# Networks, ships & reroutes: Using ABM to simulate fault tolerance response in maritime transport

**Sofia Dutto[1,*], Jan Globisz[2,*], Jakob Schlierf[3,*], and Eleonora Tung[4,*]**

[*]Università Bocconi, Milan, M.Sc. Data Science & Business Analytics

[1]ID: 3036116

[2]ID: 3150140

[3]ID: 3147567

[4]ID: 3013833

## ABSTRACT

The maritime transportation system, fundamental to the world economy, relies on the correct functioning of important straits and canals, the so called "choke-points". Using graph theory to simulate the features of the maritime transport network when important paths are no longer viable, we demonstrate the strategic importance of such narrow passages. Furthermore, implementing an Agent-based Model, we investigate the decision making of individual ships which reroute in case of choke-point faults. We find that the blockage of the Strait of Malacca would lead to most profound effects, since the major trading routes would be unavailable, with some of the most connected nodes becoming unreachable and the ship agents becoming stuck. Also, we find some evidence that early response to a blockage may lead to higher distances travelled by ships, which leads to higher costs of fuel.

Submitted for review for the journal **Nature Communications**

TOTAL WORD COUNT: 4991

In submitting this assignment:

1. We declare that this written assignment is our own work and does not include
    - material from published sources used without proper acknowledgment or
    - material copied from the work of other students.
2. We declare that this assignment has not been submitted for assessment in any other course at any university.
3. We have a photocopy and electronic version of this assignment in our possession.

## Introduction

Maritime transport is essential to the functioning of world trade. Around 80 per cent of global trade by volume and over 70 per cent of global trade by value are carried by sea and are handled by ports worldwide[19]. Hence, the flow of goods across the world is crucially dependent on the proper functioning and security of the maritime routes.

A significant proportion of maritime transport passes through at least one of so-called "choke-points". These are strategic, narrow passages that connect two larger areas to one another. In the context of maritime transport, these are typically straits or canals that see high volumes of traffic because of their optimal location. The event that motivated our research was the blockage of Suez Canal on 23 March 2021, due to the stranding of the ultra large Golden-Class Container Ship Ever Given. The blockage became an obstacle not only for the delay in delivering the containers transported by the vessel itself, but also for all the traffic flow in the Suez Canal, which came to a standstill due to the placing of the ship. In the just six days the Ever Given was drenched in, about 420 ships got stuck on both sides of the canal. With the Canal freed again, since it's capacity is just about 90 ships per day and it only permits one way traffic, the backlog took another week to dissolve. Considering that an estimated 12 per cent of global trade volume passes through the Suez Canal, comprising more than one billion tonnes of goods annually, the 6 days blockage held up goods to the value of 9.6 billion dollars[10].

In case of such an event, shipping companies have the choice of either waiting in a queue or rerouting. As for Suez canal blockage, rerouting was a far more expensive alternative. Indeed, venturing south around Africa's Cape of Good Hope adds at least 26 more days, which translates into higher fuel costs. In either case, the shipping company may be facing high demurrage, or waiting, costs.

So we can claim that the Suez canal clearly represents one of the most significant choke-points in the global maritime shipping system, along with Panama Canal and the straits of Dover, Hormuz, Gibraltar and Malacca (see Figure in the appendix for map), and that their fault represents a a threat to the resilience of the system as a whole.

These facts motivate us to answer the following research questions:

- Considering different choke-point disturbance, what outcome will emerge?
- Under different scenarios, what are the emergent properties of the disturbed network?
- Which features drive re-routing?

- What precautions should stakeholders make in case of network faults?

Methodologically, we pursue this particular research interest by employing two approaches: network analysis and Agent-based Modelling (ABM).
As a first step we investigate, through network simulations, the effects of the obstruction of the main "choke-points" in the maritime transport system. We conceive our network as an undirected weighted graph, where ports represent nodes, the routes represent edges and distances are weights. We provide a descriptive analysis of the main components of this scale-free network through graph theory and its features, such as degree distribution, path lengths, connectivity, centrality and more. After constructing our network with available data and describing it, we assess fault tolerance when important paths are no longer viable. This leads us to simulate different scenarios and study how the main characteristics of the network change.
The second layer of our study is centered around the behavior of shipping companies whose cargo vessels are affected, modelled via ABM. Every ship is an agent associated with exactly one origin, but several destinations it must reach to either pick the goods up or deliver them. Ship agents are choosing their route by optimizing an implicit cost function, with cruise costs and delivery time delay as its main components.

## Background

Other authors have investigated the maritime transport system, using both methodologies. In particular, some studies have looked at effects of choke-point closure on the maritime network, the effects of decision to reroute or employed ABM to investigate aspects of the maritime logistics, such as terminal handling. However, to our knowledge there has been no attempt to model the behaviour of individual ships under different scenarios of choke-point closure using the ABM framework. Therefore, our contribution would be to merge the two methodologies and provide insights from both.
Since our research is divided into two sequential and interconnected modules - each implementing a different approach - a necessary step is to frame our research question into the context of previously done work on the matter, respectively focusing on agent based modelling and network science.
Regarding the network science perspective, the maritime system - and in particular the global cargo ship network - has been widely studied as a network with various degrees of complexity. Xu, M., Pan, Q., Muscoloni, A. et al.(2020)[20] have investigated the structure of the global liner shipping network (GLSN), and conducted an analysis to clarify how the structural integration of a modularly segregated network is

achieved via network hubs. They studied provincial-hub, connector-hub ports and proposed the definition of gateway-hub ports, offering new insights into the GLSN's structural organization complexity and its relevance to international trade.

Kaluza P. et al (2010)[12] also constructed a network of links between ports. They showed that the network has several features that set it apart from other transportation networks, like the air transportation network. In particular, most ships can be classified into three categories: bulk dry carriers, container ships and oil tankers. These three categories do not only differ in the ships' physical characteristics, but also in their mobility patterns. The network of all ship movements possesses a heavy-tailed distribution for the connectivity of ports and for the loads transported on the links with significant differences between ship types.

Similarly, Hu Y., Zhu D. (2009)[11] presented an empirical study of the worldwide maritime transportation network in which the nodes are ports and links are container liners connecting the ports. They studied the statistical properties of the network including degree distribution, degree correlations, weight distribution, strength distribution, average shortest path length, line length distribution and centrality measures. They found that the maritime transportation system is a small-world network with power law behavior. Important nodes are identified based on different centrality measures. Through analyzing weighted clustering coefficient and weighted average nearest neighbors degree, they revealed the hierarchy structure and rich-club phenomenon in the network.

Gelareh S., Nickel S., Pisinger D., (2010)[7] studied the competitive environment of the maritime transportation system. Their paper addresses the competition between a newcomer liner service provider and an existing dominating operator, both operating on hub-and-spoke networks. The newcomer company maximizes its market share - which depends on the service time and transportation cost - by locating a predefined number of hubs at candidate ports and designing its network.

Lastly, Funk D. (2017)[6] masters thesis analyzes the maritime transportation system as a network consisting of container ports, maritime choke-points and transportation routes between them. After applying the methods and metrics of the network science to find the most central nodes, the author performs an analysis on different scenarios involving the interdiction of one or more container ports or choke-points finding that the loss of a port or the blockade of a canal can cause serious economic consequences, particularly when prearranged deliveries cannot reach their destinations or have to take long detours. Therefore, the efficiency and operability of the global economy highly depends on the resilience of this system.

ABM has been used extensively for transportation problems, since it allows to model such emergent phenomena as traffic jams. Kikuchi S., Rhee J. and Teodorovic D. (2002)[13] paper examines the link between today's transportation problems and ABM, presents recently used examples applied to transportation, and discusses their limitations. The intent of the paper is to explore a new avenue for the direction of modeling and analysis of increasingly complex transportation systems.

Similarly to our problem, Klugl F. and Rindsfuser G. (2011)[14] have suggested an "agent-based combined route and mode choice model" in which the simulated agents, moving through the network, are able to react to unpredicted events such as the closing of a link. Indeed, our setup is a type of "traffic routing" problem". The authors simulated the self-organized rerouting of travelers to new paths depending on when and where they are notified about the problem. They illustrate the feasibility and usefulness of the agent-based mode and route choice simulation using a real-world network of a small-size Swiss town. Our approach is similar in that it takes agents as moving on top of a network grid and reacting to changes in the flow of traffic and available routes.

Other parts of the maritime industry have also been studied. Davydenko I.Y., and Fransen R.W. (2019)[3], on the other hand, present an agent based model for the port nautical services, by describing the port as a complex system, which takes into account operational complexity and inter-dependency between the agents working on the handling of deep sea ships. Shobayo, P., van Hassel, E. (2019)[18] developed an ABM to analyze the effects of barge congestion and poor handling in large container seaports. An impact assessment of different scenarios was conducted to identify the most suitable that would address congestion and handling issues around container barging. The study concluded that the presence of sea vessels and the high priority given to these vessels are major causes of barge congestion in large seaports. However, there are very few studies that take ships as autonomous agents. O'Keeffe (2018)[17] uses ABM to model dry cargo shipping industry in order to identify a high fidelity representation of the system to gain a greater understanding of how aggregate level properties, but does not consider the network structure itself nor the impact of choke-point closures. In that, we conclude that our approach is genuinely novel.

## Results

### Network Analysis

Figure 1 represents the projection of the network, and it shows the nodes and links of the maritime shipping system on the world map. Ports - which act as the nodes of the network - are represented by the red dots, while routes - the edges of the network - by the red lines connecting the dots. We assume a simple, undirected graph where distances between ports are weights. Note that the below image shows direct links between ports, not the actual routes. Hence, the connections run over land.

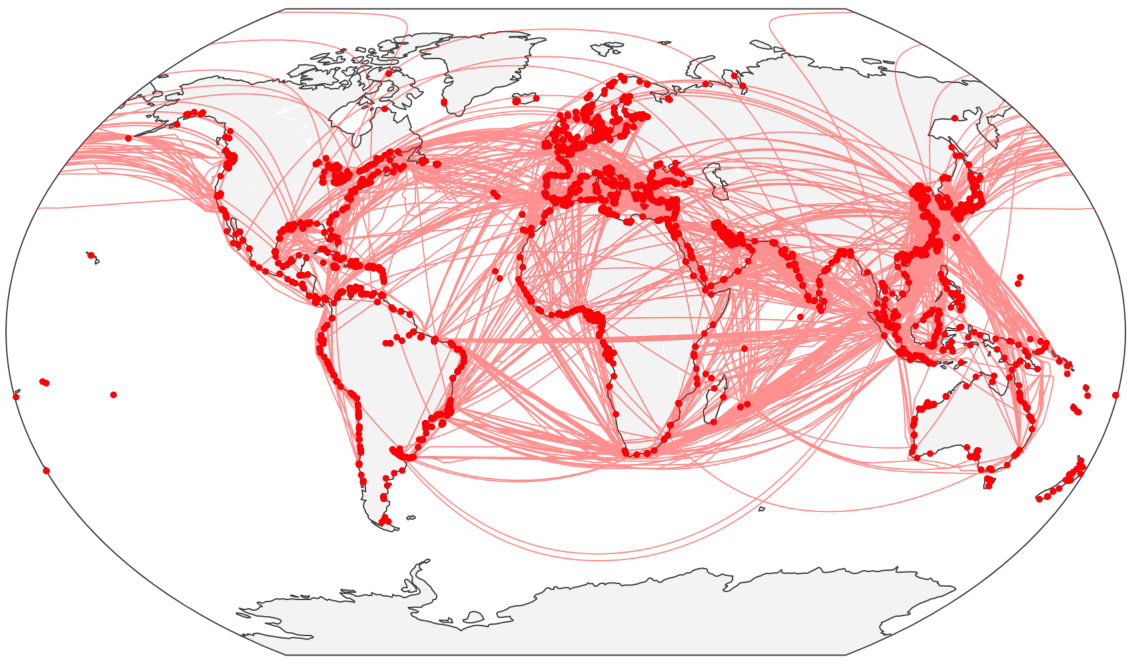

**Figure 1. Maritime shipping network**

The shipping network is composed of 2912 nodes, 29,838 edges and has an average node degree of 20.4931. The density of the network is 0.00704, meaning that very few of all the possible connections have been developed. If the graph was complete, i.e every pair of distinct nodes was connected by a unique edge, it would have had N(N-1)/2 = 4,238,416 edges. Consequently the graph has only 0,7 percent of the links it can have.

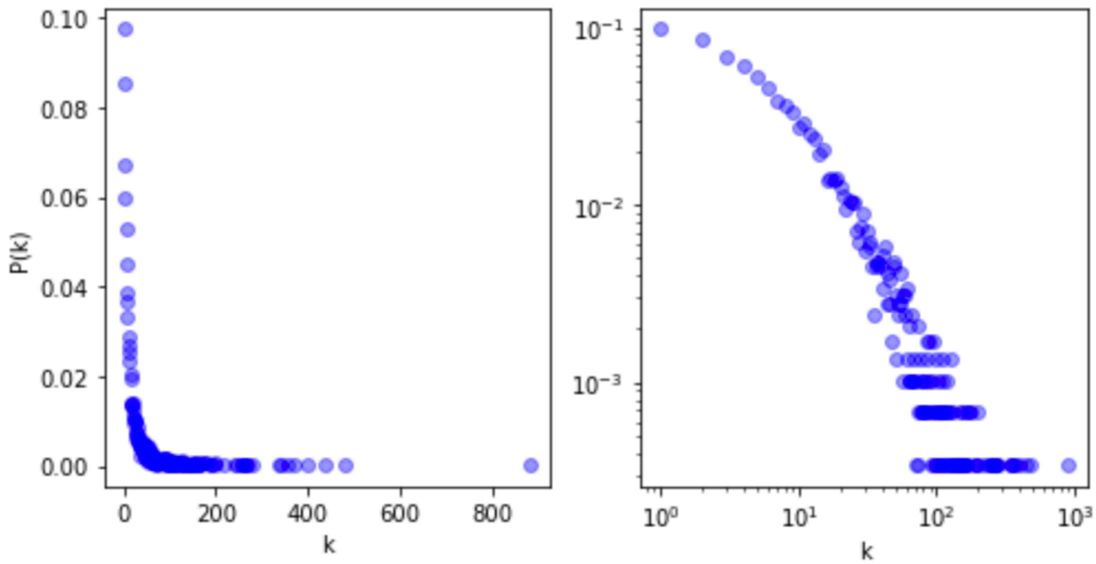


**Figure 2. Node degree distribution.** The second chart has both axes on log scale

The distribution of the node degree, as shown on Figure 2, follows a power law distribution, which takes the form $p(x) \approx x^{-\gamma}$ (where $\gamma = 1.42597$). Note that, the degree exponent is typically in the range $2 < \gamma < 3$ for scale free networks. The value we retrieved would fall in the "anomalous regime" and is is not in line with, for example, to Hu and Zhu results for the maritime network ($\gamma = 2.95$) and to other real networks, such as Internet ($\gamma = 3.42$), the protein interaction network ($\gamma = 2.89$) and the air transportation network ($\gamma = 1.8 \pm 0.2$) as presented by Barabási[1]. We suspect this may be due to the fact that the original dataset presented multiple links between several pairs of nodes, whereas the dataset we worked with was cleaned from the additional ones, allowing just one link per pair. Consequently, the majority of ports have a very small degree, while very few of them - the so called 'hubs' - present an higher one. Such wide differences in node degrees is a consequence of the network's scale-free property, which is encountered in many real networks.

We observe that that there are multiple nodes without any connection, therefore we decided to work on the largest component, i.e. a connected graph. A graph is said to be connected if there is a path between every pair of nodes. In real undirected networks, there usually is a large component - the giant component - that fills most of the network - usually between 50 and 90 percent - while the rest of the network is divided into a large number of small components disconnected from the rest. In our case, the largest component has 98 percent of the nodes of the original network and 99,9 percent of the original edges. This gives a hint on the 'isolation' of the 57 ports and 40 routes that were excluded. The average shortest path length is

1718.33 (measured in 'distance').

Its diameter, defined as the shortest path between the two most distant nodes in the network, doesn't vary with respect to the original graph and is of 12. The largest component of the graph can be seen at the center of Figure 5

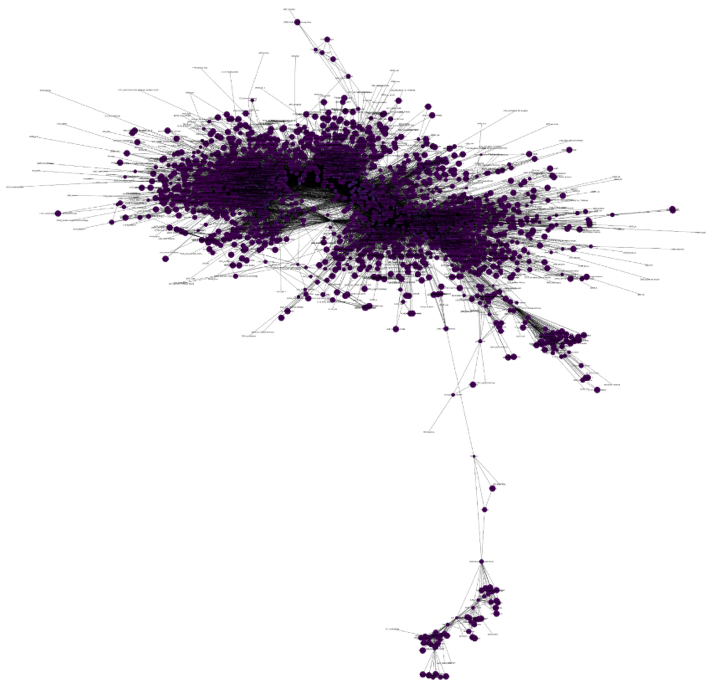

**Figure 3. Largest component of the maritime shipping network** Node color varies with degree and node size with closeness centrality

From the visualization of the largest component in Figure 3 we can see that there are two main clusters that are linked by a single node. It is interesting to notice that the smaller cluster contains ports located in northern America's lakes, between the US and Canada (Lake Erie, Huron, Michigan, Superior). These ports are connected to the main network through Montreal Port.

As for measures of the connection of nodes inside the network, we focused on triadic closure. Triadic closure can be used to understand and predict the growth of networks, although it is only one of many mechanisms by which new connections are formed in complex networks. A measure for the presence of triadic closure is transitivity, i.e. the overall probability for the network to have adjacent nodes interconnected, thus revealing the existence of tightly connected clusters. Complex networks and notably small-world networks often have a high transitivity and a low diameter. It is equal to 1 if the graph has all possible edges. Here, the transitivity of the largest component is 0.206. Note that the formula for transitivity doesn't take into account the weight of the edges. On the other hand, the average clustering coefficient - which considers the weights - is 0.015. Measures of centrality were also computed to identify the most important ports in the network. The following table shows the top 6 ports sorted by betweenness centrality with the corresponding degree. It is interesting to notice that 3 of the 6 (Tanjung, Europoort, Shangai) are also top global ports in terms of TEU ("Twenty-foot Equivalent Unit"), a measure of annual cargo capacity of the port and Europa Point falls directly in one of the choke-points: Gibraltar.

| Port | Betweenness Centrality | Degree |
|---|---|---|
| Tanjung Pelepas | 0.304 | 884 |
| Europa point | 0.085 | 437 |
| Port de Québec | 0.063 | 150 |
| Europoort | 0.058 | 338 |
| Puerto Cristobal | 0.053 | 218 |
| Shanghai Gang | 0.052 | 479 |

**Table 1. Top 6 ports** by betweenness centrality and degree

### *Blockage of choke-points*

The metrics we chose to evaluate the differences among the simulations can be summarized in the following tables.

Note that in all simulations the number of nodes remain unvaried (i.e. the number of nodes is 2912)

| Simulation | Edges | Average Degree | Average shortest path | Connected components |
|---|---|---|---|---|
| Normal Conditions | 29838 | 20.4931 | 1718.33 | 37 |
| Suez Blockage | 29365 | 20.1683 | 1738.40 | 41 |
| Hormuz Blockage | 28957 | 19.8880 | 1731.49 | 43 |
| Gibraltar Blockage | 28164 | 19.3434 | 1969.00 | 47 |
| Malacca Blockage | 28599 | 19.6422 | 1770.96 | 43 |
| Dover Blockage | 28430 | 19.5261 | 1894.32 | 45 |
| Panama Blockage | 29129 | 20.0062 | 1789.74 | 45 |
| Overall Blockage | 24306 | 16.6937 | 2129.76 | 78 |

**Table 2.** Faults simulation metrics

Ignoring the extreme case of an overall blockage, we can observe that the closing of Gibraltar Strait has the most negative effects on the network. Indeed, it significantly increases the average shortest path length and the number of single connected components in the network, while it produces the highest decrease in the number of edges.

As for the centrality measures, we found that their comparison across the different simulation doesn't lead to noteworthy results. Centrality measures' formulas refer to single nodes. Here, to compare them in the simulations, we decided to consider the highest values for each measure, that can be found in Table 5 in the appendix.

Note that in each simulation the metrics were computed referring to the largest component of the network, consistently with the first part of the analysis. Betweenness centrality, as well as Degree, Closeness and Eigenvector centrality of the nodes don't show significant changes overall. Moreover, the ports associated with the highest values tend to remain unvaried. We assume this is linked to the fact that the centrality of such nodes is not affected by the removal of the links considered here.

As for the average clustering coefficient (see appendix, Table 6 - a measure of the degree to which nodes in a graph tend to cluster together - the only significant change is observed for the overall blockage. Indeed, after the interdiction of all choke-points, the average clustering coefficient moderately decreases. Lastly, considering the diameter of the network, the blockage of choke-point tends to increase it, showing that the shortest distance between the two most distant nodes in the network becomes larger.

### Agent-based Modelling

The ABM allows us to test and verify which blockages affect the global shipping most profoundly. We simulated 90 days of shipping with 500 ships. We find that blockages indeed negatively impact the flow of goods shipped by sea. On average, our chosen blockages increased the total distance travelled by 232 643 km and the number of reroutes by 481. Table 3. presents results from simulated blockages, as a difference between the "no blockage" scenario (see Figure in appendix ).

| | Distance Travelled (km) | Ships stuck | Not reachable | Reroutes | Completed |
|---|---|---|---|---|---|
| **Dover** | 172391.56 | 3 | 13 | -105 | -53 |
| **Gibraltar** | 272363.51 | 0 | 78 | -78 | -52 |
| **Hormuz** | 549562.70 | 6 | 162 | 1476 | -62 |
| **Malacca** | 12037.29 | 13 | 223 | -36 | -41 |
| **Panama** | 128696.14 | 8 | 51 | 409 | -57 |
| **Suez** | 279071.52 | 7 | 96 | 341 | -14 |
| **Total** | 447023.66 | 31 | 302 | 1842 | -70 |

**Table 3.** Global shipping statistics (difference from "no blockage" scenario")

If a ship received a new route and it was impossible for them to reach it, this was counted as "not reachable" and when a ship decided to not re-route, whereas the path was not passable, it was "stuck" in a port. The ship could reroute, if the new path was longer, indicating a closure, and their "foresight" was high enough. Alternatively, the ships would reroute if the new route was shorter. A ship would complete a route if it had reached all of its destinations, and it was considered "successful" if managed to reach all the destinations in time.

The results suggest that the blockage that generated the most added distance, reroutes and reductions in the completed trips was Hormuz, suggesting that ships were moving to further locations and had to later go back to deliver to ports in the Persian Gulf. However, it seems that the Malacca blockage was in fact most disruptive, with most ships getting stuck and not being able to reach their original destinations.

The top most visited ports in our network reflect the strategic importance of the points, as located in the main trading routes and ports of origin and destination for large ships. Out of the top 20 in Table 4 in the appendix, the top 4 were unknown ports (NaN in our database) located in the Malacca Strait and close to Singapore, highlighting the importance of this area to the maritime transport. Other key areas include the Aegean Sea, close to Turkey. The only major ports on the top 20 most frequently visited ports are Shanghai, the world's largest port and Europoort, Europe's largest port.

Regarding the behaviour of our ship agents, we correctly observe that route changes, stuck and not reachable spike during the blockage (see appendix, Figure 7). Route changes spike again, once the route is passable. Interestingly, the rerouting tails of slowly and reflects the how agents "learn" about the particular blockages, given their foresight and location with respect to the blockage.

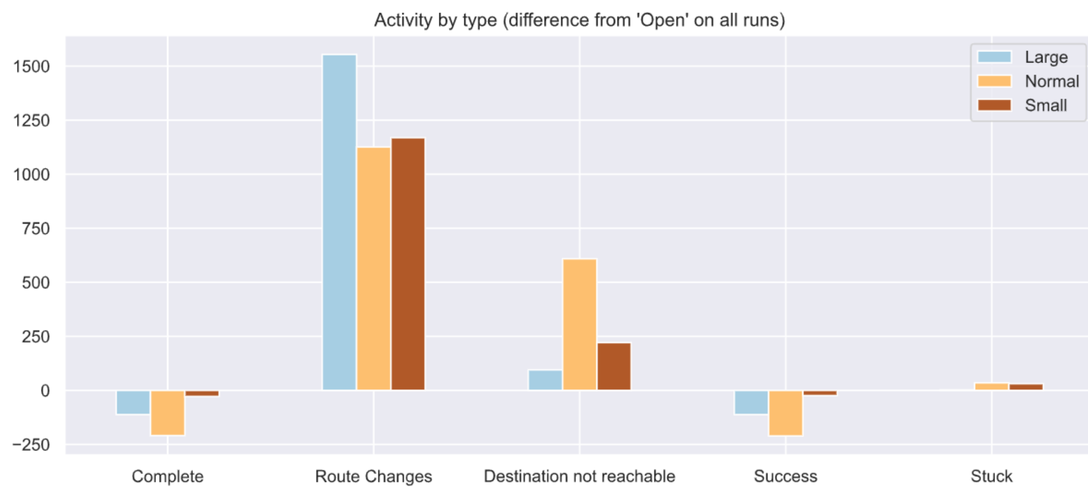


**Figure 4. Activity by type**

Looking at ship type, we can notice that largest distances are spanned by the small ships. This is somewhat unrealistic, since small ships should have preference for local trips (origin should be close to destinations) and comes from random choice of port of origin and destination.This also results in largest number of stuck occurrences. However, the closure affect largest ships the most, when it comes to increase in distance (see appendix, Figure 10). Large ships were also most likely to complete their trips, but also most likely to change their route, indicating that the key trading routes allow for multiple routes. The blockages led to a largest increase in the distance travelled and reroutes for large ships, as shown on Figure 4. The number of completed trips went down for all ship types. The large ships do not tend to get stuck, since they originate in large ports.

Foresight is the ability of ships to act quickly if they detect a change in their route. Considering its role, we observed positive correlations with the number of route changes, of not reachable destinations and stuck ships. It can be argued that foresight, or looking ahead and acting quickly leads to more reroutes and longer distances travelled, therefore is not recommended. Consequently, negative correlations were observed with the number of successes and complete trips. However, focusing on the traveled distance, it is moderately smaller for higher values of foresight (Figure 9 in the appendix). Nonetheless, all the coefficients are small, showing a quite weak correlation. Therefore, we cannot make strong conclusions on the role of foresight.

## Discussion

The presented models allow us to asses the relative importance of strategic choke-points. In that, our paper contributes towards understanding the resilience of the global maritime shipping network. Since we create a synthetic model, its conclusions are limited in their applicability. Particularly, the shipping companies are complex entities, which consider and optimise on a series of indicators, such as fuel prices, the prices of cargo, the costs of demurrage, etc. In this work, we limited ourselves to modelling a simplified route choice function. In future work, we could model agent's anticipation of reopening and develop a model of rational choice between waiting and travelling longer distances, also including other changes, such as speed of travelling. Moreover, our model is based on a simple network grid, with routes connecting the nodes. In reality, a ship does not have to go from port to port and is free to port at any point.

## Methods

### Network Analysis

For the network descriptive analysis section, we mostly relied on statistic provided by Barabási (2016)[1]. We used the Networkx library to work with graph theory statistics. Figure 1 was obtained using Geopandas library on python, which is particularly suited to work with geo-spatial data, and the Plotly package.
Figure 3 positions nodes using Fruchterman-Reingold force-directed algorithm. The algorithm simulates a force-directed representation of the network by treating edges as springs holding nodes close, while treating nodes as objects that repel each other through the so called 'anti-gravity force'. The simulation continues until the positions are close to an equilibrium.
To simulate the choke-point fault, we started from the original data set containing all routes and proceeded by cutting the edges. For each simulation (i.e. each choke-point blockage) we created a new data set where routes close to the choke-point of interest were discarded. To do so, we relied on the Haversine formula to calculate the distance between two coordinate pairs (longitude and latitude) and set a distance threshold,

so that links within such threshold were cut.

For Dover, Gibraltar, Malacca, Hormuz we considered the coordinates of single points in the middle of each strait and assigned a radius of 40, 15, 45 and 45 kilometers, respectively. Whereas, for Panama and Suez we chose two distinct points each, one at each end of the canal. More in detail, Suez Canal is identified by two points, one located at Port Said and Port Suez. Both have an assigned radius of 15 km. Panama Canal is identified by two points: one at Balboa Port and the other at Colon Port.

A visual representation of the choke-point cutting areas can be found in the appendix in Figure 11, while the radii for each choke-point are listed in Table 8. It is important to mention that the closure of choke-points, other than Panama and Suez canal could only be caused by a very major event, such as an act of naval aggression or a catastrophe.

## Agent - based modelling

The reason behind our choice of using ABM is that the questions under investigation emphasize autonomous, heterogeneous entities that operate in a dynamic environment and the output of interest is an emergent result of the individual behaviour of such entities. In our approach, the agents are ships moving through a network grid of routes (edges) connecting ports (nodes). Their goal is to reach a set of destinations in a designated time. In case of a blockage, the agents decide to either react by changing course or continue on route. We used Python and the Mesa framework.

What proceeds is the ODD ("Overview, Design Concepts & Details") protocol, as suggested by Grimm, Volker, et al. (2006)[9]:

1. **Overview**

1.1. *Purpose.* The purpose of the ABM model is to simulate the movement of ships across the maritime networks under different blockage scenarios, in order to test which factors drive the re-routing behaviour and observe the emergent phenomena, such as queues in ports.

1.2. *State variables and scales.* The model comprises two levels: ships and the maritime network. The ships are characterised by the state variables: type, speed, foresight, origin and destination. Table 9 presents the values used in modelling.

Depending on the type, ships originate in and are scheduled for different ports. Large ships originate in the largest 50 cargo ports. The probability that a ship originates in such port is the annual TEU (Twenty-foot Equivalent Unit) of that port, divided by the total TEU of all 50 ports. Smaller ships either originate or are scheduled for any port in the network, chosen at random. Such differentiation reflects the reality that the largest ships can only be handled in specific ports. Each agent is characterised by foresight: An integer value for how many steps ahead does the ship re-calculate its route and acts upon it. The agents move on a network grid, whose characteristics are described in the Results sections.

1.3. *Process overview and scheduling.* The model proceeds in day time steps. All agents move at each time step in a simultaneous fashion. At time $t$, the model introduces a choke-point blockage. At origin and at each time step, the agents calculate the distances for the optimal route using a greedy Travelling Salesman algorithm, based on Dijkstra (see appendix for pseudo code): An agent calculates the distances to all the destinations, chooses the closest available one and repeats this calculation until all destinations are included in the route (if all are reachable). Agents learn about a blockage, when they recalculate their route, but choose to act upon it, based on the "foresight" parameter. If an agent is characterised by a high foresight, they react to the closure further in advance of approaching the closure.

2. **Design Concepts**

The model is designed to observe which route closure are most disrupting to global maritime transportation and whether swift reaction leads to better outcomes. It also allows to check which types of ships will be most affected by the route closures and which closures lead to ships being stranded.

In future research, the model could be easily extended to account for different speeds of travel and port capacity. Indeed, ports could be said to be reacting to such closures by changing the prices for handling. In such extended models, we could also simulate the port prices as a sub model. Furthermore, the ships could be characterised by more features, such as what goods they carry (e.g. oil tankers would be visiting oil ports), how perishable their cargo is (e.g. live stock). These differences would then accounted for by the "success" metric, which would be measured if a specific ship has reached all of their destinations in a designated time frame and then adjust their speed and routing decisions accordingly.

3. **Details**

3.1. *Initialisation:* To simulate different blockages, we ran 7 models with 500 ships each, for 90 days. At start all routes are passable. Also, we ran a batch runner with 100 ships for 90 days, using the modelling of a Suez canal blockage only, varying the "foresight".

3.2. *Input:* The route blockage is simulated by edges being removed from the network at time t. In our models, after 30 days, the blockage is introduced and lasts for the following 30 days. Then, the route is open again for the remaining 30 days.

3.3. *Submodels:* There are no submodels used.

Our simulations and, therefore, our conclusions are limited in several key ways. Firstly, our simulations were run for a limited sample of ships (500 compared to the estimated 10 000 currently travelling through martitime routes). Secondly, our results are not stable, since we only ran the batch runner for the Suez blockage. Lastly, the models run for 90 days, which represents a small subset of days and a large proportion of those were affected by the blockages. Therefore, our approach gives more attention to unique periods of the blockages, and therefore, cannot be used for estimating the risks of such events. In that, it cannot be used to guide the risk modelling process of insurance companies.

## Data

In order to construct the maritime network, consisting of ports as nodes and ship routes as the edges, we used a data set from Novikov (2019)[15]. The data set is constructed from the readings of Automatic Identification System (AIS), which is an automatic tracking system installed on ships that transmit with regular intervals unique identification, position, course, and speed of the vessel. The data consists of hourly data from one of the AIS data providers for the bulkers and tankers, retrieved in the beginning of 2016 to the middle of 2018.

The dataset we retrieved contains three files:

- Port-to-port distances calculated along the routes (`distances.csv`)
- Port-to-port routes (`routes.csv`)
- Port information (`ports.csv`)

Additionally, we used IAPH (2018) global top 50 ports in terms of TEU to construct a probability distribution of origin and destination for the ABM.

## References


1. Barabási A. (2016). *“Network science”*. Cambridge University Press.
2. Davidsson, P., Henesey, L., Ramstedt, L., Törnquist, J., and Wernstedt, F. (2004). *“ Agent-based approaches to transport logistics.”*. 3rd International Joint Conference on Autonomous Agents and Multiagent Systems AAMAS.
3. Davydenko I.Y., Fransen R.W. (2019).*“Conceptual Agent Based Model Simulation for the Port Nautical Services”*. IFAC-PapersOnLine, Volume 52, Issue 3.
4. Emmerson, C., & Stevens, P. (2012). *“ Maritime choke points and the global energy system: Charting a Way Forward”*. Chatham House Briefing Paper, London.
5. Fu X., Ng A. KY and Lau Y., (2010). *"The impacts of maritime piracy on global economic development: the case of Somalia."* . Maritime Policy & Management.
6. Funk D. (2017).*“ Analysis of the global maritime transportation system and its resilience”*.
7. Gelareh S., Nickel S., Pisinger D., (2010). *“Liner shipping hub network design in a competitive environment”*. Transportation Research Part E: Logistics and Transportation Review.
8. Goodman P. and Reed S. (2021). *“With Suez Canal Blocked, Shippers Begin End Run Around a Trade Artery”*. The New York Times.
9. Grimm, Volker, et al. (2006).*"A standard protocol for describing individual-based and agent-based models."*. Ecological modelling.
10. Harper J. (2021). *“Suez blockage is holding up $9.6bn of goods a day”*. BBC News.
11. Hu Y., Zhu D., (2009). *“Empirical analysis of the worldwide maritime transportation network”*. Physica A: Statistical Mechanics and its Applications.
12. Kaluza P., Kölzsch A., Gastner M. T. and Blasius B., (2010). *“The complex network of global cargo ship movements”*. J. R. Soc. Interface.
13. Kikuchi S., Rhee J. and Teodorovic D. (2002).*“Applicability of an agent-based modeling concept to modeling of transportation phenomena”*.. Yugoslav Journal of Operations Research.
14. Klugl F. and Rindsfuser G., (2011). *"Agent-Based Route (and Mode) Choice Simulation in Real-World Networks"*. IEEE/WIC/ACM International Conferences on Web Intelligence and Intelligent Agent Technology.

**15.** Novikov A., (2019). *"Creating sea routes from the sea of AIS data"*. Towards Data Science. Available from: https://towardsdatascience.com/creating-sea-routes-from-the-sea-of-ais-data-30bc68d8530e

**16.** Onggo B. S. and Karatas M., (2015). *"Agent-based model of maritime search operations: A validation using test-driven simulation modelling"*. Winter Simulation Conference (WSC).

**17.** O'Keeffe, E. J. (2018) *"Agent based modelling of the dry bulk shipping sector."*. (Doctoral dissertation, UCL (University College London)).

**18.** Shobayo, P., van Hassel, E. (2019).*"Container barge congestion and handling in large seaports: A theoretical agent-based modeling approach"*. J. Shipp. Trade

**19.** UNCTAD (2018).*"Review of Maritime Transport"*.

**20.** Xu, M., Pan, Q., Muscoloni, A. et al., (2020).*"Modular gateway-ness connectivity and structural core organization in maritime network science"*. Nature Communication.

## 1 Appendix

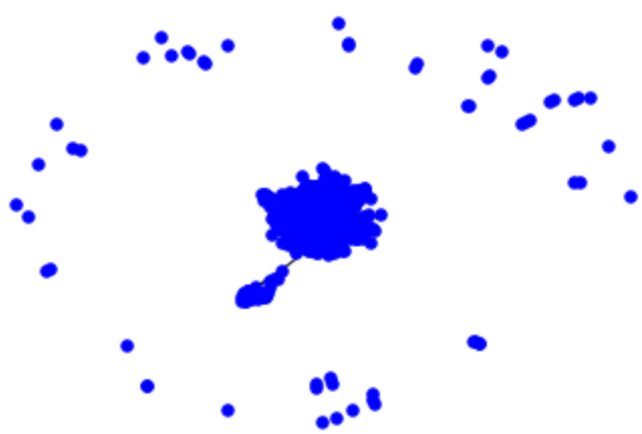

**Figure 5.** Network representation.

| Port | Betweenness Centrality | Degree |
|---|---|---|
| Tanjung Pelepas | 0.304 | 884 |
| Europa point | 0.085 | 437 |
| Port de Québec | 0.063 | 150 |
| Europoort | 0.058 | 338 |
| Puerto Cristobal | 0.053 | 218 |
| Shanghai Gang | 0.052 | 479 |
| Fujairah | 0.046 | 341 |
| Istanbul Port | 0.045 | 91 |
| Port de Montréal | 0.045 | 11 |
| Montréal (approximate) | 0.044 | 5 |
| Malacca (approximate) | 0.043 | 371 |
| Puerto de la luz | 0.042 | 266 |
| Mouillage Pointe Fortier | 0.042 | 15 |
| Port of Reserve | 0.035 | 257 |
| Hansweert | 0.031 | 278 |
| Tekirdag Port | 0.031 | 197 |
| Hong Kong | 0.027 | 400 |
| Detroit | 0.023 | 28 |
| Ain Sukhna Terminal Port | 0.021 | 128 |
| Johor | 0.021 | 357 |

**Table 4.** Top ports

| Simulation | Betweenness | Degree | Closeness | Eigenvector |
|---|---|---|---|---|
| Normal Conditions | 0.602 | 0.309 | 0.001 | 0.372 |
| Suez Blockage | 0.579 | 0.309 | 0.001 | 0.374 |
| Hormuz Blockage | 0.582 | 0.290 | 0.001 | 0.372 |
| Gibraltar Blockage | 0.564 | 0.309 | 0.0009 | 0.381 |
| Malacca Blockage | 0.659 | 0.192 | 0.001 | 0.174 |
| Dover Blockage | 0.610 | 0.308 | 0.0009 | 0.377 |
| Panama Blockage | 0.606 | 0.309 | 0.001 | 0.371 |
| Overall Blockage | 0.648 | 0.194 | 0.0008 | 0.197 |

**Table 5.** Maximum values for centrality measures

| Simulation | Average clustering coefficient | Diameter |
|---|---|---|
| Normal Conditions | 0.015 | 12 |
| Suez Blockage | 0.015 | 12 |
| Hormuz Blockage | 0.015 | 14 |
| Gibraltar Blockage | 0.014 | 13 |
| Malacca Blockage | 0.014 | 13 |
| Dover Blockage | 0.015 | 12 |
| Panama Blockage | 0.015 | 12 |
| Overall Blockage | 0.011 | 15 |

**Table 6.** Average clustering coefficient and Diameter

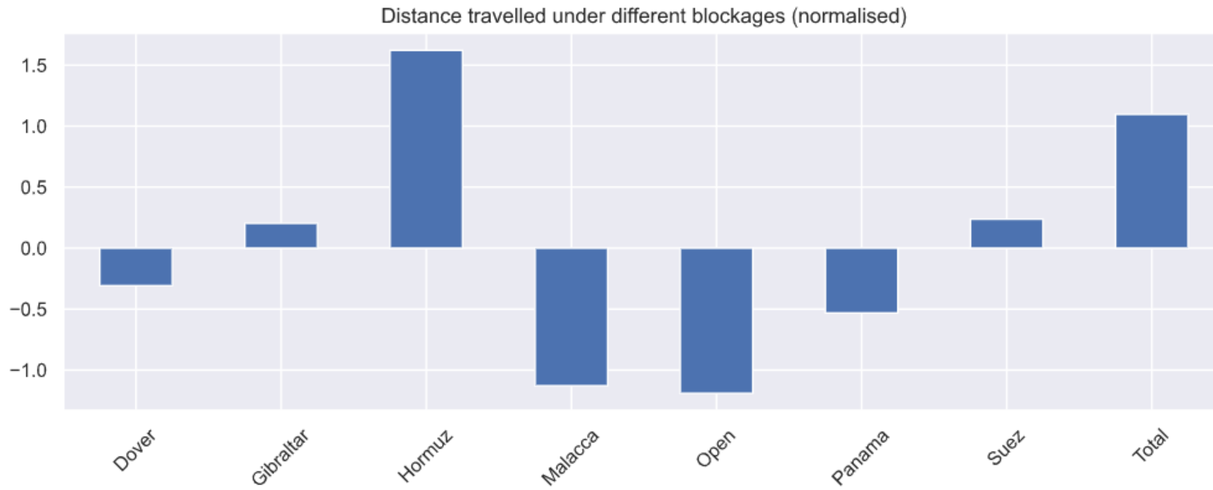


**Figure 6. Distance travelled** (normalised increase over "open")

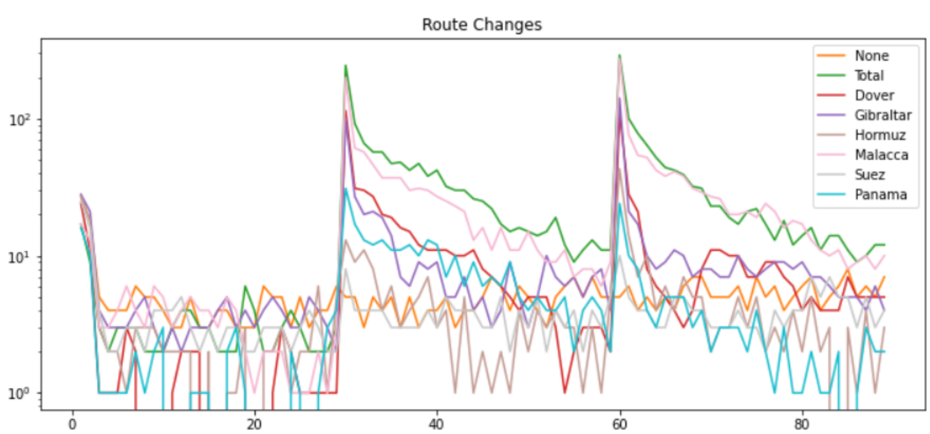


**Figure 7. Route changes** on log scale

| | Name | Freq | coords |
|---|---|---|---|
| 1 | NaN | 20026 | (102.37028212945444, 1.8290091666666664) |
| 2 | NaN | 13497 | (102.42442633128908, 1.8047319109027944) |
| 3 | NaN | 7567 | (103.15488846149456, 1.4831491666666667) |
| 4 | NaN | 7535 | (104.46545358457107, 1.6849391666666667) |
| 5 | NaN | 7399 | (24.63976747009027, 37.96943267086536) |
| 6 | NaN | 7161 | (120.61321662839978, 35.970416666666665) |
| 7 | DURBAN | 6510 | (31.083391138778502, -29.858009526506066) |
| 8 | Richards Bay | 6430 | (32.119184313341975, -28.806122923269868) |
| 9 | Izmir Liman | 6359 | (26.547129509932702, 38.675322602) |
| 10 | Çesme Liman | 6298 | (26.328729844124943, 38.7419989655) |
| 11 | daishangaoting island | 6229 | (122.2723572362936, 30.263755) |
| 12 | NaN | 6139 | (104.60349288548039, 1.44117249419086) |
| 13 | Izmir Harbour | 6104 | (26.56758063625, 38.752503418) |
| 14 | Gökçeada Harbour | 5533 | (25.887499982, 39.962074616500004) |
| 15 | Tekirdag Port | 5315 | (27.208352877600802, 40.602882932499995) |
| 16 | HONG KONG | 5227 | (114.11976109159025, 22.354190000000003) |
| 17 | Çanakkale Harbour | 4912 | (26.13409775161738, 39.996088212000004) |
| 18 | HANSWEERT | 4407 | (3.787823282608696, 51.33401) |
| 19 | KISARAZU KO | 3973 | (139.8108422040744, 35.37190006580204) |
| 20 | Shanghai Gang | 3914 | (122.04640073442107, 31.216186503499998) |

**Table 7. Top 20 most visited ports**

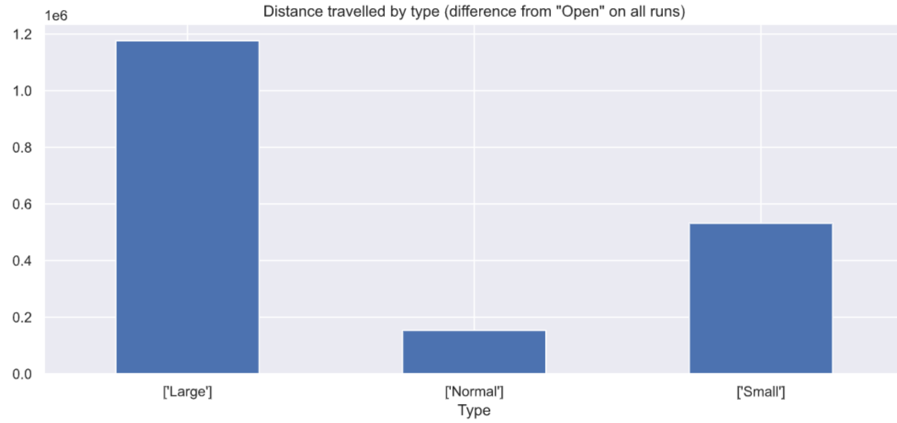


**Figure 8.** **Distance travelled by type**

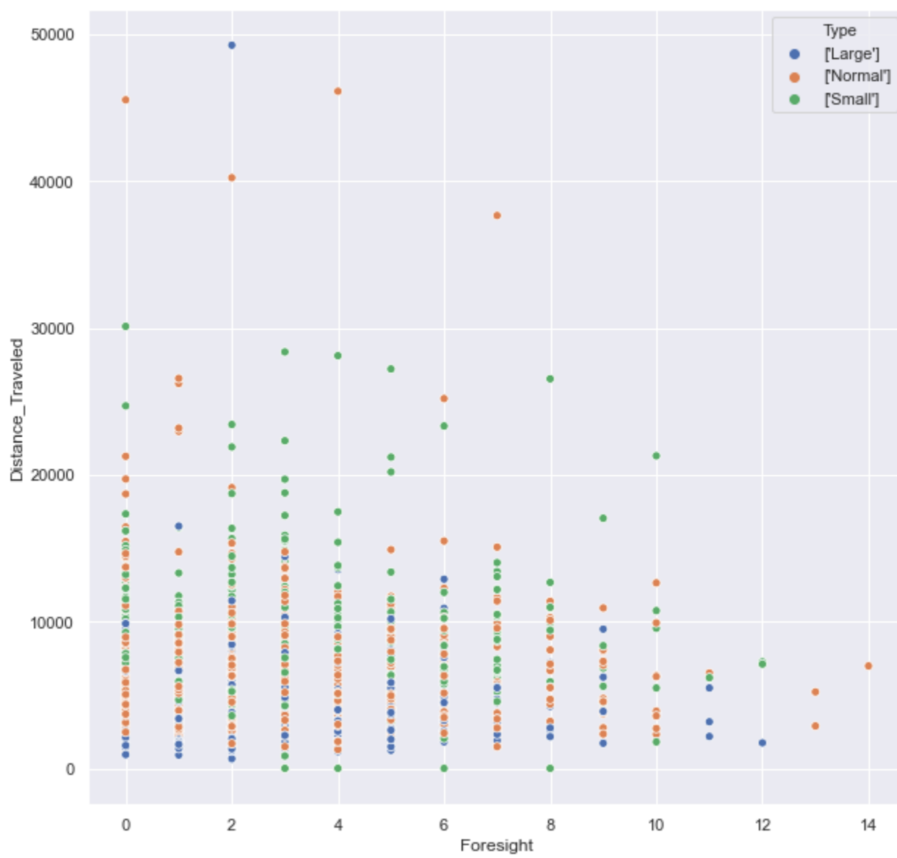


**Figure 9.** **Distance traveled by foresight**

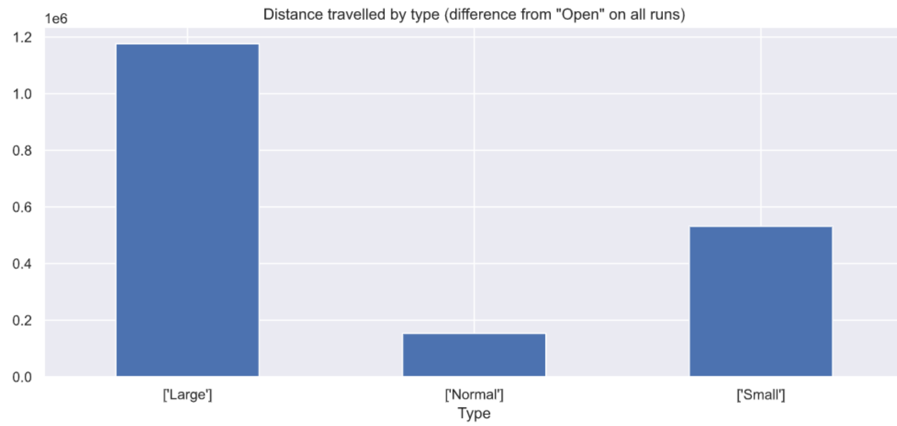


**Figure 10.** **Distance travelled by type**

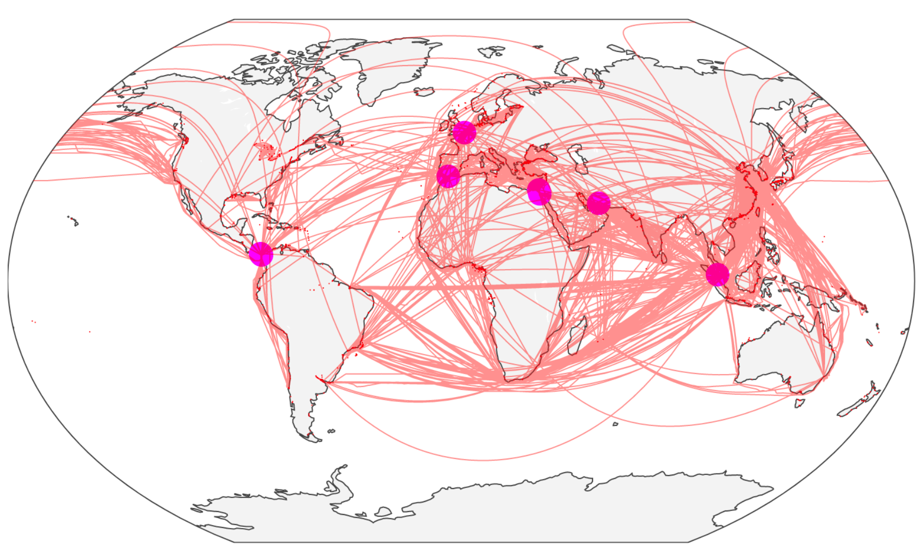

**Figure 11.** **Choke-points cutting area** If any of the points on route fall within a specific radius of the choke-point, that route is marked as "affected" by that choke-point.

| Choke-point | | Distance (km) |
|---|---|---|
| Suez | Port Suez | 15 |
| | Port Said | 15 |
| Malacca | | 45 |
| Gibraltar | | 15 |
| Hormuz | | 45 |
| Panama | Balboa | 15 |
| | Colon | 15 |
| Dover | | 40 |

**Table 8.** Choke-point blockage radius

| **Parameter** | **Ship type** | **Value** |
|---|---|---|
| Type | ——— | $\mathrm{p}_X(type)$ : $Large = 0.25; Normal = 0.5; Small = 0.25;$ |
| Origin | Large | Major port |
| | Normal | Major port |
| | Small | Random port |
| Destination | Large | Major ports |
| | Normal | Major ports + Random ports |
| | Small | Random ports |
| Foresight | all | Poisson($\lambda$) $\lambda = 0, 5, 10, 15, 20$ |
| Speed | all | 20 |
| Penalty | all | 1.5 |

**Table 9.** Parameter values used in ABM

**Algorithm 2** Pseudo code for route determination (Greedy Travelling Salesman using Dijkstra)

```
try:
    ports = [origin, destinations]
    for iteration = 1, 2, ..., length(Ports) do
        distance = dict()
        try:
            for iteration = 1, 2, ..., (length(Ports) − 1) do
                Compute distance to port using Dijkstra shortest path
            end for
            Pick port with shortest distance as next stop
            Pass route, travel distance to next stop to itinerary
            Remove next stop from port list
        catch: No route to port possible
        Count routing failure for analysis
    end for
catch: List end
```