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MARITIME DISRUPTION IMPACT EVALUATION USING SIMULATION AND BIG DATA ANALYTICS

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ABSTRACT

Disruptions in maritime networks may cause significant financial burden and damage to business. Recently, some international ports have been experiencing unprecedented congestions due to the COVID19 pandemic and other disruptions. It is paramount for the maritime industry to further enhance the capability to assess and predict impacts of disruptions. With more data available from industrial digitization and more advanced technologies developed for big data analytics and simulation, it is possible to build up such capability. In this study, we developed a discrete event simulation model backed with big data analytics for realistic and valid inputs to assess impacts of the Suez Canal blockage to the Port of Singapore. The simulation results reveal an interesting finding that, the blockage occurred in the Suez Canal can hardly cause significant congestion in the Port of Singapore. The work can be extended to evaluate impacts of other types of disruptions, even occurring concurrently.

1 INTRODUCTION

Maritime transport is the backbone of international trade and the global economy. 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 (UNCTAD 2018).

The global maritime shipping has been emphasized in recent years due to the more and more complex global supply chain network that connects land, sea, and air transportations while sea transportation typically takes longest time and is prone to disruptions (Figure 1). Recently, the maritime shipping industry has experienced unprecedented disruptions and chaos from geopolitical tensions, the Covid-19 pandemic, the war in the Ukraine, as well as natural disasters. Those disruptive events may cause port congestion,

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increase ship waiting time, disturb their service schedules, and subsequently, impact the entire supply chain including suppliers, manufacturers, freight forwarders, distributors, retailers, and customers (Evans et al. 2014). For example, one of such major supply chain disruptions in 2021 was the Suez Canal blockage.

Figure 1: Global maritime shipping.

The Port of Singapore is a transshipment hub located at a vital crossroad connecting the West and the East; it is the world's second busiest container port attracting approximately 130,000 port calls a year (Bloomberg 2022). Considering its key role as a hub connected to many ports in the world, its performance in face of major disruption would be a critical reference to global maritime shipping and supply chain risk management. Thus, the enhanced capability in quantitively assessing maritime disruptions benefits not only the Port of Singapore, but also stakeholders in supply chains as well.

In order to assess the impact of disruptive events to a port, techniques have been proposed to identify and evaluate risks (Kristiansen 2005), among which the port congestion is investigated (Pruyn, et al. 2020) under various disruptions. Simulation is another important approach though it faces the challenge on availability and accuracy of input data as much port information is confidential and hard to obtain from terminal operators or the port authority. Public or commercial data sources have to be referred to and advanced technologies like big data analytics are thus needed to process and analyze the data to generate quality simulation inputs (Chen and Zhang 2014).

The purpose of the current study is to develop a discrete-event simulation model of the Port of Singapore to quantitively assess the impacts of maritime disruptions to its operations and performances. The important inputs related to vessel inbound pattern, berth operation time, terminal capacities, etc. are obtained from the big data analytics on the public available data of both the port and vessels. The model is then used to study impacts of the Suez Canal blockage on the Port of Singapore under different blockage scenarios. In Section 2, we briefly describe the Suez Canal and the blockage. Processes of the simulation model are presented in Section 3. Detailed inputs and analytical results are given in Section 4. Simulation results are subsequently discussed in Section 5. Finally, Section 6 concludes the study and suggests the future work.

2 THE SUEZ CANAL AND THE BLOCKAGE

The Suez Canal is an important waterway between Asia and Europe. Before it was built, ships heading to Singapore from Europe would go by Cape of Good Hope, taking about 8.5 more days compared to the route through the Suez Canal assuming an average speed of 16.43 knots (Figure 2). Nowadays, an estimated 12% of global trade passes through the Suez Canal, comprising more than one billion tons of goods each year (Suez Canal 2022).

On Mar. 23, 2021, a 220,000-tonne, 400m-long Ever Given container ship ran aground after a gust of wind blew the vessel off course. It consequently blocked a total of 206 large container ships, tankers, and bulk vessels at either end of the canal according to vessels' Automatic Identification System (AIS) tracking data from Mar. 25, 2021, creating the largest supply chain disruption in 2021. The blockage continued for

6 days and 7 hours and finally was cleared on Mar. 29, 2021 and the vessel traffic resumed (Straits Times 2021b).

Figure 2: Alternative routes for shipping from Europe to Singapore (source: Vessels Value).

3 SIMULATION MODEL

In this study, we consider the container ships sailing to the Port of Singapore. To assess the impact of the Suez Canal blockage to the Port of Singapore, we built a simulation model where container ships from both the Suez Canal and other ports travel to the Port of Singapore, are served in the three container terminals of PSA, and finally leave the port upon finishing the service (Figure 3).

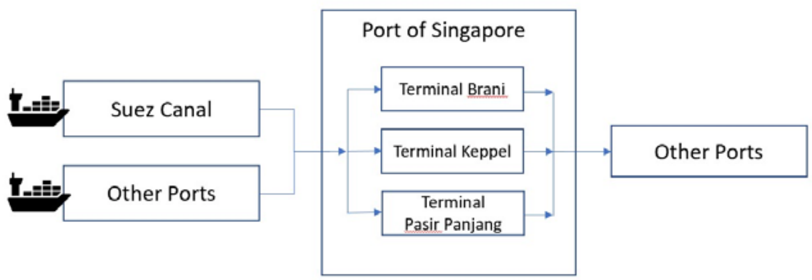


Figure 3: The conceptual diagram of the simulation model.

In the model, inputs of ship navigating through the Suez Canal and from the Suez Canal to the port of Singapore, ship navigating from other ports to the port of Singapore, berth/terminal allocation rules, berth operation time, and the port configuration are key information. Many of them are obtained through big data analysis and the relevant details are given in Section 4. In this section, only the main flows of container ships navigating to the Port of Singapore, and the operation of them receiving services within the Port of Singapore are described.

3.1 Sea Routes to Singapore

To study the impacts of the blockage in the Suez Canal to the Port of Singapore, we model the inbound container ships separately from two sources: the Suez Canal and the rest ports, respectively. Furthermore, as the giant ship was fully stuck in the canal, it can be safely assumed that no ship had passed in both directions during the blockage. Finally, vessels sailing between the Suez Canal and the Port of Singapore are also be modeled.

For the container ships from other ports, the daily arrival pattern to the Port of Singapore will also be modeled so that the total daily number of inbound container ships from both sources matches what we observe in the Port of Singapore.

3.2 Operations in the Port of Singapore

Three main container ship terminals in the Port of Singapore are considered in this study. They are terminals Brani, Keppel, and Pasir Panjang, which are operated by PSA. The terminals and the berths within them comprise the queue system that provides services to the incoming container ships. According to the AIS data in Mar. 2021, inbound container ships head to Brani, Keppel, and Pasir Panjang with probabilities of about 14%, 10%, and 76%, respectively. The median number of concurrent working berths at each one of those three terminals are 4, 4, and 28, respectively (Figure 4).

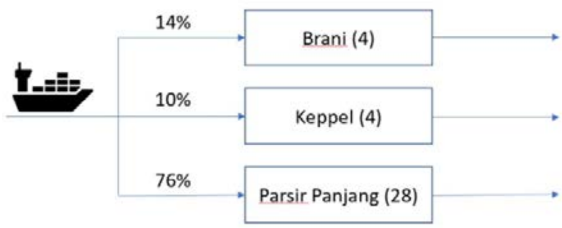


Figure 4: Three main container terminals in the Port of Singapore.

If no berth is available at the time they arrive, ships will wait at anchorages nearby to be served. We assume that only one berth is visited by each ship per port call based on the analytical results that only 6.5% of the total number of ships visited more than one berth in one port call. Upon finishing the port operation service, ships will leave the terminal for other services or head to the next port.

3.3 Performance Criteria

The simulation model is used to track the following performance criteria, e.g. vessel throughput at the Suez Canal, the daily number of vessels to the Port of Singapore from the Suez Canal, the total daily number of vessels to the Port of Singapore, durations of vessels passing through the Suez Canal and from the Suez Canal to the Port of Singapore, the handling time in the Port of Singapore, and the overall lead time from entering the Suez Canal to leaving the Port of Singapore. All the values are recorded in mean, standard deviation, and the 95th percentile.

4 MODEL INPUTS

To have a valid representation of the real maritime system, all the inputs should reflect realistic levels of uncertainty and accuracy. This is generally guaranteed through fitting historical data to statistical distribution functions and using methods like the Chi-square and Kolmogorov-Smirnov (K-S) goodness-of-fit test to find the best fit. If historical data does not exist for some processes, domain experts could be interviewed to collect relevant information.

With today's technology development in digitalization, tremendous amounts of data could be collected with relatively easy ways and critical information of vessel navigation, port operation, maritime risks, etc., can be extracted through big data analytics. AIS was designed primarily for enhancing traffic safety by providing the real-time information including ship location and cargo information. It can also provide a huge opportunity for us to extract and examine the ships' movement and port stay activities although sometimes it could be erroneous and might contain significant gaps compromising the accuracy of extracted information and intelligence.

We have developed effective models to pre-process the big spatial-temporal AIS data, detect the ship movement status, and extract the operational events based on aggregated ship movement patterns through artificial intelligence (AI) modeling (Xu et al. 2019; Yin et al. 2016; Xu et al. 2015). In this study, we use the intelligent models to determine the values of inputs for the simulation model. The AIS data has been purchased from commercial sources with important dimensions of big data: variety, velocity, variation, and veracity (Liu 2022).

4.1 Navigation Information

During the normal situation, the canal's average daily traffic totals 40 to 50 ships and the maximum authorized number is about 106 vessels per day from our analysis on the AIS data. The traveling time of a vessel through the Suez Canal is about 12-16 hours (Suez Canal 2022). The number of container ships arrival to Singapore through the Suez Canal per day is around 6 to 7.

As reported by PSA Singapore, a total of 45 blocked container vessels from the Suez Canal to Singapore were cleared by Tuesday, April 27, 2021 (Hand 2022). It is also reported that the first vessels after the Suez Canal blockage arrived in Singapore in the week of April 7, 2021 (Teo 2021). Finally, from the travel pattern extracted from the AIS data, we can safely assume that the travel time from the Suez Canal to the Port of Singapore is around 9.5 to 13 days.

4.2 Terminal Situation, Operation and Container Ship Arrival Patterns

The terminal situation, operation and container ship arrival patterns can be extracted from the AIS data of container ships. For each container ship, a port event chain can be formed by all stay events in a temporal sequence. The information of stay events, which includes the start/end time of each port call, the service location (berth/anchorage/unlabeled area), the speed and the duration, etc. can be obtained using our proposed vessel voyage event detection system for the large volume of AIS data (Xu et al. 2020).

The above proposed system contains three engines, which are 1) the AIS data error processing and interpolation engine to reconstruct vessel trajectories, 2) the grid-based aggregation engine to reduce the data size without losing the critical information, and 3) the grid-based spatiotemporal clustering engine for detecting the vessel event chain with the information of duration and location. The large-scale computation involved is further enhanced through the parallel computing.

Regarding the real Singapore port operation data, this system has been verified to achieve a high detection accuracy of the 95% for berth identification and the 99.5% for berth stay duration. In the next section, the terminal situation, operation pattern, and container ship arrival pattern are obtained using the extracted information.

4.2.1 Terminal Situation and Operation Pattern

Distributions of operation times in the above three terminals are shown in Figure 5.

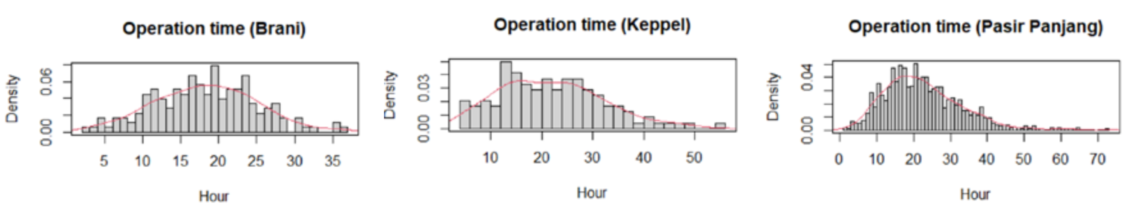


Figure 5: Distributions of operation times in the three terminals.

The mean values and standard deviations of operation times in hours are (18.24, 6.70) for Brani, (21.97, 10.32) for Keppel, and (22.48, 10.45) for Pasir Panjang, respectively. Numbers of berths operating concurrently in three terminals from Mar. 01 2021 to April 30 2021 are given in Figure 6.

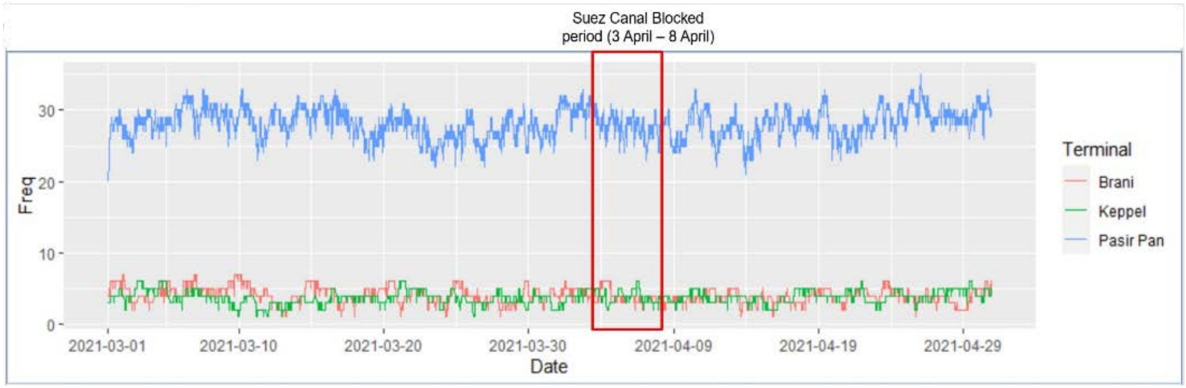


Figure 6: Numbers of berths operating concurrently in three terminals in every 15 minutes.

The figure shows no significant drop in the number of working berths in the Port of Singapore during the Suez Canal blockage. The maximal numbers of berths operating concurrently in each of three terminals, Brani, Keppel, and Pasir Panjang, are 7, 6, and 35, respectively.

4.2.2 Arrival Pattern of Inbound Container Ships

The exponential distribution is a typical choice to describe the distribution of the lengths of the inter-arrival times between two successive independent arrivals (Illowsky et al. 2013; Law 2014). In this study, we adopt the exponential distribution to model the arrival intervals of container ships in the Port of Singapore and find that the arrival intervals followed an Exponential distribution with a rate of 1.59 per hour (Figure 7).

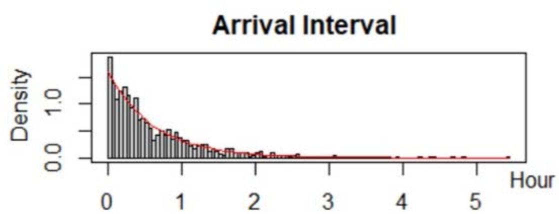


Figure 7: The pattern of ship arrival intervals.

A KS test (Pearson et al. 1972) with the null hypothesis shows the distribution function which generates the lengths of the inter-arrival times as an exponential distribution with a rate of 1.59 per hour also statistically supports the exponential distribution with a p-value of 0.19. The KS test statistic is expressed as follows.

$$D_n = \sup_x |F_n(x) - F(x)| = \sup_{0\le t\le 1} |F_n(F^{-1}(t)) - F(F^{-1}(t))| \tag{1}$$

where

$$F_n(x) = \frac{\text{number of (the lengths of the inter-arrival times} \le x)}{\text{n}} = \frac{1}{n}\sum_{i=1}^{n} 1_{[0,x]}(\mathrm{X}_i) \tag{2}$$

$$F(x) = 1 - \exp(-1.59x) \tag{3}$$

X_i is the length of the i -th inter-arrival time, $i = 1, \cdots, n$.
n is the total number of the inter-arrivals.
The overall arriving pattern of container ships (March and April 2021) is shown in Figure 8.

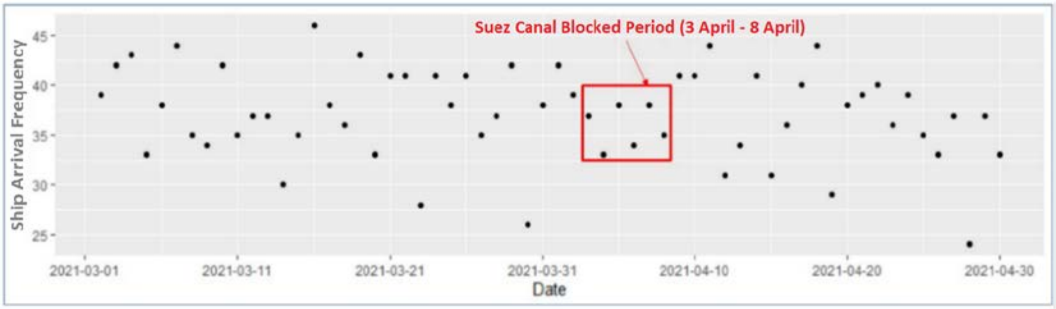


Figure 8: The overall arriving pattern of container ships.

Number of vessels' arrival per day follows a Poisson distribution with mean of 1.59*24 = 38 vessels according to the relationship between an exponential distribution and a Poisson distribution.

5 SIMULATION RESULTS AND DISCUSSION

The simulation has been implemented with two cases: the base model without risk event and the one with the blockage event in the Suez Canal. The base model needs to be first validated with the real-world data before it can be expanded to include risk events. The model implemented with the blockage events has run for five scenarios with five blockage durations of 1, 3, 6, 14, and 21 days, respectively. Each scenario has been run for 50 iterations to get statistics for evaluating performance criteria.

5.1 Base Case

The results from the base case are given in Table 1.

Table 1: Navigation statistics under the normal situation (1).

Vessel Throughput @ the Suez Canal			Number of vessels to SG from the Suez Canal			Number of total vessels to SG		
MEAN	SD	95 Percentile	MEAN	SD	95 Percentile	MEAN	SD	95 Percentile
55.11	4.16	61	6.02	2.46	10	35.84	3	40

It shows that the mean number of vessels going through the Suez Canal is about 55.11 per day with a standard deviation of 4.16. This matches the 50 vessels we observed in the data analysis. The value of the 95th percentile is 60 vessels. The mean number of container ships going through the Suez Canal to the Port of Singapore is 6.02 with a standard deviation of 2.46 and the value of the 95th percentile is 10. Finally, the mean number of total container ships to the Singapore port is 35 per day with a standard deviation of 3 and the value of the 95th percentile is 40 (Table 2).

Table 2: Navigation statistics under the normal situation (2).

Passing Suez Time (day)			From Suez to SG (day)			SG Handling (day)			Overall Leadtime (day)		
MEAN	SD	95 Percentile	MEAN	SD	95 Percentile	MEAN	SD	95 Percentile	MEAN	SD	95 Percentile
0.58	0.05	0.65	11.24	1.02	12.84	1.17	0.68	2.35	12.96	1.22	14.95

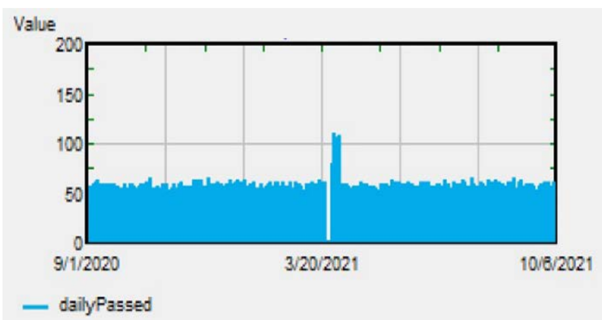
Table 2 shows that the mean time for vessels passing the Suez Canal is 0.58 day with a standard deviation of 0.05 day and the value of the 95th percentile is 0.65 day. The mean time for vessels traveling from the Suez Canal to Singapore is 11.24 days with a standard deviation of 1.02 days. The value of the 95th percentile is 12.84 days. The mean vessel handling time at the Singapore port is 1.17 days with a standard deviation of 0.68 day and the value of the 95th percentile is 2.35 days. Finally, for the overall lead time of vessels from entering the Suez Canal to leaving the Singapore port, the mean time is 12.96 days with a standard deviation of 1.22 days and the value of the 95th percentile is 14.95 days.

The results in the above two tables not only validate the simulation models, but also build a base for the comparison of performance when risk events occur.

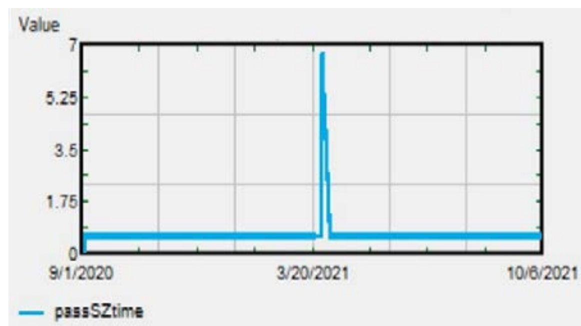
5.2 With the Suez Canal Blockage

5.2.1 Plots of Key Performance Measures

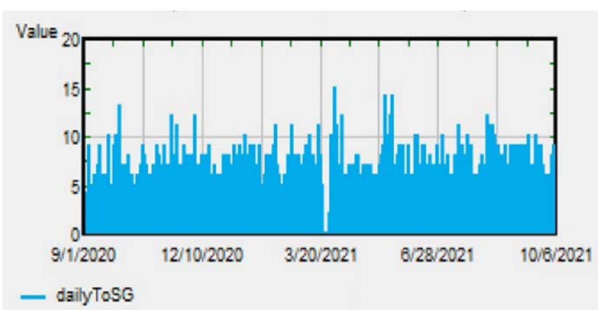
We record and plot the daily number of vessels passing the Suez Canal (a), time for vessels passing the Suez Canal (in day) (b), daily number of vessels from the Suez Canal to Singapore (c), and the total daily number of vessels arriving Singapore (d) in Figure 9 when the Suez Canal blockage lasts six days.



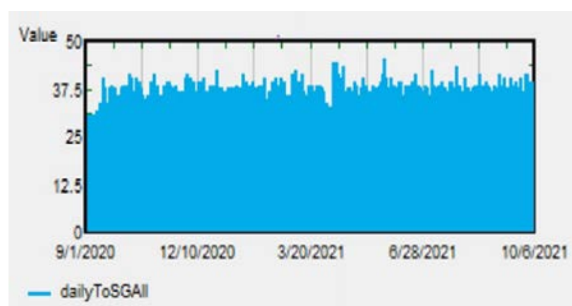
(a) Daily number of vessels passing the Suez Canal



(b) Time for vessels passing the Suez Canal (day)



(c) Daily number of vessels from the Suez Canal to Singapore



(d) Total daily number of vessels arriving in Singapore

Figure 9: Performance measures when the blockage lasts six days.

We can see that the Suez Canal experiences a high throughput right after the clearance of the blockage (Figure 9 (a)); there is a hike in the transit time through the canal during the six-day blockage (Figure 9 (b)); there is no or less vessels from the Suez Canal to Singapore following the blockage (Figure 9 (c)); the total number of vessels arriving in Singapore seems not affected significantly (Figure 9 (d)).

5.2.2 Comparison of Five Scenarios

Assuming that the Suez Canal blockage lasts for 1, 3, 6, 14, and 21 days, the results of simulation for performance statistics are listed in both Table 3 and Table 4.

Table 3 shows both numbers of blocked vessels in the Suez Canal and those heading to Singapore increase as the blockage duration increases assuming no ships reroute and leave the Suez Canal. The mean number of blocked vessels to Singapore is 41 with a standard deviation of 6 when the blockage duration is 6 days. This is in line with the fact that totally 45 blocked vessels were handled in the Port of Singapore (Hand 2022) after the Suez Canal was blocked for 6 days and 7 hours.

Table 3: Numbers of blocked vessels for different blockage durations.

Blockage Duration	**Number Of Blocked Vessels**			**Number Of Blocked Vessels to SG**		
Day	**MEAN**	**SD**	**95% percentile**	**MEAN**	**SD**	**95% percentile**
1	87	4	94	10	3	15
3	198	6	208	21	4	28
6	362	7	372	42	6	51
14	795	12	810	89	10	104
21	1183	16	1203	136	11	154

Table 4: Time related statistics with the Suez Canal blockage.

Blockage Duration	**Passing Suez Time (day)**			**From Suez to SG (day)**			**SG Handling (day)**			**Overall Leadtime (day)**		
DAY	**MEAN**	**SD**	**95 Percentile**	**MEAN**	**SD**	**95 Percentile**	**MEAN**	**SD**	**95 Percentile**	**MEAN**	**SD**	**95 Percentile**
1	1.34	0.23	1.65	11.36	1.11	12.94	1.18	1.11	2.26	13.88	1.39	16.09
3	2.90	0.48	3.62	11.15	1.06	12.92	1.31	1.06	2.56	15.36	1.44	17.86
6	5.20	0.90	6.58	11.21	1.04	12.92	1.44	1.04	2.72	17.85	1.60	20.77
14	11.31	1.99	14.50	11.23	1.01	12.88	1.40	1.01	2.77	23.93	2.25	27.90
21	16.75	2.84	21.16	11.22	1.01	12.88	1.47	1.01	2.73	29.43	3.00	34.31

From Table 4, we observe that both the mean passing time through the Suez Canal and the overall lead time increase as the blockage durations increase. The mean travel time from the Suez Canal to Singapore remains the same. This is reasonable as there is no bottleneck on the open sea and vessels can travel with their normal speed without being affected by the blockage in the Suez Canal. Interestingly, the mean handling time in the Singapore port only slightly increases as the blockage duration increases. The mean handling time is only 1.47 days even the blockage duration reaches 21 days.

5.3 Facts at the Port of Singapore Before and After the Blockage

To better understand whether the Suez Canal blockage had caused congestion in the Port of Singapore, we analyze both the indirect berthing rate and waiting times of container ships heading to Singapore port from March to April 2021. The daily indirect berthing rate is listed in Figure 10, and the average waiting time before the 1st berthing is shown in Figure 11.

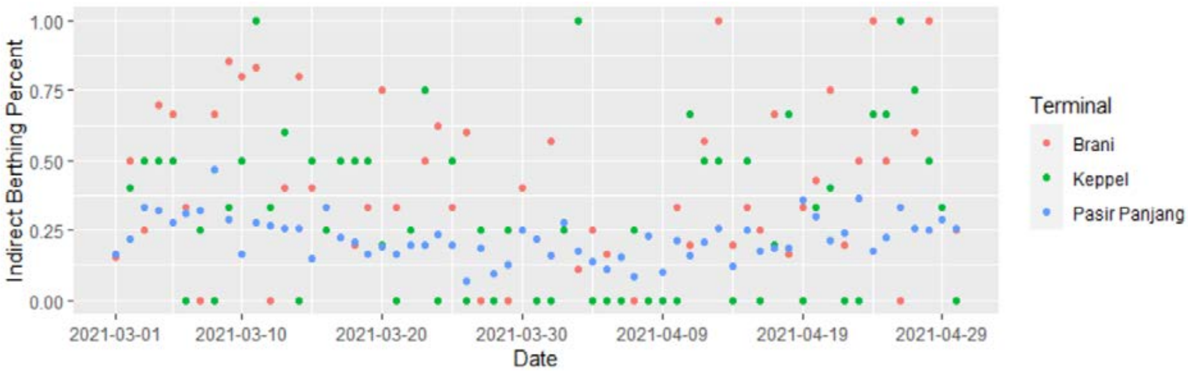


Figure 10: Indirect berthing rate (from March 1 to April 30 2021).

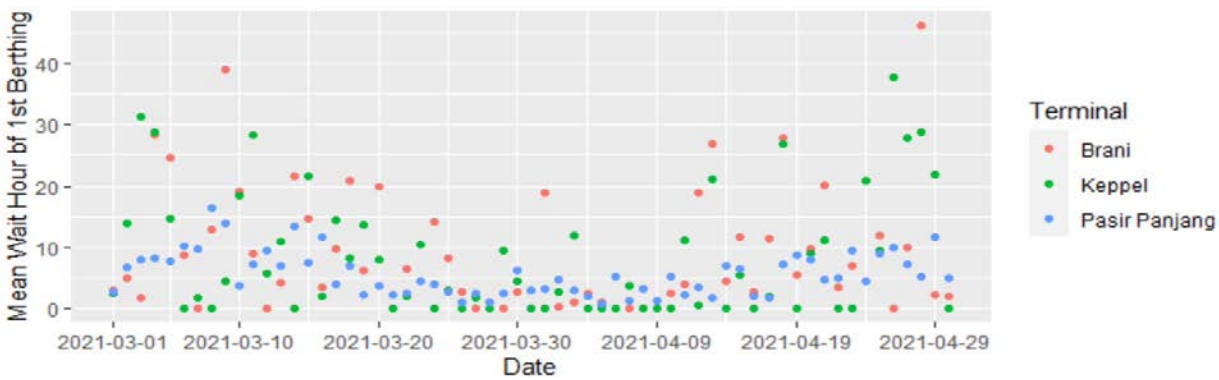


Figure 11: Average waiting hour before the first berthing (from March 1 to April 30 2021)

We further applied the Wilcox test to test if the indirect berthing rate and waiting time were significantly different in March (before the blockage) and April (after the blockage). All p-values showed that differences were not significant. Detailed results are shown in Table 5.

Table 5: Wilcox test for the difference in indirect berthing rate and waiting time in March and April 2021.

Wilcox Test	Overall	Exclude 3rd to 9th April	Overall (Pasir Panjang)	Exclude 3rd to 9th April (Pasir Panjang)
p-value (indirect berthing rate)	0.254	0.626	0.458	0.583
p-value (waiting time)	0.256	0.719	0.312	0.802

Both the simulation and data analysis showed that the Suez Canal blockage did not cause congestions in the Singapore port. The truth is that no matter how long the blockage lasts, the daily number of vessels from the Suez Canal to Singapore is capped by the throughput of the canal, which is no more than 8 container ships per day in the normal days (Table 2). This number might increase as the throughput was increased from 55.11 to the maximum daily throughput of 106 in the Suez Canal after the blockage.

Equipped with more than 48 berths and well-planned resources, the PSA Singapore could handle not only its regular workload, but also the extra number of blocked container ships as well. In fact, it was reported that totally 45 blocked vessels were cleared by April 27, 2021 in the Port of Singapore after the vessel traffic resumed on Mar. 29 (Straits Times 2021b).

6 CONCLUSION AND FUTURE WORK

In this study, we developed a discrete event simulation model backed with big data analytics for realistic and valid inputs to quantitively assess impacts of the Suez Canal blockage to the Port of Singapore.

Our study reveals that the blockage of Suez Canal can hardly cause significant congestion in the port of Singapore. Firstly, this is because the total number of container ships from the Suez Canal is capped by the throughput of the canal. Secondly, attributing to its efficiency in operation and effectiveness in capacity management, the Port of Singapore is capable to provide sufficient resources for severe disruptions. Thirdly, in reality, some container ships might reroute from the Suez Canal, thus reduce the total number of vessels being blocked as well as the number of vessels heading to the Port of Singapore. In summary, unless the number of inbound container ships from other ports increases concurrently, the blockage in the Suez Canal would not significantly congest the Port of Singapore.

The future work includes expanding the model to evaluate other types of disruptions and to propose optimized mitigation strategies. For example, if ship owners consider taking the alternative route by the Cape of Good Hope instead of waiting for the clearance of blockage, they should have the extra 8.5 sailing days well justified. The analysis on the historical data to forecast the duration of the blockage combining the scenario planning in the simulation can generate insightful decision supports needed by those ship owners. It is envisaged that ports can be empowered by the simulation model and big data analytics to help ease supply chain disruptions, and to serve as a "catch-up" port for shipping lines.

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