A PORT DIGITAL TWIN MODEL FOR OPERATIONAL UNCERTAINTY MANAGEMENT

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Abstract: Lacking information challenges the management of port operational uncertainty in estimating the situation to support a decision on reactivity planning. This paper applies Digital Twin (DT) to model a replicated virtual port operation from a real-world port of Thailand. The proposed DT model offers a tool to accelerate generating data of the port operation with configurable uncertainty. The model is validated by using generated data from the DT model compared with the real-world data. The result shows that the DT model produces the same behaviour as the real-world system. An outcome of this paper is a DT model eligible to generate port operation data for later application with machine learning to predict the port capacity under uncertainty to support reactivity planning.

Keywords: Digital Twin; Uncertainty Management; Port Operation; Berth Allocation; Reactivity

1. INTRODUCTION

In 2020, the coronavirus pandemic (COVID-19) brought several changes affecting maritime transport globally, including the port operation. Economic tensions drive the trade pattern to alternative markets and suppliers away from China e.g., South-East Asian countries. Flows of the container volume are changed according to changes on-demand, as well as the vessel capacity managed by carriers. Carriers control their costs during the situation by adjusting strategies such as service suspension and limiting container volume. In particular, carriers applied the policy of blanking scheduled sailing implying difficulties in the time controlling along its route (UNCTAD, 2020). Consequently, ports are impacted by these changes including additional operation policies for the COVID-19 outbreak. In further extreme conditions, several ports have to face challenges due to severe weather resulting in suspension of ports and the following of high container volume, the shortage of haulage and port congestion (The Loadstar, 2020a, 2020b). The environment of maritime logistics consists of various uncertainties, the most noteworthy of port functions is the ability to manage the port operation to accommodate cargos through fluctuations and unexpected circumstances (Burns, 2018).

During the period of port congestion, the vessel berthing time, including the estimated time to arrival (ETA) and the estimated time to departure (ETD) were rescheduled several times before the actual berthing. Even after the berthing, the ETDs were also updated. This implies an inaccuracy in the estimation for planning the berth allocation when the port is under an uncertain situation. Further, changes in the berth allocation have impacted to the port efficiency. Several activities of port and vessel operations depend on the berth schedule such as the scheduling of other port resources and the next vessel schedule on the berth. On each update of the ETA/ETD, all the following activities require rescheduling and this further accumulates uncertainty in the chain of port operations. Recent berth allocation models are in mathematical optimization. Several models considered uncertainty, such as the vessel arrival and vessel handling time. The uncertainty value is estimated by the probability distribution or by the port manager. However, the probability distribution is limited by the bounding range and port manager's estimation can be limited by the experience. Therefore, in order to obtain information of uncertain port situation that is consistency to the real operation, this study proposes an approach of port digital twin model for supporting the uncertainty management. The model simulates the port operation with uncertainties and generates data necessary for further prediction of vessel's ETA and ETD under the uncertain circumstance to assist the planning decision of berth allocation by evaluating port capability to maintain the plan at each moment on a more or less in the long time horizon according to the new data available at each moment.

This paper is structured as follows: Section 2 describes background of maritime container port and uncertainty. Section 3 justifies the management of berth allocation with uncertainty. Section 4 proposes the modelling of digital twin for port operation prediction. Section 5 presents results of digital twin validations and Section 6 concludes the paper.

2 BACKGROUND

2.1 MARITIME CONTAINER PORT

The growth of global containerized logistics increased every year along the ten year of 2010-2019 at the rate of 1.6% to 7.7% percents. Even in 2019, the growth rate was 3.1% lower than in 2018, it achieved 811 million TEUs of containers (twenty-foot equivalent unit). However, in 2020 the coronavirus pandemic influenced several changes of global consumption patterns in the whole supply chain, including the maritime containerized logistics. Resilience to changes became a focus in the industry perception (UNCTAD, 2020).

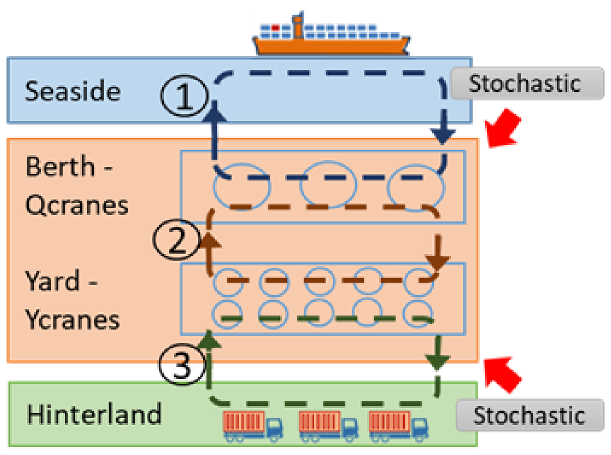
The resilience of container port operation can affect its performance, global ports and shipping supply chain.

Container port is the central spot switching containers among transportation modes (e.g., marine vessel, external truck, local barge and train). Since the handling operations are interconnected so during the operation, the container port has to interface impacts from disturbances and uncertainties from external factors and, also, internal factors. On another viewpoint, the resilience of port offers a chance to subsidize these impacts and prevents the impact size expansion to downstream of supply chain.

The maritime containerized logistics involves three major actors; Vessel liners, container ports and hinterland transportation. When an unexpected event occurs externally out of port such as vessel delay, port has an ability to adjust its resource configuration in order to accelerate/decelerate in responding to the situation. Ultimately, the port gets the vessel schedule continuing as planned and no effect influences the next vessels. However, the adjustment of port operations on the seaside can affect the other part of port operations due to the interdependency of container flows within the port.

Container port logistics transfers both import, export and transshipment containers between seaside and hinterland accesses in bidirectional flow using the same set of port resources consisting of berth space, quay cranes, internal trucks, yard cranes, reach stackers and yard storage space. Container is the microscopic element performing port operation activities to achieve its logistics purpose. On each operation activity, a container requires port resource(s) for a moving or storing activity. **Figure 1** illustrates three connecting flows of containers in the chain of port operations as follows:

FIGURE 1: FLOWS OF CONTAINERS ON PORT OPERATION



- 1. Vessel-Berth loading/unloading: on vessel arrival (a marine vessel or local barge), berth space, a number of quay cranes and a number of internal truck were allocated. The vessel stowage plan provides the list of container sequences for loading/unloading at the specific position on the vessel. Quay cranes are scheduled according to the stowage plan to transfer containers onto/from internal trucks.
- 2. Berth-Yard transferring: internal trucks transfer containers between the quay crane (Qcrane on Figure 1) and the yard crane/stacker (Ycranes on Figure 1). At the transferring points that carrier resources are switched, the container and the resource have to wait for each other. In addition, The yard crane processes the container at the specific point in the yard stack. The reshuffling of containers may be required and cause additional operation time.
- 3. Yard-Hinterland pickup/discharging: external truck or train comes into the port through the hinterland gate to pick up/discharge the container. Once the external truck arrives the yard, it waits for the yard crane/ stacker to transfer the container to/from the specific point in the yard stack. The reshuffling of containers may be required and caused additional operation time.

The port operation is a complex system involving three container flows connected by the interdependency of resource sharing. When a container is holding a resource, the other containers from the same or the connecting flow have to wait. The time of resource holding influences the performance of all container flows. In particular, when the port is affected by impacts of disturbance and uncertainty from both external and internal, performance of the container logistics on the port can become vague due to the interdependency of operation.

2.2 PORT OPERATIONAL UNCERTAINTY

Threat and uncertainty exist in the supply chain including the port operation. Port has challenges in economic crises, heath crises, natural disasters, terrorist attacks and unexpected events in operation. Their impacts can disrupt port infrastructure and operation performance. Ports require to manage various kinds of unforeseen uncertainties to level up their performance to the position of competitive excellence. Efficiency, effectiveness and resilience to disruptions are three major components for achieving the port performance. Efficiency represents the operation performance such the output productivity under a limited resource. Effectiveness represents the fulfilling of customer expectations. Resilience represents the port capability in managing threats (Notteboom, Pallis, & Rodrigue, 2022). Efficiency rarely distinguishes the situation with or without an interference. Its purpose aims to achieve a service level. While, the resilience proposes abilities that directly interact with disruptions and uncertainty.

Since this study focuses in managing uncertainty during the operation, therefore, we scope to approaches that support the operation to maintain its efficiency level by performing activities derived from resilience abilities when the port is interfered with by uncertainty/threat. Resilience is commonly defined as an ability to recover the situation from disruptions or disturbance and usually focuses in strategic solving. In engineering or physical sciences, resilience focuses on the resistance to the shocks or negative impact and the ability in returning to or resuming the stability. In ecological sciences, resilience is the ability to absorb the disturbance and to adapt to another stability. Another definition for complex adaptive systems theory, resilience is the ability to anticipate, to reactivity or to reorganization in order to minimize impact from disturbance (Notteboom et al., 2022). Port is a complex system involving several stakeholders and interdependence of sub-operations in the port system. Therefore, under the environment with various kinds of uncertainty/threat, the port resilience should have the ability to mitigate impacts resulting from uncertainty/threat in order to minimize the lost and to prevent the dispersing of negative impact to downstream operations.

Vugrin, Warren, and Ehlen (2011) and Notteboom et al. (2022) defined three major abilities to maintain port resilience as absorptive, adaptive and restorative:

- absorptive: Strength of negative impact is absorbed at a capacity level while the port operates with normal activities. Infrastructure and assets strategically are installed for handling with uncertainty in advance.

- adaptive: port has ability in anticipating negative impact from uncertainty and respond by adjusting operation activities to mitigate the strength of impact during the interference.
- restorative: port performs activities to recover the operation to its service level acceptance.

Even these strategic approaches offer the prevention and absorptive of negative impact, however, uncertainty and negative impact still exist to be managed in all areas of the port operation. We examined studies in the port operational problems with concerning in operational uncertainty in order to explore types of uncertainty interfering the port and approaches of resilience ability applied to the problem.

Several studies in port resilience measured cause-seffect of threats and assessed how these impacted to the port in the dimension of resilience capacity. Hossain et al. (2019) assessed cause-effect of the tornado to the resilience of the port capacity integrating with capacity enhanced factors such as maintenance, cyber infrastructure, additional equipment, and etc. They quantified resilience capacity in absorptive, adaptive and restorative using Bayesiam in order to suggest leading factors that potentially improve port flexibility in case of the tornado. Russell, Ruamsook, and Roso (2020) examined uncertainty factors around port areas; seaside access, yard platform, hinterland access and port system-wide. They classified levels of capacity that impacted to each uncertainty factors as static asset, adjustable operation or logistics partner interaction. They proposed strategies to improve flexibility in the fluctuation of container capacity, for example, committing contract agreements with shipping partners, applying digitalization to obtain transparency in logistics platform and extending infrastructure. These studies show that uncertainty factors and container capacity have significant relation to the port operational uncertainty. However, these studies focused on the handling with uncertainty at strategic level while the management of uncertainty in the level of port operational system is rarely derived.

Operational resilience was conceptualized in a complex network consisting of nodes and links representing the functional ability of each node and relationships in dispersing negative impact to related nodes, respectively. System functionality acted for the resilience of the network system. Ganin et al. (2016) adopt activities of operational resilience with system functionality and time dependency as illustrated in **Figure 2**.

Activities were adopted from the National Academy of Sciences (NAS) for managing the disaster resilience. Critical functionality is changed on each phase depending on the weight of negative impact and system activity performing against the impact. Interpreting this concept to the port operational system in each phase as follows:

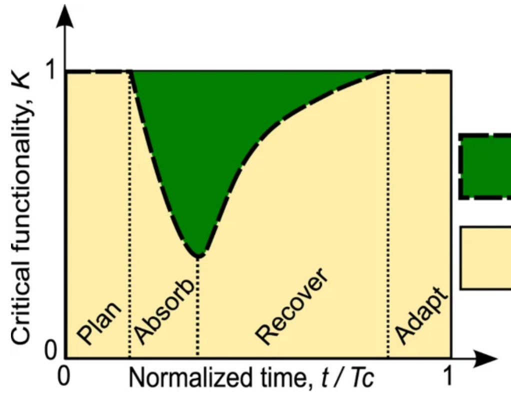


FIGURE 2: OPERATIONAL RESILIENCE AND CRITICAL FUNCTIONALITY DURING DISRUPTION CYCLE (GANIN ET AL., 2016)

• Plan activity: To anticipate uncertainty and negative impact reaching to the port. Also, to estimate critical functionality such as the port capacity in the next phase of absorbing activity. Aiming to plan the operation to be consistent with the estimated situation with minimized impact.

- Absorb activity: To perform the operation within a negative impact environment based on infrastructure and asset strategically installed for handling with uncertainty.
- Recover activity: To recover port operational service level back to normal state.
- Adapt activity: To apply the new activity

Resilience requires port capabilities in anticipation, preparation for, responding to and recovering from threat/uncertainty. Adaptive forecasting is still limited.

Various factors cause uncertainty to the global supply chain network. A major is internationalization trading e.g., exchange rate, trading barriers, competition and etc. resulting in uncertain to demand, product pricing, costs and lead times. The other factors such as natural disasters and terrorist attacks cause uncertain to operation capability as well.

Several studies consider each factor in its behaviour and impact to the port capacity. However, the port has a chance to confront several kinds of uncertainty at a time. Considering the conditions of each factor one by one seems to be a huge task for managing the port at the operational level. Therefore, we consider from the viewpoint of port operation and classify uncertainty factors into 3 kinds:

- Uncertain to demand
- Uncertain to resource availability
- Uncertain to operation interdependency

Uncertain to demand includes any possible changes of container capacity from the external to be serviced by the port, specifically to the number of containers arriving/departing the port and their arrival/departure time. Uncertain to resource availability and uncertain to operation dependency effect to the internal productivity. Uncertain to resource availability considers the capability of port facilities performing the operation, e.g., breakdown, in maintenance and etc. Uncertain to operation interdependency includes any situation circumstance affecting the cooperation of facilities in the port operation network.

The port operation faces various kinds of uncertainty. **Table 1** shows studies of the port operation in various functions concerned with uncertainty and its impact on the performance of the port function. On the berth allocation and quay crane (QC) assignment, several studies concerned in the punctual of vessel arrival time as it affects the start time of berthing and uncertainty of vessel operation time caused by the internal truck operation (Xiang & Liu, 2021), container volume (Zhen, 2015) or weather condition (Liming, Jun, & Jianfeng, 2021). In reverse, the internal truck is affected by the quay crane queue and also the yard crane (YC) queue (Huang, Wang, & Shi, 2014). Further, YC is impacted by uncertainty to the external truck arrival and uncertainty to the vessel stowage sequence (H. Yu, Ning, Wang, He, & Tan, 2021).

It is noticed that the port may have to face all of these kinds of uncertainty at the same time under the interdependency of back and forth operation relations. Not only the container is transferred between the facility linkage, but also the influence of uncertainty is transferred as well. However, solutions proposed to handle uncertainty include only some specific kinds of uncertainties while the impact of uncertainty can travel through the chain of port operations. Therefore, in order to manage uncertainty affecting the chain of port operation, we propose that the port operation management should consider uncertainty in the viewpoint of port operation as the proposed three classified types of uncertainty mentioned above.

Port operation	Uncertainty	Impact
Tugboat	- vessel arrival time - handling time	shifting of others operations
Berth and QC	- vessel arrival time - handling time - container volume - internal truck	shifting of others operations
Internal truck	- QC long queue - YC long queue	extending operation time
Storage space and YC	- ex-truck arrival - container sequence - container volume - container weight - info of stowage	extra YC moves
Intermodal (land gate)	- arrival punctuality of transportation	uncertain task for YC
Intermodal (waterway)	deep-sea vessel arrival and departure time	barge scheduling and congestion

TABLE 1: PORT OPERATIONS CONCERNING IN UNCERTAINTY AND ITS POTENTIAL IMPACT

2.3 PORT OPERATIONAL MANAGEMENT

According to the flow of port resource management proposed by Bierwirth and Meisel (2010) as shown in Figure 3, port management is separated into three areas; the seaside, yard and hinterland. At the operational level, resource planning on the seaside and on the hinterland side have impacted the resources planning on the yard. Both the seaside and the hinterland side receive demand from the external, therefore, the port resources are managed the plan accordingly to demand.

On the seaside, before a vessel trip, liner schedules port visits on its route trip. Port makes agreements on a plan of vessel visit, including the estimated of vessel arrival time(ETA), the estimated of vessel departure time(ETD), an approximated number of containers with container descriptions. Information is then used for the berth allocation. The liner and the port then make an agreement on the initial schedule of vessel visits. Planning of the other resources as connected along the resource management flow on the **Figure 3** such the workforce, quay crane and yard crane scheduling is later planned according to the berth allocation.

On the hinterland side, external transportation such as external truck and train are serviced by the schedule and non-schedule(stochastic arrival) depending on the port policy. Yard crane and internal transportation are reserved based on the gate policy with a condition that seaside vessels usually have a higher priority in holding port resources.

Based on the flow of resource management, the berth allocation seems to be the critical point. During the operation when there are changes that shift the schedule of the berth, plans of the other resources can be impacted through the flow. On the uncertain about demanding such as vessel delay, it directly impacts the start time of berthing. On the uncertain to resource availability such as machine breakdown, this can affect the vessel operation time resulting in a long time of berth allocation. Even the high traffic of external truck arrival with uncertain to operational dependency can also influence the vessel operation time.

The other resources and the other vessels may or may not be impacted by the change of berth allocation. However, acknowledging of how much time the berth allocation will be changed from the plan in advance allows a spare time for the port to make a decision and prepare for the reactivity of port resources.

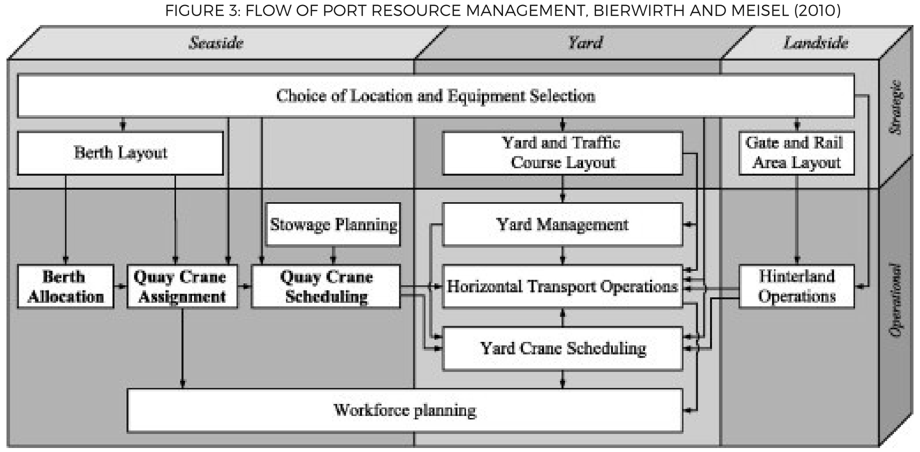
3 RELATED WORK: BERTH ALLOCATION MODEL

Berth allocation models perform majorly in two approaches. First, the proactive planning is performed before the actual berthing e.g., the rolling-time horizon (Zhen, 2015) and/or the robust buffer time (Iris & Lam, 2019). Second, the reactive planning is performed after an incident disrupted the original plan e.g., delay of vessel arrival, to search for the re-planning solution of all affected vessels by minimizing the change impact in delay time and recovery cost comparing to the baseline (Xiang, Liu, & Miao, 2018). However, the information used for the reactivity seems to be limited of uncertainty type and static, not actually from the recent operation situation where uncertain factors can be different by the nature of uncertainty. It is difficult for the planning in the abnormal situation with unknown dynamic uncertainty such as congestion. The incapacity to apply the current planning is the trigger event for the reactivity. Our goal is to predict this incapacity as early as possible.

To our best knowledge, few studies address the use of data based on dynamic characteristics of uncertainty in the berth allocation model. The actual plan of vessel arrival and handling time may deviate from the estimation and disrupt the baseline schedule. For the vessel arrival, J. Yu et al. (2018) predicts uncertainty from data mining to learn the ship arrival based on dynamic tracking of vessel AIS data.

The estimation of handling time is limited, Umang, Bierlaire, and Erera (2017) used a finite set of the dynamic model which has not yet reflected the actual operation situation. Cahyono, Flonk, and Jayawardhana (2020) use the actual states of vessel arrival and operational status concerning uncertainty in the operational constraints but the collected dataset is still limited in a range of time. In addition, as

FIGURE 3: FLOW OF PORT RESOURCE MANAGEMENT, BIERWIRTH AND MEISEL (2010)



mentioned in the section 2.3, the port operation functions cooperate and are interdependent. The trace of uncertainties is connected to the operational performance.

The proposed approaches in literature integrate only some parts of uncertainties. Given the numbers of uncertainties presented above, it is obviously very difficult to develop a model integrating all these uncertainties. Moreover, not all uncertainties are directly observable (e.g., human error) and, therefore very difficult to model.

For uncertainties that cannot be directly observed, we can, however, observe their effects on the performance of port operations. Thus, in order to predict the incapacity to apply the planning, we propose to develop a digital twin allowing to generate in an accelerated way a sufficient volume of data to apply machine learning for the prediction of congestion. The following section aims at introducing the notion of a digital twin and our approach to creating this digital twin.

4 DIGITAL TWIN OF PORT OPERATION

4.1 DIGITAL TWIN

The term Digital Twin(DT) was defined as a mirroring space model or mirroring product in the context of product life management (PLM) by the University of Michigan in 2002 (Grieves & Vickers, 2017). The model represents the vision of the physical object through its lifecycle. DT model facilitates the creation, building, testing, and monitoring the product or process in 'virtual', offering the exploration into the product/process without risk in operation. The model is composed of a real space containing physical object(s), a virtual space containing virtual object(s) and a linkage of data flow between the real space to the virtual space. Later, the term focus is shifted to the area of complex systems such as aerospace, manufacturing, and production.

In the industry of port management, leading ports have implemented smart sensors and communication technology, such as 5G network, camera, AR, VR and etc. to support the digital twin of virtual port operation in real-time. The digital twin offers a visual view similar to the satellite with the real-time update elements in the port spacing area, promoting the accuracy in positioning the cargo element.

Among literature work in DT for the port operation, a few works were studied using information from the DT to support a decision in the operation. Hofmann and Branding (2019) proposed a DT to support truck dispatching operators. The IoT platform acquired input data for the database. The simulate-based DT was then updated and provided information of the current system status to the integrated algorithm. The algorithm evaluated and suggested the dispatching solution for the operator. Zhou et al. (2021) used information of DT as a realistic prediction of port performance when the port was under possible disruptive events and the post-event recovery actions were taken. This work claimed to be the first study applying granularity of uncertainties to the port operation digital twin.

4.2 MODELLING OF DIGITAL TWIN

The digital twin proposes abilities to visualize the port operation, to generate/estimate information and to input uncertainty factors that might occur as scenarios in the operation. These abilities not only perform in the real-time manner, but information further promotes an accuracy of the operation estimation in a nearly coming time. However, we have not yet found the study of digital twin replicating the port operation system during the confronting to uncertainty factors.

The virtual system of the DT generally represents the vision of physical object(s) similar to the simulation. However, in addition to the simulation capability, the virtual system must have the same behavior as the real system. They must be synchronized in all its life under two trading of data/information. First, on changes to the physical system, the virtual system must be able to calibrate with the real situation. Second, the virtual system should be able to generate useful output to act on the physical system. Modelling a DT model should consider these synchronizations between the physical-virtual systems.

This research is interested in the impact of uncertainty factors resulting on the berth allocation, specifically in the deviation of vessel berthing time and the deviation of vessel departure time. DT is used to represent the port operation with uncertainty factors in the future time-space. By using data of a real port system, the virtual environment of port operation is modelled. Data of container arrivals is used as input to proceed the operation. The uncertainty factors are used to trigger operational interference. DT then fast-forwards the operation with these settings to the future space. Finally, the vessel berthing time and departure time are observed as the output of DT.

On the first synchronization of physical-to-virtual, the validation for ensuring virtual operation behavior is conducted through operation output. By applying the same set of input captured from the physical operation, the virtual system should produce the same behavior of output comparing to the physical output.

On the second synchronization of virtual-to-physical, this model generates output of the vessel berthing time and departure time in the future hours. They can be compared to the berth allocation plan to specify the time deviation and further impact on other vessels/resource plans. The generated information is the feedback to the physical operation by supporting the reactivity decision, which includes the impact of recent uncertainty factors into consideration.

Modelling the DT for port operational uncertainty management proceeds in four steps, 1)Data acquisition, 2)Simulation modelling, 3)Generation of simulation data and 4)Model validation. Three operational uncertainty factors are included; uncertainty due to the external demand, uncertainty due to the internal resource availability and uncertainty due to the operational interdependency.

4.2.1 Data acquisition

Four areas of data collection are required from the physical operation. The first dataset is for constructing the port operation environment including, the physical layout, the number of port facilities, their capabilities and operation policy. The second dataset is data of container inputting the port operation. The third dataset is uncertainty factors for triggering changes to the port operation. Finally, the fourth dataset is the output of port operation consisting of the deviation of vessel berthing time and departure time.

1. Port operation environment consists of the following of data elements:

- Port physical layout: travel time of a container between operation stations depends on distance. The virtual distance space should be the same as the physical space.
- Port facility: includes the number of facilities and their capability.
- Port operation policy: policies of operation task are different on each port e.g., the sequence of vessel loading/unloading or yard allocation. This data supports the operation time of DT to work similarly to the physical operation.

2. Container input for the port operation on each transportation mode arrival concerns on both data of the time and the number. The arrival of motor vessels is based on schedule plans, while local barges usually depend on the arrival of motor vessels. The transferring rate of vessel containers depends on the committed speed/number of quay crane. The arrival rate of external truck is various by the time of the day.

3. Uncertainty factors triggering the operation assuming that the first and second dataset are used to construct a fundamental structure for DT execution at normal scenarios. This dataset is for executing operation scenarios with uncertainty. Only data of the vessel arrival pattern which contains changes to the original arrival plan is required on this dataset for external demand uncertainty. For the internal resource uncertainty, the availability/capability of port facility is configured by the number decreasing/increasing. While the operational interdependency depends on the whole operation condition, not direct configurable.

4. Output of the port operation towards the research interest, the vessel berthing time and the vessel departure time are the output. Collecting this data from physical system to compare with the virtual system for DT model verification.

4.2.2 Simulation modelling

The DT is modelled in microscopic discrete event-based simulation by considering containers as the microscopic object. Simulation transfers a container between two port facilities creating a linkage of operation time between them. This facility-facility link bonds a numeric information. Simulation can apply uncertainty as an event interfering operation time so assuming that a container is also a carrier transmitting an impact of uncertainty. Through its travel on port facilities, the simulation output of vessel operation time and departure time is then interpreted as the accumulated result of an uncertainty impact through a time-space.

4.2.3 Generation of simulation data

According to two physical-virtual synchronizations mentioned earlier in this section, two sets of output generated for 1)validating the physical-to-virtual synchronization and 2)making use of output to feedback on the virtual-to-physical synchronization.

To validate the DT model, the simulated output is used to compare with the output of physical system under the condition that they must be from the same timing or the same event. This experiment captured output for validation on events of vessel arrival and departure.

For further analysis of virtual-to-physical, the pattern of simulated output depends on the purpose of data usage. This DT model purposes to support the reactivity and to be aware the upcoming of uncertainty impact beforehand, the simulated output should be executed continually in advance. Periodical data is chosen.

4.2.4 Model validation

Ensuring that the virtual and the physical port operation generate the same behavior. After the operation with the same set of input, the process behavior and system output are expected to be similar. The validation is separated to input and output validations.

- Input validation: inputs ('truck arrival rates' and 'vessel arrival deviation') are based on distributions, the validation ensures simulation input is similar to the physical system.
- Output validation: to compare 'vessel operation deviation' and 'vessel departure deviation' validating the final output of the port system processing under an uncertain environment.

5 EXPERIMENTATION

5.1 CONTEXT

The experiment used the case of a port in Thailand. The port is a cargo seaport service, both container and breakbulk shipments. For the container ships, the port facilitates ten quay cranes on 1,000 meters hybrid berths for motor vessels and local barges, transferring 20-25 container moves per hour. On the yard, it consists of 23 blocks with 24 rubber tyred gantry cranes (RTGs) for transferring export containers at the rate of 18 container moves per hour and 21 blocks with 25 reach stackers (RS) for stacking import containers. The port provides 131 units of the internal truck for transferring containers between the berth quay and the yard via a 3,000-meter connecting bridge. On the land connecting side, five entrances and three exits are for external truck carriers of export containers. Three entrances and three exits are for external truck carriers of import containers.

5.2 DATA ACQUISITION

Data used for this study was mainly collected under the collaboration with a port of Thailand.

1. Data for virtual operation environment: the inquiry of information regarding the physical layout, the number of facilities, capabilities of facilities and operational policy such as berthing allocation, container loading/unloading, yard allocation, and etc., are gathered on an interview. Additional information of port physical dimension is collected by the Google Earth. The **Figure 4** shows the layout of port yard configured on the port application (left) and the physical yard layout (right).

FIGURE 4: PORT YARD LAYOUT

2. Container input for the port operation: the port connects external access to the seaside and to hinterland trucks. The historical transaction of container arrival and departure in the year 2018 is provided. The information related to the flows of containers are extracted e.g., the ratio of each container type, the number of import/export containers accessing on each transportation modes, frequency of transportation arrival/departure and etc.

Additional information of vessel visits is collected through the port website. It provides information of the vessel plan and visiting status such as the estimated time to arrival (ETA), the estimated time to departure (ETD), the actual time to arrival (ATA), the actual time to departure (ATD) and berth number. Patterns of vessel visits are collected based on the information as illustrated in the **Figure 5**.

Further, the input number of containers generated into the virtual operation should have the similar pattern with the physical operation as well. Then, data distributions are fitted to acquire statistics of external truck arrival rate and vessel transferring rate.

Note for the input of vessel information for executing the DT model on this experiment, the vessel arrival time is based on raw historical data while the number of containers carried by the vessel is calculated based on the statistics of vessel transferring rate due to the limit of data acquisition. Therefore, the result of the operation time and departure time of each vessel from the virtual operation cannot be compared directly to the vessel result in the physical operation. The comparison is made on the deviation of vessel operation time and the deviation of vessel departure time instead.

3. Uncertainty factors triggering the operation: the vessel arrival pattern shown in the **Figure 5** representing the berthing plan of vessels on the top of the figure and the actual berthing period of vessel on the bottom of the figure. Each box represents a vessel, its left edge is arrival time and its right edge is departure time. The same box id on the top section and the bottom section are compared to visual the difference of the plan of vessel berthing and the actual of vessel berthing. Based on this information, the deviation times to the plan of all vessels are specified and fitted into distributions.

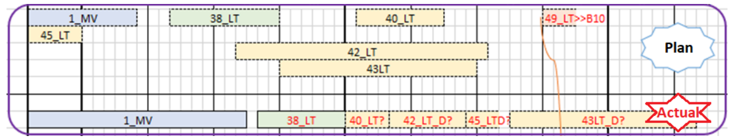


FIGURE 5: A PATTERN OF VESSEL VISITS (PLAN VS. ACTUAL)

4. Output of port operation: as noted in '2. Container input for the port operation' above, the output of 'vessel operation time' and 'vessel departure time' produced from the virtual operation should be compared to the physical operation in order to validate the DT model. Due to the limitation, the deviation of results should be used for the model validation instead. Therefore, dataset of the vessel information from the physical system is calculated for the deviation of vessel operation time and the deviation of vessel departure time (shown in the **Figure 6**) for later to compare with the virtual operation output.

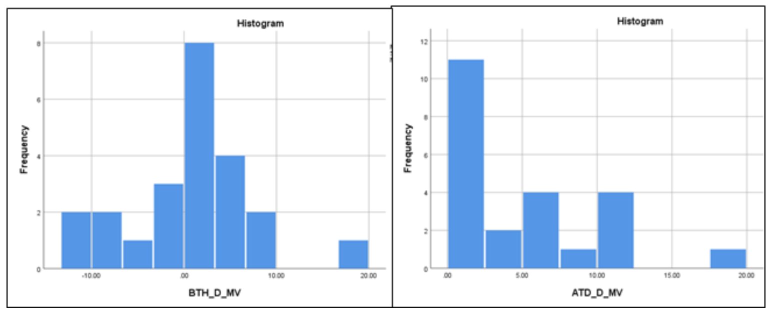


FIGURE 6: DISTRIBUTION OF VESSEL OPERATION TIME DEVIATION (LEFT) AND VESSEL DEPARTURE TIME DEVIATION (RIGHT)

5.3 SIMULATION MODELLING

DT operation environment is programmed to the AnyLogic simulation based on data collected from 5.2. First, data for the virtual operation environment is used to construct the port infrastructure consisting port layout, position of facilities, instance of internal transportation and etc. The physical port layout is transformed to fit in the grid-based layout of simulation with the same dimension as illustrated in the **Figure 7**.

Then, discrete events of container operation activities are implemented in four major operation flows; vessel unloading to import/export yard, vessel loading from the export yard, external truck unloading to export yard and external truck

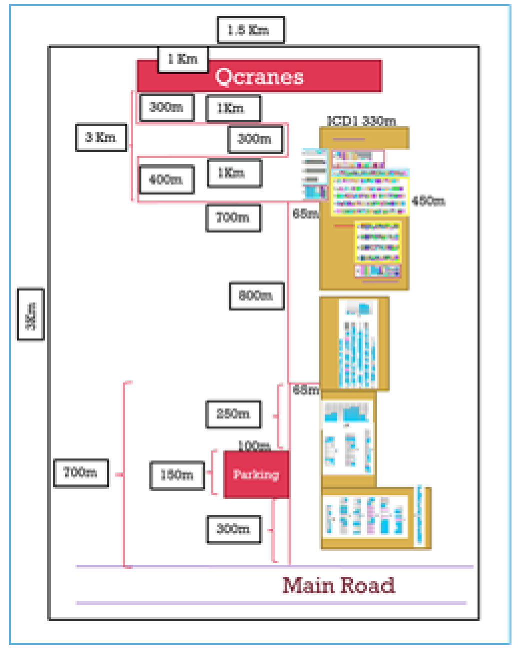
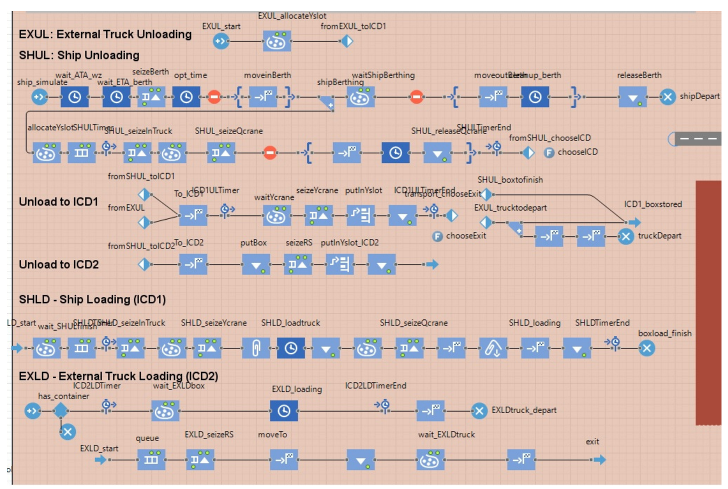


FIGURE 7: DRAFT OF PORT LAYOUT FOR THE SIMULATION

loading from import yard, as shown in the **Figure 8**. Vessels and external trucks are input sources of the model. Vessels are generated into the berth in the virtual space at the time of ETA plus an uncertainty of arrival time. While the external trucks are generated at an arrival rate depending on the day and the hour. Containers are then processed through the port operations as programmed in the flows until loading and unloading of containers to/from the vessel are complete. The vessel is then departed and the next vessel comes to the port on its ETA schedule. Note that uncertainty is configurable to entities of the simulation such external truck and port facility. The **Figure 9** shows the 3D model of port operation simulation.

FIGURE 8: EVENT-BASED SIMULATION FLOW OF CONTAINERS IN THE PORT OPERATION



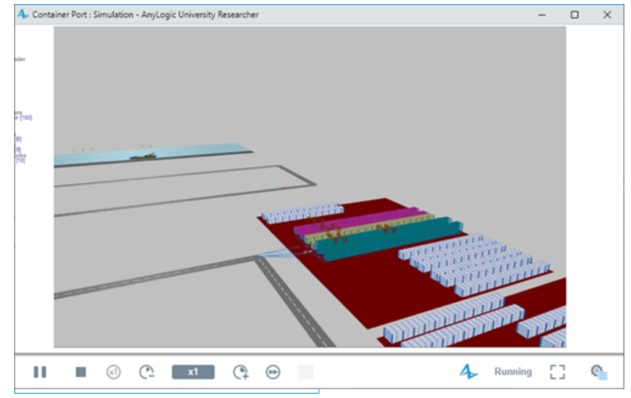


FIGURE 9: SIMULATION OF PORT OPERATION

5.4 RESULT: GENERATION OF SIMULATION DATA

A set of 28 input vessels was simulated for 16 days of the port operation. On the arrival of each vessel to the virtual berth, the actual arrival time was recorded. Once the loading and unloading operations were complete and vessel departed, the actual departure time was recorded as the example shown in **Table 2**. The plan of the first vessel arrival was Feb 12, 20:00:00, but it actually arrived the berth on the same day 20:58:38 with 58 minutes delay. The vessel finished the operation of container transferring and departed on Feb 13, 12:02:17.

The vessel operation time was calculated from 'actual departure' - 'actual arrival', the first vessel operation time was 15 hours and 3 minutes. The vessel departure time was the 'actual departure'. These two data parameters are the output of simulation performed based on the port input such arrivals of vessels and external trucks and the port operation process flows.

TABLE 2: SIMULATION OUTPUT OF VESSEL ARRIVAL AND DEPARTURE

Plan Arrival	Actual Arrival	Actual Departure
Feb12 20:00:00	Feb12 20:58:38	Feb13 12:02:17
Feb13 08:00:00	Feb13 16:39:22	Feb13 20:25:16
Feb14 00:30:00	Feb14 00:47:18	Feb14 04:09:41
Feb14 04:12:00	Feb14 04:28:00	Feb14 12:22:00
Feb14 11:18:00	Feb14 12:36:34	Feb14 15:31:25
Feb14 15:24:00	Feb14 15:48:20	Feb15 01:04:44
Feb15 08:06:00	Feb15 08:21:39	Feb15 10:11:21
Feb17 09:18:00	Feb17 09:32:35	Feb17 15:14:04
Feb17 15:00:00	Feb17 15:30:41	Feb18 01:10:14
Feb17 19:42:00	Feb18 01:28:03	Feb18 03:12:32

5.5 SIMULATION VALIDATION

The source of model input ('truck arrival rates', 'vessel arrival deviation') and model output ('vessel operation deviation', 'vessel departure deviation') are historical data from the physical operation that are validated.

Each model input constructs its statistic distribution. By comparing among distribution shapes using Q-Q plot, the most fitted shape is selected, e.g., truck arrival rate is in Weibull(19.271, 1.847) for weekdays and in Normal distribution(34.22, 14.266) for the weekend. On virtual arrival of vessels, the schedule is based on historical data with a deviation time. The vessel arrival deviation is Gamma(0.7,5). The number of vessel loading/unloading containers are calculated from the vessel transferring rate of each vessel type. Simulation applies selected distributions into the model. Output data generated by the simulation are later compare with the distribution shape such as the **Figure 10**.

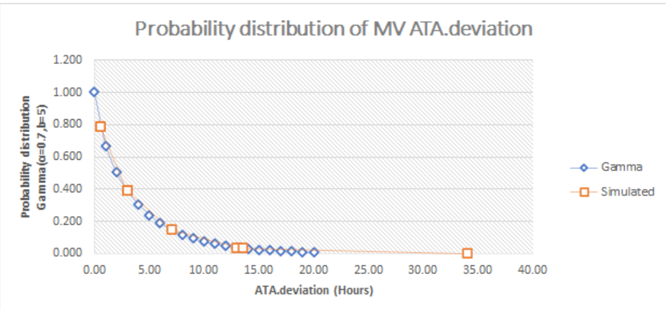


FIGURE 10: INPUT VALIDATION OF VESSEL ARRIVAL DEVIATION

Different from the output validation, simulation output data records are compared directly with historical data. Generally, about 43.5% of results, the difference of vessel operation time are about ± 1 hour. In Figure 11, the average of operation deviation time from the historical data and the simulated data are slightly different. The local barge with the less number of containers (about 1-200 containers) spent less operation time than the physical system. While the motor vessel with a larger number of containers (about 200-2000 containers) spent more operation time than the physical system, as shown in **Figure 11**.

6 DISCUSSION AND CONCLUSIONS

Adjusting the port operation plan under the uncertain circumstance is challenged. Estimating an uncertain situation of a complex environment involving various stakeholders and

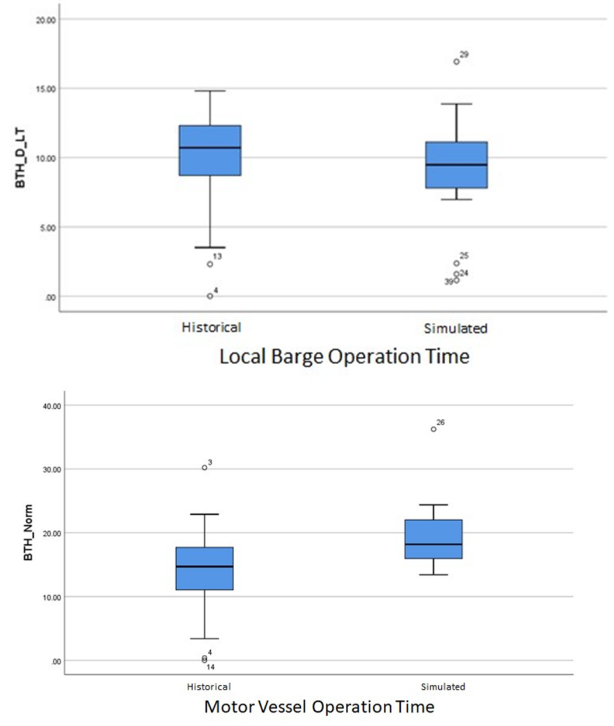


FIGURE 11: OUTPUT VALIDATION OF VESSEL OPERATION TIME

operation interdependency is limited. Currently, it is lacking of the model to acquire information of port operation with uncertainty for operational decision. Therefore, it is difficult for the port to manage uncertainty and make a precise decision of the plan reactivity such the time when the original plan becomes incapacitated.

The presented digital twin model was constructed based on the real physical port infrastructure and the synchronization run was executed using historical data as input to the model. The Results of the virtual and the physical system have similar behavior except in the case of high volume of container arrival. The expansion of the difference in the two systems could be wider than the small volume of container arrival. The operation tuning in the virtual system may improve this. In addition, the port consists of several operation components. This model did not use data of the whole operation in the same time horizon.

The model is validated for physical-to-virtual synchronization. The usage of virtual data for virtual-to-physical applications can be explored. We aim at using periodic data of port facility status to observe the ability to maintain the berth planning by predicting the estimated time to departure (ETD) of vessel in the future time horizon.

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