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Simulation-Based Severe Weather-Induced Container Terminal Economic Loss Estimation

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Container terminals play a critical role in maritime supply chains. However, they show vulnerabilities to severe weather events due to the sea-land interface locations. Previous severe weather risk analysis focused more on larger assessment units, such as regions and cities. Limited studies assessed severe weather risks on a smaller scale of seaports. This paper aims to propose a severe weather-induced container terminal loss estimation framework. Based on a container terminal operation simulation model, monthly average loss and single event-induced loss are obtained by using historical hazard records and terminal operation records as model inputs. By studying the Port of Shenzhen as the case study, we find that the fog events in March lead to the longest monthly port downtime and the highest monthly severe weather-induced economic losses in the studied port. The monthly average loss is estimated to be 30 million USD, accounting for 20% of the intact income. The worst-case scenario is found to be a red-signal typhoon attack which results in nearly 20% decrease in the month's income. The results provide useful references for various container terminal stakeholders in severe weather risk management.

Keywords: port risk; severe weather; container terminal operation; container terminal loss estimation; worst-case scenario; simulation

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1. Introduction

Container terminals are critical transportation infrastructures in global maritime supply chains. Due to their special locations, container terminals are vulnerable to various types of severe weather events from both sea-side and land-side, such as rain, wind, fog and typhoon (Brooke, 2003; Leander and Lin, 2015; Oskin, 2015). Severe weather events affect the smooth operations of terminals, which include container ship berthing and unberthing, container loading and unloading, stacking as well as gate operation. Once a terminal's operation is disrupted, the delay of container movements tends to

disseminate through the maritime supply chains to port users and to hinterland manufacturers who use the port service. The inoperability of a terminal leads to decrease of the container throughput, and thus results in losses of terminal incomes (Lam et al., 2017). It is reported that, a 5-day port downtime is able to lead to a loss of 65 million USD for the Port of Dalian (Kelly, 2011). The consequences led by severe weather events to container terminal are not confined to the decrease of income, in some conditions, terminal operators receive complaints from shipping companies and even lose ship calls. In 2003, Typhoon Meami made its land fall in the Busan Port. The violent typhoon event caused a long-term port recovery period of 8 months and drove several major port users away (Flynn, 2003; Lee, 2003).

Although severe weather-induced container terminal disruption is critical to academics and industries, the research of this topic is scanty relative to other container terminal research topics. While the literature on severe weather-induced port disruption management is growing, many questions remain unanswered. In particular, two research questions are of interest:

- (1) What types of severe weather have affected or have potentials to affect the operations of a container terminal?
- (2) How to estimate the severe weather-induced container terminal economic losses?

Analysing the severe weather risks on a scale of a seaport is challenging. One reason could be the complexity of port operations. The other reason lies in the data limitation resulting from the ill recordings of severe weather-induced port downtime and the confidentiality of port management. Therefore, this paper aims to deal with such difficulties and answer the mentioned research questions by firstly identifying major severe weather types occurred within port areas worldwide via means of literature review, news review and port document review. Subsequently, a severe weather-

induced container terminal economic loss estimation framework is developed, in which direct economic loss is estimated based on actual terminal operation records and the established terminal severe weather database.

Simulation technique, as a widely used terminal operation planning and management tool (Keceli, 2016), is adopted here to assess the terminal economic loss. By combining a group of primary terminal operations, a container terminal operation simulation model is developed through the software package of ARENA (Kelton, 2002). The developed model is verified and validated with actual terminal operation records.

The largest container terminal in the Port of Shenzhen is studied for its large container throughput and its natural vulnerability against several types of severe weather events. By using the terminal operation simulation model, the estimation of a single severe weather event-induced container throughput decrease and economic loss are achieved under different hazard magnitudes. Average severe weather events-induced monthly decreased container throughput and port economic loss are also quantified for the same terminal. Results show their industrial applicability for container terminal operators in terms of severe weather management and the formulations of terminal severe weather contingency plans. Outputs can also be useful references for other container terminal stakeholders, such as local regulators, shipping companies, ocean carriers, and (re)insurance companies regarding the decisions on container terminal site selection, bunkering port selection, vessel route planning, and port cat-insurance pricing.

The rest of the paper is organized as follows. Section 2 reviews literatures regarding port disruption management and port severe weather analysis with 3 major research gaps being identified. Section 3 shows the proposed loss estimation framework in detail, which include the establishment of the terminal operation simulation model,

the identification of severe weather types threatening terminal operations as well as the method for terminal economic loss estimation. By studying the Port of Shenzhen, Section 4 presents a real-world application of the proposed framework. Results, discussion and implications are presented in Section 5. At last, conclusions with main contributions of this paper are shown in Section 6.

2. Literature review

Regarding port disruption management studies, three major research topics are addressed in the previous literature: the estimation of port loss during port downtimes (Pachakis and Kiremidjian, 2004; Na and Shinozuka, 2009; Zhang and Lam, 2015; Burden et al., 2016; Uğurlu, et al., 2016); the selection of optimal risk reduction methods/strategies (Werner et al., 1997; Lam and Su, 2015; Zhao et al., 2017); and the formulation of guidelines for the evaluation of port damages (Ronza et al., 2009). It is found that most of the port loss estimation research address earthquake-induced loss. This may result from the availability of specific port risk databases, such as the databases established in the extensive research on hydraulic structures seismic behaviour in the discipline of harbour engineering (for example, Werner, 1998; Atsushi et al., 2004; Roeder et al., 2005). The research of other causes, such as severe weather events are limited.

Regarding severe weather studies, previous research works focused more on larger scales of regions, countries, and cities (see Pethick and Crooks, 2000; United Nations Development Program (UNDP), 2004; Cardona, 2005; Dilley, 2005; Hanson et al., 2011; Yu et al., 2015; Kermanshah and Derrible, 2016). Few studies conducted severe weather analysis within the area of a single critical infrastructure, such as a seaport. The possible reason may lie in the difficulty in the acquisition of hazard data on

smaller scale research units. Regarding wind hazard, Zhang and Lam (2015) estimated the extreme wind event-induced port loss by using the predicted port disruption period. In order to assess the influences on the Key Performance Indicators (KPI) of terminal operations induced by extreme weather events, Chhetri et al. (2016) developed an agent-based simulation model by using the Port of Sydney as an illustration example. The reviewed works paved ways for the future studies in port disruption management against disasters. However, still, insufficient works have addressed the worst-case scenarios, in which ports are affected by disasters with high magnitudes or long return periods. Additionally, the estimation of disruption periods is based on urban weather databases in the previous works, which sacrifices the accuracy comparing with using actual port recordings.

In summary, 3 major literature gaps are identified in terms of research on port disruption management and port severe weather analysis. Firstly, the literatures on severe weather-induced port disruption are limited compared with other disruption causes. Secondly, worst-case scenarios are missing from previous severe weather-induced port disruption studies. Lastly, urban disaster databases are adopted when assessing port risks and the use of port hazard data is restricted. Therefore, in order to bridge the identified research gaps, this paper attempts to estimate the severe weather-induced container terminal economic loss by establishing a terminal severe weather database and considering worst-case scenarios. As such, the accuracy of the proposed method can thus be enhanced. A detailed illustration of the proposed method is carried out in the next section.

3. Method

3.1 Severe weather-induced terminal economic loss estimation framework

This section presents a step-by-step illustration of the proposed method for severe weather-induced container terminal loss estimation. As shown in Figure 1, after selecting a target terminal, a terminal operation simulation model is established. This simulation model is then verified and validated through the actual terminal operation records. By adding the failure data of severe weather-induced terminal downtimes in the model, simulated container throughputs under intact and disrupted conditions are obtained. Decreased container throughput is calculated as the difference between the intact throughput and the disrupted throughput. The estimated terminal economic loss is thus obtained based on the decreased throughput and information regarding the income per box. Finally, validation of the proposed method is carried out by comparing the simulated loss and the loss in reality. Detailed procedures are presented in the following sections, including the simulation model development (Section 3.2), the severe weather type identification and port downtime acquisition (Section 3.3). Finally, the method for the estimation of port economic loss is presented (Section 3.4).

Figure 1. Severe weather-induced terminal economic loss framework.

3.2 Container terminal operation simulation model

3.2.1 Model establishment

As shown in Figure 2, a typical container terminal consists of four subsystems: ship navigation system, container loading and unloading system, storage system, as well as collection and distribution system. Arena is employed to simulate the container loading and unloading process in this study.

Figure 2. A typical layout of a container terminal.

The whole procedure of a container ship visiting a terminal in the simulation model is shown in Figure 3. Once a ship enters the port via the port's waterway, a berth is allocated to the ship. The ship will be waiting in the anchorage if there is no available berth at the moment. Once a berth becomes available, the ship is towed into the berth by tug boats. While approaching the berth, quay cranes are allocated to the ship based on the volume of containers on board the ship to be loaded and/or unloaded. The process of loading and unloading starts after berthing, after which the ship will leave the terminal when all the containers to be handled are finished. The detailed descriptions of each procedure are presented in the following paragraphs.

Figure 3. Terminal operation simulation flow chart.

Ship arrival is modelled as a queueing system in the model. The statistical distribution function of interval time of ship arrival is estimated by the “Input Analyser” function in Arena, which selects the distribution function with the minimum square error of the input data. The determined distribution function is then inputted in the “Time Between Arrivals” in the “Create” module. In previous port simulation studies, exponential distribution is the most frequently used distribution for creating ship traffic (Dragović et al., 2017). However, it is admitted that the use of real operation data for different terminals is conducive to enhance the accuracy of the simulation outputs.

After a ship entity is created, it is moved to the next phase of berth allocation. The size of the ships and the number of containers to be handled on board one ship is different from another, which results in different sizes of berth allocated and different numbers of quay cranes deployed. Hence, in this study, ships are grouped by the number of lift per call (LPC, total moves of quay crane trolley per ship call), based on which the berth is allocated. The first-come-first-served (FCFS) and first-in-first-out (FIFO) allocation strategies are employed in this model, assuming the berth allocation is not affected by the contracts signed between shipping companies and the terminal (Du et al., 2015; Iris et al., 2015; Iris et al., 2017) and/or the consideration of cargo connection in transshipment ports. In the simulation model, the possibilities of ship arrival in each LPC group are set by “N-way by Chance” in the “Decide” module. Subsequently, by using an “Assign” module, variables like “LPC_1_Qty”, “LPC_2_Qty”, “LPC_3_Qty”, etc. could be defined so that the probability distributions for each variable are set up in the model. Until this step, the created ship entity is channelled with an allocated berth.

The availability of the allocated berth is checked subsequently. The ship is able to move to the berth and start loading and unloading if the allocated berth is vacant; otherwise, the ship will need to wait in a queue until the berth becomes available. In the model, a Boolean type of variable for berth availability is defined in an “Assign” module. If the variable value is 1 (which means the allocated berth is available), the ship entity will go on to approach the berth. This berthing process is simulated by an “Assign” module where a batch of process time is defined, showing in Table 1. The best-fitted distribution expressions of the process time are obtained from the “Input Analyzer” and are put in the “Assign” module. If the variable equals to 0 (which means the allocated berth is not available at the moment), the ship entity will go on to a different “Assign” module where a queue model is defined. A “Hold” module is linked to the queue module to ensure that the ship will be waiting in the queue until there is available berth.

Table 1. Process time of a container ship at a seaport.

Process time	Description	Calculation
Berth accessing time	The time tug boats use to drag container ships to the allocated berth	The difference between the actual time of berthing and the actual time of arrival.
Idle time before	The time terminal operators use to prepare for cargo handling after the ship is berthed	The difference between the operation commence time and the actual time of berthing
Container loading and unloading time	The time cranes work on the container handling	The difference between the operation complete time and the operation commence time
Idle time after	The time for arrangement after the end of cargo handling until the ship is unberthed	The difference between the actual time of departure and the operation complete time

The next step is the quay crane allocation in the simulation model. Similar to the process of berth allocation, the crane allocation is also decided based on the LPC. The probability distributions of the quay crane number in each LPC group are obtained by “Input Analyzer” and are assigned in an “Assign” module. A “Decide” module is added in the model to check the availability of quay cranes. The ship will be deployed with

quay cranes if there are available ones; otherwise, the ship waits in a queue until cranes become available. It is noted that, in this study, the non-crossing constraint of quay cranes is not adopted and the cranes are simulated to be unmoving during the container handling process. In the model, “Seize” module and a “Release” module are used to allocate a berth resource to a ship entity. “Delay” modules are used to depict the “IdleTimeBefore” and “IdleTimeAfter”. Subsequently, the container loading and unloading process is simulated with a “Process” module. Finally, a “Dispose” module is used to simulate ship departure. As the basis for the further estimation of port loss, container throughput is determined to be the model output in this study. By using the “Record” module, the model statics are recorded. The recorded container throughput is then used to validate the established model by comparing with the actual terminal throughput, which is illustrated in detail in the next section.

3.2.2 Model validation

Before the process of model validation, the model is verified by observing the animation of the ship entity. By setting the “Max Arrivals” in the “Create” module into 1 and lower down the running speed, it is observed that no error pops up from the creation of the ship entity until the disposal of the same ship entity. It can be seen that the established model runs as the model builders’ intentions and is thus verified.

The validation is conducted by the correlated inspection approach (Law and Kelton, 1991). The confidence interval of the sample mean is firstly constructed. Subsequently, the confidence interval of the variance between the point estimate of difference and the observed difference is generated in order to determine whether the difference of the model output and the terminal throughput are statistically significant (Iyer Sivakumar and Chin, 2001).

The model validation is conducted on a monthly basis since monthly data are used in the case study. The model output and the system throughput in 2016.8 are compared in this section as an illustration. The validations of the other cases are conducted in the same way with the results presented in Appendix A. For the purpose of wearing off the possibly atypical initial conditions, the warm-up period is found and specified in the “Run Setup” field. As shown in Appendix B, the moving average of the model outputs becomes stable around after 4 days. Thus, a warm-up period of 4 days is identified and the comparison between the model outputs after 4 days and the terminal throughput is achieved.

With different random seed, the model inputs are used for multiple replications. An initial replication number of 10 is set and is further adjusted to 93 by using Equation (1) (Kelton, 2002).

$$n \cong n_0 \frac{h_0^2}{h^2} \quad (1)$$

n_0 – the initial replication numbers;

h_0 – the half width of the results obtained from n_0 replications;

h – the ideal half width.

Out of 93 replications, a 95% confidence interval is built for the sample mean. Table 2 shows the generated confidence intervals and the gap between the terminal throughput and the sample mean. It is observed that the terminal operation model over predicts the average throughput by 0.56%. The 95% confidence interval for the throughput is (1.1168, 2.2459) for the intact case, in which the actual terminal throughput, namely 1.1354, is included. The 95% confidence interval is also given to the disrupted case, which is (0.52, 1.0503).

Table 2. Terminal operation model input and output under intact conditions.

Date	Container throughput_Intact (million TEU)	Simulation output_Intact (million TEU)	Difference (%)	95% Confidence interval_Intact output (million TEU)	95% Confidence interval_Disrupted output (million TEU)	95% confidence interval_Variance (million TEU)
201608	1.1354	1.1290	0.56	(1.1168, 2.2459)	(0.52, 1.0503)	(-0.1109, 0.1236)

To calculate the 95% confidence interval of the variance of the point estimate difference and the observed difference, Equations (2) to (5) are adopted. As shown in Table 2, the interval of (-0.1109, 0.1236) contains 0, which means the difference between X_1 and $\hat{Y}_{(n)}$ is not statistically significant. Through the correlated inspection approach, it can be seen that, the simulated results agree well with the actual container throughput of the Port of Shenzhen.

$$\hat{W}_{(n)} = X_1 - \hat{Y}_{(n)} \quad (2)$$

$$W_i = X_1 - Y_i \quad (3)$$

$$V_{\hat{W}_{(n)}} = \frac{\sum_{i=1}^n [W_i - \hat{W}_{(n)}]^2}{n-1} \quad (4)$$

$$\hat{W}_{(n)} \pm t_{n-1, (1-(\alpha/2))} \sqrt{V_{\hat{W}_{(n)}}} \quad (5)$$

$\hat{Y}_n$ – Sample mean of the n replications;

Y_i – Model output of the i th replication;

n – Replication number of running;

$\hat{W}_{(n)}$ – The point estimate of the difference between the terminal throughput and the sample mean of the model output;

X_1 – Terminal throughput;

W_i – Observed difference of the terminal throughput and the model output of the i th replication;

$V_{\hat{W}_{(n)}}$ – Variance of point estimate of the difference and observed difference;

$\hat{W}_{(n)} \pm t_{n-1, (1-(\alpha/2))} \sqrt{V_{\hat{W}_{(n)}}}$ – The 100(1- α)% confidence interval of the variance.

3.3 Severe weather type identification and terminal downtime acquisition

Types of severe weather affecting seaports vary along with the weather condition of seaport's location. For example, seaports lying in a typhoon basin are more vulnerable to the hazard of typhoon comparing with other ports. Therefore, to identify the severe weather types a terminal facing is the first and core step within the whole loss estimation framework. In some cases, information of severe weather, such as the date and time of occurrence, the duration of events, the magnitude of hazards, as well as the port downtimes are recorded by port operators. However, for ports without such recordings, literature review is an alternative method for the acquisition of such data. Taking references to the natural disaster classification from EM-DAT (EM-DAT, 2009), Table 3 shows a summary of severe weather types affecting port operations. Port documents are collected worldwide, including port disaster contingency plans, port disaster reduction plans and related port news. It is noted that the port documents collected are not restricted to container terminal' documents, since the hazard information recorded by other types of ports are also meaningful references for container terminals in the same region.

Table 3. Severe weather types affecting port operations.

Hazard group	Hazard sub-group	Hazard main type	Hazard sub-type	Reference
Meteorological	Storm	Tropical cyclone	Typhoon/Hurricane	Brooke, 2003; Chambers, 2003; Zhuhai Port Authority, 2011; Flinders Ports, 2014; Dalian Port, 2015
		Convection storm	Hail	
			Lightning/thunderstorm	
			Rain	
			Sand/dust storm	
			Winter storm/blizzard	
			Storm/surge	
			Wind	
	Extreme temperature	Cold wave	nil	
		Heat wave	nil	
		Severe winter conditions	Snow/ice	
Hydrological	Fog		Frost/freeze	
		nil	nil	

Having identified the types of severe weather that affect the normal operation of a terminal, the next step is to obtain the magnitude of hazards, the frequency and the induced-port downtime of the severe weather events that occurred within the terminal area. The sum of port downtime during a specific study period is obtained as the product of single event-induced port downtime and the occurrence frequency of severe weather events. Consequently, the link between severe weather magnitudes and terminal downtime is established. Generally, the acquisition of terminal severe weather data and terminal downtime is by referring to the terminal logs. However, when such recordings are absent, consultations of terminal operators or referring to other terminal logs with similar conditions could be alternatives. A detailed illustration of the data acquisition for the case of Shenzhen Port is carried out in section 4.

3.4 Port economic losses estimation

Port economic loss induced by severe weather events is the target we aim to estimate in this study. The port economic loss is determined by the reduction of production and

income caused by severe weather-induced port physical damages and is estimated by the following equations (Cao and Lam, 2018):

$$EL = \sum_{n=1}^N C_n^{load\&unload} T_n^{de}; \quad (6)$$

$$T_n^{de} = T_n^{int} - T_n^{dis}. \quad (7)$$

EL – Direct economic loss of the port caused by one catastrophe event;

N – Number of terminals in the study port;

$C_n^{load\&unload}$ – The loading and unloading charge per TEU at the n th terminal;

T_n^{de} – Decreased container throughput at the n th terminal;

T_n^{int} – Container throughput at the n th terminal under intact condition;

T_n^{dis} – Container throughput at the n th terminal under disrupted scenario.

4. Case study

Primary data are collected from the largest container terminal in the Port of Shenzhen, which contains 16 berths, 81 quay cranes and 222 gantry cranes. The Port of Shenzhen is selected because it's international influences in container transportation. Moreover, it is threatened by severe weather conditions like heavy wind, storm, fog and typhoon. News reports regarding severe weather induced-port closures and operation disruptions are frequent (Chambers, 2003; Frittelli, 2005; Smythe, 2013; Lam and Su, 2015; Lam and Lassa, 2017). However, few loss quantification methods are found addressing this issue in the literature. In 2013, the Port of Shenzhen initiated the development of a terminal severe weather database, covering the information of the occurrence of severe weather events and terminal downtimes. Thus, comprehensively considering the terminal size, the weather condition and data availability, the Port of Shenzhen is selected as the case study.

4.1 Acquisition of severe weather-induced port downtime

The established terminal severe weather database allows the use of actual port downtimes as the model inputs. Since 2013, a number of 170 severe weather events that lead to terminal disruptions are recorded. Statistical analysis of the occurrence of severe weather, their signal levels (magnitudes), as well as the port downtimes is carried out in this section. The results of the analysis could be useful references for ports with similar sizes and climate conditions but without such recordings.

It is noteworthy that only main hazards in the hazard chains are considered as severe weather types when generating terminal downtimes in this study. Secondary hazards are recorded; however, they are not counted in the accumulation of port downtimes for the avoidance of calculation duplications. For example, out of the 64 recordings of rain-induced port disruptions from 2013 to 2017, 12 recordings coupled with wind events and 19 recordings coupled with thunder and lightning events. In this case, only the 64 recordings of rain events are counted, while the recordings of wind, thunder, and lightning events are omitted. However, when wind hazard is the main hazard leading to port disruptions, the wind event is considered as one severe weather event and is recorded in the database.

Based on the above data filter rules, the average monthly port downtimes induced by severe weather for the Port of Shenzhen are summarized and shown in Figure 4. It can be identified that the hazards of wind, rain, fog, and typhoon are the 4 major types of severe weather affecting the port operation. The occurrence of the severe weather events shows certain seasonal characteristics. To be more specific, wind events centre in January, November and December; rain events focus in months from April to September; fog events happen more in February, March and April; and typhoon events are more frequent from June to October. In terms of port downtimes, March suffers the

longest terminal disruption time among all months. Fog and wind events lead to an average of 7-day disruption in March wherein fog-induced port downtime accounts for 96% out of the whole downtime. April, July and August experience a shorter disruption time of around 4 days a month with fog and typhoon being the main leading factors. The rest of the months face an average disruption period of 1 to 2 days due to multiple hazard factors.

Figure 4. Average monthly severe weather-induced port downtimes, 2013-2017.

The severe weather-induced terminal downtimes are further analysed sorting by hazard signal levels. Hazard signal levels are released by local weather bureaus based on real time meteorology conditions' severities, based on which terminal operators are able to make decisions on timings of pausing and resuming terminal operations. In practice, as shown in Table 4, some terminal operators enact their own hazard signal levels by referring to the signal levels issued by weather bureaus. Different anti-hazard actions are taken by terminal operators based on the level of hazard signal released. Examples of these actions are presented in Figure 5 against the hazard of typhoon. The commencement and termination of these actions mark the shutdown and resume time of the terminal and at the same time lay foundations in the estimation of port downtimes.

Table 4 Severe weather signal levels.

Source: Authors, based on information provided by the Port of Shenzhen

Severe weather type	Signal level	Signal mark	Signal level description
Wind	Blue		The wind speed has reached 12m/s or more or will reach 12m/s or more in the next 6 hours within the port area.
	Yellow		The wind speed has reached 15m/s or more or will reach 15m/s or more in the next 6 hours within the port area.
	Red		The wind speed has reached 20m/s or more or will reach 20m/s or more in the next 6 hours within the port area.
Rain	Yellow		There is a possibility of rainstorm in the next 6 hours or a possible continuous heavy precipitation within the port area.
	Orange		The precipitation has reached 50mm or more in the past 3 hours and the rain tendency may last within the port area.
	Red		The precipitation has reached 100mm or more in the past 3 hours and the rain tendency may last within the port area.
Fog	Yellow		The visibility of a dense fog is less than 500m and more than 200m and this situation may last or there is a possibility of fog with a visibility of less than 500m in the next 12 hours within the port area.
	Orange		The visibility of a dense fog is less than 200m and more than 50m and this situation may last or there is a possibility of fog with a visibility of less than 200m in the next 6 hours within the port area.
	Red		The visibility of a dense fog is less than 50m and this situation may last or there is a possibility of fog with a visibility of less than 50m in the next 2 hours within the port area.
Typhoon	White		There is a possibility of typhoon in the next 48 hours.
	Blue		The average Beaufort wind force scale has reached level 6 or there is a possibility of typhoon in the next 24 hours within the port area.
	Yellow		The average Beaufort wind force scale has reached level 8-9 or the gust wind scale has reached level 9-10 and this situation may last; There is a possibility of typhoon with Beaufort wind force scale level 8 or more or gust wind force with 11 or more in the next 24 hours.
	Orange		The average Beaufort wind force scale has reached level 10-11 or the gust wind scale has reached level 11-12 and this situation may last; There is a possibility of typhoon with Beaufort wind force scale level 10 or more or gust wind force with 11 or more in the next 12 hours.
	Red		The average Beaufort wind force scale has reached level 12 or more and this situation may last; There is a possibility of typhoon with Beaufort wind force scale level 12 or more in the next 12 hours.

Figure 5. Terminal actions before, during and after a typhoon event.

Source: Authors, based on information provided by the Port of Shenzhen

Based on the descriptions of the severe weather signal levels, Figure 6 shows the accumulated port downtimes under each signal level for each severe weather type. As can be seen from Figure 6 (a), regarding wind hazard, the accumulated downtime under blue signal is the longest, followed by the downtime under red signal and yellow signal. January, February and November are strong wind-prone months, since all the red and yellow-level wind events occur in this three months. Moreover, December is a wind-frequent month, however, all the wind events are with less severe signal levels. In aspects of rain hazard, as shown in Figure 6 (b), the yellow-level rain-induced port downtime is the highest among all the three signal levels with the orange and red levels flushing with each other. April to September are rain-frequent months, while July, August and September experience most of the heavy rains. In terms of fog hazard, as can be seen from Figure 6 (c), February to May are fog-frequent months, in which March and April's conditions are particularly severe. Regarding typhoon hazard, it is observed from Figure 6 (d) that the Port of Shenzhen faces the threat of typhoon from July to November. Furthermore, July, August and October are three months facing severe typhoon events.

Figure 6. Annual average port downtimes (in days), sorted by signal levels. (a) wind-induced; (b) rain-induced; (c) fog-induced; (d) typhoon-induced, 2013-2017.

Source: Authors, based on information provided by the Port of Shenzhen

The probability distributions of the single event-induced port downtime and the frequency of occurrence in each month are shown in Appendix C. The port downtime information is added to the intact model for the simulation of disrupted container throughput. The decreased container throughputs are thus obtained as the difference of the intact throughput and disrupted throughput, which is further used for the estimation of terminal economic losses. The estimation of severe weather-induced port economic losses is carried out on a single severe weather event basis and a yearly average basis. The results and the discussions of results are illustrated in Section 5.

4.2 Acquisition of container terminal operation data

Actual terminal operation records involving compulsory model inputs were collected. The record covers the operation data from 1st August 2016 to 31st July 2017. As can be seen from the above analysis, the monthly average port downtimes show seasonal characteristics. At the same time, the monthly throughput of the Port of Shenzhen shows a seasonal fluctuation as well associated with the Sino-foreign trade volumes. Thus, to use the same ship arrival pattern and LPC allocation information as the inputs for all hazard types will lead to inaccuracies in estimations. As a result, for each severe weather type and magnitude, the month with the longest disruption period is adopted. In this manner, the ship arrival pattern and LPC allocation information of this month are used as model inputs for the case. The month selection for each case is presented in Table 5.

Table 5. Inputs adopted for calculating the decreased throughput and port economic loss.

Case	Data used
Wind_blue signal	December
Wind_yellow signal	January
Wind_red singal	January
Rain_yellow signal	April
Rain_orange signal	Ma y
Rain_red singal	September
Fog_yellow signal	March
Fog_orange signal	April
Fog_red singal	March
Typhoon_white signal	November
Typhoon_blue signal	October
Typhoon_yellow signal	July
Typhoon_orange signal	August
Typhoon_red singal	July

For the purpose of illustration, the statistical analysis of the model inputs in January 2017 is presented in Figures 7-10. The model inputs of the other months are analysed in the same way. From Figures 7 to 10, the histograms of the ship arrival

interval, the LPC grouping, the quay crane efficiency, as well as the idle time are shown. The probability distributions for each input are obtained by the “best fit” function in the “Input analyzer” of Arena which selects and adopts the distribution with the lowest square error (Kelton, 2002). The “fit all” summary and the distribution summary are shown in Appendix D and Appendix E.

Figure 7. Distribution of ship arrival, 2017.1.
Source: Authors, based on information provided by the Port of Shenzhen

Figure 8. Distribution of number of containers handled, 2017.1.
Source: Authors, based on information provided by the Port of Shenzhen

Figure 9. Distribution of quay crane efficiency, 2017.1.
Source: Authors, based on information provided by the Port of Shenzhen

Figure 10. Distributions of ship idle time, 2017.1.
Source: Authors, based on information provided by the Port of Shenzhen

Considering the satisfied replication numbers to run the simulation model, an initial 10 replications have been run to obtain the h_0 (in Equation (1)) of container throughput for each case. The generated h_0 is used for the calculation of the number of replications to achieve the minimum possible half width of a 95% confidence interval. By simultaneously considering the best accuracy and the calculation time, a 2% margin of error (from the sample mean) is determined to be the ideal half width of a 95% confidence interval. By using Equation (1), a satisfied replication number of 93 is finally determined, which is the maximum updated replication number among all cases.

After rerunning the model with the satisfied replication number, the new half widths of all cases are within the 2% margin of error. Since the n is more than about 30 and the estimates of the sample standard deviation remain about the same for larger sample size for every case (see details in Appendix F), the use of Equation (1) is justified (Kelton, 2002).

5. Results, discussion and implications

This section presents the results of severe weather-induced port economic loss estimation, performed on the case of the Port of Shenzhen. In order to realize the worst possible scenarios induced by severe weather events to the terminal, the results are calculated on a single-event basis and are presented in Section 5.1. Furthermore, in Section 5.2, for investigating the severe weather influence in different months, the monthly average losses are estimated for each severe weather type respectively. In addition, several applications and implications of the results for various end-users are discussed.

5.1 Single-event throughput decrease and port economic loss

As shown in Figure 11, it can be seen that the percentage of estimated reduced throughput in intact throughput as well as the estimated port economic loss for each case. As expected, the results show stepwise distribution patterns as the signal level goes up in cases of wind, fog and typhoon. However, the result distribution of the case of rain shows a flatten pattern. It is also interesting to find that the average economic loss induced by an orange-signal level rain event is less than the amount induced by a yellow-signal level rain event. This mainly results from the less throughput in May, with which the orange-signal level rain event induced economic loss is estimated. Besides, the port downtimes induced by these two signal level rain events are similar

and usually within half a day. This result would be implied to terminal operators that lower signal level events may give rise to higher

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be implied to terminal operators that lower signal level events may give rise to higher losses in large container volume months. Thus, when drawing up terminal disaster contingency plans, both magnitudes of hazards and current month throughput are needed to be considered simultaneously. Special attentions should be paid by terminal operators in months with high throughput and high magnitude hazard possibilities, such as fog events in March and April, as well as typhoon events in July and August.

Figure 11. Single severe weather event induced port loss.

The worst-case scenario happens when a red-signal level typhoon event attacks the terminal. It causes nearly 30 million USD of economic loss within several days, which accounts for approximately 20% of the income under intact conditions. From 2013 to 2017, the longest terminal downtime record in the Port of Shenzhen is caused by Typhoon Nida in July 2016. This red-signal level typhoon event causes the terminal an operation disruption of nearly a week. Another important point to note is that, this kind of catastrophe would cause serious physical damages to the terminal structures and equipment, which leads to long-term recovery periods of several weeks to several months (Nadkarni, 1998; Frittelli, 2005). The long-term terminal recovery period would drive liner shipping companies away temporarily or even permanently to alternative ports in the vicinity. In 2003, after the strike of Typhoon Maemi (disrupted scenario 11: A Category 3 typhoon impacted the Port of Busan at a very near strike distance of 76km), the Port of Busan lost half of its customers because of serious damages of quay cranes, quay walls and yard equipment. Kwangyang Port and Masan Port are chosen as alternative ports by ocean carriers and key manufacturers, such as LG Electronics (Flynn, 2003; Lee, 2003). As of September 13, 2005, the Washington Post listed on its website, in 2005, Hurricane Katrina (disrupted scenario 11: a Category3 hurricane with an even shorter strike distance at 65km) made its landfall in the Port of New Orleans and other Lower Mississippi ports. Shipping lines serving the affected ports diverted their operations to Houston, Freeport, Pensacola and Port Everglades (Alexander and Irwin, 2005).

Fog events are also able to cause long term terminal disruptions. The longest disruption record in the Port of Shenzhen is found of approximate 5 days in March 2014. The major reason for the long-term downtime is because the low visibility induced by

fog. The low visibility affects terminal operations of ship berthing and unberthing, pilotage, as well as container collection and distribution. Nevertheless, comparing with the typhoon hazard, less physical damages are induced, since physical damages can be limited to a large extent by taking anti-fog actions in due time.

Although frequencies of worst-case scenarios are low, however, they possess the potentials to cause tremendous losses to the terminal physically and in economic. Thus, specific terminal catastrophe contingency plans should be enacted for the preventions of possible irreparable consequences.

5.2 Monthly average throughput decrease and port economic loss

The estimated monthly average severe weather-induced terminal economic loss for the Port of Shenzhen is shown in Figure 12. The proportion of the decreased income in the intact income is also shown. It is observed that March suffers the highest income loss out of the 12 months, reaching nearly 30 million USD per month, which accounts for nearly a quarter of the intact income. Fog events are the main hazard. April, July and August experience a decreased income of around 18 million USD per month with a decreased percentage of around 13%. The main factor giving rise to income losses in April is fog, while the main causes in July and August are typhoon and rain. The rest of the months' monthly average economic losses fluctuated around 4 million USD, which accounts for around 5% in the intact income.

Figure 12. Monthly average severe weather induced port loss.

The terminal loss is further analysed by the types of severe weather events. As presented by bar charts, the port loss is shown in Figure 13. By using line charts, the decreased container throughput is able to be visualized as the areas between the two lines. It can be seen that, although wind and rain are more frequent hazards than fog and typhoon, the latter two leads to much larger income losses. As can be seen from Figure 13 (c), the terminal in March and April should have processed larger container volumes if there were no disruptions induced by severe weather events. We should also point out that a variety of uncontrolled factors influence the throughput of a terminal, such as the volatility of the world trade volume and the adjustment of shipping calls by shipping companies. However, a growth trend of container throughput in March is found after the lowest throughput in winter. As such, the main factor leading to decreases in container throughput being severe weather-induced port disruptions is justified. Regarding typhoon hazard (as shown in Figure 13 (d)), it affects two months with the largest throughput, namely July and August. Although the throughputs of these two months still rank the highest among all the 12 months, they should have been higher if there were no or fewer typhoon attacks.

Figure 13. Decreased container throughput and port economic loss, by months. (a) wind-induced; (b) rain-induced; (c) fog-induced; (d) typhoon-induced.

It is noted that the estimated severe weather-induced port economic loss for the Port of Shenzhen is seen as a lower bound since only the income of container loading and unloading is considered in the framework. Other port incomes, such as incomes of value-added services, inventories, disbursement accounts are not included due to the data availability. As a first attempt, the results obtained reflect the severe weather risks encountered by terminals in a quantified way. More concrete results are obtained compared to the traditional qualitative empirical analysis. A variety of terminal stakeholders, such as terminal operators, local regulators, ocean carriers, shipping companies, and (re)insurance companies are able to conduct their risk analysis based on the results. For example, by comparing the pre-set acceptable risk level and the

estimated decreased port economic loss, terminal operators are able to adjust the terminals disaster contingency plans. Local governments and shipping companies are more informed in port site selection and route planning in a way that locations or ports with serious severe weather conditions should be avoided.

5.3 Method validation

To test the accuracy of the proposed model, we propose a validation approach by comparing the severe weather-induced port economic losses calculated by actual records and by the proposed simulation model. By using the data from 2014 to 2015 as an example, the difference between the estimated intact container throughput and the actual container throughput is calculated. This difference refers to the decreased container throughput in reality and can thus be used as a benchmark. The losses are then calculated by using the two methods and are compared in Table 6. It can be seen that, the port economic losses obtained from the proposed method and the benchmarks are comparable. This illustrates the accuracy and reliability of the proposed model.

Table 6. Method validation.

Year	Severe weather-induced port economic loss (USD)							
	Wind		Rain		Fog		Typhoon	
	Reality	Simulation	Reality	Simulation	Reality	Simulation	Reality	Simulation
2014-2015	28028071	33052703	23881907	28499661	67665403	80860939	23550214	26080572

6. Conclusion

This study evaluates severe weather-induced container terminal economic loss by a simulation-based method. A container terminal operation simulation model is firstly established for obtaining the reduced container throughput under various severe-weather conditions. Data collected as inputs for the model include process time for each ship call, lift per call, number of berth allocated and number of quay cranes deployed. Container

throughput, as the basis for further calculation of declined economic losses, is identified as the model output. The use of actual terminal operation records and terminal weather records makes it possible to not only justify the validity of the established simulation model, but also the proposed method. A real-world application is achieved by using the Port of Shenzhen as an example. Four major conclusions are reached. Firstly, wind, rain, fog and typhoon are the 4 major types of severe weather types affecting the Port of Shenzhen. Secondly, March, April, July and August suffer the highest severe weather-induced losses with monthly average losses of around 24 million USD, accounting for nearly 17% of intact incomes. Fog is the main hazard in March and April, whilst typhoon affects July and August the most. Thirdly, although wind and rain events are more frequent than the other two hazards, these two hazards induce around a tenth the amount of fog and typhoon-induced losses. Fourth, red-signal level fog events, orange-signal level typhoon events red-signal level typhoon events are among the worst cases which lead to economic losses of around 50% in the intact income.

This paper makes three major contributions to the research and practice fields on port-related risk modelling and management. Firstly, this study advances knowledge of the scopes and features of severe weather types that affect terminal operations and enables the use of actual severe weather-induced terminal downtime as the simulation model input. Secondly, this research addresses the current research gaps by evaluating severe weather-induced terminal economic losses, with a special focus on worst-case scenarios. Thirdly, the results of this study could be useful references for other similar-sized container terminals facing similar climate conditions without severe weather recordings. In addition, various port stakeholders such as port operators, service providers, carriers and shippers are able to find usefulness of the results in applications of port disruption management, risk mitigation, routing planning and port site selection.

For (re)insurance companies, the outputs of this research show their attractiveness as a part of catastrophe risk modelling, and the basis for port-related catastrophe insurance product pricing.

The proposed framework could be applied to other hazard types, such as hail, heat wave, earthquake and tsunami. In future studies, physical losses induced by both main hazards and secondary hazards are worth of consideration in the framework.

References

- Alexander, K. and N. Irwin. 2005. "Port Comes Back Early, Surprisingly." Washington Post, September 13. <http://www.washingtonpost.com/wpdyn/content/article/2005/09/13/AR2005091302073.html>
- Atsushi, N., I. Koji, and S. Takahiro. 2004. "Seismic design of port structures." *Journal of Japan Association for Earthquake Engineering* 4(3), 195-208.
- Brooke, J. 2003. "Typhoon Hits South Korea Economy." The New York Times, September 17. <https://www.nytimes.com/2003/09/17/business/typhoon-hits-south-korea-economy.html>
- Burden, L. I., G. Rix, and S. Werner. 2016. "Development of a risk framework for forecasting earthquake losses in port systems." *Earthquake Spectra* 32(1), 267-284.
- Cao, X., and J. S. L. Lam. 2018. "Simulation-based catastrophe-induced port loss estimation." *Reliability Engineering & System Safety* 175, 1-12.
- Cardona, O. D. 2005. *Indicators of disaster risk and risk management: program for Latin America and the Caribbean, summary report*. Inter-American Development Bank report.
- Chambers, S. 2003. "Pusan picks up pieces of typhoon carnage." Lloyd's List, September 16. <http://www.lloydslist.com/ll/sector/containers/article145387.ece>
- Chhetri, P., G. B. Jayatilleke, V. O. Gekara, A. Manzoni, and B. Corbitt. 2016. "Container terminal operations simulator (CTOS)-Simulating the impact of extreme weather events on port operation." *European Journal of Transport & Infrastructure Research* 16(1), 195-213.
- Dalian Port. 2015. *Dalian Port comprehensive emergency contingency plan*. Dalian Port report. <https://wenku.baidu.com/view/a8578807cfc789eb172dc881.html>
- Dilley, M. 2005. *Natural disaster hotspots: a global risk analysis (Vol. 5)*. World Bank Publications.
- Dragović, B., E. Tzannatos, and N. K. Park. 2017. "Simulation modelling in ports and container terminals: literature overview and analysis by research field, application area and tool." *Flexible Services and Manufacturing Journal* 29(1), 4-34.
- Du, Y., Q. Chen, J. S. L. Lam, Y. Xu, and J. X. Cao. 2015. "Modeling the impacts of tides and the virtual arrival policy in berth allocation." *Transportation Science* 49(4), 939-956.
- EM-DAT. 2009. *General Classification*. <http://www.emdat.be/classification>
- Flinders Ports. 2004. *Port emergency plan*. Flinders Ports report. <http://www.flindersports.com.au/>
- Flynn, M. 2003. "Hanjin bullish over box bonanza." Lloyd's List, November 29. <http://www.lloydslist.com.ezlibproxy1.ntu.edu.sg/ll/sector/ship-operations/article147795.ece>

- Frittelli, J. 2005. *Hurricane Katrina: Shipping Disruptions*. Washington, DC: Congressional Research Service, Library of Congress, RS22257.
- Hanson, S., R. Nicholls, N. Ranger, S. Hallegatte, J. Corfee-Morlot, C. Herweijer, and J. Chateau. 2011. "A global ranking of port cities with high exposure to climate extremes." *Climatic change* 104(1), 89-111.
- Iris, Ç., D. Pacino, S. Ropke, and A. Larsen. 2015. "Integrated berth allocation and quay crane assignment problem: Set partitioning models and computational results." *Transportation Research Part E: Logistics and Transportation Review* 81, 75-97.
- Iris, Ç., D. Pacino, and S. Ropke. 2017. "Improved formulations and an Adaptive Large Neighborhood Search heuristic for the integrated berth allocation and quay crane assignment problem." *Transportation Research Part E: Logistics and Transportation Review* 105, 123-147.
- Keceli, Y. 2016. "A simulation model for gate operations in multi-purpose cargo terminals." *Maritime Policy & Management* 43(8), 945-958.
- Kelly, H. 2011. "China penalises Dalian port executives for oil spill." Lloyd's List, November 25. <https://lloydslist.maritimeintelligence.informa.com/LL028134/China-penalises-Dalian-port-executives-for-oil-spill>
- Kelton, W. D. 2002. *Simulation with ARENA*. New York, U.S.: McGraw-Hill.
- Kermanshah, A., and S. Derrible. 2016. "A geographical and multi-criteria vulnerability assessment of transportation networks against extreme earthquakes." *Reliability Engineering & System Safety* 153, 39-49.
- Lam, J. S. L., and J. A. Lassa. 2017. "Risk assessment framework for exposure of cargo and ports to natural hazards and climate extremes." *Maritime Policy & Management* 44(1), 1-15.
- Lam, J. S. L., C. Liu, and X. Gou. 2017. "Cyclone risk mapping for critical coastal infrastructure: Cases of East Asian seaports." *Ocean & Coastal Management* 141, 43-54.
- Lam, J. S. L., and S. Su. 2015. "Disruption risks and mitigation strategies: an analysis of Asian ports." *Maritime Policy & Management* 42(5), 415-435.
- Law, Averill M., and W. David Kelton. *Simulation modeling and analysis*. Vol. 2. New York: McGraw-Hill, 1991.
- Leander, T., and T. Lin. 2015. "Explosions near Tianjin port leave more than 44 dead and disrupt shipping." Lloyd's List, August 13. <http://www.lloydslist.com.ezlibproxy1.ntu.edu.sg/ll/sector/ship-operations/article466475.ece>
- Lee, I. 2003. "Busan Port's Clients Skittish After Typhoon." The Chosunilbo, September 22. http://english.chosun.com/site/data/html_dir/2003/09/22/2003092261018.html
- Na, U. J., and M. Shinozuka. 2009. "Simulation-based seismic loss estimation of seaport transportation system." *Reliability Engineering and System Safety* 94(3), 722-731.
- Nadkarni, S. 1998. "Partial reopening at Kandla Port." Lloyd's List, June 27. <http://www.lloydslist.com.ezlibproxy1.ntu.edu.sg/ll/sector/ship-operations/article302491.ece>
- Oskin, B. 2015. "Japan Earthquake and Tsunami of 2011: Facts and Information." Livescience, May 7. <https://www.livescience.com/39110-japan-2011-earthquake-tsunami-facts.html>
- Pachakis, D., and A. S. Kiremidjian. 2004. "Estimation of downtime-related revenue losses in seaports following scenario earthquakes." *Earthquake Spectra* 20(2), 427-449.
- Pethick, J. S., and S. Crooks. 2000. "Development of a coastal vulnerability index: a geomorphological perspective." *Environmental Conservation* 27(04), 359-367.
- Roeder, C. W., R. Graff, J. Soderstrom, and J. H. Yoo. 2005. "Seismic performance of pile-wharf connections." *Journal of Structural Engineering* 131(3), 428-437.
- Ronza, A., L. Lázaro-Touza, S. Carol, and J. Casal. 2009. "Economic valuation of damages originated by major accidents in port areas." *Journal of Loss Prevention in the Process Industries* 22(5), 639-648.

- Iyer Sivakumar, A., and S. C. Chin. 2001. "A simulation based analysis of cycle time distribution, and throughput in semiconductor backend manufacturing." *Computers in Industry* 45, no. 1 (2001): 59-78.
- Smythe, T. C. 2013. *Assessing the impacts of Hurricane Sandy on the Port of New York and New Jersey's Maritime responders and response infrastructure*. Natural Hazards Centre.
https://hazards.colorado.edu/uploads/quick_report/smythe_2013.pdf
- Uğurlu, Ö., S. Erol, and E. Başar. 2016. "The analysis of life safety and economic loss in marine accidents occurring in the Turkish Straits." *Maritime Policy & Management* 43(3), 356-370.
- United Nations Development Programme [UNDP]. 2004. *Reducing Disaster Risk, A Challenge for Development*. <http://www.undp.org/content/undp/en/home/librarypage/crisis-prevention-and-recovery/reducing-disaster-risk--a-challenge-for-development.html>
- Werner, S. D. (Ed.). 1998. *Seismic guidelines for ports*. Boston, U.S.: ASCE Publications.
- Werner, S. D., S. E. Dickenson, and C. E. Taylor. 1997. "Seismic risk reduction at ports: Case studies and acceptable risk evaluation." *Journal of waterway, port, coastal, and ocean engineering* 123(6), 337-346.
- Yu, S., S. W. Kim, C. W. Oh, H. An, and J. M. Kim. 2015. "Quantitative assessment of disaster resilience: An empirical study on the importance of post-disaster recovery costs." *Reliability Engineering & System Safety* 137, 6-17.
- Zhang, Y., and J. S. L. Lam. 2015. "Estimating the economic losses of port disruption due to extreme wind events." *Ocean & Coastal Management* 116, 300-310.
- Zhao, X., H. Yan, and J. Zhang. 2017. "A critical review of container security operations." *Maritime Policy & Management* 44(2), 170-186.
- Zhuhai Port Authority. 2011. *Zhuhai City port natural disaster contingency plan*. Zhuhai Port report.
<http://www.doc88.com/p-491186774836.html>

Appendix

Appendix A Model validation

Case	Data used	Terminal throughput_Intact (million TEU)	Simulation output_Intact (million TEU)	Difference (%)	95% confidence interval_Variance (million TEU)	95% Confidence interval_Intact output (million TEU)	95% Confidence interval_Disrupted output (million TEU)
Wind_blue	201707	1.2217	1.2169	0.40	(-0.0715, 0.0811)	(1.2089, 2.4258)	(1.1976, 2.4122)
Wind_yellow	201701	1.1025	1.0941	0.76	(-0.1089, 0.1257)	(1.0819, 2.176)	(1.0272, 2.0764)
Wind_red	201701	1.1025	1.0941	0.76	(-0.1089, 0.1257)	(1.0819, 2.176)	(0.9934, 2.0097)
Rain_yellow	201704	0.9681	0.9674	0.07	(-0.1206, 0.122)	(0.9548, 1.9222)	(0.9049, 1.8301)
Rain_orange	201705	1.0643	1.0572	0.67	(-0.1021, 0.1164)	(1.0458, 2.103)	(0.9935, 2.0012)
Rain_red	201609	1.0912	1.0824	0.80	(-0.1044, 0.122)	(1.0707, 2.1531)	(1.004, 2.0345)
Fog_yellow	201703	0.8806	0.8823	-0.20	(-0.1238, 0.1203)	(0.8697, 1.752)	(0.7276, 1.4777)
Fog_orange	201704	0.9681	0.9674	0.07	(-0.1206, 0.122)	(0.9548, 1.9222)	(0.8158, 1.6505)
Fog_red	201703	0.8806	0.8823	-0.20	(-0.1238, 0.1203)	(0.8697, 1.752)	(0.3412, 0.6936)
Typhoon_white	201611	1.0099	1.0068	0.30	(-0.118, 0.1241)	(0.9943, 2.0011)	(0.9796, 1.9778)
Typhoon_blue	201610	0.9567	0.9644	-0.80	(-0.1291, 0.1138)	(0.9517, 1.9161)	(0.6362, 1.2868)
Typhoon_yellow	201707	1.2217	1.2169	0.40	(-0.0715, 0.0811)	(1.2089, 2.4258)	(0.8234, 1.6597)
Typhoon_orange	201608	1.1354	1.1290	0.56	(-0.1109, 0.1236)	(1.1168, 2.2459)	(0.52, 1.0503)
Typhoon_red	201707	1.2217	1.2169	0.40	(-0.0715, 0.0811)	(1.2089, 2.4258)	(0.4811, 0.9688)

Appendix B Generation of the warm-up period of the simulation model

Appendix C Probability distribution of port down time and frequency of severe weather events in the Port of Shenzhen, 2013-2017

Severe weather type	Magnitude	Single event-induced port downtime probability distribution	Frequency											
			January	February	March	April	May	June	July	August	September	October	November	December
Wind	Blue	2 * BETA(0.585, 2.33)	0.4	0.8	0.4	0.2	0.2	0.4	0.2	0.4	0.2	0.8	0	1.4
	Yellow	0.16 + LOGN(0.789, 0.893)	0.6	0.4	0	0	0	0	0	0	0	0	0	0
	Red	1.23 + EXPO(0.829)	0.4	0	0	0	0	0	0	0	0	0	0.4	0
Rain	Yellow	LOGN(0.266, 0.28)	0.2	0	0	1	1.8	1.6	2	1.8	0.4	0	0	0
	Orange	TRIA(0.03, 0.086, 0.59)	0	0	0	0	1.4	0.4	0.4	0.4	0.2	0	0	0
	Red	0.01 + LOGN(0.555, 0.449)	0	0	0	0	0.2	0	0.4	0.4	0.2	0	0	0
Fog	Yellow	LOGN(0.962, 1.12)	0.2	1.2	3	1.6	0.2	0	0	0	0	0	0	0.2
	Orange	7 * BETA(0.514, 1.33)	0	0.4	1	0.8	0.2	0	0	0	0	0	0	0
	Red	3.66 + 1.01 * BETA(0.622, 0.602)	0	0	0.2	0	0	0	0	0	0	0	0	0
Typhoon	White	0.04 + 0.38 * BETA(0.627, 0.612)	0	0	0	0	0	0.2	0	0	0	0	0.2	0
	Blue	0.68 + LOGN(0.703, 0.698)	0	0	0	0	0	0	0.2	0.4	0.2	0.4	0	0
	Yellow	1 + 4.58 * BETA(0.511, 0.819)	0	0	0	0	0	0.2	0.6	0	0.2	0	0	0
	Orange	2 + 5 * BETA(0.348, 0.474)	0	0	0	0	0	0	0	0.4	0	0.2	0	0
	Red	4.32 + 3.66 * BETA(0.595, 0.618)	0	0	0	0	0	0	0.2	0.2	0	0	0	0

Appendix D Fit all summary of model inputs

Statistics	Function	Square Error	Statistics	Function	Square Error
Ship arrival interval	Weibull	0.00127	LPC_1	Beta	0.00869
	Gamma	0.00138		Uniform	0.00986
	Beta	0.00237		Weibull	0.0114
LPC_2	Beta	0.011	LPC_3	Beta	0.0224
	Uniform	0.0116		Weibull	0.0231
	Weibull	0.019		Uniform	0.0232
LPC_4	Beta	0.0174	LPC_5	Beta	0.211
	Erlang	0.0232		Gamma	0.284
	Exponential	0.0232		Exponential	0.298
LPC_6	Beta	0.211	LPC_7	Beta	0.211
	Gamma	0.285		Gamma	0.283
	Exponential	0.298		Exponential	0.298
Quay crane efficiency	Normal	0.00822	Idle time before	Beta	0.00225
	Weibull	0.00901		Lognormal	0.0104
	Beta	0.0106		Weibull	0.0254
Idle time after	Beta	0.00648			
	Lognormal	0.00979			
	Exponential	0.0406			

Note: The types of functions are displayed in ascending order based on the values of square errors.

Appendix E Distribution summary

Statistics	Distribution			Chi Square Test		Data Summary	
	Type	Expression	Square Error	Test Statistic	Corresponding p-value	Sample Mean	Sample Std Dev
Ship arrival interval	Weibull	-0.001+WEIB(0,0)	0.001268	4.67	0.701	1.99	1.85
LPC_1	Beta	18 + 977 * BETA(0, 0)	0.008691	17.4	0.0443	463	287
LPC_2	Beta	1e+003 + 988 * BETA(0, 0)	0.010973	8.74	0.202	1480	278
LPC_3	Beta	2e+003 + 985 * BETA(0, 0)	0.022402	12.7	0.0143	2440	291
LPC_4	Beta	3.02e+003 + 806 * BETA(0, 0)	0.017425	1.54	0.226	3360	265
LPC_5	Beta	4.02e+003 + 435 * BETA(0, 0)	0.210537	13.1	< 0.01	4240	308
LPC_6	Beta	5.24e+003 + 553 * BETA(0, 0)	0.210537	13.1	< 0.01	5520	391
LPC_7	Beta	6.16e+003 + 418 * BETA(0, 0)	0.210537	13.1	< 0.01	6370	296
Quay crane efficiency	Normal	NORM(0, 0)	0.008215	22.9	< 0.005	2.2	0.337
Idle time before	Beta	1 + 53 * BETA(0, 0)	0.002247	5.17	0.277	4.87	7.39
Idle time after	Beta	25 * BETA(0, 0)	0.006481	49.1	< 0.005	1.04	1.75

Note: The test statistic and corresponding p-values for LPC_5, 6, and 7 are under Kolmogorov-Smirnov Test.

Appendix F Model output standard deviation comparison between 10 replications and 93 replications

Case	Standard deviation_10 replications	Standard deviation_93 replications	Difference
Wind_blue	28905	38460	-33%
Wind_yellow	89298	59099	34%
Wind_red	89298	59099	34%
Rain_yellow	58669	61139	-4%
Rain_orange	62981	55054	13%
Rain_red	67326	57068	15%
Fog_yellow	45244	61504	-36%
Fog_orange	58669	61139	-4%
Fog_red	45244	61504	-36%
Typhoon_white	86235	61014	29%
Typhoon_blue	42418	61200	-44%
Typhoon_yellow	28905	38460	-33%
Typhoon_orange	44186	59090	-34%
Typhoon_red	28905	38460	-33%