Network Position and Throughput Performance of Seaports

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CHAPTER 10

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César DUCRUET, Sung-Woo LEE and Ju-Miang SONG

Abstract

The determinants of throughput volume at a given set of ports have rarely been approached from a network perspective. This paper proposes a set of novel indicators describing the relative situation of seaports in the worldwide maritime network of container shipping in 2006, which are distinguished among five categories: circulation (calls, vessels, and operators), foreland (distance to other ports and distribution of connections), connectivity itself (number of connections to other ports), centrality (betweenness and eccentricity), and neighbourhood (strength and clustering indices). Main results help to classify ports according to their location and function in the network, while they stress which parameters most influence throughput volumes. Although centrality indicators highly correlate with throughput, the latter seems to be influenced mostly by the geographic parameter of the maximum distance link to another port.

1 | Introduction

The quantitative analysis of seaports is a traditional approach of port and maritime geography aiming at understanding, among other things, the factors most influencing ports' performance and, therefore, competitiveness. A large literature on port choice and port selection insists more on the qualitative aspects of performance besides other economic factors such as cost and productivity (Ng, 2009; Notteboom, 2009). Another body of research groups together various port-related indicators describing different aspects of a port's life (e.g. traffic, infrastructure, number of calls), either for highlighting types of ports or to insist on which factor seems most relevant for comparing ports except from the classic figure of annual throughput (Joly and Martell, 2003). A wide set of possible measures have thus been proposed, some being measurable and other not (De Langen et al., 2007), all placed under the general name of "port performance indicators" or PPIs.

Because covering this large research field exhaustively would run beyond the scope of this paper, the present research aims at exploring to what extent other kinds of port performance indicators may be drawn from network analytical tools. Since ports are critical nodes in maritime (and land) networks, it seems very natural to expect that their position in such networks may be expressed by means of other variables than local characteristics but on relational measures. Such measures are already extensively used in the wider research area of “network science” that is composed of various elements from graph theory, social network analysis, and complex networks. Based on recent works introducing such approaches to the maritime world (Ducruet and Notteboom, 2010), this paper wishes to push further the statistical analysis of a varied set of indicators, notably in relation with the classic one of throughput, in order to verify which of these indicators best influence ports’ performance.

The remainder of the paper are as follows. Section 2 introduces the data on vessel movements used for building graphs of the global maritime network in which the position of ports will be measured from various perspectives. Section 3 presents the results of a factor analysis while Section 4 runs a multiple regression analysis. Finally, concluding remarks are given in Section 5 as well as some possible avenues for future research in this direction.

2 | Data and methodology

Data on worldwide vessel movements was obtained from Lloyd’s Marine Intelligence Unit (LMIU) for the year 2006[1]. It allowed building the global graph of inter-port links with ports themselves considered as nodes. Ports are also characterized by their throughput in TEUs using Containerisation International data for 2006. Such data has the advantage of covering most of the world’s fleet of containerships (about 98% of total fleet capacity), while it offers high precision in the information: daily vessel movements are recorded as well as the capacity (TEU) of the ships.

For a full investigation of the interdependence between throughput volume and network position, we have distinguished among two types of graphs. One graph is the one of direct links between ports, taking into account successive calls between previous and next ports only. The other graph adds indirect links to the former, thus including all intermediate calls between all ports welcoming the same vessels.

Five categories of indicators were calculated for each graph in order to be compared with throughput data (see Table 1):

- Circulation indicators simply count the number of vessels, calls, and operators for each port after one year of movements;
- Foreland indicators provide the geographic dimension of distance (average and maximal) between each port and other ports connected, while adding a measure of foreland diversity reflecting upon the distribution of traffic;

[1] http://www.seasearcher.com/

- Connectivity indicators are local measures defined by the number of ports connected (degree); the weighted degree is the sum of all traffic links for a given port, and the nodal degree is the number of maximal flow connections with other ports. For instance, a large port is likely to attract the maximum traffic flow of many secondary ports, while the latter may have only one maximum flow directed to a larger port;
- Centrality indicators are classic measures of accessibility. They complete connectivity indicators by the fact that they illustrate the position of ports on the level of the entire graph: betweenness centrality is the number of positions on possible shortest paths and eccentricity is a normalized measure of farness from other ports;
- Neighbourhood indicators calculate the relative position of ports vis-à-vis their direct neighbours considering the configurations of their relations (strength, Strahler, clustering)[2].

Table 1. List of indicators

Type of measure	Variable	Definition
Circulation	No. Vessels	Number of different vessels having called at the port through the year
	No. Calls	Number of times a vessel has called through the year
	No. Operators	Number of different operators having called the port through the year
Foreland	Max. distance to another port	Maximum orthodromic distance (km) among all connections to other ports
	Avg. distance to other ports	Average orthodromic distance (km) among all connections to other ports
	Foreland diversity index	Relative diversity index applied to ports' worldwide traffic distribution at country level (inverse of the sum of differences in shares compared with world average)
Connectivity	Degree	Number of ports connected
	Weighted degree	Sum of traffic on all connections
	Nodal degree	Number of ports connected by dominant flows (i.e. maximum flow links)
Centrality	Betweenness centrality	Number of positions on possible shortest paths in the entire graph
	Weighted betweenness centrality	Number of positions on possible shortest weighted paths in the entire graph
	Eccentricity	Normalized measure of remoteness from all other ports
Neighbourhood	Clustering coefficient	Probability for direct neighbours to be connected with each other
	Strahler index	Ramification level
	Strength index	Strength of adjacent connections with other ports

Source: own elaboration based on LMIU data

Among the variables, the affinity with throughput volume may be appreciated by comparing linear correlations (Table 2). Results are very similar regardless of the type of graph

[2] Appendix 1 provides formulas for main network measures.

considered except for foreland diversity, degree centrality, weighted degree, betweenness centrality that have slightly lower correlations in the graph of all links. Unsurprisingly, highest correlations are observed with circulation indicators (vessels, calls, and operators) and with weighted degree that is equivalent to total vessel traffic. Other measures are more complex and better depict the topological dimension of ports' position. Among the latter, only betweenness centrality exceeds 0.8 in the graph of direct links. Nodal degree, degree centrality, and foreland diversity have also significant correlations (over 0.7) with throughputs. Weighted betweenness, eccentricity and distance measures all exhibit moderate correlations. Neighbourhood measures in general are negatively correlated with throughput. This may be explained by the fact that large ports multiply their connections to other ports, while the latter are not necessarily connected with each other. This is typically an expression of the hub-and-spoke configuration with one pole connecting numerous satellites. Smaller ports have higher strength and clustering indices because they are more likely to form cliques[3] with their neighbours.

Table 2. Linear (Pearson) correlations with TEU throughput by type of graph

Type of measure	Variable	Direct links graph	All links graph
Circulation	Vessels	0.921	0.921
	Calls	0.906	0.906
	Operators	0.792	0.794
Foreland	Maximum distance	0.392	0.266
	Average distance	0.285	0.293
	Foreland diversity	0.702	0.703
Connectivity	Degree centrality	0.760	0.627
	Nodal degree	0.750	0.731
	Weighted degree	0.897	0.802
Centrality	Betweenness centrality	0.810	0.521
	Weighted betweenness centrality	0.280	0.189
	Eccentricity	0.441	0.436
Neighbourhood	Clustering coefficient	-0.311	-0.414
	Strahler	-0.034	0.043
	Strength	-0.275	-0.335

Source: own elaboration based on LMIU data

[3] A clique is defined as a maximal complete subgraph of at least 3 nodes

3 | Factor analysis

The factor analysis of all indicators (including throughput) was applied without rotation and on each type of graph. Results for the situation of indicators on each factor (or principal component) may be summarized as follows (Table 3):

- Overall, the composition of factors is very similar between the GDL and the GAL;
- F1 groups together TEU throughput, circulation indicators (operators, vessels, calls), and degree centrality, indicating that large ports are those of intense maritime activity deploying many links to other ports. These top indicators are opposed to the neighbourhood indicators of clustering and strength. Thus, F1 has a strong hierarchical logic in which highly correlated indicators go together;
- F2 is built on an opposition between TEU throughput, circulation indicators, nodal degree on the one hand, foreland indicators (distance to other ports, foreland diversity), and eccentricity on the other. We interpret this trend as an opposition between a hierarchical logic (similar to F1) and a geographical logic: centrally located ports have more throughput than remotely located ports;
- F3 shows an interesting opposition between connectivity (nodal degree), centrality (betweenness) indicators and foreland/neighbourhood indicators. Only in the GAL, throughput is significantly included in the group of foreland/neighbourhood indicators. This means that in the GAL, ports belonging to dense neighbourhoods generally generate more traffic than centrally located ports, which role is better explained by a bridge (or intermediate) function between dense neighbourhoods. Indeed, some ports may act as strategic pivots between regions without generating large traffics, as seen in the case of Anchorage (Fleming and Hayuth, 1994);
- F4 will not be interpreted due to its different composition in the GDL and the GAL, and because port throughput does not appear as a significant contributor to the observed trends.

The extent to which such results possess a geographic dimension can be verified in Figures 1a and 1b (direct links and all links). Because F1 is too much influenced by throughput itself, we concentrate the interpretation of F2, F3 and F4. In terms of the main ports represented[4] on F2, there is an opposition between some major hub ports and some major gateway ports. Asian hub ports are grouped together with European gateway-hubs (Rotterdam, Hamburg) in the trend of throughput, nodal degree and number of calls. These ports are local-global pivots ensuring the redistribution of containers within and between maritime regions. They are opposed to "classic" gateway ports (e.g. US ports) which manage to connect long-distance flows: their situation in the Pacific and their importance in trans-Pacific trades (USA-Asia) clearly explain the influence of foreland (distance) indicators on their grouping on F2, as these ports generate moderate throughput volumes. The dominance of their gateway functions tends to negatively impact their centrality in the maritime network, because our measures do not take into account hinterland accessibility. In turn, the average distance of major hub ports' connections is lowered by the intensity of their hub-and-spoke activities towards local secondary ports. We clearly observe a geographic divide between the Europe-

[4] see Appendix 2 for most representative ports.

Asia maritime corridor having high internal connectivity (cf. neighbourhood) and the rest of the world more characterized by long-distance connections.

Table 3. Results of the factor analysis by type of graph

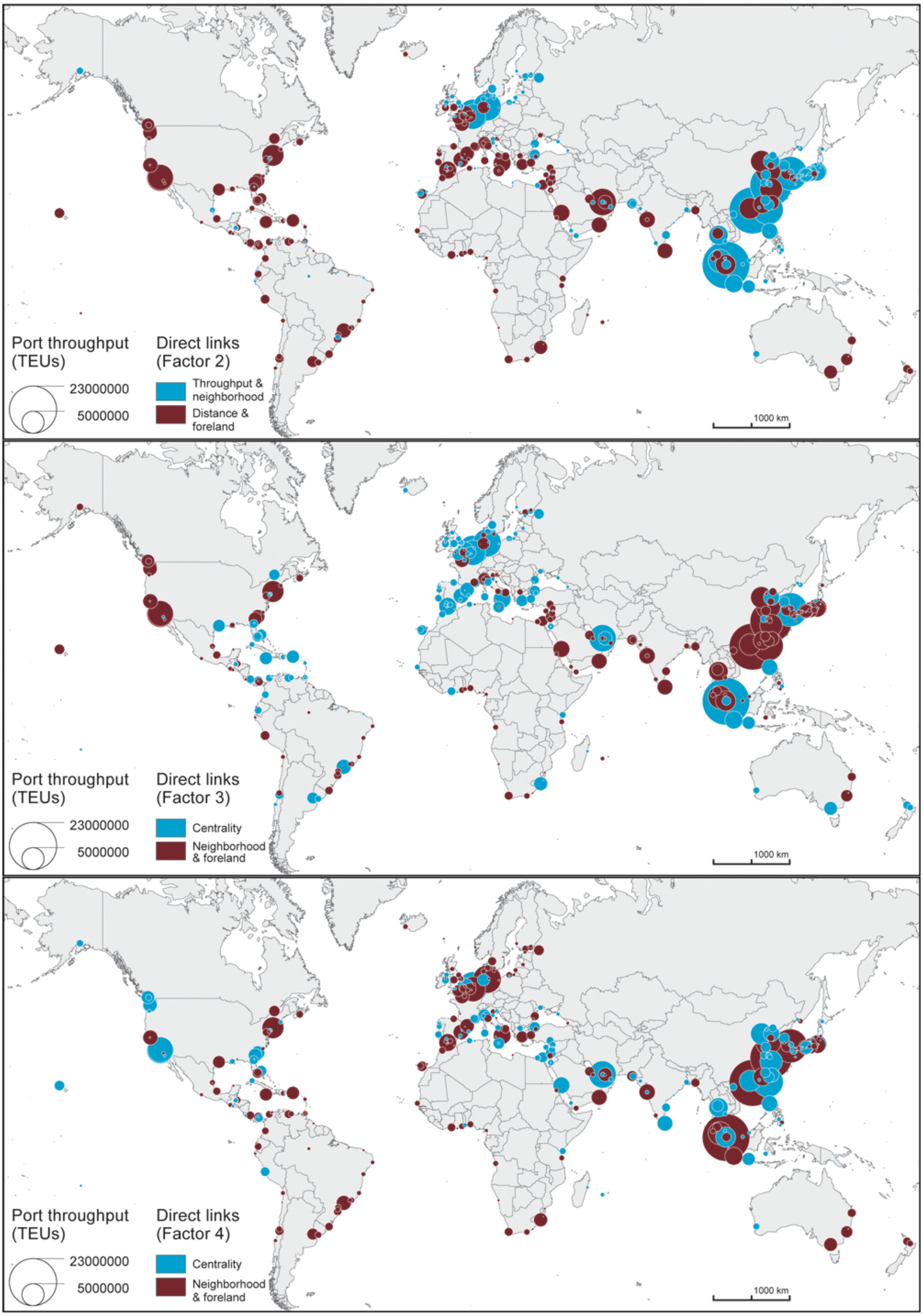
Value	Graph of direct links (GDL)				Graph of all links (GAL)			
	Factor 1	Factor 2	Factor 3	Factor 4	Factor 1	Factor 2	Factor 3	Factor 4
Eigenvalue	9.054	1.812	1.407	1.029	8.437	2.034	1.536	0.962
% of Var.	56.587	11.323	8.791	6.433	52.730	12.712	9.603	6.011
Cum. %	56.587	67.910	76.701	83.134	52.730	65.442	75.045	81.055
Throughput (TEUs)	0.886	-0.313	0.076	0.004	0.856	-0.317	-0.254	0.056
Operators	0.939	0.002	0.115	-0.008	0.957	0.016	-0.070	-0.056
Vessels	0.956	-0.178	0.104	0.023	0.942	-0.188	-0.196	-0.003
Calls	0.905	-0.336	0.061	0.023	0.889	-0.330	-0.218	0.066
Nodal degree	0.837	-0.307	-0.156	0.059	0.705	-0.416	-0.200	0.143
Maximum distance	0.650	0.630	0.237	0.054	0.544	0.724	0.008	0.005
Average distance	0.508	0.634	0.253	0.145	0.527	0.672	-0.297	-0.024
Betweenness centrality	0.865	-0.295	-0.129	0.041	0.644	-0.091	0.172	-0.193
Clustering coefficient	-0.575	-0.322	0.709	0.040	-0.732	-0.012	-0.633	0.070
Degree centrality	0.943	0.025	-0.007	0.007	0.917	0.236	0.152	-0.086
Strahler	-0.080	-0.139	-0.096	0.874	0.131	0.303	0.130	0.839
Strength	-0.519	-0.345	0.744	-0.026	-0.502	0.287	-0.750	0.081
Weighted betweenness centrality	0.310	-0.185	-0.124	-0.468	0.254	-0.182	0.306	0.382
Eccentricity	0.714	0.430	0.212	-0.009	0.791	0.480	0.165	-0.105
Weighted degree	0.884	-0.304	0.095	0.074	0.803	-0.329	-0.250	0.096
Foreland diversity	0.804	0.187	0.280	-0.092	0.804	0.174	-0.196	-0.058

Source: own elaboration based on LMIU data and StatiXL software

On F3, results slightly differ according to the type of graph considered, although the overall logic is similar. In the GDL, the influence of distance indicators on the grouping of many Asia-Pacific ports together is apparent (Canada, US, Mexico, China, Japan) as opposed to a number of local hub ports having a higher centrality in the network (e.g. Surabaya for Indonesia, Bandirma for Turkey, Pietarsaari for Finland, and Aalborg for Denmark-Iceland). The latter ports are regional hubs redistributing cargoes to peripheral ports. In the GAL, the opposition has a clearer geographic distribution, with many Asia-Pacific ports and hubs opposed with several European (Scandinavia-Baltic and Atlantic) ports. In both figures, Europe appears as a rather distinct group characterized by higher centrality (and throughput) than neighbourhood. Such results may illustrate the fact that regardless of their size, European ports have a good position globally compared with other ports, which remain more embedded regionally for an equivalent throughput size. Such pattern may suggest the permanency of a centre-periphery pattern of international trade inherited from the past.

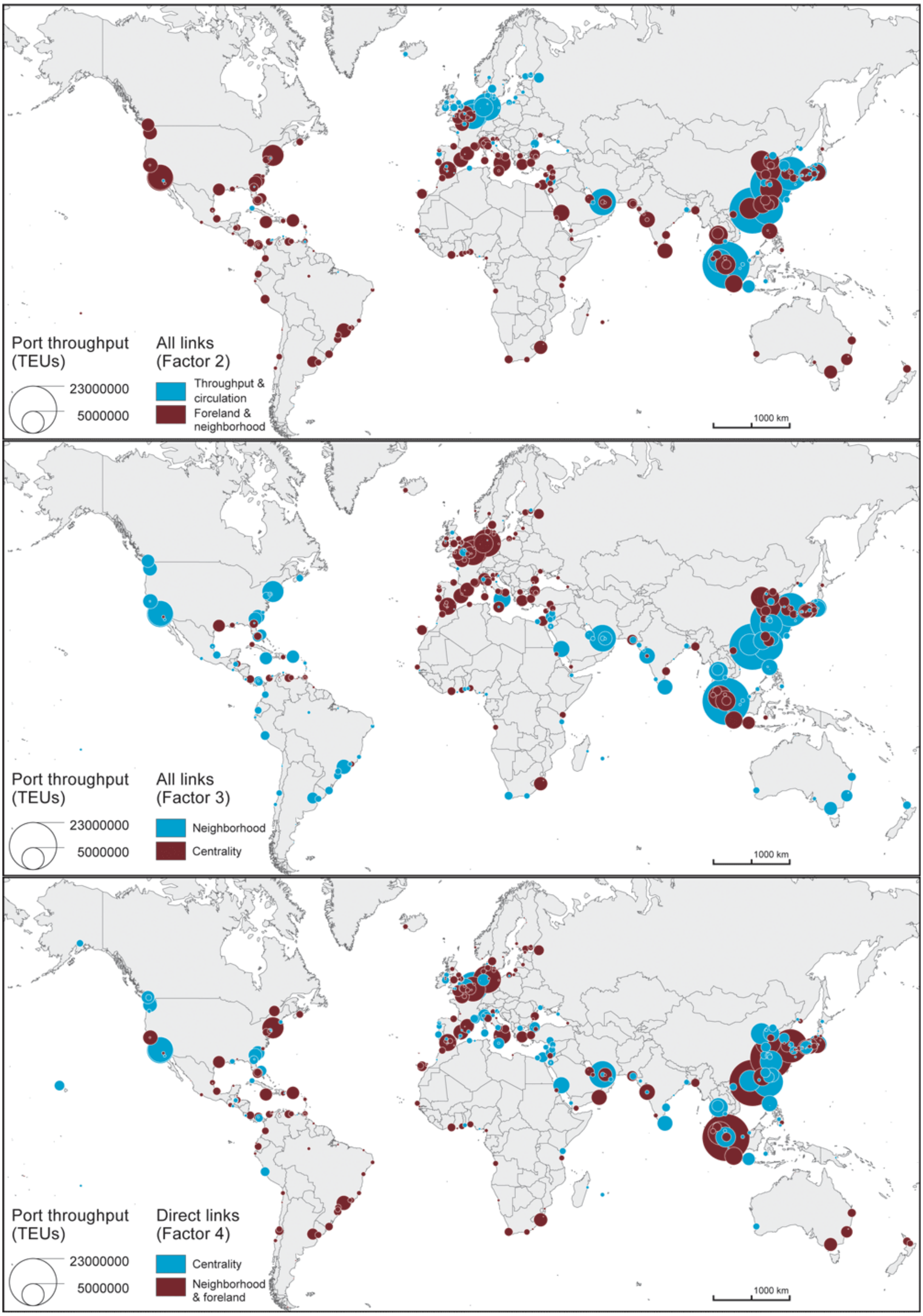
On F4, an East-West belt is made of more central ports of all throughput sizes, from Los Angeles to China. The opposite profile points at major (hub) ports with long-range connections (foreland) as well as strong local embeddedness (neighbourhood), and their distribution is comparable in the GDL and in the GAL.

Figure 1a. Position of ports on each factor (graph of direct links)



Source: own realization based on LMIU and Containerisation International data

Figure 1b. Position of ports on each factor (graph of direct links)



Source: own realization based on LMIU and Containerisation International data

4 | Multiple Regression Analysis

In this section we wish to assess the effects of network indicators on throughput by means of an exploratory study. We use AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion) in order to select suitable combinations of network indicators in all cases by imposing penalty to explanatory variables in excess. Of course, such methods do not exclude possible shortcomings due to the variables chosen. For each type of graph, we select 2 models which AIC and BIC is near to minimum with high Adjusted R-square. Then the selection of the final model is based on the works of Anderson et al. (1972) and Allen (1974) proposing to adopt the model with minimum of the PRESS, which equals the sum of squares of predicted residual errors. Table 4 shows the best criteria of possible cases and the selected criterion of the model in each graph.

Table 4. Criterion of Variable Selection

	Graph of direct links (GDL)		Graph of all links (GAL)	
	Best	Finally Selected	Best	Finally Selected
R-Square	Max : 84.54%	84.20%	Max : 83.15%	82.87%
Adjusted R-Square	Max : 83.76%	83.74%	Max : 82.53%	82.46%
(AIC)	Min : 6716.1889	6716.1889	Min : 5894.2948	5894.2948
BIC	Min : 6718.9119	6718.9119	Min : 5897.0185	5897.0185

The analysis of variance (ANOVA) is presented in Table 5, where the P-value in both graphs is smaller than 0.0001, meaning that the model is significant at 5% level. In both cases, the selected model for each graph can explain about 83% of throughput's variance (dependent variable), which is a satisfactory result (Table 6).

Table 7 shows the coefficients of selected network indicators and the P-values of each coefficient. We have seven network indicators in the GDL and five in the GAL. Four indicators affect TEU throughput in both graphs: vessels, operators, maximum distance to another port, and weighted degree. The coefficients of number of vessels and number of operators are respectively positive and negative in both graphs. It means that whatever the type of graph considered, the more vessels and the lesser operators, the more throughput increases. However, the sign of the coefficients for "maximum distance to another port" and weighted degree is different both in the GDL and in the GAL. If the maximum distance to another port increases, then port throughput decreases in the GDL, but contrastingly increases in the GAL. The influence of weighted degree is the reverse to the maximum distance to another port. The role of distance is thus paradoxical: while larger ports connect longer distances on average, this is complicated by some remotely located ports (e.g. Pacific and Oceania, South Africa) generating less traffics. Thus, distance is both a measure of good performance and a measure of remoteness: it does not have the same meaning for all ports.

Table 5. ANOVA results

	Source	DF	Sum of squares	Mean Square	F Value	Pr > F
Graph of direct links (GDL)	Model	7	6.440927E14	9.201324E13	183.44	<.0001
	Error	241	1.208827E14	5.015881E11		
	Corrected Total	248	7.649754E14			
Graph of all links (GAL)	Model	5	6.217753E14	1.243551E14	204.13	<.0001
	Error	211	1.285381E14	6.091855E11		
	Corrected Total	216	7.503135E14			

Table 6. Complementary results

	Graph of direct links (GDL)	Graph of all links (GAL)
Root MSE	708229	780503
Dependent Mean	735777	824218
Coeff Var	96.25591	94.69624
R-Square	0.8420	0.8287
Adj R-Sq	0.8374	0.8246

Three indicators including foreland diversity index, betweenness centrality, and weighted betweenness centrality are selected in the GDL only. The average distance to other ports is selected and has a negative influence on throughput in the GAL.

In both graphs (GDL and GAL), the most influential indicator is the maximum distance to another port. Such result was not easily predictable based on simple correlations. It means that whatever the type of graph considered, ports with long-range connections are more likely to generate large throughputs than ports with short-range connections. This is a very clear illustration of the importance of geographic parameters in shaping port hierarchies. Ports with wider radiance and geographic reach, of course, are likely to connect trunk lines of high density where ocean carriers deploy their largest vessels. As seen in the factor analysis, there is also the influence of conjectural phenomena with the overwhelming importance of trans-Pacific trades in the current pattern of container shipping networks, with major US and Asian ports connecting with each other through weighty shipping lines.

Table 7. Parameter estimates

	Label	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Graph of direct links (GDL)	Intercept	1	12274	69748	0.18	0.8605
	No. vessels	1	10756	1082.53567	9.94	<.0001
	No. operators	1	-12768	3517.18958	-3.63	0.0003
	Max. distance to another port	1	-25.10418	15.41028	-1.63	0.1046
	Foreland diversity index	1	-1850.02870	1011.58465	-1.83	0.0687
	Weighted degree	1	0.01027	0.00363	2.83	0.0051
	Betweenness centrality	1	11.07465	6.22764	1.78	0.0766
	Weighted betweenness centrality	1	2.26709	0.73670	3.08	0.0023
Graph of all links (GAL)	Intercept	1	-5353.56807	77282	-0.07	0.9448
	No. vessels	1	12459	922.70239	13.50	<.0001
	No. operators	1	-12730	3976.01767	-3.20	0.0016
	Max. distance to another port	1	42.83943	24.68682	1.74	0.0841
	Avg. distance to other ports	1	-162.24881	64.55029	-2.51	0.0127
	Weighted degree	1	-0.00005430	0.00002313	-2.35	0.0198

5 | Conclusion

This exploratory research has provided floor for a reflection on the influence of network position on throughput volumes. Although maritime networks are volatile with regard to land-based fixed networks (e.g. road, rail), their characteristics and configurations also express important realities of trade and port development. The main results of this paper confirm the importance of centrality in the network but, also, the influence of geographic distance between ports. Ports reaching further distance through direct or indirect shipping connections are more likely to generate container throughput than ports connecting nearest ports. While such results would need further verification in terms of statistical goodness and policy implications, it paves the way towards complementary research in this field, perhaps by looking at how throughput growth (instead of sole volume) can be explained by network position and its possible changes. Yet, the measure of distance remains paradoxical because it does not overlap entirely the port hierarchy: some smaller ports that are remotely located also connect long distance links. This phenomenon is directly caused by the physical embedding of ports in a spatial network. Perhaps, a zoom at ports of comparable size, such as the world's largest ports facing similar issues, would provide more interesting results in terms of functional differentiation and specialization.

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Appendix 1. Illustration of main network measures

Measure	Description	Formula
Degree centrality	Number of adjacent nodes (k)	$k_i = C_{\mathrm{D}}(i) = \sum_{j}^{N} x_{ij}$
Weighted degree	Sum of link weights (s)	$s_i = C_{\mathrm{D}}^{w}(i) = \sum_{j}^{N} w_{ij}$
Transitivity, Clustering coefficient	Number of observed triads divided by maximum possible number of triads	$C_i = \frac{2\lvert\{e_{jk}\}\rvert}{k_i(k_i - 1)}$
Strength index	Probability for adjacent links to belong to cycles of length 3 and 4	$w_s(u) = \frac{\sum_{e \in adj(u)} w_s(e)}{deg(u)}$
Eccentricity (or Koening number, associated number)	Number of links needed to connect the farthest node	$e(x) = \max_{y \in X} d(x, y).$
Betweenness centrality (or shortest-path betweenness)	Number of occurrences on all shortest paths	$C_{\mathrm{B}}(i) = \frac{g_{jk}(i)}{g_{jk}}$
Weighted betweenness centrality (or flow betweenness)	Traffic flow through node i between nodes j and k divided by maximum possible traffic between j and k	$C_i^F = \frac{\sum_{j<k \in \mathbf{G}} m_{jk}(i)}{\sum_{j<k \in \mathbf{G}} m_{jk}}$

Source : adapted from various sources

Appendix 2. Statistical description of the indicators

Indicator	Mean		Median		St. dev.		Max		Min	
	direct	all	direct	all	Direct	all	direct	all	direct	all
Vessels	92.4	92.4	26.5	26.5	190.1	190.1	1857.0	1857.0	1.0	1.0
Calls	623.8	623.8	181.5	181.5	1587.3	1587.3	18198.0	18198.0	1.0	1.0
Operators	38.5	38.5	19.0	19.0	51.1	51.1	336.0	336.0	1.0	1.0
Maximum distance	3595.3	6715.2	2059.1	9073.7	3611.6	3811.9	10018.4	10018.6	0.0	0.0
Average distance	942.7	2221.6	461.7	2115.2	1203.4	1711.9	9811.0	9738.4	0.0	0.0
Foreland diversity	81.0	81.0	71.0	71.0	32.1	32.1	277.3	277.3	50.4	50.4
Degree centrality	30.3	156.2	20.0	130.0	31.7	117.7	226.0	610.0	1.0	6.0
Nodal degree	2.9	3.1	2.0	1.0	4.1	8.2	39.0	94.0	1.0	1.0
Weighted degree	9545765.8	49276316.8	1510825.0	3406765.0	28280603.3	168347922.4	340268827.0	2210600634.0	1849.0	1.0
Betweenness centrality	6123.2	2270.7	1306.5	387.7	16402.5	5922.4	174516.0	83246.2	0.3	0.1
Weighted betw. centrality	16149.5	6961.9	3584.0	879.7	53817.6	16155.9	840440.0	135225.0	2.0	0.1
Eccentricity	0.8	0.7	0.8	0.8	0.1	0.1	1.0	1.0	0.4	0.3
Clustering coefficient	0.5	0.6	0.4	0.6	0.2	0.2	1.0	1.0	0.0	0.2
Strahler	2289.3	12137.6	2303.3	12600.4	121.5	2540.2	2381.0	13810.5	1.0	1.0
Strength	0.3	0.4	0.3	0.4	0.1	0.1	0.5	0.7	0.0	0.2
Throughput (TEUs)	**766433.8**		**158851.0**		**2212855.8**		**23192200.0**		**5.0**	

Appendix 3. Results of the factor analysis with most significant ports

Graph of direct links (GDL)			Graph of all links (GAL)		
Factor 1	Factor 2	Factor 3	Factor 1	Factor 2	Factor 3
Singapore	Boston(USA)	Portland(OR USA)	Singapore	Kudamatsu	Varna
Hong Kong	New Orleans	Visakhapatnam	Hong Kong	Altamira	Szczecin
Shanghai	Tampa	Ensenada(MEX)	Busan	Vancouver(CAN)	Constantza
Busan	Wilmington(NC USA)	General Santos	Shanghai	San Francisco	Aalborg
Rotterdam	Bremerhaven	Guangzhou	Rotterdam	Port Elizabeth	Leixoes
Hamburg	Portland(OR USA)	Kawasaki	Hamburg	Baltimore	St. Petersburg
Kaohsiung	Oakland	Vancouver(CAN)	Kaohsiung	Sydney	Riga
Port Klang	Houston	Civitavecchia	Antwerp	Fremantle	Poti
Ningbo	Savannah	Kolkata	Port Klang	Mejillones	Ghent
Antwerp	Tanjung Pelepas	Trieste	Ningbo	Auckland	Bilbao
Yokohama	Tacoma	Progreso	Qingdao	Veracruz	Seville
Qingdao	Manzanillo(PAN)	Banjul	Bremerhaven	Mobile	Belfast
New York	Vancouver(CAN)	Salaverry	Tokyo	San Vicente	Recife
Tokyo	Rio de Janeiro	Kandla	Xiamen	Caldera(CRI)	Gdynia
Xiamen	Los Angeles	Lazaro Cardenas	Nagoya	Paranagua	Tees
	Kolkata	Ghent		Oranjestad	Tacoma
	Mazatlan	Pietarsaari		Sakai	Lazaro Cardenas
	Ahus	Goole		Shanghai	San Francisco
	Visakhapatnam	Camden(NJ USA)		Bergen	Santander
	Doha(QAT)	Halmstad		Rotterdam	Tanga
	Puerto Deseado	Bandirma		Warrenpoint	Qui Nhon
	Kaohsiung	Surabaya		Melilla	Kudamatsu
	Cagayan de Oro	Aalborg		Kiel	Manzanillo(CUB)
	Salaverry	Iskenderun		Bar	Busan
	Shanghai	Palma(Maj)		Hamburg	Eilat
	Rotterdam	Raahe		Almeria	Oranjestad
	Hamburg	Boston(GBR)		Norrkoping	Mejillones
	Busan	Tekirdag		Busan	Puerto Deseado
	Hong Kong	Uusikaupunki		Hong Kong	Hong Kong
	Singapore	Norrkoping		Singapore	Singapore

Source: own elaboration based on LMIU data and StatiXL software