Yasuhiro AKAKURA
National Institute for Land and Infrastructure Management, MLIT, Japan
akakura-y83ab@mlit.go.jp

Analysis of Deterioration of Port Function and Long Offshore Waiting under Global Shipping Crisis

Abstract
Global shipping crisis has become a crucial issue, causing delays in delivering various goods and leading to shortages of those goods. Transport demand surged in the second half of 2020; however, the container transport capacity was insufficient owing to the lack of container boxes, ships, and sudden labor shortages due to the spread of COVID-19. Numerous container ships have been waiting at offshore for days at major ports, especially in North America, China, and Europe, causing a considerable deterioration in the punctuality of the world's container services. In this study, the deterioration of port functions of the world's major ports under the current crisis is analyzed. Furthermore, offshore waiting times and volumes at the terminals of the Los Angeles/Long Beach and Singapore ports are estimated using Automatic Identification System data. Additionally, an automated calculation system estimating the waiting time–volume of each terminal is developed. The container handling efficiency of the Los Angeles/Long Beach port was found to continuously decrease, while that of Rotterdam and Shanghai ports remained rather stable; the waiting time–volumes at the Singapore-port terminals were comparatively small. Furthermore, the significance of data accuracy for analyzing port/terminal performance is discussed.

Keywords: *Port Performance, Terminal Congestion, Berth Occupancy, Container Handling Efficiency, AIS.*

1. Introduction

The global shipping crisis has become a crucial issue, causing shortages of imported consumer goods, including Christmas gifts, especially in North America and Europe. In the second half of 2020, after the COVID-19 first wave had subsided, container transport demand surged substantially in these continents supported by strong consumer expenditure. For example, the imported containerized cargo weight in the US increased drastically after

September 2020 compared with the same month of 2019 as shown in Figure 1, despite strong capacity constraints.

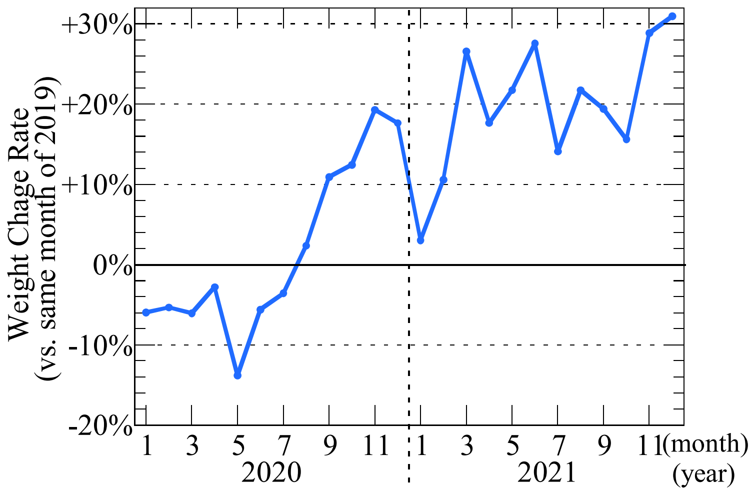


Figure 1 - Weight change of US imported containerized Cargo
Data Source: USA Trade Online

Container transport capacity consists of container boxes, ships, cranes, chassis, and storage spaces at terminals and warehouses, and it was insufficient to fulfill the surging demand. Furthermore, the spread of COVID-19 infection has incurred sudden disruptions due to labor shortages at many ports, as shown in Table 1. As a result, numerous container ships have been waiting for days to be berthed offshore at major ports, especially in North America, China, and Europe, causing a significant deterioration in the punctuality of world container services. These delays of ships have been passed on to other terminals, and the issue has been difficult to resolve in a short period. Global schedule reliability, the rate of arrival of container ships within the next days of schedules, dropped from 78% in 2019 to 36% in 2021 (Sea-Intelligence, 2022). Sophisticated and lean supply chains, such as just-in-time systems, have been damaged fatally by these unreliable and excessively expensive services. Comparatively high-value commodities were forced to select air transport alternatively, as the weight of US auto parts imported from Asia by air surged after the second half of 2020, as shown in Figure 2, even though the world auto production has suffered a downswing due to lack of semiconductors since the second half of 2021. Simultaneously, many shippers, presumably, have given up exporting their low-value cargoes. It was estimated that $15.7 billion of US export was lost by port congestion in the US between May and November 2021 (Steinbach, 2022).

Table 1 - Disruption of port function due to COVID-19 (After 2H ’20)

Period	Country	Contents
After Winter '20	US	Handling capacity of West Coast ports, especially Los Angeles /Long Beach port, have been insufficient, and many ships have been waiting at offshore of these ports (worsened after Summer '21)
Nov '20	UK	Efficiency of container handling has drastically deteriorated and CMS-CGM and MSC introduced port congestion surcharge
Dec '20	China	Calling at Dalian port was suspended
May to Jun '21	China	Port calling at Yantian port closed for 1 month, and many ships waited at offshore of Yantian and other neighboring ports or omitted their calls at these ports
Jul to Sep '21	Vietnam	Congestion of major ports have deteriorated
Aug '21	China	Meishan Terminal of Ningbo port was closed for 2 weeks by 1 positive case
Oct '21	UK	Maersk skipped Felixstowe because of terrible congestion
Mar to May '22	China	Congestion of Shanghai port has worsened after local authorities escalated lockdown measures in the city

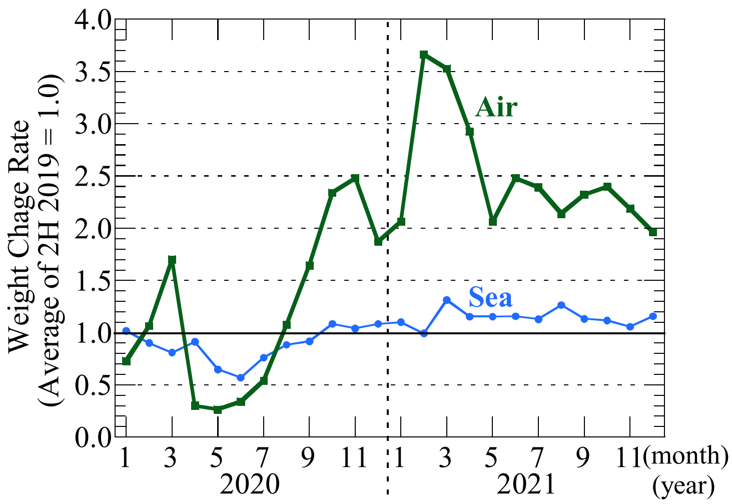


Figure 2 - Weight change of US imported auto parts by mode

Data Source: USA Trade Online

Based on the abovementioned background, deterioration of port functions of world major ports under the current shipping crisis, causing long offshore waiting, was analyzed by calculating berth occupancy and container handling efficiency of each port. Furthermore, offshore waiting times and volumes at the terminals of the Los Angeles/Long Beach and Singapore ports were estimated using Automatic Identification System (AIS) data. Additionally, based on the concept that offshore waiting data are crucial as an index for evaluating the soundness of terminal operations, an automated calculation system that estimates the waiting times and volumes of each terminal was developed.

2. Literature Review

Many previous studies have discussed port congestion because it is one of the crucial issues facing not only each port but also the entire maritime economy. Among them, factorial analysis and countermeasures for port congestion were mostly discussed. For example, Gidado (2015) categorized port congestions in Africa, such as ship berth congestion, vehicle gate congestion, and cargo stack congestion, and identified the consequences of port congestion on Logistics and supply chain operations. Jiang *et al* (2016) developed a theoretical model for analyzing the port congestion internalization of the shipping lines, considering the knock-on effect, i.e., the congestion delay passed on from one port-of-call to the next. Jiménez *et al* (2021) applied a multiagent platform in the Port of Cartagena to alleviate potential congestion in multiclient liquid bulk terminals, promoting a consensus where the overall vessel waiting time is reduced. Bolat *et al* (2020) discussed the most important factors of port congestion using existing works of literature. Pruyn *et al* (2020) used Markov chain analysis to predict port waiting time in the bulk shipping industry, which is caused by port congestion.

Among the previous studies relating to port congestion, recently, the analysis utilizing AIS data formed one category. AbuAlhaol *et al* (2018) proposed port congestion indicators from AIS data to alert for congestion levels that can be correlated with weather, high demand, or a sudden collapse in the capacity due to strike, sabotage, or other disruptive events. Kim and Lee (2018) proposed a new deep neural network model using AIS data to predict the medium- and long-term traffic of the caution area. Bai *et al* (2021) investigated how port congestion affects maritime transportation freight rates for liquefied petroleum gas seaborne trade using AIS data. Pen *et al* (2022) proposed high-frequency container port congestion measures using AIS data for monitoring changes in port performance.

There were some analyses related to port congestion amid the current global shipping crisis. As mentioned earlier, Steinbach (2022) assessed the US foreign trade effects of port congestion and container shortages using event studies and concluded that the US exported 24.5% fewer containers between May and November 2021, amounting to export losses of $15.7 billion. Gui *et al* (2022) developed a methodology for identifying and prioritizing port congestion risk during the COVID-19 pandemic. However, as to the current crisis in that numerous container ships have been forced to wait offshore, no study analyzed the relationship between offshore waiting and terminal operation.

As to offshore waiting due to terminal congestion, Los Angeles and Long Beach ports are probably the only port authorities that publish the number of offshore waiting ships; however, the statistics eventually do not show the real number after the change of the queuing system of both ports in mid-November 2021. Gao *et al* (2016) traced container ship navigation in Japan's Seto Inland Sea and its oceanic waters using AIS data and identified offshore anchoring ships whose speeds over the ground were below 3 knots and positions were not near any berths at ports. Akakura and Takahashi (2021) proposed a method for estimating the offshore waiting time of each ship by calculating the total time and hourly ship speed between entering the port and the berthing terminal and detecting anchoring signals using AIS data. As a result, the offshore waiting time–volume was related to the berth occupancy ratio, total twenty-foot equivalent unit (TEU) capacity of berthing ships, and actual delays of arrivals and overtime stays. However, these studies did not target the many ships' long waiting times after mid-2020.

In contrast, as the delay of container services worsened more and more, some companies have started information services relating to port congestion and offshore waiting. Marine Traffic provides the numbers and times of anchoring ships at designated offshore waiting sea areas for the port congestion index as a pathfinder. Clarkson started offering a port congestion index: share of carrying capacities at ports, including offshore waiting, to profile the impact of port congestion on various shipping markets. Lloyd's List Intelligence (LLI) often indicates the number and capacity of offshore anchoring ships in its articles. Vessel Value provides average delay hours and number of waiting ships by ship type as port congestion data. As for container shipping, eeSea and Kuehne+Nagel provide the number of waiting container ships, and IHS Markit and World Bank Group started the service "The Container Port Performance Index" to offer various port performance indicators relating to not only offshore waiting but also gantry crane moves, although the data coverage was limited to only major shipping companies. These information services are useful for grasping the outline of port congestion; however, the data provided is categorized basically by port not by terminal. Additionally, many of these companies do not show a detailed method for generating data, and inconsistency was found with the official offshore waiting ships' data of Los Angeles/Long Beach port.

The contribution of this present study to the literature is two-fold: First, the deterioration in port function indices, such as berth occupancy and container handling efficiency, are analyzed, considering the accuracy of ship movement data. Second, terminal-based offshore waiting times and volumes are estimated, and the relationship offshore waiting and quayside efficiency of terminals amid the global shipping crisis is revealed.

The remainder of this paper is structured as follows. In Section 3, the deterioration of port functions of the world's major ports under the current crisis is analyzed. In Section 4, offshore waiting times and volumes at the terminals of the Los Angeles/Long Beach and Singapore ports are estimated for a detailed analysis of terminal operation. In Section 5, a discussion of the importance of data accuracy and offshore waiting data is held. In Section 6, conclusions are given.

3. Port Performance under Crisis

3.1. Data and Method

Changes in the port functions of the world's major ports were analyzed using LLI ship movement data. Table 1 shows the structure of the LLI data, illustrating the actual arrival and sail dates/times of ports and anchorages. These dates/times were arranged using the AIS data received at each port. The waiting offshore of a port was recorded as arrival and sail at anchorage, and the arrival time at each port in the ship movement data indicates the time when a ship arrived in front of the calling berth and slowed to almost a stop, according to the comparison of the LLI data with AIS data (Akakura and Takahashi, 2021). The analysis targets were Los Angeles/Long Beach, Rotterdam, Singapore, and Shanghai ports as the world's top-tier and severely congested ports.

Table 2 - Structure of LLI ship movement data

IMO No.	VESSEL NAME	TEU	PLACE NAME	CNTRY	ARRIVAL DATE/YIME	SAIL DATE/TIME
981****	**********	14,300	Singapore	SGP	2021/6/2 0:39	2021/6/3 4:15
981****	**********	14,300	Cai Mep	VNM	2021/6/4 23:51	2021/6/5 14:53
981****	**********	14,300	Yantian	CHN	2021/6/8 1:47	2021/6/9 3:52
981****	**********	14,300	Ningbo	CHN	2021/6/11 12:09	2021/6/12 8:14
981****	**********	14,300	Yangshan	CHN	2021/6/13 4:51	2021/6/14 9:20
981****	**********	14,300	Long Beach Anch.	USA	2021/6/27 16:05	2021/7/2 1:46
981****	**********	14,300	Long Beach	USA	2021/7/2 4:11	2021/7/5 6:01
981****	**********	14,300	Oakland	USA	2021/7/6 15:13	2021/7/7 13:29
981****	**********	14,300	Busan	KOR	2021/7/19 3:19	2021/7/20 1:34
981****	**********	14,300	Yangshan Anch.	CHN	2021/7/20 22:49	2021/7/23 12:18
981****	**********	14,300	Yangshan	CHN	2021/7/23 14:26	2021/7/24 6:10
981****	**********	14,300	Ningbo Anch.	CHN	2021/7/24 17:23	2021/7/26 14:37
981****	**********	14,300	Ningbo	CHN	2021/7/26 16:34	2021/7/27 12:54

Source: LLI

In this study, the port performance of each port was analyzed by calculating the following indices: berth occupancy ratio and average berthing time per TEU as the representation of quayside efficiency. Berth occupancy ratio R is the ratio of time and space occupied by berthing ships, as shown in Equation (1):

$$R = \frac{\sum_{Ship} (L_{Ship} \cdot T_{Ship})}{L_{All} \cdot T_{All}}, \quad (1)$$

where L_{Ship} and T_{Ship} are the occupied length (Figure 3) and time of the ship and L_{All} and T_{All} are the all berth length and time, respectively.

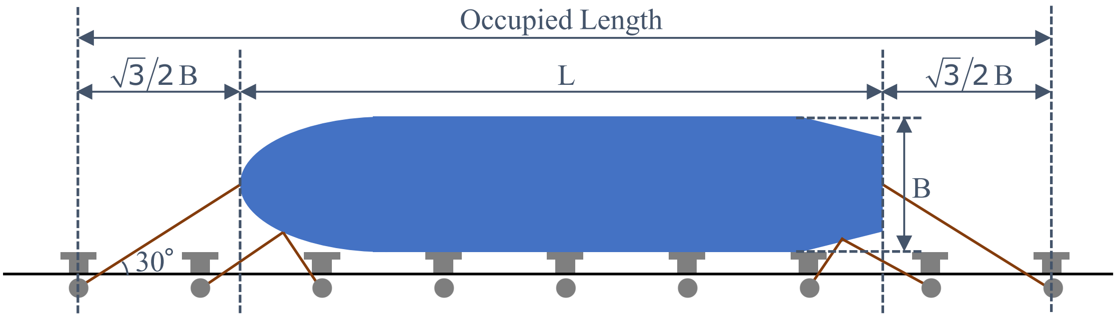


Figure 3 - Occupied length of berthing ship

Average berthing time per TEU E (min/TEU) indicates the efficiency of container handling and is calculated using Equation (2):

$$E = \frac{\sum_{Ship} T_{Ship}}{V}, \quad (2)$$

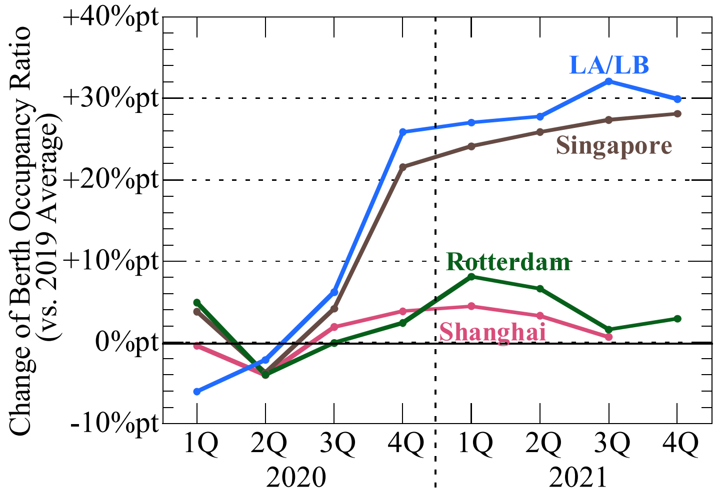
where V (TEU) is the container throughput of ports.

The prerequisite of this time series analysis is the assumption that the condition for the berthing of ship and container handling of each port has not changed considerably. The frequency of extremely bad weather, such as strong wind, high wave, and thick fog, which disturbs smooth port operation has changed by season and year. The total number of gantry cranes at container terminals in Singapore and Shanghai ports had increased 3% and 4%, respectively, when comparing 2021 with 2019. However, generally, these slight changes have little impact on the analysis result.

3.2. Change in Port Performance

Figure 4 shows the calculation result of the berth occupancy ratio of each port based on berthing time and occupied length of each ship. The increase in the berth occupancy ratio of the Los Angeles/Long Beach and Singapore ports after the fourth quarter of 2020 was considerably larger than that of Rotterdam and Shanghai. The average berth occupancy ratio of the Singapore port in 2021 reached 90%, which was an abnormal level and meant almost no margin for berthing space and time on this calculation result, while the maximum berth occupancy ratio of Los Angeles/Long Beach port in 2021 was

67%. The berth occupancy ratios of various terminals at world major ports before the current global shipping crisis were approximately 60% or less (Akakura and Takahashi, 2021). Here, as it confirmed that some ships called not terminal but shipyard at the Singapore and Shanghai ports, the ships staying over one week continuously were excluded from its data.



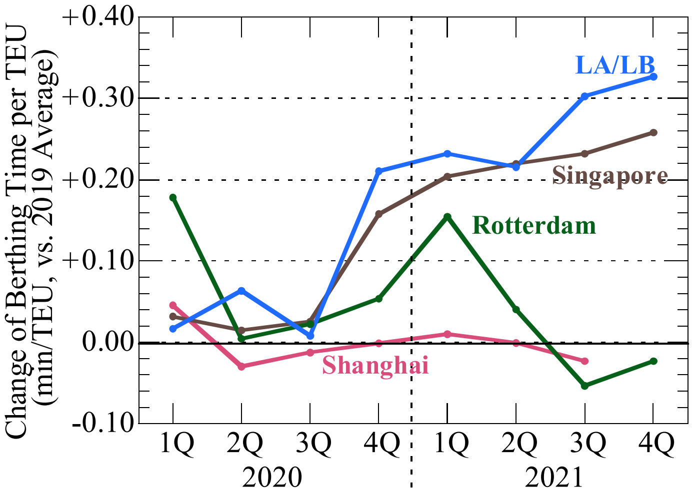
Berth Occupancy Ratio

Port	2019
Los Angeles Long Beach	34.6%
Rotterdam	51.1%
Singapore	63.6%
Shanghai	49.8%

Figure 4 - Change of berth occupancy ratio

Figure 5 indicates the change of berthing time per throughput TEU, as the index representing the handling efficiency of a ship to shore. This index depends on berthing ship size because, for larger ships, more cranes can be utilized for loading and unloading container boxes. Therefore, comparison between disparate ports is meaningless; however, monitoring the changes in the same port is significant. The change of berthing time per TEU of the Los Angeles/Long Beach and Singapore port surged after the fourth quarter in 2020, i.e., the degradation of container handling efficiency substantially, whereas that of Rotterdam port increased in the first quarter of 2021 but returned to the same level of 2019 in the following quarter.

Next, the relation of the two calculation results was analyzed, as the both indices connected through berthing time. From the results, changes in port performance were divided into two categories, as shown in Table 3. The first category is located at “1a” in Table 3, Rotterdam and Shanghai ports. Both indices were stable, even though many ships were forced to wait offshore. The other category is located at “2b” in Table 3, showing that the port functions at the quayside of the Los Angeles/Long Beach and Singapore ports have deteriorated severely. There were no ports located at “1b,” where berthing times were stable but times per TEU deteriorated, meaning slump of



Berthing Time per TEU

Port	2019
Los Angeles Long Beach	0.47
Rotterdam	1.16
Singapore	0.57
Shanghai	0.35

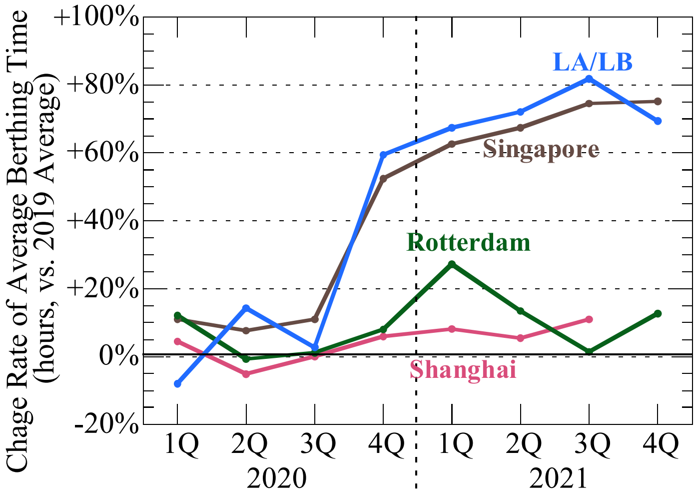
Figure 5 - Change of berthing time per TEU

Table 3 - Dimensions of change in port performance

		Berting Time per TEU	
		a.Stable	b.Surge
Berth Occupancy Ratio	1.Stable	1a Rotterdam Shanghai	1b
	2.Surge	2a	2b LA/LB Singapore

container handling, or at "2a," where berthing times were prolonged but handling efficiencies were stable, meaning enabling an increase of handling container volume drastically, in Table 3.

The deterioration of port functions of the Los Angeles/Long Beach and Singapore ports were due to the prolonged berthing time. Figure 6 shows the average berthing time of all ports. In the figure, the surge of the Los Angeles/Long Beach and Singapore ports after the fourth quarter in 2020 was prominent, increasing the maximum from 70% to 80% of the 2019 average, although their average berthing time in 2019 differed greatly: that of the Los Angeles/Long Beach port was more than three times longer than that of the Singapore port. Most of the container services calling at the Los Angeles/Long Beach ports are East–West trunk lines, while those of the Singapore port contain many feeder services in Southeast Asia.



Average Berthing Hours

Port	2019
Los Angeles Long Beach	67.4
Rotterdam	40.2
Singapore	21.7
Shanghai	16.6

Figure 6 - Change of average berthing time

3.3. Ambiguous Data

Based on the LLI ship movement data, the quayside performance of Singapore deteriorated severely. Simultaneously, the berth occupancy ratio reached an abnormal level. Additionally, the number of anchoring ships at offshore areas of the Singapore port based on the LLI data was substantially low, as indicated in Figure 7. These numbers were the average of anchoring ships at noon of each day. The number of anchoring ships at offshore areas of the Singapore port was underestimated, compared with the other reports, such as Varley and Murray (2021), 54–102 container ships waiting offshore of the port from July to November 2021.

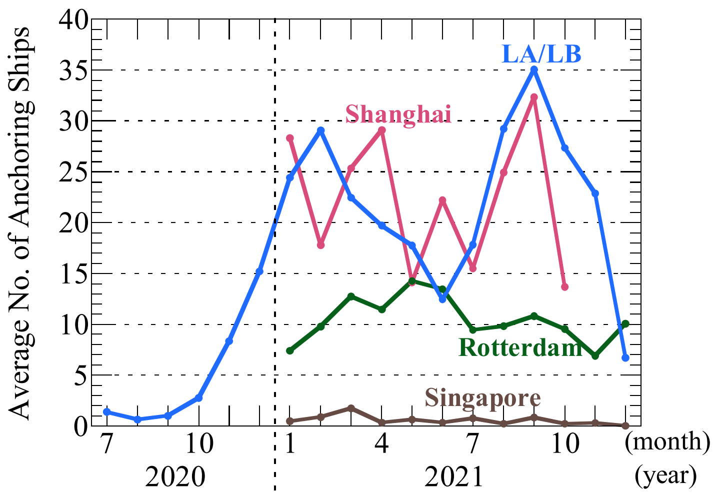


Figure 7 - Number of anchoring ships at offshore area by LLI data

It was considered that the anchoring of ships around the Singapore port probably was not recorded properly by LLI. From the comparison with AIS data, anchoring periods of some ships offshore of the terminal were included during their arrival and departure times at the port, as shown in Figure 8. In this case, berthing time in LLI ship movement data was 47 hours, even though true berthing time was only 17 hours and anchoring time at the east offshore of the terminal was approximately 30 hours. Additionally, some ships without berthing at any terminal at the Singapore port were identified as calling ships in LLI data. Figure 9 shows an example of a ship passing through the strait and temporarily anchoring offshore the terminals for bunkering or other purposes.

From this comparison, the analysis result relating to the Singapore port stated in the previous section is not reliable. Therefore, further detailed terminal-based analysis targeting the Los Angeles/Long Beach and Singapore ports was done using AIS data, as mentioned in the next section.

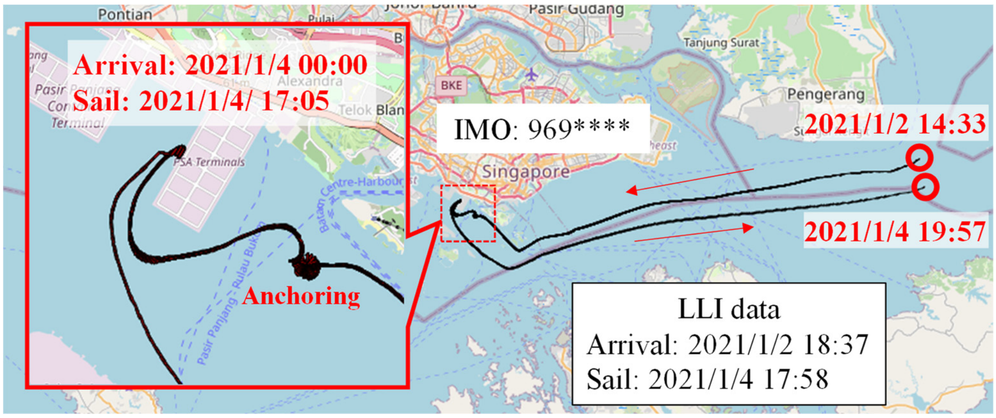


Figure 8 - Comparison LLI data with AIS data (Anchoring Ship)

Figure 9 - Comparison LLI data with AIS data (Passing Ship)

4. Offshore Waiting under the Crisis

4.1. Estimation Method

Akakura and Takahashi (2021) constructed a method for identifying offshore waiting ships and estimating the waiting times of ships. Here, the same method was adopted. Offshore waiting ships were identified by the following criteria:

(1) Ships that had the record of "At Anchor" in the navigational status of the AIS signal;
(2) Ships that continued at a ship speed of fewer than 3.0 knots over the ground in the AIS signal for more than 2 hours;
(3) Ships whose total time from port entry to berthing was equal to or greater than the times of ships in (1) and (2).

Here, criterion (2) corresponds to ships that forgot to switch the "At Anchor" signal on, while criterion (3) corresponds to waiting ships that loiter or slow down. Before calculating the total times from port entry to the berthing of ships, the area for identifying port entry and berthing for each port/terminal was first set, as indicated in Figure 10. The port entry areas were set broadly enough to cover the anchoring, loitering, and slowing down locations. The results of the total time calculation of all berthed ships were placed in ascending order by terminals, as shown in Table 4. In this case, the offshore waiting ships are identified as ships No. 7 to 12. Ships No. 7, 11, and 12 correspond to criterion (1), ship No. 9 corresponds to criterion (2), and ships No. 8 and 10 correspond to criterion (3). The offshore waiting times were calculated as total times minus the required maximum times of normal navigation without waiting; total time minus 3 hours in Table 4. The waiting times of ships that moved between terminals were also estimated in the same manner. Finally, waiting time–volume per berth length was calculated by assuming 60% of slot utilization rate to monitor how many and how long containers had to wait offshore of terminals.

The estimation targets were the terminals of the Los Angeles/Long Beach and Singapore ports from mid-November 2020 to mid-January 2021.

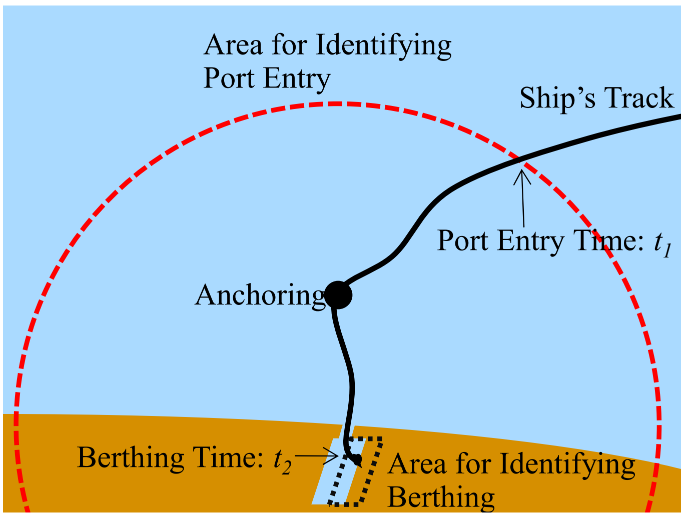


Figure 10 - Image of settings for identifying offshore waiting ship
Source: Akakura and Takahashi (2021)

Table 4 - Image of estimation of offshore waiting times

Total Time	Ship											
t_2-t_1	1	2	3	4	5	6	7	8	9	10	11	12
1	13.8	13.7	17.4	12.6	11.0	15.5	9.0	10.4	9.8	8.2	10.6	10.3
2	12.7	12.9	11.7	10.6	9.9	6.5	0.6	4.2	2.4	8.7	0.8	8.4
3			1.5	2.0	2.7	3.1	3.1	3.8	0.7	3.9	0.7	0.0
4							10.7	5.0	1.3	4.1	0.7	0.0
5							3.3	2.1	4.8	3.5	0.7	0.0
6									1.1	5.4	0.9	0.2
7						Offshore Waiting Time				0.6	0.9	0.1
8											0.8	0.0
9											5.8	0.0
10											9.7	0.0
11											7.3	0.0
12											4.2	0.0
13												2.8
14												10.0
15												1.2

Legends

- Normal Navigation
- At Anchor Signal
- Speeds < 3.0kt
- Anchor Signal & Speeds < 3.0kt

※ Numbers in cells mean average ship speeds

Source: Akakura and Takahashi (2021)

4.2. Estimation Result

Figure 11 shows the change in the estimated number of the waiting ships at the Los Angeles/Long Beach and Singapore ports every hour of all days. The number of waiting ships ranges from about 10 to over 30 in both ports. To evaluate the accuracy of the estimation result, Figure 12 illustrates the comparison of this study's estimation with statistical data of waiting ships published by the Los Angeles port. The estimation result reproduced the statistical data with good accuracy. Here, the time of port stats for each day cannot be found, so the mark was set at noon of each day.

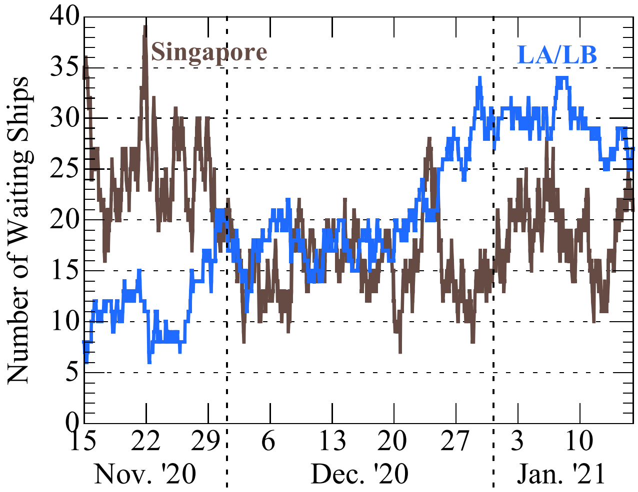


Figure 11 - Number of offshore waiting ships

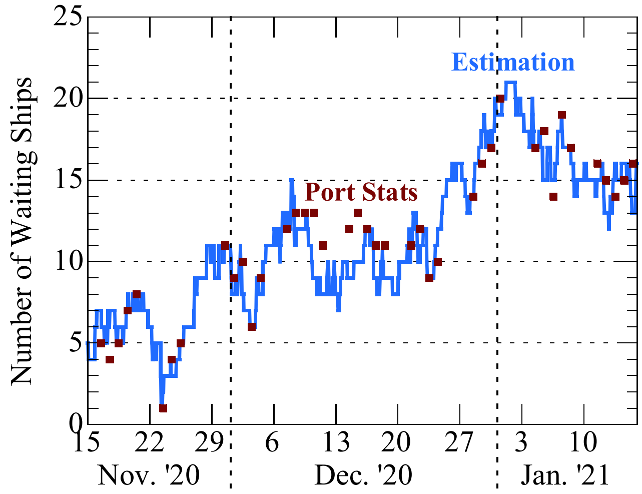


Figure 12 - Comparison of LA port stats and this study's estimation

The waiting times of ships differed considerably among both ports. Figure 13 shows the share of waiting times of ships at both ports, in addition to the total of five ports in October 2019 (Akakura and Takahashi, 2021). The share of more than 36 hours of waiting times at the Los Angeles/Long Beach port exceeded 80%, whereas the waiting times for approximately half of the ships at the Singapore port were equal to or shorter than 6 hours. The distribution of the share of waiting times at the Singapore port was similar to that of five ports in 2019, which means that the Singapore port might have succeeded in suppressing the waiting times toward the same level before the current shipping crisis.

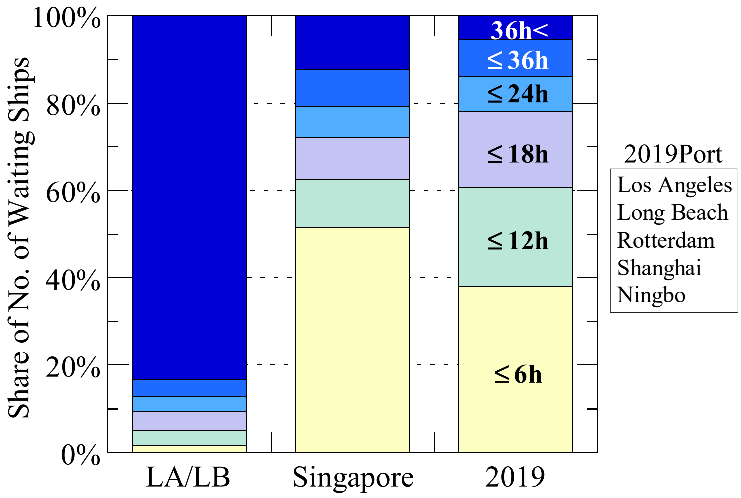


Figure 13 - Share of waiting times of ships

Figure 14 illustrates the estimated result of offshore waiting by a terminal. The left axis/green line is the average share of the number of waiting ships among all berthing ships. The shares of around half of the terminals at the

Los Angeles/Long Beach ports exceeded 80%, while that of Pier C was only 9%. The shares of all terminals at the Singapore port were equal to or less than 60%. The right axis/blue bar is the waiting time–volume per berth length per month. The time–volume of terminals at the Los Angeles/Long Beach port differed greatly from below 200 to above 8,000 h*TEU/m/month, compared with the curbed figures of those of the terminals at the Singapore port. These results of the terminals in the Los Angeles/Long Beach ports indicated the importance of terminal-based analysis.

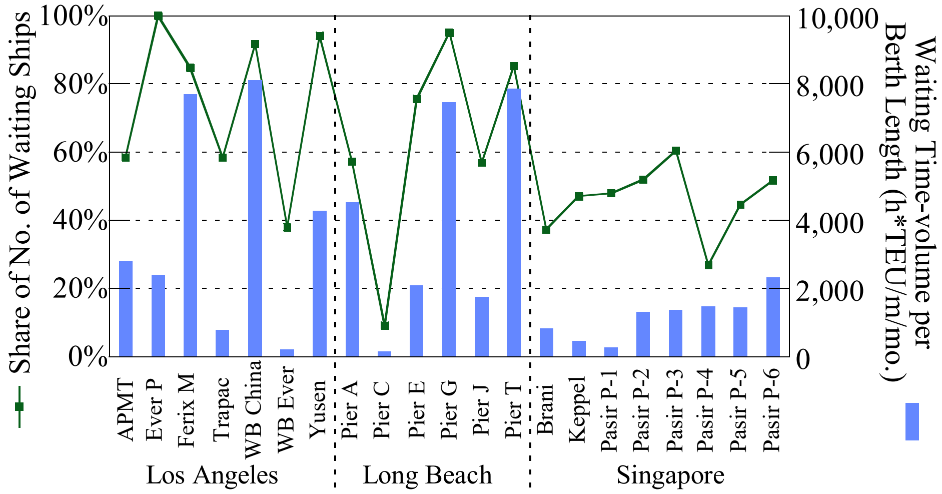


Figure 14 - Estimation Result of Offshore Waiting by Terminal

4.3. Consideration about Terminal Operation

Berth occupancy ratio was also calculated by the berthing and leaving of each ship traced using AIS data. Table 5 shows the comparison of the berth occupancy results presented in Section 4 based on LLI ship movement data with that of this subsection. As for the Los Angeles/Long Beach ports, both calculation results were at the same level, although both terms were not identical. However, there was a huge gap between both calculation results of Singapore port: the LLI ship movement data arguably could not classify offshore waiting and berthing at the terminals. From this result, it was revealed that the average berth occupancy ratio of the Singapore port has been stable amid the current global shipping crisis, as the average ratio in 2019 was 63.6%, as shown in Figure 4. This means that, in Table 3, the Singapore port should be placed at "1a" instead of at "2b."

Table 5 - Comparison of calculation result of berth occupancy ratio

Port	LLI Movement data		Analysis by AIS data	
Los Angeles Long Beach	4Q-'20	60.4%	15, Nov. '20~ 15, Jan. '21	60.2%
	1Q-'21	61.6%		
Singapore	4Q-'20	85.2%	15, Nov. '20~ 15, Jan. '21	62.3%
	1Q-'21	87.8%		

Since waiting time–volume is assumed to be linked to terminal congestion, the relationship between the berth occupancy ratio and offshore waiting time–volume per berth length was calculated, as shown in Figure 15. All data were one-month long, with two points for each terminal: November 15, 2020, to December 15, 2020, and December 16, 2020, to January 15, 2021, as the figure of some terminals changed substantially. Akakura and Takahashi (2021) analyzed this relation by five ports' data of October 2019, indicating the exponentiation relation between berth occupancy ratio and waiting time–volume, within the ratio below 70% and the waiting time–volume below 1,600 h*TEU/m/month, as indicated by the gray-hatched area in Figure 15. Also, it was revealed that many ports are still in this range amid the current crisis. The terminals outside the range could be classified into two categories: (1) terminals of extra-large waiting time–volume but under-70% of berth occupancy ratio, and (2) terminals of above 70% of berth occupancy ratio. Almost all the terminals classified in category (1) were at the Los Angeles/Long Beach port, and the berthing time was probably restricted to maintain the efficiency of container handling. For example, if there is not enough space for storage containers in yards, the terminal operators might instruct the next berthing ship to wait until the terminal's preparation is complete. The berth occupancy ratio of terminals classified in category (2) leached around 80%, which is virtually the upper limit, considering that the ship's occupied lengths in Figure 3 are almost smaller than the total berth length and vacant times are needed to change ships. Notably, the different waiting time–volume of terminals at the Singapore port were mostly below the regression curve, while those of the terminals at the Los Angeles/Long Beach port were much above the regression curve. From the hearing survey, it is said that stringent control of berthing time is almost unique to the Singapore port. This may enable subsequent ships to plan their berthing time and slow down before anchoring. As for the Los Angeles/Long Beach port in this period, ships must reach within 40 miles offshore of the port to get in the waiting queue, thereby making ships experience longer waiting time. This waiting system of the port was changed in November 2021 to count ships in the waiting queue when they sail from previous ports.

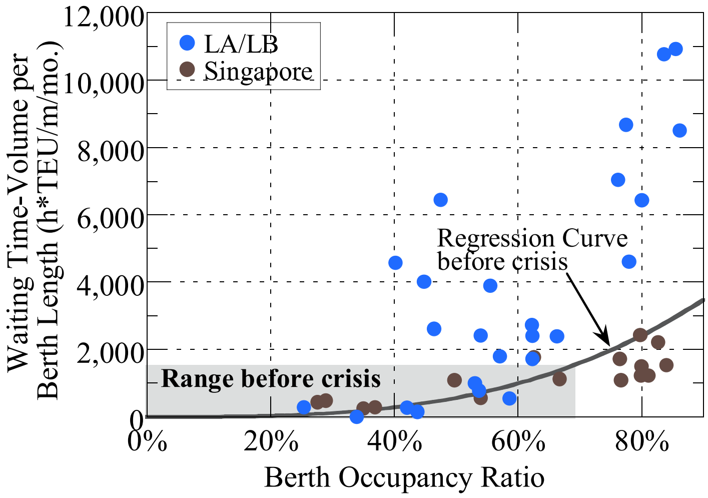


Figure 15 - Berth occupancy ratio vs. waiting time-volume

5. Discussion

5.1. Data Accuracy Issue

Thus far, port performance under the current global shipping crisis was analyzed using LLI ship movement data in Section 3, and terminal-based detailed analysis was performed using AIS data in Section 4. The analysis result relating to the Singapore port in Section 3 was inappropriate because offshore waiting periods of some ships were included between arrival dates/times and sail dates/times of the port. Now, this kind of analysis is already available, such as The Container Port Performance Index by IHS Markit and the World Bank Group; however, there is a possibility that the data are ambiguous. One of the main data sources for this kind of service is from shipping companies; however, a data accuracy issue is also found in the data from the shipping companies. For example, the website of Ocean Network Express provides arrival, berthing, and departure date/time of every port and ship; offshore waiting ships should take longer times between arrival and berthing, compared with normal navigation ships. However, it was confirmed that offshore waiting times sometimes were not included between arrival and berthing depending on ports and ships.

The situation for data on offshore waiting is the same. As mentioned earlier, many companies have started to provide the number of waiting ships; however, the validation of data accuracy conducted by these companies has not been found. As the Los Angeles/Long Beach port is probably the only port providing offshore waiting ship data, the number of waiting ships from the LLI ship movement data was added to Figure 12 to compare the accuracy in Figure 16, indicating the number was smaller than official port statistics. The data of Marine Traffic, eeSea, and Kuehne+Nagel also showed differences from the data of the Los Angeles/Long Beach port, as far as it confirmed. The promotion of the availability of various data is desirable because it facilitates relevant decisions of shippers and shipping companies and can lead to improving the services of ports and terminals by creating a competitive environment. Simultaneously, these companies must provide the data definition and accuracy to not mislead users.

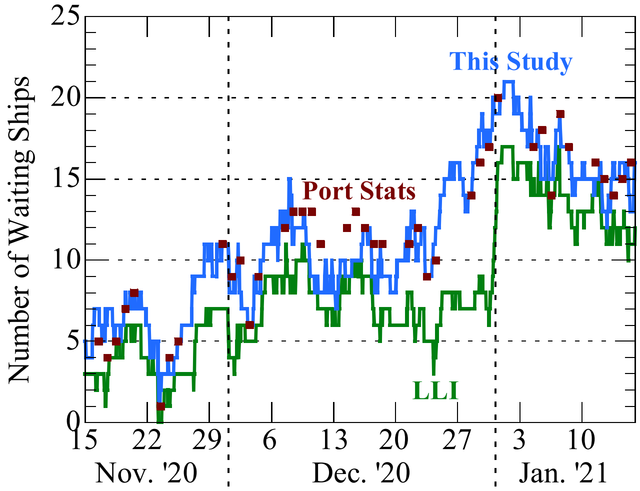


Figure 16 - Data Comparison of No. of waiting ships at Los Angeles

5.2. Automated Calculation System for Offshore Waiting Data

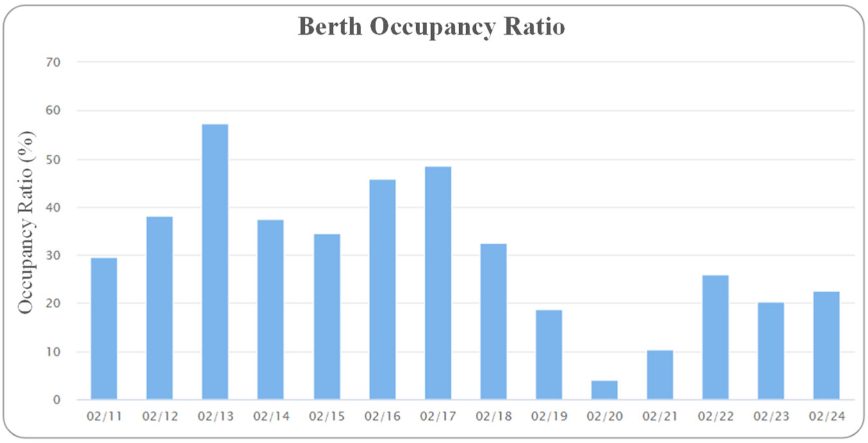
The offshore waiting conditions of each port are now vital information not only for terminal operators but also for shipping companies and shippers. However, almost all the ports fail to provide the data on waiting ships. Additionally, offshore waiting time–volume widely varied among terminals within the same port, as shown in Figure 14. Shippers that reserve services for spot cargoes can utilize this data to avoid services calling at terminals with large offshore waiting time–volumes. Furthermore, waiting time–volume can be one key performance indicator for judging the soundness of terminal operation, and it can be considered when discussing the efficiency and necessity of investment in a terminal.

Considering this condition, an automated calculation system that estimates the waiting time–volume of each terminal was developed. The target was container terminals at the Yokohama port and the duration of the trial operation was one-month long in February 2022. Figure 17 shows a sample output of the system. This system is designed to list all berthing ships at each terminal, identify offshore waiting ships, and calculate the waiting time–volume of the ships, every time date changes, automatically. Simultaneously, the system can calculate the berth occupancy ratios of terminals of the previous day based on the berthing times of the ships. None of the errors were detected during the trial, indicating the effectiveness of the system, i.e., it can be introduced at every port easily if AIS data is available.

Berthing Ships/Waiting Condition

No.	Vessel Name	TEU Capacity	Wait	Time	Time -Volume	Starting Point
1	*************	2226	-	-	-	Port Entry
2	*************	239	-	-	-	Port Entry
3	*************	962	-	-	-	Port Entry
4	*************	834	-	-	-	Port Entry
5	*************	46	◎	11	303.6	Port Entry
6	*************	69	-	-	-	Detamachi Terminal

Changes in the Past Two Weeks



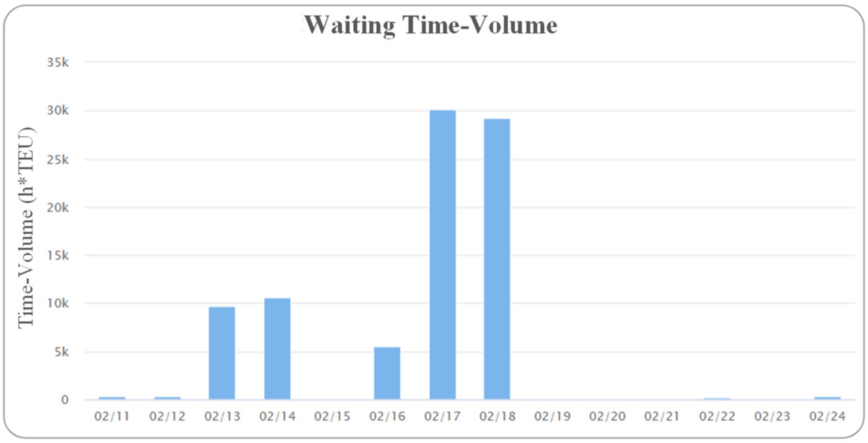


Figure 17 - Output sample of automated calculation system

6. Conclusions

The global shipping crisis triggered by demand surges and capacity constraints has caused long offshore waiting at congested terminals worldwide. This crisis has had a fatal impact on the global supply chain, causing shortages of various goods, especially in North America and Europe.

To alleviate the congestion of terminals, analyzing port/terminal performance, including offshore waiting, is crucially required.

This study analyzed the port performance of the world's major ports using LLI ship movement data. It was revealed that changes in port performance under the current crisis were classified into two categories: ports with a rather stable berth occupancy ratio and berthing time per TEU, and ports with surges of both indices. Concomitantly, an ambiguous definition of ship movement data at the Singapore port was found, implying that the analysis result relating to the port was not reliable.

Furthermore, offshore waiting times and volumes of terminals of the Los Angeles/Long Beach and Singapore ports were estimated utilizing AIS data. Based on this result, the performances of terminals were classified into three categories: terminals operating under the same range before the current crisis, terminals with extra-large waiting time–volume and normal berth occupancy ratio, and terminals with an upper limit of berth occupancy ratio. Among the terminals in the third category, the waiting time–volumes at the terminals of the Singapore port were relatively small, while those of the terminals in the Los Angeles/Long Beach port were very large. The share of waiting ships and waiting time–volume widely varied among the terminals at the Los Angeles/Long Beach port. This indicates the importance of terminal-based analysis.

The significance of data accuracy was emphasized when analyzing port/terminal performance. Ambiguous definitions of data may lead to irrelevant results. Furthermore, considering that offshore waiting data is vital under the current crisis, an automated calculation system that estimates the waiting time–volume of each terminal was developed.

The contribution of this study to the literature is as follows: (1) This study analyzed the deterioration in port functionality indices while considering the accuracy of ship movement data. (2) It estimated terminal-based offshore waiting times and volumes and analyzed the relationship of offshore waiting with quayside efficiency of terminals amid the global shipping crisis.

The author would like to continue port and terminal performance analyses to contribute to solve the clogging problem of the global supply chain. To alleviate the current congestion, it is crucial to perform analysis using accurate data.

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