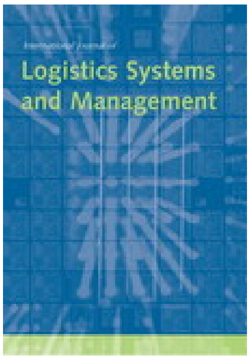

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On the liner shipping network design: the Maritime Silk Route case study

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Abstract: The Maritime Silk Route is a crucial channel for economic exchanges between China and Europe. In the year 2018, the sea route between Asia and Europe moved more than 24 million TEU. In this context, the optimal design of liner services is of crucial importance. We present a general framework for the optimal design of these services. First, we develop a gravity model representing the spatial interaction between ports. Then we obtain a minimum spanning tree by means of Kruskal optimisation and finally we use the Louvain method to determine the communities within the network. Two scenarios are discussed. The first gives more importance to distances, while the second gives more importance to port throughputs. The paper discusses the main differences between the two cases and highlights which ports gain or lose connections depending on the market environment. The resulting graphs are a good reference for designing better services.

Keywords: maritime network; network design; minimum spanning tree; MST; gravity model; importance matrix; maritime services; complex graph.

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Biographical notes: Iñigo L. Ansorena is a Civil Engineer and obtained his PhD from the Polytechnic University of Madrid. He is specialised in ports and he is the author of several studies and publications related to port issues. His research interests include graph theory and network modelling other issues.

1 Introduction

The global containerised trade is moved through a combination of liner shipping services that link ports all around the world. According to the World Shipping Council (2019a), more than a half of the value of seaborne trade is moved in such highly interconnected system. In total, the World Shipping Council (2019b) estimates that there are almost 500 liner shipping services providing regular services all over the world. A large share of globalised containerised trade is carried across the major east-west containerised trade arteries, namely Asia-Europe, the Trans-Pacific and the Transatlantic. The latest Review of Maritime Transport (UNCTAD, 2019), indicates that the Asia-Europe trade moved 24.4 million twenty-foot equivalent units (TEU) in 2018. The eastbound direction

(Northern Europe and Mediterranean to East Asia) moved 7.0 million TEU, while the westbound (East Asia to Northern Europe and Mediterranean) moved 17.4 million TEU. This major route between Asia and Europe is the focus of the one belt one road (OBOR), a Chinese initiative, which includes a wide range of activities, countries and industries, see Wang et al. (2018).

In the OBOR context, the design and perfect organisation of liner shipping services is a crucial problem for global carriers. Although there are many studies that have analysed this major trade lane, few have attempted to optimise the liner shipping network design (LSND). We aim to bridge this gap through a basic framework based on three steps. In the first one we elaborate the maritime network, which is based on a basic gravity model. Then in the second step we obtain the best routes with the best sequence of ports through a minimum spanning tree (MST) and finally, in the third step we determine the best organisation for the regular services. The rest of the paper is organised as follows. The Sections 2 and 3 present the literature review and the study context with a special attention to data collection. Then Sections 4 and 5 present the methodology and the results respectively, and finally Section 6 brings the conclusion and proposes future research.

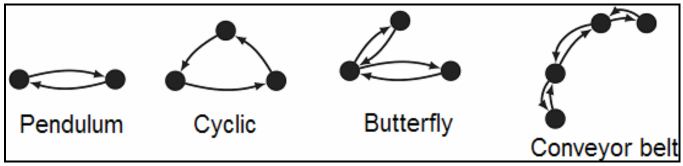
2 Literature review

The LSND problem aims to organise the ship routes (port rotations, type and number of ships to deploy), which fulfils the container shipment demand at minimum cost (Wang et al., 2013). Moreover, when the routes and capacities of the liner ships are known, it is possible to determine the optimal speed of the liner ship serving a certain route (Muldera and Dekkera, 2014).

One of the most typical configurations of maritime networks is the hub-and-spoke configuration. According to Hu and Hu (2015), the hub-and-spoke configuration exploits economy of scale in transportation and reduces logistics operational cost through collaborations among nodes. But the terminology for route types goes beyond the hub-and-spoke concept. In this regard, we can distinguish between simple routes (pendulum or cyclic routes) and non-simple routes (butterfly or conveyor belt routes), see Guericke (2014). Pendulum routes alternate between two ports; cyclic routes call more than two ports without calling a port twice per round trip; butterfly routes are cyclic routes that call one port twice; and conveyor belt routes (or routes with multiple butterfly ports) call more than two ports and visit more than one port twice per round trip, see Figure 1. In general, it is assumed that all routes perform a round trip.

Several studies have addressed the LSND problem from different perspectives and with different objectives. For example, in Fagerholt (2004) the routes are given as input to an integer programming problem, and then the routes that minimise the total transportation costs and satisfy the demand at each port are determined. Brouer and Desaulniers (2012) proposed a mixed integer program that optimises the removal and insertion of several port calls on a liner shipping service. More recently, Müller and Tierney (2017) proposed a simulated annealing solution approach for liner shipping fleet repositioning and Wibisono and Jittamai (2017) proposed a multi-objective evolutionary algorithm for a ship routing problem in maritime logistics collaboration. Apart from the aforementioned studies, others have already addressed the LSND problem, each with its own scope and assumptions. However, there is still a lack of research that attempts to analyse the context of the Maritime Silk Route in the 21st century, see Wang et al. (2013).

Figure 1 Route types



Source: Guericke (2014)

But how can we address this problem? Past literature suggests that there are many variables involved in the design of liner services, e.g., cargo sources, demand for shipping services, transit times, quality of port infrastructure and distances between ports, among others. In this sense, we must use a model that somehow includes the existing spatial interaction between the nodes. We assume that the gravitational model is a good basis and preferable to other spatial models for building the maritime network (e.g., potential models or retail models), since this is a simple and representative model that explains interactions between ports in an easy way.

Once the whole network is elaborated, we must find the most efficient route. To do this, a two-step procedure, based on MST optimisation and clustering techniques, is proposed. The MST will reveal the ports with the strongest interaction, while the community detection technique will detect groups of well connected ports on that route. The combined method with the optimisation direction followed in this study is a novelty, although the techniques used at each stage are not new.

On the one hand, MST optimisation uses the well-known Kruskal (1956) method. This procedure has already been used for the optimisation of maritime networks, see for example the optimisation of the maritime network of the port of Valencia in Ansorena and Valdecantos (2021).

On the other hand, to detect well connected groups of ports (i.e., communities) it is necessary to optimise a quality function named modularity. Optimising modularity is NP-hard problem (Brandes et al., 2007), and consequentially many heuristic algorithms have been proposed in previous studies, see e.g., hierarchical agglomeration (Clauset et al., 2004), simulated annealing Guimerà and Amaral (2005) and Reichardt and Bornholdt (2006), spectral algorithms (Newman, 2006) and extremal optimisation (Lung et al., 2014). One of the most popular and cited algorithms in the community detection literature is the Louvain algorithm originally proposed in Blondel et al. (2008). It was found to be one of the fastest and best performing algorithms in comparative analyses, see Lancichinetti and Fortunato (2009) and Yang et al. (2016).

Modularity optimisation has also been used in port studies. Two recent examples are Ansorena (2018) that used it to interpret the Liner Shipping Connectivity Index at the country level, and Ansorena (2020) that has recently used the Louvain method to extract clusters in the maritime network of the port of Algeciras Bay. We believe that the combination of both techniques is crucial to design better liner services.

3 Study context

In the 21st century, the Maritime Silk Route is a sea channel for economic exchanges between China and other parts of the world. According to Wang et al. (2017), it aims to enhance exchanges with other neighbouring countries and regions, to develop a strategic cooperative economic zone facing the South China Sea, the Pacific and India oceans, and to focus on the integration of economy and trade with Asia, Europe and Africa as a long-term development goal. According to the World Shipping Council (2019b) the trade route is currently operated by around 20 liner shipping services. A typical liner service between the Far East (FE) and North Europe (NE) covers 21,000 nm, calls at 15 ports per voyage (six calls in NE and nine in FE), spends three weeks for port stay and 55 days at sea, see OECD/ITF (2015).

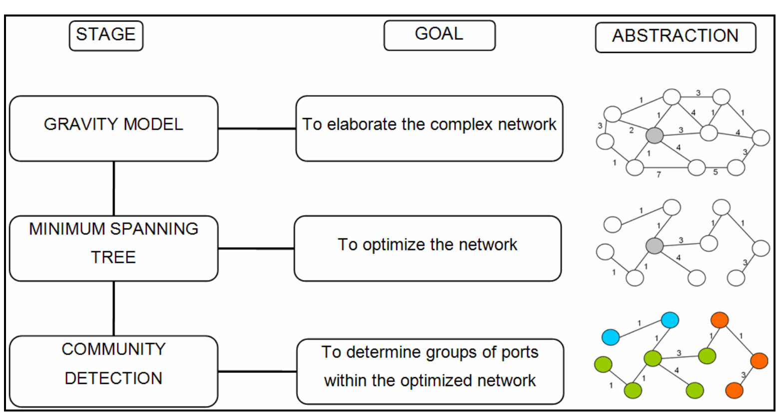
In this study, the initial dataset was collected from Lachner and Boskamp (2011) and Nightingale (2018). We use the first source to obtain the origin/destination matrix 'd_{ij}' and the second source to obtain the annual port throughput of 58 selected ports in six areas within the trade route: NE, Western Mediterranean Sea, Eastern Mediterranean Sea, Suez Canal and Middle East, South-East Asia and FE Asia. The collected data together with the results of the experiment are available in the Mendeley repository: http://dx.doi.org/10.17632/zdnzsfndj5.1.

4 Methodology

4.1 General framework

As explained above, the methodology is based on three steps, see Figure 2. In the first one we elaborate the complex network through a gravity model based on maritime distances and annual port throughput (in TEUs). Then in the second step we optimise the network through the MST algorithm (Kruskal, 1956). Finally, in the third step we determine groups of well connected ports following the Louvain method (Blondel et al., 2008).

Figure 2 General framework (see online version for colours)



Source: Own elaboration

4.2 Gravity model

The gravity model is based on the assumption that the attraction between two nodes (ports) is proportional to their annual container throughput and inversely proportional to their respective distance, see equation (1).

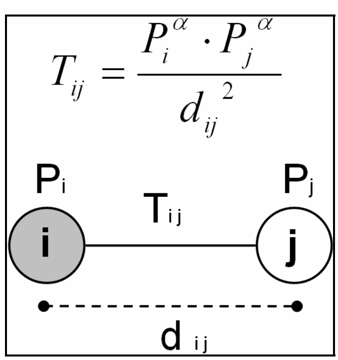
$$T_{ij} = P_i^{\alpha} \cdot P_j^{\lambda} \big/ d_{ij}^{\beta} \tag{1}$$

where

- P_i and P_j: Importance of ports, '*i*' and '*j*', given in terms of annual port throughput.
- d_{ij}: Distance between ports '*i*' and '*j*'.
- 'β': A parameter of transport friction related to the efficiency of the transport system between two ports. This friction is rarely linear as the further the movement the greater the friction of distance. For instance, two ports which are serviced by numerous liner services will have a lower 'β' index than if they were serviced by only one regular liner service.
- 'α' and 'λ': Two parameters that represent the potential to attract cargo volumes (attractiveness) and the potential to generate cargo volumes (emissivity), respectively. The first, 'α', is related to the nature of port activities at the destination, for instance, a port having important transhipment activities will attract more containers. In contrast 'λ' is related to port activities at the port of origin, for instance, a hub in a developed country will generate more traffic.

For the sake of simplicity, in this study we assume that the separation is squared to reflect the growing friction of distance in maritime transport, i.e., $\beta = 2$. In addition we consider undirected edges so there is no need to make any distinction between attractiveness ad emissivity, i.e., $\alpha = \lambda$. Thus, spatial interaction only depends on the annual container throughput, the distance and the value of 'α' parameter, see Figure 3. It is important to remark that the structure of the underlying demand, called cargo flows in shipping, is substituted by the annual container throughput of the ports. Extending this concept to the rest of nodes we obtain a complex network where the nodes are ports and the weighted (and undirected) edges represent the strength of the spatial interaction between them.

Figure 3 Network elaboration



Source: Own elaboration

In sum, using the annual port throughput (P_i) we can deduce the importance matrix 'P_{ij}', where each element of P_{ij} represents the importance of the connection between two ports. Then using P_{ij} together with the squared-distance matrix (d_{ij}^2) we can deduce the interaction matrix 'T_{ij}' [via equation (1)]. Finally, the elements of T_{ij} are used as the weights of connections within the entire network.

4.3 Minimum spanning tree

Once we have obtained the network we can optimise it through the MST algorithm. The Kruskal (1956) algorithm finds a MST for a connected weighted graph adding increasing cost arcs at each step. This means it finds a subset of the edges that forms a tree that includes every node, where the total weight of all the edges in the tree is minimised. If the graph is not connected, then it finds a minimum spanning forest (a MST for each connected component). Kruskal technique can be described as follows:

- create a forest F (a set of trees), where each node in the graph is a separate tree
- create a set S containing all the edges in the graph
- while S is non-empty and F is not yet spanning
  - remove an edge with minimum weight from S
  - if the removed edge connects two different trees then add it to the forest F, combining two trees into a single tree.

As mentioned in the previous section, this method has been successfully used in Ansorena and Valdecantos (2021). However, there is an important difference between the aforementioned study and the present one. In the former, the weight factor of the connections between ports is the number of liner services. In contrast, in the present study we focus on spatial interactions. Therefore, the weight factor of the connection between ports 'i' and 'j' is now obtained from the T_{ij} matrix. The application of the MST algorithm eliminates unnecessary ties connecting ports with a low level of interaction. In other words, long sea distances between ports with low performance levels are removed.

4.4 Community detection

In this stage we borrow the Louvain method which is a community detection technique originally proposed in Blondel et al. (2008). This method detects communities through the optimisation of a quality function known as Modularity which is defined as:

$$Q = \frac{1}{2m} \sum_c \left[e_c - \delta \frac{K_c^2}{2m} \right] \tag{2}$$

Louvain method tries to maximise the difference between the actual number of edges in a community (e_c) and the expected number of such edges which can be expressed as:

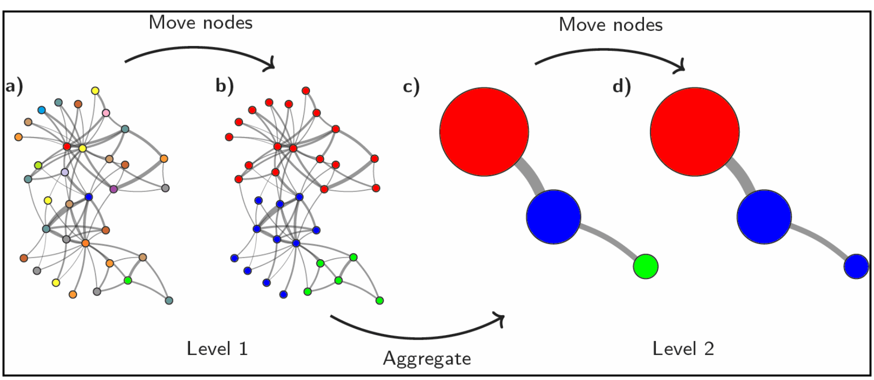
$$\delta \frac{K_c^2}{2m} \tag{3}$$

where

- K_c is the sum of the degrees of the nodes in community c.
- m is the total number of edges in the network.
- δ is a resolution parameter. Higher resolutions lead to more communities, while lower resolutions lead to fewer communities.

The essential idea of this measure is to reveal how non-random the network structure is by comparing the actual structure and its randomisation where network communities are destroyed. The value of modularity varies between −1 and 1, which measures the density of links inside communities as opposed to links between communities. As explained in Blondel et al. (2008), the algorithm is established in two steps that are repeated iteratively. First, it looks for 'small' groups by optimising modularity in a local manner. In the starting point, the algorithm assigns a different community to each node of the network. So, in this initial partition there are as many communities as nodes. Then, for each port '*i*', the algorithm takes the neighbours '*j*' and evaluates the gain of modularity that would take place by removing '*i*' from its community and by placing it in the community of '*j*'. The port '*i*' is then placed in the community for which this gain is maximum, but only if this gain is positive. If no positive gain is possible, '*i*' stays in its original group. This process is applied repeatedly and sequentially for all nodes until no further improvement can be achieved and the first step is then complete. Therefore, the first step finishes when a local maximum of the modularity is attained, i.e., when no individual move can improve the modularity. In practice, one therefore evaluates the change of modularity by removing '*i*' from its community and then by moving it into a neighbouring community.

Figure 4 How the Louvain method works (see online version for colours)



Source: Adapted from Traag et al. (2019)

The second step consists in building a new association whose nodes are the communities established during the first step. To do so, the weights between each pair of nodes are given by the sum of the weight of the links between nodes in the corresponding two communities. Links between nodes of the same community lead to self-loops for this community in the new network. Once this second process is completed, it is then possible to reapply the first step of the algorithm to the resulting weighted network and to iterate. Therefore, the two steps are repeated iteratively until a maximum of modularity is attained.

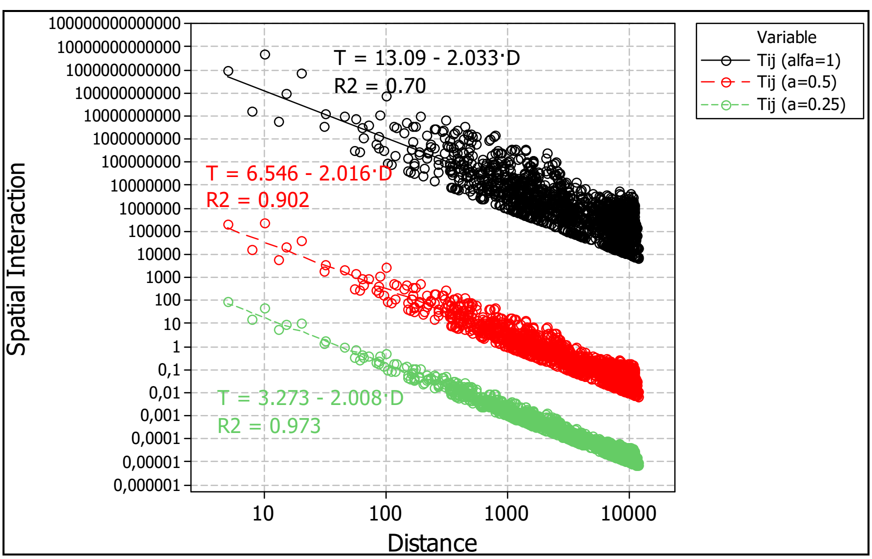
In sum, the method starts from a singleton partition wherein each node is in its own community, see Figure 4(a). The algorithm moves individual nodes from one community to another to find a partition, see Figure 4(b). Based on this partition an aggregate network is created, see Figure 4(c). The algorithm then moves individual nodes in the aggregate network, Figure 4(d). These steps are repeated until the quality (modularity or objective function) cannot be increased further. As a result we obtain groups of well-connected nodes (ports).

Finally, it will also be interesting to pay attention to bridge nodes. As the name suggests, the bridge node acts as a bridge between two clusters. In other words it plays an intermediary role by providing accessibility to other clusters (or regional markets) within the network.

5 Results and discussion

As explained in the methodology we use the annual container port throughput to deduce the importance matrix 'P_{ij}'. Then we use P_{ij} and the squared-distance matrix d_{ij}^2 to obtain [via equation (1)] the spatial interaction matrix T_{ij}, which is used to elaborate the network. Since T_{ij} depends on the 'α' coefficient and this parameter is not known beforehand, we have elaborated two cases depending on the 'α' coefficient: $T_{ij}^{\alpha=1}$, $T_{ij}^{\alpha=0.25}$.

Figure 5 Spatial interaction vs. distance (see online version for colours)



Source: Own elaboration

In sum, each complex network is described by its own symmetric matrix (T_{ij}). The elements of these matrices are representing the spatial interaction between ports, i.e., the strength of the maritime tie between each pair of ports. In total each network has 58 ports and 1,652 undirected ties. To better understand the relation between distances (d_{ij}) and spatial interactions (T_{ij}) see Figure 5. Here we have plotted both magnitudes on a logarithmic-scale chart, where each data point represents a connection between two ports. As a result, we observe that the spatial interaction decreases with distance and the goodness of fit performs better for a lower 'α' coefficient. Both aspects are consistent with the gravity model.

The first network (the one deduced from matrix: $T_{ij}^{\alpha=1}$) gives more relevance to the numerator, i.e., the annual port throughputs, while the second one ($T_{ij}^{\alpha=0.25}$) gives more relevance to the denominator, i.e., the distance between ports.

If more relevance is given to the container volumes ($T_{ij}^{\alpha=1}$) the network tends to support hubs, e.g., Rotterdam, Singapore, Shanghai or Shenzhen, see Table 1. This is the general trend observed in the last decades. The strongest hubs move more containers through more connections and increase the traffic-gap with other ports. Alternatively, if more relevance is given to the denominator ($T_{ij}^{\alpha=0.25}$) then the network tends to avoid the previous hubs, but this has not been a typical picture in the past. This may occur when some facets of maritime transport (e.g., fuel costs, freight rates, etc.) have a deeper impact on the configuration of the network than the traffic volume itself.

Table 1 Winners and losers according to the number of connections (degree)

Port	$T_{ij}^{\alpha=0.25}$	$T_{ij}^{\alpha=1}$	*Degree*	*Gain/lose*
Rotterdam (NL RTM)	3	8	+5	Gain
Singapore (SG SIN)	5	8	+3	Gain
Shanghai (CN SHA)	3	5	+2	Gain
Shenzhen Chiwan (CN CWN)	3	5	+2	Gain
Busan (KR PUS)	3	4	+1	Gain
Qingdao (CN TAO)	2	3	+1	Gain
Yokohama (JP YOK)	1	2	+1	Gain
Bremerhaven (DE BRV)	3	2	–1	Lose
Colombo (LK CMB)	2	1	–1	Lose
Felixstowe (GB FXT)	2	1	–1	Lose
Fuzhou (CN FOC)	3	2	–1	Lose
Gothenburg (SE GOT)	3	2	–1	Lose
Hong Kong (CN HOK)	3	2	–1	Lose
Kobe (JP UKB)	2	1	–1	Lose
Liangyungang (CN LYG)	2	1	–1	Lose
Ningbo (CN NGB)	2	1	–1	Lose
Port Klang (MY PKL)	2	1	–1	Lose
Salalah (OM SLL)	3	2	–1	Lose
Shimizu (JP SMZ)	2	1	–1	Lose
Zeebrugge (BE ZEE)	3	1	–2	Lose

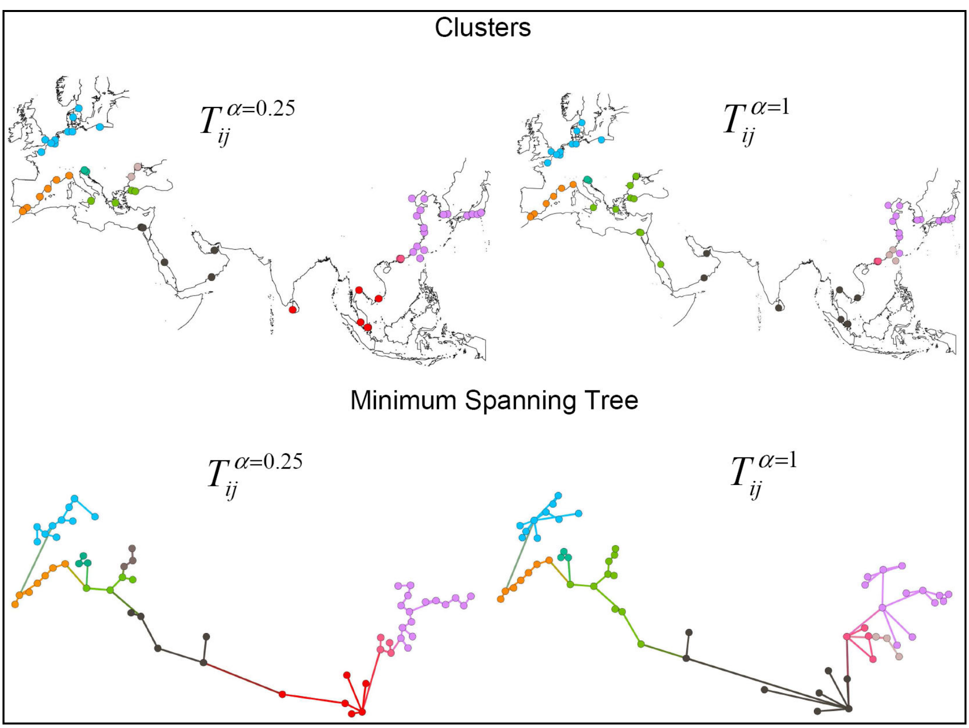
Source: Own elaboration

It is also important to note that the majority of ports have the same number of connections (degree) in both scenarios. However, there is a group of ports that gain/lose connections depending on the scenario, see Table 1. From the perspective of liner shipping companies, this is crucial when they plan to consolidate services through alliances, when they plan to consolidate routes to serve more locations with fewer ships, or even when they try to reduce fuel costs.

In regard to the community detection stage, as explained before, Modularity is a quality function that takes into account the network configuration and in particular the degree of nodes (i.e., the number of connections to other nodes). As a result of the Louvain method, we obtain a similar number of groups (8 vs. 9) together with a similar Modularity index (0.233 vs. 0.385) in both cases.

The main difference between the two network-structures is in the Middle East, see Figure 6. In the first case $(T_{ij}^{\alpha=1})$, there is not a specific group in that area (see that Suez and Jeddah fall in the Mediterranean group and Salalah and Jebel Ali fall in the South East Asia group). In contrast, the second case $(T_{ij}^{\alpha=0.25})$ has a specific group that includes all these ports. Although there are other minor differences in the Black sea and the FE, we can conclude that both structures are similar.

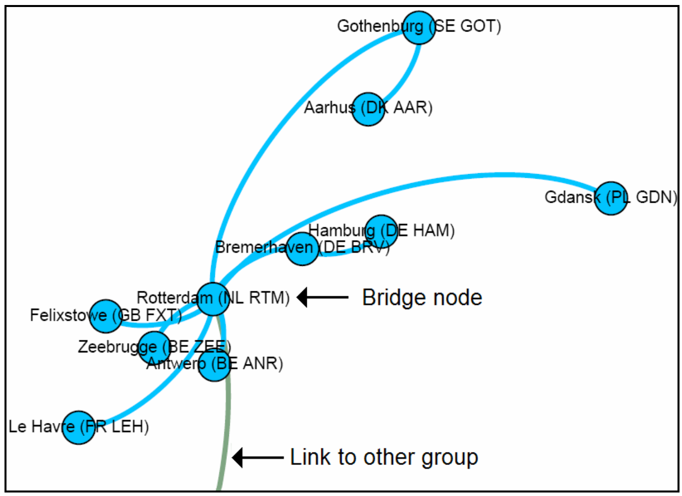
Figure 6 Groups and MST deduced from $T_{ij}^{\alpha=0.25}$ matrix and $T_{ij}^{\alpha=1}$ matrix (see online version for colours)



Source: Own elaboration

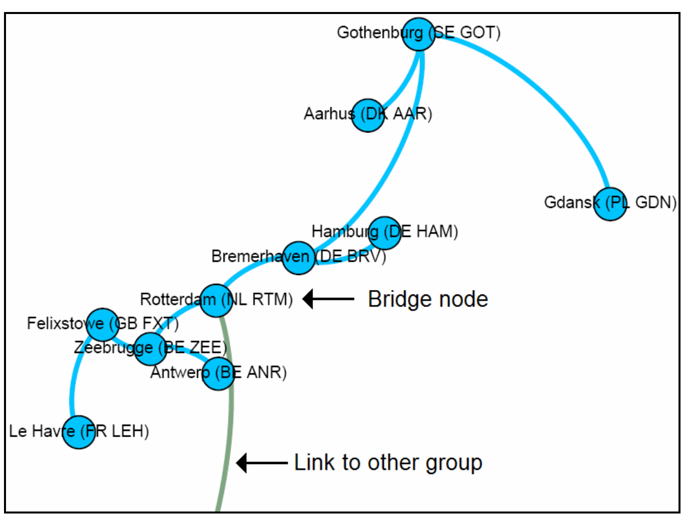
It is also interesting to discuss the role of two main hubs (Rotterdam and Singapore) that work as bridge ports to other groups. In the case of Rotterdam, when the model is $T_{ij}^{\alpha=1}$ the port gains connections and strengthens its role as a main hub. Alternatively, when the model is $T_{ij}^{\alpha=0.25}$ the port loses connections but conserves its role as a bridge node to other groups, see Figures 7 and 8 respectively.

Figure 7 North Europe $(T_{ij}^{\alpha=1})$ (see online version for colours)



Source: Own elaboration

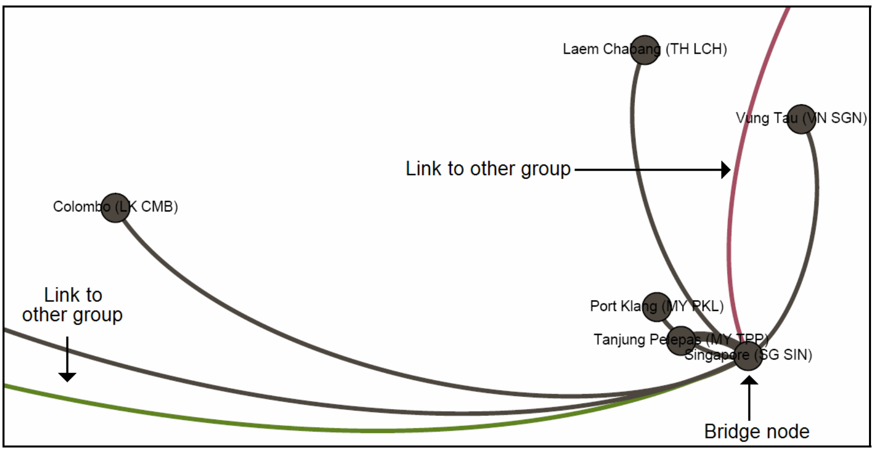
Figure 8 North Europe $(T_{ij}^{\alpha=0.25})$ (see online version for colours)



Source: Own elaboration

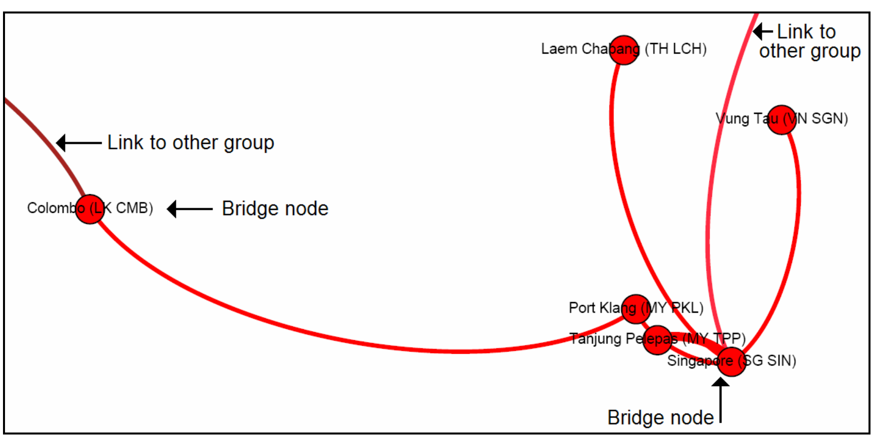
This pattern is not fully followed in other regions such as South East Asia. Here, when the model is $T_{ij}^{\alpha=0.25}$ Singapore loses some connections and also part of its role as a bridge node to the Middle East. In other words, Colombo plays down the importance of Singapore as a port of transhipment to the Middle East region, see Figures 9 and 10 respectively. The prevalence of one scenario over the other may represent a market opportunity for the port of Colombo. Although it still has a long way to go, as Singapore's annual traffic is approximately six times that of Colombo.

Figure 9 South East Asia $(T_{ij}^{\alpha=1})$ (see online version for colours)



Source: Own elaboration

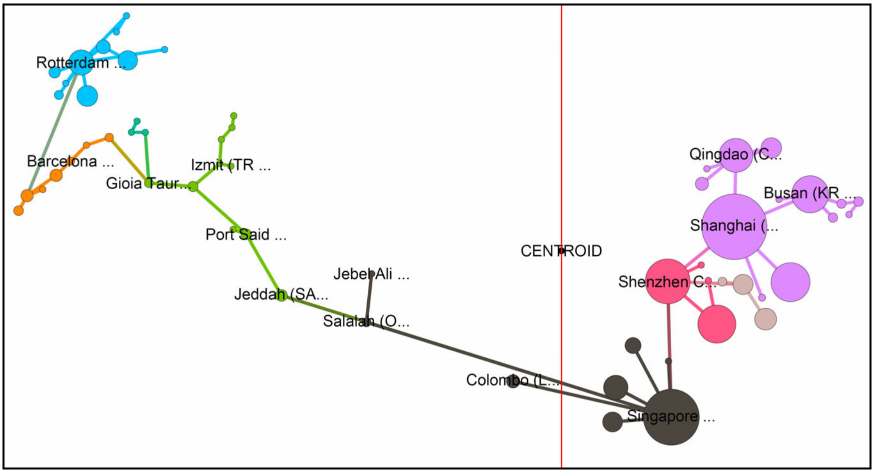
Figure 10 South East Asia $(T_{ij}^{\alpha=0.25})$ (see online version for colours)



Source: Own elaboration

Finally, it is important to note that FE ports are dominant in terms of port traffic. This can be clearly seen in Figure 11 where the size of the nodes is proportional to the annual port traffic in 2017. Figure 11 also shows the position of the centre of the network (long = 88.34210; lat = 28.57591) with a vertical red line splitting the network into two parts. Once again, the port of Colombo could be a winner in the future, but in this case because of its proximity to the centroid. The same can be said for the Indian ports not covered by the current network.

Figure 11 The dominant role of the east bound (see online version for colours)



Source: Own elaboration

6 Conclusions and future research

The elementary formulation of the gravity model can be adapted to reflect maritime networks. In this study we use such formulation, $T_{ij} = f(P_i, P_j, d_{ij})$, to elaborate the FE to NE maritime network and then the graph theory to optimise it. Usually, connectivity varies across seaports as it is dependent on numerous factors. From this view-point, the gravity model is a good starting point to build the network since the spatial interaction between two ports is a function of the port-attributes, i.e., annual throughputs, pondered by the distance between ports.

Shipping lines try to minimise operating costs in a highly competitive scenario, under the pressure of fuel prices, freight rates and port competition. Numerous studies have addressed LSND and maritime connectivity, each with their own scope and assumptions. However, few of them have attempted to establish a basic framework to find a more efficient network. This paper has shed new light on the Maritime Silk Route showing the best organisation and the best connected ports through MST optimisation and clustering. The resulting graphs can be considered as 'patterns' to design better services. The main advantage of these descendant-services is that they can improve the port choice and therefore increase the efficiency of the whole network.

The main drawback of the study lies in the fact that we are considering a very simplified model elaborated with just two variables: port throughput and distance. But in the real world the port choice is a more complex problem which involves many variables, e.g., quality of service, demand for shipping services, quality of ports infrastructure. Apart from the gravitational model, there are other models that can be used to measure spatial interactions and build the network. Destination choice models, for example, are considered an extension of the gravity models that provide a wider range of factors explaining the assignment of spatial interactions.

Future research should therefore be directed towards the development of a more complex model. The importance of the network nodes will be defined not only by the distances and the annual port throughputs, but also by other attributes that are strategic in the context of port competition, for example, the average and maximum size of ships, port costs and handling costs, etc. Some of these parameters can be obtained through technical surveys or even on the websites of port authorities (port costs as a function of the gross tonnage of container ships) and terminal operators (handling costs as a function of the number of crane movements).

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