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Mapping routine interactions in port operations: Insights from social network analysis

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RESUMEN

El análisis de redes sociales demuestra ser un instrumento valioso para comprender y representar visualmente relaciones complejas entre diversas entidades dentro de una red. Este estudio tiene como objetivo explorar la aplicación del análisis de redes sociales en el contexto de las operaciones portuarias hinterland. En pos de este objetivo, examinamos las interacciones entre varias partes interesadas, incluidas las autoridades portuarias, los conductores de camiones, las empresas de agentes portuarios, los vigilantes, las empresas de importación/exportación y los operadores de terminales. Como resultado, revelamos patrones, identificamos cuellos de botella y descubrimos oportunidades para aumentar la eficiencia y la colaboración dentro de este sistema. Esta investigación contribuye al cuerpo de conocimiento existente sobre la utilización del análisis de redes sociales dentro de la industria marítima y, al mismo tiempo, proporciona información para mejorar el rendimiento portuario.

Palabras clave: *Análisis de redes sociales – Métricas a nivel de red – Métricas a nivel de nodo – Operaciones portuarias.*

ABSTRACT

Social network analysis proves to be a valuable instrument for comprehending and visually representing intricate relationships among diverse entities within a network. This study aims to explore the application of social network analysis within the context of hinterland port operations. In pursuit of this aim, we examined the interactions amongst various stakeholders, including port authorities, truck drivers, port agent companies, vigilant guards, import/export firms, and terminal operators. As a result, we unveiled patterns, pinpointed bottlenecks, and unearthed opportunities to amplify efficiency and collaboration within this system. This inquiry contributes to the existing body of knowledge concerning the utilization of social network analysis within the maritime industry while also providing insights to enhance port performance.

Keywords: *Social Network Analysis – Network-level Metrics – Node-level Metrics – Port Operations.*

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INTRODUCTION

Maritime ports serve as vital economic infrastructures situated at the nexus of land and sea, enabling efficient foreign trade through sea routes (Szwankowski, 2000). Their primary objective is to meet the transportation demands of both maritime and land sectors within their respective regions (Szwankowski, 2000). Ports are dynamic socio-economic spaces encompassing a wide array of functions, blending maritime and land transportation processes, advanced technical equipment, and trade-related activities involving the movement of goods and people (Montwill, 2014).

As significant economic centers, port infrastructures often find their place in densely populated urban areas. They provide an extensive range of services and cater to a diverse clientele, such as shippers, forwarders, transport companies, and logistics operators (Nagi et al., 2021). Moreover, they facilitate large-scale domestic and international trade operations, fostering the exchange of goods on a global scale (Montwill, 2014). The efficiency of a port hinges on effective port management practices (Milani et al., 2015).

The management of maritime ports entails intricate and continuous oversight across various operations while considering the interests of all stakeholders involved (Nagi et al., 2021). These stakeholders can be categorized as internal (longshoreman, pier man, foremen, operational management, warehouse staff) and external (suppliers, local communities, government, importing and exporting companies) (Notteboom & Winkelmans, 2002).

Ports face diverse risks stemming from natural disasters (geological variations, meteorological phenomena) as well as human-induced hazards (oil spills, fires) (John et al., 2016; Kaundinya et al., 2016). Such risks can impact supply chains, the environment, and the safety of individuals within port areas (Nagi et al., 2019).

Port stakeholders interact in different risk scenarios, giving rise to unique network structures within each port (Nagi et al., 2021). These structures reflect the complex port operations and play an important role in knowledge transfer and cooperation between organizations (Reagans & MCevily, 2003). Analyzing network structures can enhance this cooperation (Nagi et al., 2021).

To investigate the structure of interactions and strengthen cooperation between stakeholders, the social network analysis (SNA) method can be used (Tomaél & Marteleto, 2013). This method allows for examining the existing links between actors and analyzing phenomena such as social influence, resource mobilization, and information flow (Giurca & Metz, 2018).

In this context, the present study addresses the following research question: "How do social interactions influence the port environment, encompassing operations, safety, and environmental aspects?". To answer this question, an empirical study was conducted in a southern Brazilian port, utilizing a mixed quantitative and qualitative approach to analyze node-level and network-level metrics. The study aims to demonstrate how diverse interactions among port actors impact the operational dynamics (hinterland) of the port.

THEORETICAL REVIEW

The theoretical underpinning of this study is organized into three key sections. The first section delves into the background of social network analysis theory, providing a comprehensive overview. The second section focuses on the main metrics, encompassing node- and network-level metrics. Finally, the third section contextualizes the application of social network analysis within the port environment, highlighting its significance and relevance.

Social Network Analysis background

Social network analysis originated in the early twentieth century, acknowledging that social connections weave a fabric that shapes individuals' behaviors (Granovetter, 1973). In order to advance this theory, quantitative data collection techniques, such as questionnaires, were initially devised, and the resulting data were visualized through sociograms (Fialho, 2014).

During the period from 1958 to 1968, Paul Erdös and Alfréd Rényi made significant contributions to network analysis through the publication of eight influential articles. Their work revolutionized the study of networks and laid the foundation for the theory of random graphs (Miceli, 2006). Erdös and Rényi proposed that graphs, serving as representations of the world, possessed a fundamentally random nature. They suggested that the connections between these networks' vertices were also random (Barabási & Crandall, 2003).

However, one of the most significant studies on social network structure was conducted by Stanley Milgram in 1967 (Borgatti et al., 2018). Although Frigyes Karinthy, a Hungarian writer, first mentioned the theory of Six Degrees of Separation in 1929 in his work titled "Chains" from the collection of short stories "Everything is Different" (Barabási & Crandall, 2003), it was Milgram who extensively examined the theory, also known as the "Small World" phenomenon. Milgram (1967) proposed that society is not merely composed of random connections between individuals but tends to be divided into social classes and cliques, where most or all members are connected.

Another essential concept in social network analysis is the notion of the "strength of weak ties" studied by Mark Granovetter (1973; 1983), which argues weak ties play a vital role in information diffusion. Besides, Ronald Burt further explored the concept of "structural holes" in 1992, emphasizing that individuals who bridge disconnected people can control communication flows (Eranus et al., 2016; Rodan, 2010). The concept is linked to ideas of social capital, in that whoever establishes the connection between two people who are not connected can control that communication (Freeman, 1978; Schultz-Jones, 2009).

An additional influential contribution to social network theory was made by Barabási and Albert in 1999, who introduced the concept of "scale-free networks.". Barabási and Albert's research revealed that networks do not form randomly; instead, the growth of networks and the likelihood of a new connection forming with an existing vertex exhibit preferential attachment (Barabási & Albert, 1999). In other words, scale-free networks incorporate both growth and preference in connection formation.

With the advent of Barabási and Albert's proposal, studies on homophily in networks have considerably expanded. Homophily, a concept from the 1950s attributed to Paul Lazarsfeld and Robert K. Merton, refers to the tendency for interactions between actors who share many similar or socially significant attributes. This idea can be encapsulated in expressions such as "birds of a feather flock together" or "similarity breeds companionship" (Espinosa-Rada & Ortiz, 2022). These attributes can encompass various factors, including place of residence and nativity, age, gender, ethnicity, educational level, socio-economic status, as well as attitudes, beliefs, interests, hobbies, and behaviors (Lozares & Verd, 2011; Zanata & Silva, 2011).

Presently, social networks can be characterized by strong ties, weak ties, and structural holes while also exhibiting properties of small-world networks and scale-free networks. Network studies have evolved significantly with contributions from various areas of knowledge (Terra et al., 2022).

Social Network Analysis metrics

The metrics used in social network analysis (SNA) are classified according to the level of analysis, which can be divided into dyad level, node level, and network level (Borgatti et al., 2018). However, Tables 1 and 2 present only the metrics referring to the node and network levels, respectively.

Centrality analysis, also referred to as node-level analysis, is a widely used technique in social network analysis for evaluating the significance and influence of individual nodes within a network (Grando, 2016). This approach enables several important tasks, including identifying the role of actors as intermediaries, influential individuals, or isolated nodes in the network. It measures the importance of a node in relation to a group of nodes, provides insights into its interaction behavior and level of engagement with other actors, and facilitates the mapping of centrality within a social network (Newman, 2010).

Table 1

Node-level social network analysis metrics

Metric	Description
OutDegree	Number of outbound links
Indegree	Number of links in the entry
OutEigenvector	Influence based on outgoing links
Betweenness	Number of shortest paths between pairs of nodes passing through a given node

Source: Grando (2016)

The network-level analysis can provide valuable information about the overall structure of a network, its attributes, and the interplay between nodes. It enables the examination of how nodes are connected and the impact of these connections on the network's functioning (Fialho, 2014). This approach offers various avenues for analyzing social networks, including identifying connection patterns, measuring network density, evaluating the degree of centralization of actors and groups, analyzing information propagation, and identifying bridges and gaps within the network (Borgatti et al., 2018).

Social Network Analysis in ports

Social network analysis (SNA) has demonstrated its utility across various scientific domains, including within port contexts (Nagi et al., 2021). The connectivity between ports and their hinterlands plays a pivotal role in the port competition, yet it encounters obstacles due to the diverse modalities of the port's intermodal system and the absence of direct connections with all logistics nodes (Deshmukh & Song, 2022). In this regard, researchers have explored the application of SNA as an empirical tool for assessing port-hinterland connectivity.

Two highly referenced studies in port literature employing social network analysis include Maya-Jariego et al.'s (2016) evaluation of the equilibrium between intra and inter-professional relationships within fishing communities, and Liu et al.'s (2018) examination of the spatial disparities in the maritime network on both a global and local scale, specifically in the context of international trade.

Whereas studies such as Kanrak et al. (2019) reviewed the literature on SNA applications in marine transportation, comparing SNA metrics and their possible applications in the port context. Ducruet and Notteboom (2022) used SNA to analyze the interdependence between ports and discuss the factors that can lead to gaps or overlaps in their interaction networks. In another research endeavor, Ducruet et al. (2010) applied the concepts of "Small Worlds" and scale-free networks to investigate how hub-and-spoke strategies employed by ports and ocean carriers influenced the structure of a port network. Their study focused on container movement across the Atlantic Ocean from 1996 to 2006. All the studies mentioned exemplify the significance of SNA in comprehending the dynamics and relationships within the port context.

Table 2

Net-level social network analysis metrics

Metric	Description	Source
Mutuals	The relationship between mutual nodes depends on the nodes' connective status/structure/position.	Srivastav & Nath (2016)
Breadth	It is a measure that refers to the extent or reach of a node's connections in a network.	Remis et al. (2016)
Connectedness	It represents the ability of a node in the network to access other nodes in the network through direct and indirect paths.	Zhang et al. (2013)
Degree centralization	It refers to the degree distribution of nodes in a network, focusing on inequality in the degree distribution between nodes.	Golbeck (2013)
Average degree	It refers to the average number of connections (or degree) each node has.	Borgatti et al. (2018)

Source: Authors (2023).

METHOD

This paper adopts an exploratory mixed-method design to achieve triangulation, which involves converging results from different methods. We analyzed social phenomena through the lens of social network theory, which is a broad and consolidated area of interest (Letenyei, 2003). Moreover, network analysis is a field that studies the structure and position of networks. It has established various concepts to understand these aspects, and many of them have been mathematically formalized. This enabled the use of computers to detect and measure these concepts in data (Borgatti et al., 2018). As for the scientific procedure, we used a case study, which is favorable for studying complex contemporary phenomena in real-world settings (Yin, 2017), mainly complex socio-technical systems (Vespignani, 2012).

The case studied is a port located in southern Brazil, which is a port authority organization responsible for managing five docking berths and overseeing the operations of over 300 workers on a weekly basis for hinterland port activities. The stakeholders are composed of several distinct groups. Firstly, there is the public port authority, which consists of 20 workers. Additionally, there are 64 vigilant guards (VG) responsible for security, a team of seven workers dedicated to cleaning staff, and five port operator companies (POC). The number of port agent companies (PAC) and import/export companies is not specified. Moreover, a workforce management body for independent port work employs 150 staff members. Furthermore, there are 50 truck drivers assigned to each berthed ship. Between September 2022 and May 2023, the total transportation volume through the port reached approximately 512,975 million metric tons. During this period, the primary cargoes transported included inputs for fertilizer production, barley, beef tallow, and wheat. The methodological steps for collecting and analyzing data consist of 4 steps described below.

The first step involved field study through observations and informal conversations regarding the routine activities at the studied port. Social interactions and material practices among different port actors were observed, both in person and remotely, through various forms of communication such as face-to-face interactions (verbal, signals), documents (regulations, informational posters, checklists, Standard Operating Procedures - SOPs), and electronic means (radio, telephone, computer). In addition, as we were members of the port's health and safety team within an environmental management project, we were on a daily basis involved in observing both safety conditions and social interactions and material practices during port operations with ships over a period of nine months, totaling over 180 hours, including interviews for a better understanding of the setting. From a research standpoint, these observations can be classified as direct in the midst of operations (in loco) and unsystematic because they did not occur at regular intervals and times but rather occasionally and spontaneously, except we tried at least to observe the same time quantity of each actor, although we considered the saturation criterium as a final cut-off point. Informal conversations were conducted in both group and individual settings. Altogether, the observations allowed working around the sensitivities of participants and conversations, while the participants freely express their opinions and experiences without a predetermined set of questions.

The second step involved sorting data related to the previously collected information by using coding and then outlining a custom data collection method for the next step. After analyzing the data through thematic analysis, which aims to identify and interpret patterns of meaning within the data (Creswell, 2018), four interaction types (attributes) have emerged as focal points for deeper exploration. Besides, the necessity to establish binary relationships, distinguishing between the presence or absence of interactions, has also been highlighted. In addition, the studied nodes were defined as entities, where an occupational group represents a node, and 17 representative entities were identified considering the context of involvement in port operations with ships. Therefore, this process-tracing was chosen as the context for the networks related to the 4 previously encoded attributes.

The third step involved semi-structured interviews collecting data with participants briefed on the research's context and the theme of interactions, which is described in detail below.

a. *Authorization*: is the process by which actors who need validation or confirmation are granted approval to initiate or proceed with their activities. It encompasses the interaction through which events or actions are sanctioned for these individuals.

b. *Complaint*: involves the act of conveying concerns, misunderstandings, deficiencies, and issues to the relevant individuals. These complaints can be either formal or informal in nature. Formal complaints follow hierarchical channels and involve addressing third parties, while informal complaints are more like feedback or guidance exchanged between individuals without hierarchical connections. The purpose of complaints is to express dissatisfaction with deficiencies, deviations, or problems arising from specific situations and to request changes in events, behaviors, or outcomes.

c. *Inspection*: is the process of conducting a thorough examination or observation of activities to ensure their compliance with predetermined standards or established regulations.

d. *Information*: refers to the exchange of data concerning the status of operations taking place at a port.

To summarize, at this step, in-depth interviews were conducted where the interviewers (always 2) explored the experiences, opinions, and perspectives of the interviewee with the aim of uncovering perception nuances. The answers were cross-checked for accuracy. For instance, one individual claimed to interact significantly with another in a certain attribute. At the same time, the latter did not confirm being approached or seeking interaction in relation to that attribute. Besides, to enhance the reliability of the responses, a minimum of two individuals were interviewed per node. These interviews lasted around 1 hour and consisted of open-ended questions, encouraging the interviewee to provide detailed and thoughtful answers.

The fourth step involved the analysis of social networks itself. During the theoretical review for this study, four node-level metrics of interest and five net-level metrics were identified. The scope of the analysis encompassed quantitative descriptions using software and qualitative descriptions provided by the authors based on interviews and observations as a backup. Tischer (2022) emphasized the importance of maintaining context and developing qualitative descriptions of the network data. The calculation of metrics and graph generation was performed using the UCINET software (Borgatti et al., 2002).

RESULTS AND DISCUSSIONS

In this section, we have structured the analysis into node-level social network analysis and net-level analysis, providing the findings related to network authorization, complaint inspection, and information.

Social network analysis at the node level

Authorization network (n^1)

In the analysis of the Authorization network within the examined port context, it was observed that actors A1, A3, A14, and A13 exhibited the highest social centrality based on the OutEigenvalue metric, ranked in descending order of degree. The OutEigenvalue metric, which is a variant of degree centrality, measures the number of nodes connected to the neighboring nodes of a given node. Consequently, the significance of a node depends on the importance of its neighboring nodes. Figure 1 illustrates larger nodes for those actors who exert a greater influence over the entire network, extending beyond their direct connections. These central actors engage with other central actors, showcasing a stronger power of influence within the Authorization network. Notably, these actors include operational manager, warehouse manager, labor inspectors, and importing/exporting companies. The Authorization network enables the exploration of bureaucratic/hierarchical influence exerted by the involved actors. Please refer to Table 3 for further details.

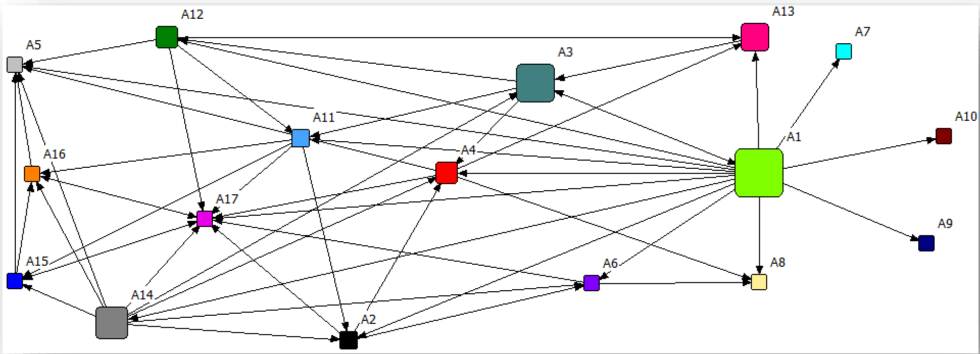

Figure 1. The OutEigenvalue of actors in the Authorization network

Table 3.

Node-level metrics in the Authorization network

		Metrics			
Code	Actor	Out Degree	In Degree	Betweenness	Out Eigenvector
A1	Operational manager	14.000	1.000	34.250	0.723
[redacted]	[redacted]	3.000	3.000	13.000	0.062
A3	Warehouse manager	4.000	3.000	49.000	0.506
A4	Load scale worker	4.000	4.000	23.500	0.125
A5	Maintenance	0.000	6.000	0.000	0.000
A6	Port guard	2.000	3.000	1.750	0.000
A7	Cargo tax notifier	0.000	1.000	0.000	0.000
A8	Vigilant guard	0.000	3.000	0.000	0.000
A9	Cleaning staff	0.000	1.000	0.000	0.000
A10	HSE Technician	0.000	1.000	0.000	0.000
A11	POC	4.000	3.000	10.667	0.031
A12	PAC	4.000	2.000	1.500	0.140
A13	Import/export companies	1.000	3.000	32.000	0.251
A14	Labor inspector	8.000	1.000	0.667	0.344
A15	Pier man	3.000	3.000	1.500	0.000
A16	Longshoreman	2.000	4.000	1.500	0.000
A17	Truck driver	2.000	9.000	9.667	0.000

Complaint network (n^1)

In the analysis of the Complaint network, certain actors were found to have higher social centrality based on the InDegree metric. These actors include A1, A6, and A8. This indicates that they have many direct connections in the network and are located closer to the network center. The InDegree metric measures the number of direct connections a node has within the network, representing the number of nodes it is directly linked to. In this context, it implies that these individuals receive most of the complaints.

Upon analysis of the OutDegree metric, which measures the number of interactions initiated by an actor, it was discovered that A6, A7, and A9 are the least likely to voice complaints. Alternatively, when considering the InDegree metric, which reflects the number of interactions in which an actor is approached by others, A2, A9, A12, and A13 receive a smaller number of complaints.

Within the Complaint network, certain actors stand out. A12 and A13, representing a shipping agency and an import/export company, respectively, receive the fewest complaints. These actors typically maintain a distance from field operations. Conversely, actor A6 (Port Guard) files one of the fewest complaints, reporting to operational management, vigilant guards, pier men, and labor inspector, in this way establishing connections with these actors. A6 also reports to a significant external actor, the Unified Public Security System.

A7 (Cargo tax notifier), who is employed by import/export companies, plays a pivotal role. They offer insights into problems and report to cargo clerks, and load scale workers with whom (this latter) they share physical space. Their activities are synchronized, sequenced, and interdependent.

A9 (Cleaning staff), comprising seven members, has the lowest overall degree in the Complaint Network. This team has limited interactions, both in terms of initiating and receiving complaints. Figure 2 illustrates that this actor is represented by the smallest node in the network.

The Complaint network reflects each actor's situational awareness, ownership feeling, and responsibility load once it identifies actors who are less or more engaged in complaint interactions within the network, both in initiating and receiving complaints from others. Please refer to Table 4 for more information.

Table 4. *Node-level metrics in the Complaint network*

		Metrics			
Code	**Actor**	**Out Degree**	**In Degree**	**Betweenness**	**Out Eigenvector**
A1	Operational manager	13.000	12.000	43.269	0.343
[redacted]	[redacted]	12.000	3.000	5.518	0.335
A3	Warehouse manager	10.000	9.000	14.968	0.298
A4	Load scale worker	6.000	9.000	7.261	0.147
A5	Maintenance	8.000	9.000	5.165	0.220
A6	Port guard	4.000	12.000	1.817	0.141
A7	Cargo tax notifier	3.000	11.000	7.261	0.102
A8	Vigilant guard	6.000	13.000	6.186	0.184
A9	Cleaning staff	2.000	3.000	0.561	0.067
A10	HSE Technician	8.000	10.000	10.822	0.203
A11	POC	12.000	9.000	9.810	0.326
A12	PAC	9.000	4.000	16.519	0.273
A13	Import/export companies	9.000	1.000	0.435	0.247
A14	Labor inspector	11.000	11.000	9.295	0.290
A15	Pier man	9.000	7.000	2.762	0.251
A16	Longshoreman	10.000	7.000	3.212	0.272
A17	Truck driver	8.000	10.000	6.140	0.197

Source: Authors (2023)

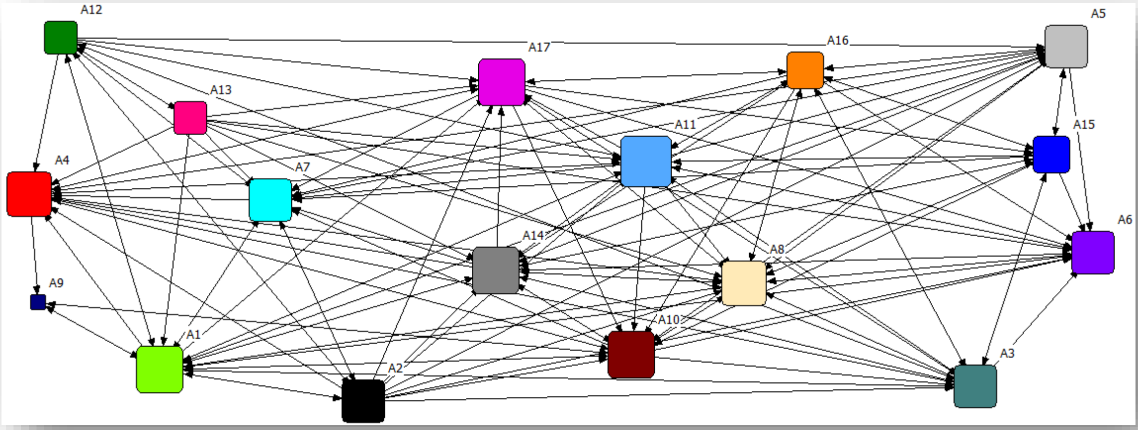

Figure 2. The Degree of the actors in the Complaint network

Inspection network (n[1])

Similar to the Authorization network, the Inspection network, namely, revealed the actors most engaged in inspection activities, being A1, A10, A11, and A14. Conversely, actor A17 emerges as the most inspected actor, exhibiting the highest degree of entry (InDegree). Actor A1 (operational manager), and A10 (health and safety and environmental technician), interact extensively with other actors, examining their activities. Similarly, actor A11 (agents representing port operator companies) and A14 (labor inspectors) play prominent roles in conducting field observations. These actors possess managerial responsibilities or oversee third-party activities. For instance, health and safety and environmental technicians are responsible for ensuring occupational and environmental well-being within the port environment, while agents coordinate ship unloading and oversee truck loading operations at a managerial level.

It is noteworthy that actor A17 (truck drivers) exhibits a high InDegree score, even though its overall Degree score is not particularly high, as depicted in Figure 3. This indicates that A17 is the most sought-after actor for inspections. Figure 3 illustrates several incoming arrows (7 edges) directed toward actor A17. The Inspection network can reflect the actors' workload, particularly regarding the ethical and mental weight associated with specific responsibilities, tasks, or situations. Inspection interactions often involve challenging decisions entailing moral values, ethical principles, or ethical conflicts. They require an awareness of the moral impact and the accompanying moral responsibility associated with actions or decisions. The moral burden may vary depending on circumstances and an individual's ethical sensitivity. Refer to Table 5 for further details.

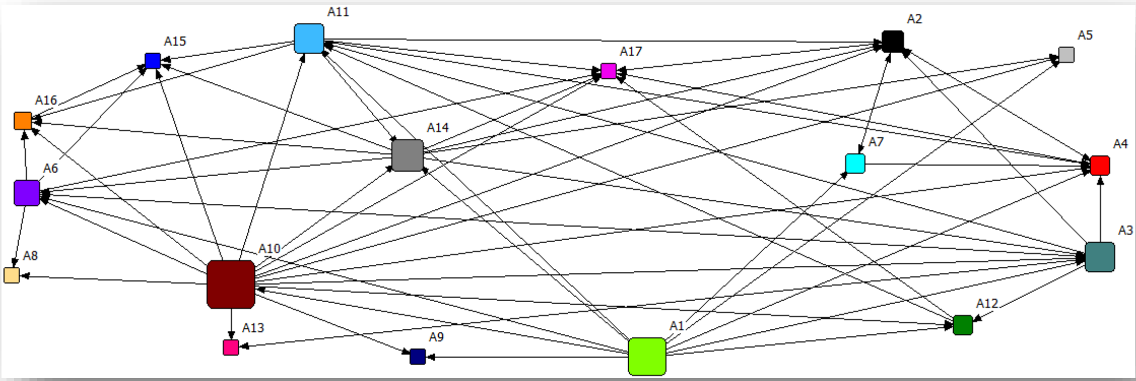

Figure 3. The Degree of actors in the Inspection network

Table 5.

Node-level metrics in the Inspection network

		Metrics			
Code	**Actor**	**Out Degree**	**In Degree**	**Betweenness**	**Out Eigenvector**
A1	Operational manager	10.000	0.000	0.000	0.790
A2	Cargo clerk	3.000	6.000	7.200	0.060
A3	Warehouse manager	6.000	3.000	7.167	0.233
A4	Load scale worker	2.000	6.000	1.033	0.037
A5	Maintenance	0.000	3.000	0.000	0.000
A6	Port guard	4.000	4.000	6.367	0.000
A7	Cargo tax notifier	2.000	2.000	0.167	0.060
A8	Vigilant guard	0.000	2.000	0.000	0.000
A9	Cleaning staff	0.000	2.000	0.000	0.000
A10	HSE Technician	14.000	1.000	1.833	0.488
A11	POC	6.000	4.000	15.033	0.172
A12	PAC	2.000	3.000	0.367	0.107
A13	Import/export companies	0.000	2.000	0.000	0.000
A14	Labor inspector	7.000	3.000	12.833	0.181
A15	Pier man	0.000	5.000	0.000	0.000
A16	Longshoreman	1.000	4.000	0.000	0.000
A17	Truck driver	0.000	7.000	0.000	0.000

Source: Authors (2023)

Information network (n^1)

The Information network revealed the actors that most seek information on port operations. The Betweenness metric identified the actors with the highest degree of intermediation, i.e., those who relate to peripheral actors. Actors A11 and A12, which represent port operator companies and port agencies, respectively, showed the highest intermediation. These actors play a strategic role in the dissemination of information. Figure 4 shows the interactions of information-seeking actors, with blue edges representing reciprocity in information exchanges, while black edges represent asymmetric interactions. It is important to note that the size of the nodes was adjusted to represent the metric in question. The Information network reflects the integration and influence of actors in the context studied. Please consult Table 6 for additional information.

Table 6.

Node-level metrics in the Information network

		Metrics			
Code	**Actor**	**Out Degree**	**In Degree**	**Betweenness**	**Out Eigenvector**
A1	Operational manager	10.000	7.000	8.366	0.314
A2	Cargo clerk	12.000	8.000	13.338	0.370
A3	Warehouse manager	5.000	8.000	2.656	0.208
A4	Load scale worker	9.000	8.000	11.424	0.240
A5	Maintenance	5.000	3.000	0.833	0.181
A6	Port guard	5.000	3.000	1.391	0.163
A7	Cargo tax notifier	4.000	9.000	2.036	0.143
A8	Vigilant guard	4.000	3.000	0.843	0.110
A9	Cleaning staff	0.000	0.000	0.000	0.000
A10	HSE Technician	0.000	11.000	0.000	0.000
A11	POC	10.000	13.000	26.473	0.323
A12	PAC	9.000	12.000	20.703	0.281
A13	Import/export companies	6.000	11.000	6.480	0.205
A14	Labor inspector	11.000	4.000	3.332	0.364
A15	Pier man	9.000	5.000	3.879	0.275
A16	Longshoreman	10.000	5.000	3.596	0.301
A17	Truck driver	8.000	7.000	8.650	0.219

Source: Authors (2023)

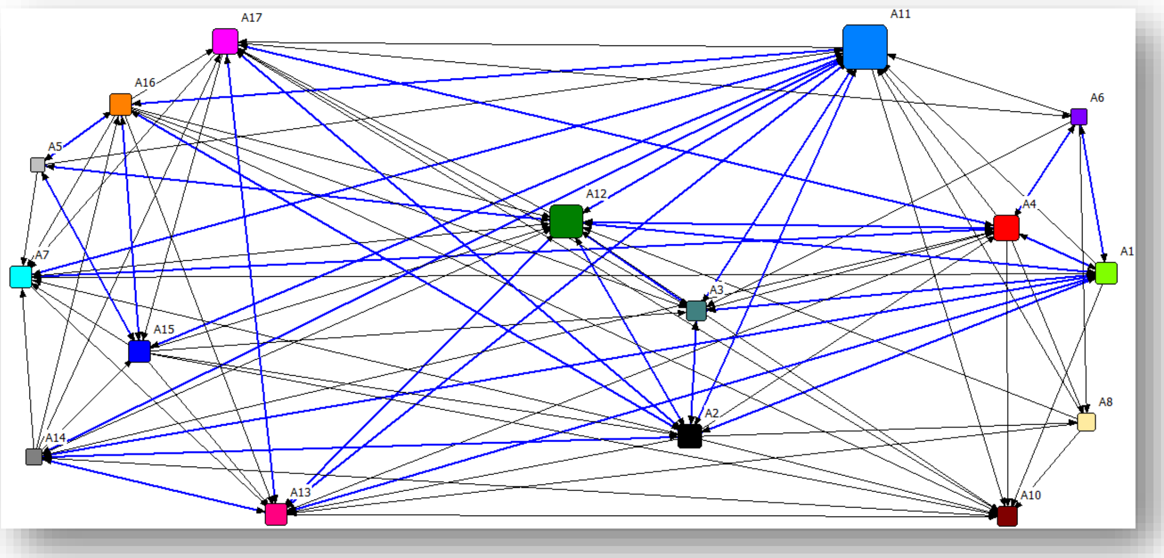

Figure 4. The Betweenness of actors in the Information network

Note: *in blue reciprocal ties*

Social network analysis at the network level

Authorization network (n^0)

The analysis of the Authorization network reveals noteworthy values in the Degree Centralization (0.592) and Breadth (0.585) metrics. These metrics indicate that the network under examination has a limited number of central actors, and the authorizations issued by these actors spread moderately throughout the network of interactions, as evidenced by the Connectivity metric with a score of 0.522. However, this metric also indicates that the network has low efficiency in transmitting and influencing the authorizations issued by the central actors.

Conversely, the Average Degree metric (3.000) of the network is the lowest among the analyzed networks, suggesting that there are few direct connections between actors. Furthermore, the Mutuality metric (0.022) implies that interactions within the network are predominantly unilateral.

Based on these findings, we can conclude that the Authorization network exhibits a well-defined hierarchical structure but has limited capacity to transmit authorizations across the network efficiently. Moreover, the predominantly unilateral nature of authorizations reflects a highly vertical decision-making process. These results align with the node-level analysis, where central actors demonstrate greater influence within the Authorization network, confirming the presence of bureaucratic influence among actors. Please refer to Table 7 for further details.

Table 7.

Net-level metrics of the Authorization network

Metrics	#
# of nodes	17
# of ties	51
Avg Degree	3
Deg Centralization	0.592
Connectedness	0.522
Breadth	0.685
Mutuals	0.022

Source: Authors (2023)

Complaint network (n^0)

The analysis of the Complaint network reveals notable values in the Degree Average (8.235), Connectedness (1.000), and Mutuality (0.301) metrics compared to the other three networks. So, it resembles that complaint interactions are efficiently transmitted within the network, with an average of eight neighboring actors. Furthermore, the ability of a complaint to reach other actors, whether directly involved or not, is high. Notably, actors who initiate a complaint have a higher likelihood of receiving a complaint in return, underscoring the two-way nature of these interactions.

Conversely, the Complaint network demonstrates the lowest scores in the Degree Centralization and Breadth metrics. The low Degree Centralization score implies central actors are more evenly distributed throughout the network. Additionally, the low Breadth score suggests that complaints are short-range, as all actors are closer to each other within the network.

Since complaints occur during daily work activities and can be initiated by any actor, regardless of their role in the institution, the findings of the network-level metrics in the Complaint network are consistent. Furthermore, these results mirror the trends observed in the node-level analysis, highlighting the rapid spread of complaint interactions and the shared importance attributed by actors to complaints. This indicates a broad situational awareness and a sense of belonging shared among the actors. Please refer to Table 8 for further details.

Table 8.

Net-level metrics of the Complaint network

Metrics	#
# of nodes	17
# of ties	140
Avg Degree	8.235
Deg Centralization	0.237
Connectedness	1.000
Breadth	0.254
Mutuals	0.301

Source: Authors (2023)

Inspection network (n^0)

The Inspection network exhibits similar scores to the previously analyzed Authorization Network in the Average Degree (3.353) and Mutuality (0.015) metrics. These findings indicate that inspection interactions predominantly occur unilaterally. Thus, actors have few overall connections. However, the Inspection network obtains the highest values in the Breadth (0.724) and Degree Centralization (0.604) metrics. These results suggest that inspections are primarily conducted by central actors who interact with nearly all other actors in the network. Conversely, the network obtains the lowest score in the Connectedness metric (0.357), indicating a distance between actors whose interactions aim to inspect the activities of other actors.

The results reflect that only a few network actors are responsible for inspections, while peripheral actors, who comprise most of the network, respond to these inspection interactions. These characteristics align with the nature of inspection interactions, as in most organizations, only a limited number of actors are assigned to conduct inspections, typically those in managerial roles with greater staff responsibilities. This dynamic holds true within the context of the port as well. Please refer to Table 9 for additional details.

As observed in the node-level analysis, actors A1, A10, A11, and A14 exhibit the highest scores in the OutDegree metric, indicating their involvement in a greater number of inspections. However, the low score in the Connectivity metric suggests two potential scenarios. Firstly, despite inspections being conducted across various activities and these actors being highly engaged in such interactions, there may be a lack of coordination among inspections. This lack of coordination could compromise their role of expertise and potentially result in failures to adhere to standard work procedures. Secondly, there may be a decentralization of inspection interactions, meaning that different actors conduct inspections without centralized coordination.

Table 9.

Net-level metrics of the Complaint network

Metrics	#
# of nodes	17
# of ties	57
Avg Degree	3.353
Deg Centralization	0.604
Connectedness	0.357
Breadth	0.724
Mutuals	0.015

Source: Authors (2023)

Information network (n^0)

The Information network did not obtain the highest or lowest scores among the metrics analyzed at the network level. Nevertheless, it scored high on the Connectedness, Average Degree, and Mutuality metrics, while scoring low on the Degree Centralization and Breadth metrics. Interestingly, these scores resemble those of the Complaint network.

These findings indicate that the Information network features a significant number of interactions among its actors, facilitating the efficient and reciprocal transmission of information regarding port activities. All actors within the network are actively engaged and participate in the ongoing activities. Such outcomes are particularly crucial in this type of network, as high connectivity promotes the seamless flow of information, allowing it to reach its intended destination rapidly and without loss.

These net-level results align with the node-level results, emphasizing the significance of information exchange and the active involvement of all actors within the Information network. Please refer to Table 8 for additional details.

Table 10.

Net-level metrics of the Information network

Metrics	#
# of nodes	17
# of ties	117
Avg Degree	6.882
Deg Centralization	0.354
Connectedness	0.827
Breadth	0.375
Mutuals	0.235

Source: Authors (2023)

CONCLUSIONS

The paper employed social network theory through social network analysis (SNA) to examine the interactions among actors in the port hinterland. The study aimed to understand the complexity and organization of these interactions, investigating their interconnectedness and underlying structure. By analyzing different types of interactions, the study contributed to gaining insights into how people connect, influence each other, and collaborate within the port hinterland environment, ultimately enhancing our understanding of social functioning in this context. The empirical study focused on the operational dynamics of a port in southern Brazil. To the best of our knowledge, no comparable study has delved into the occupational human factor within a port environment by using SNA.

The findings revealed characteristics at both the network and node levels. A well-defined hierarchy was observed in the Authorization network, but with limited efficiency in transmitting authorizations. Operational manager, warehouse manager, labor inspector, and import/export companies emerged as central actors with significant influence. In the Complaint network, interactions were distributed throughout the network, with certain actors engaging in fewer complaints while others received fewer complaints. The Inspection network involved only a few actors conducting inspections, with central actors playing a crucial role. Actor A17 (truck driver) was the most sought-after actor for examination. The Information network exhibited a large number of interactions, facilitating efficient and reciprocal information transmission.

Given our focus on the interplay of professional roles within an organizational framework, it is apt to employ organizational theories, such as contingency theory. Nonetheless, it is crucial to acknowledge a potential limitation. While a case study can yield valuable insights within a specific organizational context, its findings may not seamlessly translate or be universally applicable to diverse organizational settings. The contingency theory underscores the significance of factoring in distinct situational elements, implying that strategies effective in one case may not yield the same results in a different context marked by varying environmental conditions and contingencies. This can potentially limit the broader applicability of the insights gained from the case study. In practice, the findings can be used to improve aspects related to the management of social relations, the distribution of power, or the management of public services of the port enclave.

Some recommendations for future research include delving deeper into the Information network, with a specific focus on examining the advancements of knowledge management and how the diffusion of information impacts operational dynamics within ports. Furthermore, it is important to strengthen the application of social network analysis in the port industry, particularly by analyzing network-level metrics, as our current research focused on only a limited subset of the available options. Additionally, exploring the correlation between node-level and network-level metrics with environmental and occupational risk management in port environments can provide valuable insights. Lastly, applying social network analysis as an additional method for developing occupational health and safety plans and fostering environmental education in port settings holds significant potential.

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