Modelling Container Terminal Resilience Measurement by Considering Hinterland Losses

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Abstract. Due to its significance, specifically in archipelagic countries, seaports have been long believed to play a considerable role in the freight transport network. The ongoing expansion of world trade also promotes container transport, which offers a more efficient movement process. Therefore, over the years, numerous studies elaborated the framework concept and practical strategies to improve the efficiency of container terminal (CT). However, CT is recently challenged by reliability issues resulting from natural disasters and disruptive man-made events. The resilience level of CT is then substantially required to investigate its system ability to handle disruption events. Since CT disruption directly impacts the hinterland, this paper then proposes a model to measure CT resilience by considering the hinterland losses, which are rarely explored. This paper also incorporates the customs process, the transport link between CT and hinterland, and its quantitative measurement for calculating hinterland losses. To represent the uncertain condition of transport links, the Monte Carlo simulation structure is invoked to generate the random probability event.

1. Introduction

As gateways of domestic and international trade, seaports play a vital role in the economic effectiveness of many countries. Its performance is practically believed to greatly influence logistics costs (see [1-2]), which shape the economic effectiveness and competitiveness, and thus, the topic of port efficiency attracts a huge number of studies (e.g., [3-7]). In addition, the rapid change of trading market reflects containers’ essential position as transport equipment, which then seriously restructures trade patterns and manufacturing strategies [8]. Another report also shows the considerable increase of container shipment, specifically in the developing countries [9].

Despite its essential increase, container transport faces challenges relating to the seaport disruption, which may be caused by natural phenomena and man-made disasters (e.g., labor unrest, technological accidents) as well. The risk of disruption possibly directly impacts not only port operations but also several supply chain parties, even influencing regional and global activities. For instance, after the 2011 tsunami, around 7% of total containers handled were impacted by to the seaport shutdown [10]. In addition, vehicle manufacturers are severely affected by port disruptions, especially in terms of export activities and material supplies [11-12]. This fact then conveys a conclusion about the close relation between ports and their hinterlands. Several researches have tried to capture the relation between a seaport and its hinterland (e.g., [13-14]). However, the impact of port disruption to its hinterland within the framework of resiliency still leaves room for exploration.
Literatures define the term ‘resilience’ in several ways. [15] describes resilience as a system’s ability to reduce the probability of disruption, the impact of disruption, and its recovery time. [16] states that resilience is the ability to recover to a certain level after being affected by a disruption event. Other scholars illustrate resilience based on its key features, namely, robustness, redundancy, resourcefulness, and rapidity [17-18]. Based on the concepts of resilience, several papers on port disruption analysis were thus written. [13] investigated the quantitative measurement of port resilience from the shipper’s perspective. [16] proposed a strengthened conceptual framework of seaport for dealing with a small-scale disaster. Bayesian belief network has also been used to model seaport related variables as well as to investigate resilience strategies [19]. The utilisation of real time and statistical port data has been conducted by [20] to develop an integrated system in order to forecast and to evaluate the seaport risk in extreme storms.

Although recent studies calculated the impact of port disruption to the hinterland, less attention was paid to the incorporation of CT operation. As the performance of CT depends on the operation productivity [21], which is constructed by equipment activities, disruption to certain equipment delivers different impacts to the hinterland. For instance, the disruption of QC activities may deliver a more severe impact compared to other activities. This paper thus proposes a measurement model which not only involves hinterland impact analysis but also takes into account the operation process to estimate the impact better.

The rest of the paper is arranged as follows: the following section describes the system and modelling framework. The third section elaborates the case study to investigate the impact of disruption to CT by involving CT operation and hinterland analysis. Finally, the fourth section summarizes the methodologies, results, and analyses in the paper.

2. Measurement Model

2.1. Definition of resilience and measurement model

By deliberating various definitions of resilience, this paper then delineates the term ‘resilience’ to build the measurement model. The resilience of CT refers to the system ability, with instant recovery response, to maintain performance level during disruptions as well as to reduce the economic losses of hinterland activities. The required time to transfer container to hinterland is thus selected as the performance indicator, which has a direct connection to the hinterland losses. Therefore, the resilience level in the $u$-disruption event is formulated as below:

$$R(u) = \frac{z_0 - \Delta z(u)}{z_0}$$

$sJ.$

$$\Delta z(u) = z_0 - z(u)$$

$$z(u) = \left[ \frac{1}{M} \sum_{m=1}^{M} W^1_m (q_{m1}, p(n_{m1}, u)) + \frac{1}{M} \sum_{m=1}^{M} W^2_m (q_{m2}, p(n_{m2}, f_g, C_g, u)) + W^3 (q^3, p(n^3, u)) + W^4 (\theta, \tau) + W^5 (f_l, C_l, \theta, \tau) \right]$$

where,

$R(u)$ : resilience level against disruption event $u$,

$z_0$ : transport time to arrive at hinterland without any disruption,

$z(u)$ : transport time to arrive at hinterland in $u$-disruption event

$\Delta z(u)$ : container delay time due to $u$-disruption event,

$u$ : vector set of disruption events,

$\zeta$ : acceptance level of CT performance,
The resilience level is calculated by considering not only the delay time due to the disruption $u$ but also the performance acceptance level (i.e., $\zeta$). The level illustrates the persistent performance level that needs to be preserved. For instance, if the acceptance level is set equal to two, the delay time must be maintained to be less than twice of moving time in the normal condition. In the case that the delay is greater than the persistent performance level, it can be stated that the CT system has failed to handle the disruption event. The required time to move container to hinterland is simply estimated by summing the transferring time in the CT (i.e., $W^1_m$, $W^2_m$, $W^3$, $W^4$) and in the transport links (i.e., $W^5$).

As inferred in Equation (3), the disruption event possibly strikes the Quay Crane (QC) operations, links capacity, which serve truck trailer unit (TTU), as well as the rubber tyre gantry cranes (RTGC) operations.

### 2.2. Definition of resilience and measurement model

The CT operation model is then expressed in this section, which is constructed by considering the import processes in the CT. The demand is set deterministically to represent the planned order of industrial raw material, even though the vessel size may be varied. The size then determines the number of QCs assigned, where each ship is assisted by 2 or 3 QCs. The QC productivity also varies based on certain distributions, which also occurs in terms of TTU and RTGC productivity. The horizontal movement of container between ship and container yard is handled by TTU, in which its productivity is directly impacted by the travel time along the horizontal link in the CT. Since the travel time is a function of link capacity and link flow, the reduction of link capacity in the disruption events possibly toward the increasing delay, and then, it truthfully affects the bigger process of port operation. Hence, the Bureau of Public Roads (BPR) function (see Equation (4)) is included to illustrate the flow and capacity interactions, as it is described below.
\[ a_s = \sum_g \left( a_s^0 + 0.5 \left( \frac{f_s}{C_g(\omega)} \right)^{1.5} \right) \]  

(4)

where:

- \(a_s\): travel time (hour) of link-\(g\).
- \(a_s^0\): travel time of link \(g\) at free flow condition.

The container is continued to the CY, which is managed by RTGC. The handling time is calculated based on the queuing theory by considering the fluctuation of RTGC productivity. To illustrate the actual process of container transportation in CT, the model also takes into account the customs processes of import product, which divides containers into four line classes (i.e., red, yellow, green, and priority line) based on the risk of commodity. The red line is specified for the commodity with a high risk and importers with insufficient track records, which then requires physical and document assessments. On the other hand the green and priority lines are set for the lowest risk of commodity as well as importers with trusted profiles, and thus, it needs a shorter time to pass the customs processes. Such classes are then invoked in the model by generating a random number by following a certain distribution, which is derived from the CT actual condition.

2.3. Resilience definition and measurement model

To link the CT with hinterland, the model considers three different modes of transportation for the container, namely truck, train, and ship/vessel. The ship mode is closely related to the inland waterways mode, which obtains growing attention in Indonesia. The travel time of railway mode in this case might be considered deterministic, while for the ship mode, the speed variation during the voyage is randomly propagated based on a certain distribution:

\[ a_{\text{ship}} = \frac{d_{\text{ship}}}{v_{\text{ship}}(\tau, \Theta)} \]  

(5)

where:

- \(u_{\text{sea}}\): travel time of ship mode
- \(d_{\text{ship}}\): trip distance
- \(v_{\text{ship}}\): vessel speed

Unlike the ship mode, the variation of traffic flow and road capacity should strongly affect the truck travel time. Hence, the BPR function is also used to estimate the travel time at the connecting link by reflecting the uncertainty of traffic and road capacity. As disruption of CT operation influences the hinterland activity, estimating the losses is thus beneficial. The hinterland is further simplified as the industrial cluster, which requires raw material to ensure production activities as well as to continue their supply to the customers.

The losses probably lie on the direct and indirect loss, in which the direct loss corresponds to the commodity damage, and the indirect loss relates to the production/manufacture delay due to lack of raw material. To illustrate such conditions, the model then invokes the economic losses estimation, which is proposed by [14]. Equation (6) shows the direct loss estimation, which accounts the unit value of commodities, its volume, the transport cost, and the storage cost.

\[ L_{\text{direct}} = p_{\text{raw}}V_{\text{import}}\Delta z(u) + c_{\text{raw}}V_{\text{import}}\Delta z(u) \]  

(6)

where,

- \(L_{\text{direct}}\): direct loss due to commodities damage,
The losses which are further considered are derived from the production delay in the CT hinterland. Since the delay which occurs in the CT sequentially affects the production in the hinterland, Eq. (7) illustrates the three different types of impact. In case of delay time due to disruption below the remaining time of raw material inventory, the disruption then gives no impact to the production, which is described by the first row of Eq. (7). The second row explains the condition that the delay time is bigger than the raw material buffer time, though the product stock is still sufficient to provide the supply. In this condition, the manufacturer in the hinterland incurred the losses in term of production process. If the product stock is insufficient to maintaining the normal flow to the costumer, the manufacturer then suffers the cancelation losses.

\[
L_{\text{direct}} = \begin{cases} 
0 & \text{for } \Delta z(u) < I_{\text{raw}} \\
p_{\text{prod}}V_{\text{prod}}(\Delta z(u) - I_{\text{raw}}) & \text{for } I_{\text{raw}} < \Delta z(u) < I_{\text{raw}} + I_{\text{prod}} \\
p_{\text{prod}}V_{\text{prod}}(\Delta z(u) - I_{\text{raw}}) + r_{\text{cancel}}p_{\text{prod}}V_{\text{prod}}(\Delta z(u) - I_{\text{raw}} - I_{\text{prod}}) & \text{for } I_{\text{raw}} + I_{\text{prod}} < \Delta z(u)
\end{cases}
\]  

(7)

where,
- \(L_{\text{direct}}\) : production loss due to the delay,
- \(p_{\text{prod}}\) : unit value of product,
- \(V_{\text{prod}}\) : volume of production,
- \(I_{\text{raw}}\) : buffer time of raw material stock to continue the production,
- \(I_{\text{prod}}\) : buffer time of product stock to provide the costumer supply
- \(r_{\text{cancel}}\) : cancellation rate

3. Numerical Experiment
The proposed model for measuring the resilience is then tested in a network (see Figure 1), including a CT and an industrial cluster as its hinterland. The CT operation incorporates the transferring process from the vessel to the gate facilities. The process involves the handling activities of QC, TTU, RTGC and customs. The attribute of handling equipment is derived from the actual CT data set, which are utilized as the simulation input.

In this experimental case, in the normal condition, CT is assumed to be armed by 1 dock with the simultaneous operation of 3 units of QC, 15 units of TTU, and 15 units of RTGC. In terms of customs process, the type of class and its required times are varied, where the random number follows the triangular distribution, which is generated within the framework of Monte Carlo simulation. The demand is assumed equal to 1500 containers that are carried by a single vessel.

| Variables          | Units  | Min  | Max  | Mode |
|--------------------|--------|------|------|------|
| QC Service Time    | minutes| 2.00 | 3.00 | 2.50 |
| TTU Speed          | km/hr. | 10.00| 25.00| 15.00|
| RTGC Service Time  | minutes| 5.00 | 8.00 | 7.00 |
| Customs Process    | day    | 4.64 | 11.07| 6.76 |
The connecting link to the hinterland is only operationalised by the truck mode, where the traffic flow is set based on an actual data set of connection link in Indonesia. The industrial cluster is equipped by the following information to estimate its losses due to the disruptions of CT.

![Test Network](image)

**Figure 1. Test Network**

| Parameters          | Value                      |
|---------------------|----------------------------|
| \( p_{\text{raw}} \) | 1 bil. Rp./unit cont.       |
| \( c_{\text{raw}} \) | 0.1 bil. Rp./unit cont.     |
| \( p_{\text{prod}} \) | 1 bil. Rp./unit             |
| \( V_{\text{prod}} \) | 100 unit/day               |
| \( I_{\text{raw}} \) | 2 days                     |
| \( I_{\text{prod}} \) | 4 days                     |
| \( r_{\text{cancel}} \) | 1 %/day                   |

**Table 2. Input for calculating the hinterland losses**

Before discussing the resilience measurement more deeply, it is important to present the base condition of CT performance and its hinterland connection. In the normal condition, the container needs on average 140.11 hours (i.e., 5.84 days) to arrive in the hinterland, with the longest time being spent at the customs process (i.e., 112.21 hrs).
The resilience level of CT is then estimated in the case of QC shutdown, decrease of link capacity in the CT, and RTGC operation shutdown, in which the acceptance level is set as 1.5. The summary of scenarios is illustrated at below.

### Table 3. Disruption Scenarios

| Scenario | Number of Available Facilities | Decrease of Link Capacity |
|----------|--------------------------------|---------------------------|
|          | QC    | RTGC |                      |
| Sce. A   | 1     | 15   | 0                      |
| Sce. B   | 2     | 15   | 0                      |
| Sce. C   | 3     | 6    | 0                      |
| Sce. D   | 3     | 9    | 0                      |
| Sce. E   | 3     | 15   | 35%                    |
| Sce. F   | 3     | 15   | 70%                    |
| Sce. G   | 1     | 6    | 70%                    |

As shown in Table 3, the first and second scenarios (i.e., Sce. A and B) reflect the situation of QC shutdown, in which the performance of other facilities remains unchanged. Furthermore, such kinds of scenarios are positioned in the Sce. C to Sce. F to illustrate the single disruption event of RTGC and link capacities. The RTGC disruption is modelled by setting the number of available units to be less than the normal condition. The interruption of TTU productivity is demonstrated by the decrease of link capacity, which directly influences its travel time for moving container within horizontal area of CT. To capture the simultaneous disruption events, the last scenario (i.e., Sce. G) is proposed by putting together the worst scenarios of disrupted facilities.

The defined disruption events are then tested in the network to investigate its impact to the CT performance and the resilience level. The required time to transport the container is firstly elaborated, which specifically receives a huge attention from the container owners. Since the model incorporates the CT and hinterland connection, the required time can be estimated not only in terms of the time to pass CT, which is generally conducted by other studies, but also the time to arrive at the hinterland.

As can be seen in Figure 2, the required time to transport the container to the hinterland corresponds to the type of facilities disrupted, in which the disruption of QC activities toward the highest increase of required time. The shutdown of available QC, which is illustrated by Sce. A, possibly increases the required time up to 25.58%. Moreover, the decrease of available RTGC also substantially raises the arrival time in the hinterland, where the container experiences an arrival delay of around 1.12 days. The capacity decrease of link is estimated to affect the CT operation, though its impact is less than the disruption of QC and RTGC. In addition, the simultaneous disruption of facilities seriously shapes the delay that multiply the arrival time to 29%.
The similar tendency is also indicated by the resilience level, in which the shutdown of QC and RTGC significantly reduces the resilience level of CT (see Figure 3). The decreasing of available QC successfully degrades the CT system ability to handle container, which is illustrated by the decrease of resilience level. As the hinterland losses calculation is included, it can be inferred that the lesser value of resilience level delivers a higher total loss incurred by hinterland. The decrease of resilience level,
which subsequently escalates the arrival time, directly suffers the hinterland production and distribution performances that are implied by total losses. Hence, the protection of resilience level is strongly needed to alleviate the significant impact to the hinterland. Furthermore, the distraction of link capacity does not disturb the resilience level, which conveys a conclusion relating to the retrofit or recovery activities that need to be prioritised. Such facts can further be utilized to program the retrofit and recovery activities to deal with the disruption events.

4. Conclusions
This paper proposes a measurable model to calculate the resilience level of CT by taking into account the hinterland losses. Different to previous studies, the CT facilities productivity and its interaction are also modelled, where the operation of QC, TTU, RTGC and custom process are taken into consideration. To investigate the disruption impact, the model also incorporates the quantitative measurement to calculate the hinterland losses, which is constructed by considering the direct and indirect losses. The connection between hinterland and CT is provided by the transport links, where the uncertainty of transport links is integrated by invoking the Monte Carlo simulation-based procedure. The resilience level is then presented by capturing the potential delay due the disruption event. The numerical examination reveals that the lesser resilience level provides the higher total losses suffered by hinterland. Therefore, this model is may be applied to evaluate the retrofit and recovery activities when encountering disruption events.

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