\alpha = 2.50$ for $x \geq 90$. That is, for all ports with a degree higher than 90. We then followed a standard approach of using a *goodness-of-fit* test to quantify the plausibility of our hypothesis. The p-value generated was 0.68, far higher than the recommended



(a) Degree distribution.

(b) Salience distribution.

(c) Link betweenness distribution.

Figure 1: Network metrics.

0.1. We can therefore comfortably accept the hypothesis that the network is scale-free with $2 \leq \alpha$, at least for ports of high degree.

The intact network that has not been subjected to any attack strategy will be referred to as the *baseline* network. The distribution of the salience of the baseline network is shown in Figure 1b. This displays the classical bathtub shape that results from the accumulation of scores at the boundary values as found by Grady et al. [25]. It is notable that 92.3% of the links have a salience score between 0 and 0.05 and are thus non-salient, while only 6.0% of links are considered salient with a score greater than 0.95. This suggests that very few links feature in the shortest path sets of the majority of the nodes.

Considering the standardised link betweenness distribution, it is notable that 99.6% of the links have scores lower than 0.005 and the maximum score is only 0.068. Figure 1c shows the distribution of scores for the remaining 0.4% of the links. An explanation for such a distribution is that there are multiple shortest routes between two ports that a container could travel and thus the network is not that reliant on individual links to act as bridges between sub-communities of ports. At first glance this may seem contradictory to the salience results as multiple shortest paths would imply that more links are included in shortest path trees (evidence of the small-world characteristic). However, as a consensus-based variable, salience considers the overlap of the shortest path sets for all nodes in the network. Therefore, although a large subset of links feature in alternative shortest paths (lowering the betweenness scores of individual links), there is little overlap between shortest path trees and therefore little consensus regarding individual link salience.

4.1. Link disturbance strategy

This study compares the effectiveness of two link disturbance strategies: one based on weighted link betweenness and one based on weighted link salience. In both cases the inverse of the link weight (total TEU capacity) is used as the relational distance. In other words, the greater the TEU capacity on a link the shorter the relational distance between the two nodes it connects. Both strategies are adaptive, to increase effectiveness.

Salience offers an intrinsic classification of links (salient or non-salient) and therefore an intuitive identification of links to remove in a targeted link disturbance. In the salience-based disturbance, all links with salience ≥ 0.90 are removed in an iteration. The salience of the resulting network is calculated and again all links with salience ≥ 0.90 are removed in the next iteration. The betweenness-based strategy removes the same number of links in each iteration as the salience-based strategy, but it selects the links based on highest link betweenness scores. After each iteration link betweenness is recalculated before determining the next set of links to remove.

The decision of how many iterations are sufficient depends on the study's objectives. Wang et al. [55] describe the difference between the statistical mechanics and transport geography perspectives. The former is concerned with statistical properties and boundary values which enable distinct classification and analytical evaluation whereas geographers are intent on the spatial structure, roles and relational connections that embody the real-life network. This study, leaning more towards transport geography, monitored the following three stopping criteria:

1. **Validity of network representation.** The global container shipping network is not static. Any significant disturbance would elicit a market response that attempts to revert or repair the network to a suitable alternative. Practically there would be no point in investigating network properties beyond realistic scenarios. Therefore the simulations should terminate once the underlying network is vastly different from the baseline network in terms of the number of ports (nodes), services (links) or cumulative weight (TEU capacity).
2. **Degradation of selection mechanism.** The evident bimodality of the link salience distribution is the mechanism whereby the number of links removed in both strategies is determined. It is also the mechanism identifying which links to remove for the salience-based strategy. Therefore, once the bimodal property is lost, the selection mechanism has degraded and the simulations should stop.
3. **Convergence of metrics.** Once the metrics by which *robustness* and *flexibility* are quantified converge around a value, continuing the simulations offers diminishing insights.

Using the terminology of Thadakamalla et al. [52] the primary interest is to investigate the *robustness* and *flexibility* of the network under both attack strategies. *Robustness* is an indication of how many disruptions a network can endure before the functionality is destroyed. The functionality of a network is maintained as long as the majority of nodes remain connected. The weakly connected component in a directed graph is the largest collection of nodes for which there exists at least one directed path connecting each node-pair. Therefore, monitoring the breakdown of the weakly connected component is an indicator of network robustness [1, 7, 10, 23, 27, 49, 53]. The clustering coefficient is the ratio of the number of links between the first order neighbours of a node and the total number of possible links. It gives an indication of the tightness of clusters and probability of alternative paths and will be tracked to establish the impact on the network's *flexibility*.

5. Results

The baseline network has 1 113 nodes and 15 916 links and the largest weakly connected component includes 1 111 (99.8%) of the nodes. After ten iterations of the betweenness and salience disruption strategies, evaluation against the three stopping criteria indicated that the simulations should be terminated. Firstly, the validity of the networks beyond ten iterations would be questionable as close to a third of the links had been removed. In the salience network the links that were removed constituted 25% of the TEU capacity which already represented a significant change. However, the betweenness network which prioritised the removal of heavily weighted links in the barycenter had lost 75% of its TEU capacity, rendering it but a shadow of reality. Secondly, as discussed in Section 5.3, the bimodality of the link salience distribution in the salience network had been significantly degraded, making the selection of links for following iterations ineffectual. Finally, the *robustness* and *flexibility* metrics had reached a plateau. In fact, the robustness metrics did not show much change from the baseline as discussed in Section 5.1, while the *flexibility* of the salience network was already showing minimal change from iteration four onwards (Figure 3b).

5.1. Robustness

From applications in epidemiology and internet security the concept of a *critical point* arose to quantify the minimum number of nodes that must be infected by a contagion before infection of the entire connected component is inevitable. Translated to disruption of transport networks, the critical point, p_c, would be the number of nodes removed before the network becomes disconnected. Cohen et al. [10] develop formulas for computing the p_c for scale-free networks in the case of random errors. They confirm analytically and through simulation that scale-free networks are robust against random attacks as the p_c approaches 100% when $\alpha \leq 3$. Expanding their work to targeted attacks on scale-free networks, they show analytically that these networks break down long before the calculated p_c is reached. This extreme vulnerability to targeted attack is especially true for networks with $\alpha \leq 3$ and is greatest in networks with $\alpha = 2$ [11]. Pastoras-Satorras and Vespignani [45] go one step further to prove that in cases of targeted attack on scale-free networks, a critical point cannot be analytically determined. Given that the *baseline* network is a scale-free network with $2 \leq \alpha$ and a targeted link disturbance strategy is followed, a critical point can not be numerically evaluated to determine robustness, rather the size of the connected component should be tracked to determine whether it is disconnected at any point.

After ten iterations the weakly connected component remains intact in both the salience and betweenness networks where it encompasses 99.6% and 99.2%, respectively. This seems counter-intuitive given the high vulnerability of scale-free networks cited by other studies. However, our strategy removes links not nodes, and while nearly a third of the links had been removed after ten iterations this only resulted in 20 and 25 nodes being completely disconnected in the salience and betweenness networks, respectively. Furthermore, these disconnected nodes had very low degrees ≤ 6. This shows that the global container shipping network is highly robust to large-scale changes in service configuration. It is highly unlikely that a hub will be disconnected from the network even if a large proportion of the 'most between' or 'most salient' links are removed. One can thus assume that a container will always be able to find its way from its origin to its destination port, but the efficiency of the route it takes may be affected.

5.2. Flexibility

The clustering coefficient of the initial network has an average ratio of 0.54 with 17.2% of the nodes having completely connected neighbourhoods. This implies that a great many nodes have first order neighbours that are well-connected with one another. Such well-connected communities offer transshipment alternatives to containers on their journey from origin to destination. An example is that of a container travelling from Shanghai in China, to Rotterdam in the Netherlands that is scheduled to be transshipped at Algeciras, Spain, just off the Strait of Gibraltar. For some reason the vessel is re-routed in the Mediterranean Sea and does not stop at Algeciras, but rather at one of its first order neighbours, namely Alexandria (Egypt), and the container is offloaded there. Luckily there is a measure of *flexibility* in this routing as Alexandria also has a direct link to Rotterdam and therefore the container can be transshipped from there without incurring additional handling costs.

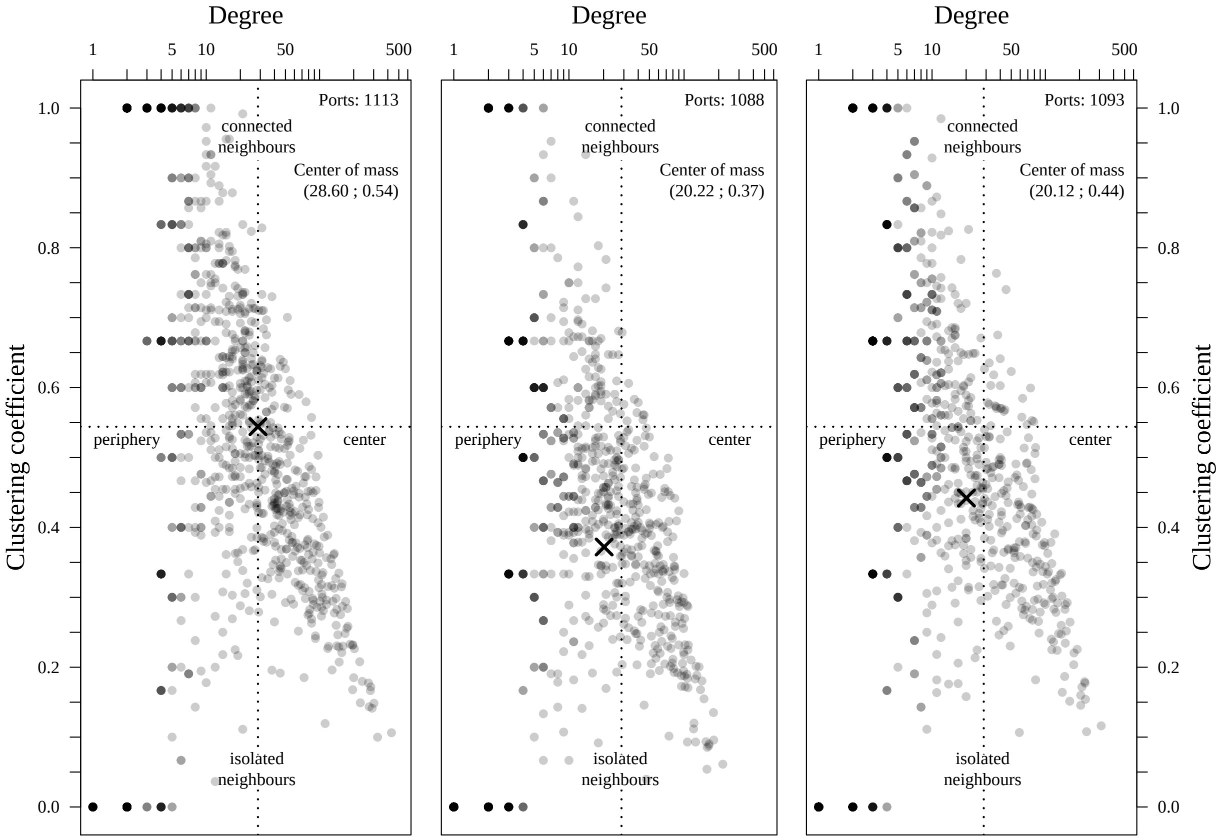
However, the clustering coefficient of a port can have a very different practical implication depending on the port's degree. If some remote island port with a degree of two has a clustering coefficient of one, it simply means that its two neighbours are also linked. On the other hand, if a highly connected transshipment port in South-East Asia has a degree of 200 and a clustering coefficient of one, that would represent remarkable cohesion and a formidable cluster of connectivity. Keeping in mind the highly heterogenous degree distribution of the baseline network, degree and clustering coefficient must be considered in tandem (Figure 2) before making any sweeping statements regarding the network's flexibility.

In the baseline network (Figure 2a) we observe that only a few exceptional nodes with very high degree have high clustering coefficients as well (upper right quadrant) while a fair proportion of the nodes with medium degree have connected neighbours (upper left quadrant). In fact, 46.9% of the nodes with clustering coefficients higher than 0.5 have a degree greater than 10 but only 2.8% of those have a degree greater than 50. The baseline network therefore has a fair number of cohesive, mid-sized neighbourhoods, while the most dominant hubs have very low clustering as Fraser et al. [22] also observed.

After ten iterations of disruption, both strategies have reduced the network's flexibility as observed in the distribution's shift downward, but the betweenness strategy (Figure 2b) has had a more pronounced impact than the salience strategy (Figure 2c), shifting the center of mass down to 0.37 compared to 0.44 in the salience network. This can be seen more clearly in Figure 3a where the cumulative clustering coefficient distribution of the baseline network is compared to those of the terminal betweenness and salience networks.

Why would the betweenness strategy be so much more effective if, after all, both strategies prioritise links in the network's shortest paths? Recall that the global container shipping network, like many real-world hub networks, presents a core-periphery structure where the core comprises highly connected and often highly central nodes. The barycenter of the network would overlap greatly with the nodes and links inside this core. Betweenness prioritises links in this barycenter. Therefore it is highly likely that a link with high betweenness connects a node-pair that features in the first order neighbourhoods of multiple reference nodes. Removing this link would simultaneously remove it from multiple neighbourhoods, thus impacting the clustering coefficients of multiple reference nodes. The result is a faster reduction of the average clustering coefficient over time. The salience strategy, on the other hand, prioritises links that are more evenly spread throughout the network and therefore the likelihood of affecting multiple neighbourhoods when removing a high-salience link is smaller.

According to Thadakamalla et al. [52], *flexibility* is an indication of the presence of alternate paths and a measure of the potential for dynamic rerouting. We observe that the betweenness strategy effectively reduces flexibility within the core of the network which coincides with prominent



(a) Baseline network

(b) Betweenness disruption strategy.

(c) Salience disruption strategy.

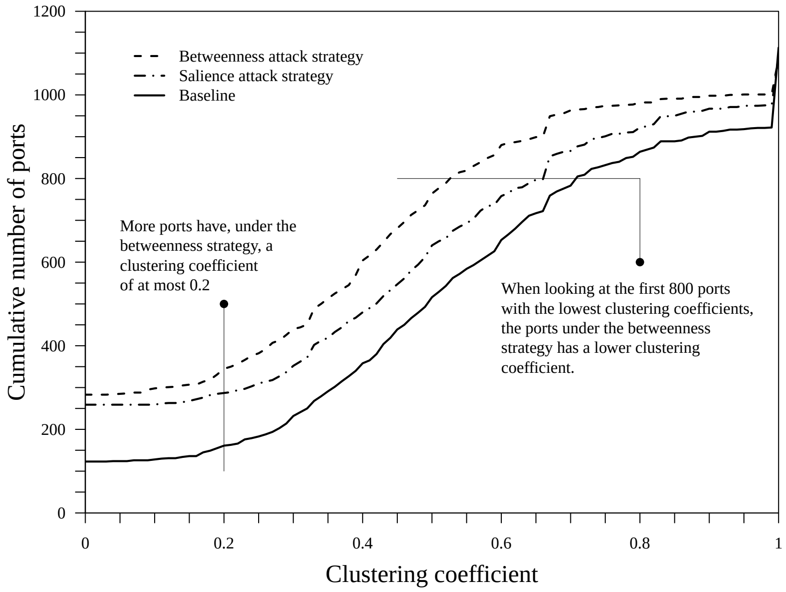
Figure 2: Clustering coefficients of ports in the network as a function of its degree. Darker dots represent multiple ports superposed on one another having the same degree and clustering coefficient values. The results of disruption strategies are after ten iterations. In each plot the vertical dotted line is at degree 28, which is the mean degree of the baseline network. The horizontal dotted line is at a clustering coefficient value of 0.54, which is the mean of the baseline network.

shipping regions such as South-East Asia, Northern Europe, the Mediterranean, and the Caribbean. This ultimately reduces transshipment options and choice for the cargo owner. Although betweenness was more effective, the impact of the salience strategy should not be discounted and based on the fact that both strategies had a marked impact on the clustering coefficient's distribution we infer that the network's flexibility is indeed vulnerable to disruption.

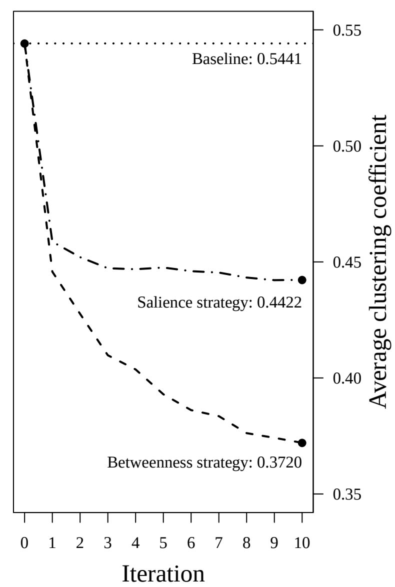
To conclude the discussion on the networks' clustering coefficient, attention is drawn to the time series of the average clustering coefficient values (Figure 3b). Notice that both strategies reduce the average coefficient sharply in the beginning and then the change tapers off. To explain this we need to consider that the mechanism whereby the disruptions is designed is becoming less effective.

5.3. Terminal salience and betweenness

The bathtub shape of the salience distribution is its distinctive characteristic, showing that most links are either salient (i.e. feature in the majority of shortest path sets) or not [25]. Consider the



(a) A comparison of the clustering coefficient distribution of the baseline network to that of the networks resulting from ten iterations of the betweenness and salience disruption strategies.



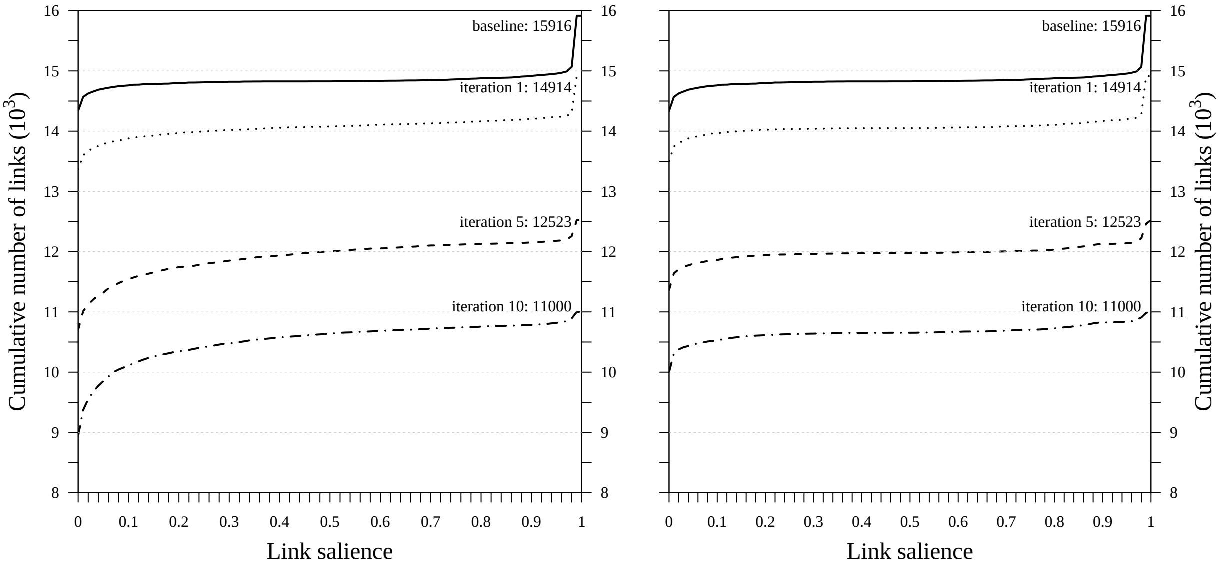
(b) Change in the average clustering coefficient for the betweenness and salience disruption strategies.

Figure 3: Strategy comparison

terminal salience distributions of both disruption strategies, as shown in Figures 4a and 4b. The bathtub shape is significantly degraded by the salience strategy while the betweenness strategy has a less pronounced impact on this bimodality. This degradation indicates that the salience strategy reduces the degree to which shortest path sets overlap. When removing a highly salient link, one removes a link that features in the shortest path sets of many reference nodes' shortest path sets. As shortest path sets are repopulated after disturbance, it is clear from the results that commonality is not restored between reference nodes. Ultimately this also results in fewer links having high betweenness scores as there is a greater variety amongst the shortest paths in the network (Figure 5a).

The betweenness strategy also reduces the salience and betweenness distributions, but to a lesser degree (Figures 4a and 5a). As a large proportion of the most salient links are not located in the barycenter of the network, the betweenness strategy would not remove them, herein lies the primary reason for the conservation of the bathtub shape. Regarding betweenness, when high betweenness links are removed, the very fact that the barycenter is highly connected allows for one of two alternatives. Either an alternate shortest path exists whose links will now carry greater weight, thus having increased betweenness scores, or the inherent flexibility enabled by the high connectedness of the core will allow for efficient rerouting. The caveat to the latter would be that flexibility itself is also being degraded over time.

Practically, when the global container shipping network has a strongly bimodal salience distribution, it is evidence of a well-defined skeleton that embodies those links where many different liner services consolidate to travel the same sections of the ocean. A bimodal salience distribution thus represents consolidation opportunities for container cargo. This consolidation potential is important to shipping lines, logistics service providers and cargo owners who are continuously seeking



(a) Betweenness disruption strategy.

(b) Salience disruption strategy.

Figure 4: Change in the link salience distribution for different disruption strategies.

out economies of scale to drive down costs. Therefore, despite the fact that the salience strategy did not have as a pronounced effect on *flexibility*, it does impact consolidation opportunities in the global container shipping network.

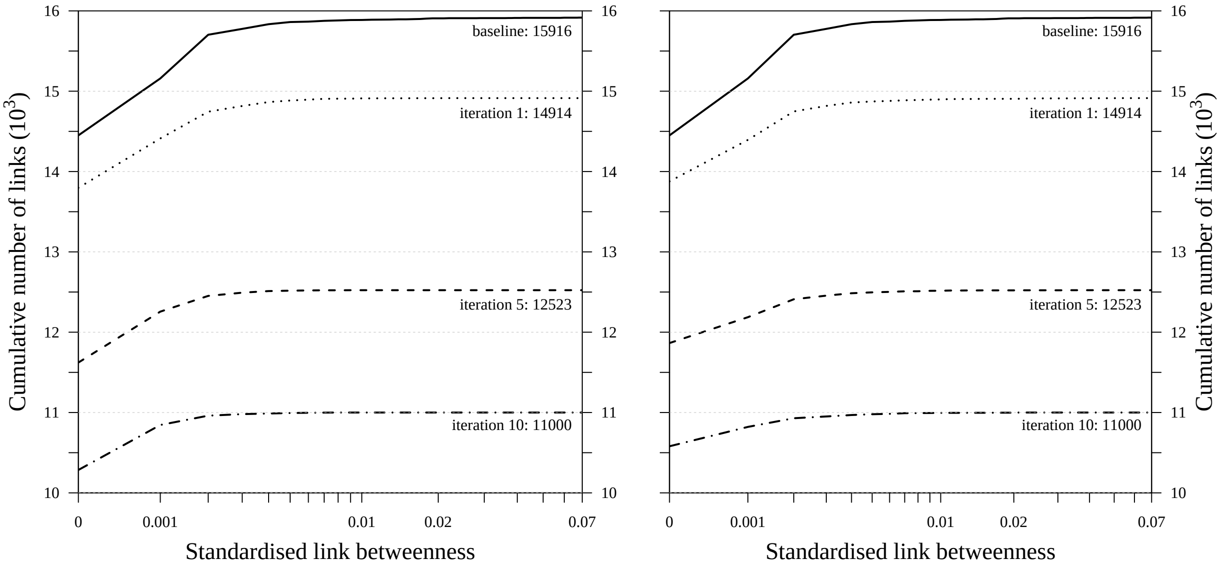
6. Conclusions

This paper has taken a first step in analysing the vulnerability of the global container shipping network's *flexibility* and *robustness* to changes in service configuration from a complex network perspective. Flexibility and robustness are related to the cohesiveness of communities and connections between these communities.

Two adaptive, targeted link disturbance strategies were used to disturb the network over ten iterations. One strategy used weighted betweenness as a link selection variable while the other used weighted salience. Both these variables are derived from the shortest paths of the network, the distinction being that betweenness represents the fraction of individual shortest paths a link features on while salience, as a consensus-based variable, is the fraction of shortest path sets it features on. Betweenness prioritises links in the barycenter of the network while salience identifies the skeleton of the core-periphery structure of the network.

The network proved to be highly robust in response to both disruption strategies. No large communities were isolated even after a third of the network links were removed. Thus the global container shipping network remains functional, even when faced with paradigmatic changes to service configurations. These results echo what other studies like that of Ducruet and Notteboom [20] observed.

On the other hand, the network's flexibility was vulnerable to both disruption strategies as reflected in the reduction of the average clustering coefficient over time. The betweenness strategy was more disruptive than the salience strategy in this regard, owing to the fact that it almost



(a) Betweenness disruption strategy. (b) Salience disruption strategy.

Figure 5: Change in the weighted link betweenness distribution for different disruption strategies.

exclusively targets links in the highly connected core of the network - impacting multiple neighbourhoods with each link removal. Therefore, any service reconfiguration that removes the most between links in the network would greatly impact transshipment alternatives. This is an important insight for cargo owners and logistics service providers who use the network created by the collective service design of many shipping lines. As the ‘most between’ links are removed, the options to dynamically reroute containers in response to unforeseen circumstances in the supply chain, diminishes.

While the salience strategy was less effective in reducing the network’s flexibility, an unanticipated observation showed that it is highly effective in reducing the opportunities for shipping lines, cargo owners or logistics service providers to consolidate container freight. This strategy effectively destroys the common skeleton that connects the network, thereby reducing the commonality of shortest path sets.

The study has shown that the global container shipping network is vulnerable to both link disruption strategies, albeit for different reasons. A strategy that removes the ‘most between’ links of the network limits options available to cargo owners and logistics service providers to reroute containers when facing unforeseen circumstances. Whereas a strategy that removes the ‘most salient’ links of the network reduces consolidation opportunities that, in the face of increasing supply-demand mismatch, could gravely affect the bottom line of shipping lines. The most salient or between links in the network are not always the links that carry the most traffic and could be overlooked as unimportant. The results of this paper serves as a caution to decision makers when considering the impact of service reconfiguration in the global container shipping network.

7. Acknowledgement

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