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Digital twin for decision making to manage port operation with uncertainties : a knowledge approach based on machine learning.

Siraprapa Wattanakul

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**Digital twin for the decision making to
manage port operation with uncertainties.**

An approach based on knowledge from machine learning.

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Par

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Pour l'obtention du grade de

Docteur en Informatique

Digital twin for the decision making to manage port operation with uncertainties : an approach based on knowledge from machine learning

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Introduction

Global containerized logistics had been growing every year along the ten year of 2010-2019 due to market demand with the increased rate of 1.6% to 7.7% per year. Even in 2019, the growth rate was dropped for 3.1% lower than in 2018, the container usage achieved 811 million TEUs of containers (twenty-foot equivalent unit). Nonetheless, in 2020 and 2021 the coronavirus pandemic influenced several changes of global consumption pattern in the whole supply chain including the maritime containerized logistics. These changes show an example of uncertainty in the demand of logistics operation. In addition, there are various more kinds of uncertainty such as machine breakdown, dependency to partners' operation and others unexpected events during the logistics operation. Its effect has further influenced to the adjacent or downstream operations including the container port. Among members of global supply chain, container port is the point interchanging containers among several transportation accesses e.g. trucks, trains, local barges, marine vessels and etc. Port is the point receiving uncertainty from various external parties while it is also the point that has potential to subsidize uncertainty in order to remain the logistics plan of containers.

The port operation is complex. The port system is connected by resource sharing interdependently bonding the three container flows. When a resource proceeds a container, the others containers in the same flow or in the connected flow have to wait. When the resource is held, performance of the connected container flows

are impacted. Specifically, the period that the port is influenced by disturbance or uncertainty impact of both internal or external, performance of the container logistics on the port can become vague due to the interdependency of operation. Due to the complexity of the operational system, this study is then explored into the planning of port resources to specify the critical point for monitoring the existence of uncertainty in the port operational system.

Illustrated in the Figure 1.3, Bierwirth, Meisel proposed the flow of port resource management, three areas of a port are divided as seaside, yard and hinterland for resource management. The model defines the flow of operation planning in each port area under the limitation scoped by the physical layout, location and equipment at the strategic level. This implies differences of physical operation on each particular port such as route direction, container travelling distance and time. While, the operation planning of each particular port is generally in the same/similar sequence and dependence of procedure as defined in the model.

Uncertainty and resilience to changes has become a highlight in the industry perception [116]. Global supply chain consists of various kinds of risk events such as currency, transit time variability, accuracy of forecasts, dependency and etc. An interesting of these risk events is that they are linked to each other in complex patterns. For example, an error forecasting over an operation lead time causes a lost and the management tends to overreact in the next plan resulting over consuming of resources. Transportation transit time and prediction accuracy are in the top considerations of risks among global supply chain managers due to the high variability of operation lead time[69].

It is ambiguous to specify all factors relating the operation lead time, especially at the port. Vessel liners believe that 90% of their schedule unreliability sources is the unexpected waiting time and productivity at the port [81]. On the other hands, the vessel liners have influences to the variability of turnaround time as well. Port is the

central spot switching containers among transportation modes on both seaside and hinterland side and it interfaces to various logistics service operators. Each operator has different perspective in keeping the schedule, some is oriented to the reliability while some is more resilience to delay. Therefore, not only the containers that the port has to handle with these operators but also uncertainty factors that made the actual operation cannot be performed as planned. In addition to the external uncertainties, inside the port itself, the operational uncertainty is also the case that the port has to handle.

Threat and uncertainty exist in the supply chain. The global supply chain network consists of various factors causing uncertainties. In the internationalization trading, the exchange rate, competition and trading barriers are the major factors causing uncertainties to demand, product pricing, costs and lead times. For the factors such as natural disasters and terrorist attacks cause uncertainties to the operation capability. The other factors such as health crises can influence the capability of operation workforce as well. In addition, the operation itself, unexpected events/disturbances can be exploded.

As well as the port, its challenge is to handle various of uncertainty factors which are random in occurrence.

In 2020, the coronavirus pandemic (COVID-19) brought several changes affecting maritime transport globally. Economic tensions drove the trade pattern to alternative markets and suppliers away from China e.g. South-East Asian countries. Then, flows of the container volume were changed as consequence to the changes in demand, as well as the vessel capacity managed by vessel liners[116]. In addition, ports are directly impacted by the pandemic in the change of procedure that additional operation policies for the COVID-19 outbreak were applied costing more operation time [107]. Last, UK's ports were attacked by severe weather [106]. Both the pandemic and the additional factors of congestion such as adverse weather and industrial

action(strikes) contribute congestion to port operation directly and indirectly during the pandemic period [35].

As a result of these threats, several UK's ports were suspended. Later, they faced to several operational difficulties which are high demand to process container volume, shortage of haulage, 140-minute average truck turnaround time and etc. [106]. After the situation had passed for a month, the status reports of the port showed declining of the traffic but the actual service time of vessels are still deviated from the estimated time to arrival (ETA) and the estimated time to departure (ETD) even the ETA-ETDs were rescheduled for a few times.

The proposed approaches in literature integrate only some parts of uncertainties. Current knowledge of uncertainty that is used for the estimation of berth allocation models is limited in the level of statistics at a particular point of port operation, not involved with port interdependency. Meanwhile, uncertainty is not occurred to be stabilized in one operation. Uncertainty magnitude is changed during a passing of time and through the containers travelling in the chain of port operation. Therefore, in order to quantify how much the uncertainties impacting the chain of port operation, the knowledge of uncertainty in dynamic changes impacting to each operation of the port should be captured.

Due to the limitation of existing data to obtain information about uncertainty and it is lacked of knowledge about operational uncertainty, we propose the global framework based on digital twin of the port operation to model the virtual port operation. The digital twin has a main purpose of port replicating to integrate uncertainty into the operational data for later to construct the knowledge base of operational uncertainty for supporting port manager's decision. The framework consist of 3 main stages to conduct the proposed approach. First, the Port Component Extraction defines components for constructing the victual port operation based on the real-world port. Second, the Microscopic Simulation builds the virtual operation based

on the extracted components. The operation is simulated with uncertainty. Last, the Macroscopic Prediction receives the simulation output as the dataset for prediction modelling. Linkages among port operations and uncertainty are explored to construct as the knowledge base to predict port operation states.

Organization of the thesis

This thesis consists of 5 chapters. After a general introduction the rest of the content organized as follows :

- Chapter 1 : description of the industrial context of this study, the maritime port operations and resource management ; the industrial and scientific issues are highlighted (uncertainty, data traceability, knowledge limitation, decision toward uncertainty...) and the main research questions are defined.
- Chapter 2 : State of the Art. This chapter discusses the review methodology that is related mainly to the knowledge for dealing with operational uncertainty, traceability data in supply chains, digital twin and prediction models. The advantages and limitations of some approaches are highlighted in this chapter to introduce and justify our contributions.
- Chapter 3 : Methodology. This chapter discusses the proposed conceptual framework. This framework defines the Digital Twin of the port and consists on three main stages : port component extraction, microscopic simulation and macroscopic prediction. The different steps of the modelling of the digital twin is detailed in this chapter, and some validation scenarios are presented.
- Chapter 4 : Microscopic Simulation. This chapter discusses the proposed infrastructure and the simulation model used in the Digital Twin of the port. The port operations are described and the uncertainty factors detailed. The simulation model is calibrated based on these factors and validate using real data. The results of the simulation are discussed at the end of the chapter.

- Chapter 5 : Macroscopic prediction. This chapter presents the prediction model based on a Recurrent Neural Network (RNN) algorithm and the Long Short-Term Memory (LSTM) architecture that we developed. Two experimentation related to ... are described and the results are discussed.
- Chapter 6 : Conclusion and Perspective. This chapter summarizes the thesis and research contributions. It highlights the challenges of this research, which can be considered in the future to improve the findings.

Chapitre 1

Context and Research Problem

1.1 Industrial contexts

Global containerized logistics had been growing every year along the ten year of 2010-2019 due to market demand with the increased rate of 1.6% to 7.7% per year. Even in 2019, the growth rate was dropped for 3.1% lower than in 2018, the container usage achieved 811 million TEUs of containers (twenty-foot equivalent unit). Nonetheless, in 2020 and 2021 the coronavirus pandemic influenced several changes of global consumption pattern in the whole supply chain including the maritime containerized logistics. These changes show an example of uncertainty in the demand of logistics operation. In addition, there are various more kinds of uncertainty such as machine breakdown, dependency to partners' operation and others unexpected events during the logistics operation. Its effect has further influenced to the adjacent or downstream operations including the container port. Among members of global supply chain, container port is the point interchanging containers among several transportation accesses e.g. trucks, trains, local barges, marine vessels and etc. Port is the point

receiving uncertainty from various external parties while it is also the point that has chances to subsidize uncertainty in order to remain the logistics plan of containers.

1.1.1 Maritime port operation

Container port is a part of global supply chain servicing as a connector point on the logistics network. The logistics of containerized commodities via the maritime involves three major logistics service providers ; vessel liner, container port and hinterland transportation. The logistics of container should be conducted based on the arranged schedules committed by the shipper and every logistics service providers along its travel route. As illustrated in 1.1, the logistics starts from the Point-of-Origin(POO); the factory transports containers by the hinterland transportation such as truck, train or barge to the Port-of-Loading (POL). At the POL, containers are loaded to the vessel liners according to the agreement on the bill of lading (BoL) specifying the travelling route and schedule from the Port-of-Loading (POL) to the Port-of-Transshipment (POT) and finally to the Port-of-Destination (POD). At the Port-of-Transshipment, containers are unloaded from one vessel for transiting to another vessel. Once they are reached to the Port-of-Destination, hinterland transportation picks them to their destination on the land.



FIGURE 1.1 – Actors in maritime containerized logistics

The major role of container port is to transfer commodities among transportation modes based on the pre-arranged schedule of transportation. When an unexpected event occurred relating to the schedule such as the delay of a vessel, the port has potential ability offering an adjustment on the configurations of port resources to

accelerate/decelerate as a reactivity to the circumstance. Ultimately, the schedule of upcoming vessels are maintained as planned without negative effect. However, due to the interdependency of container flows within the port, an adjustment to a part of port operations potentially effects the others parts of port operation.

Operation flows and interdependency

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 1.2 illustrates three connecting flows of containers in the chain of port operations as follows :

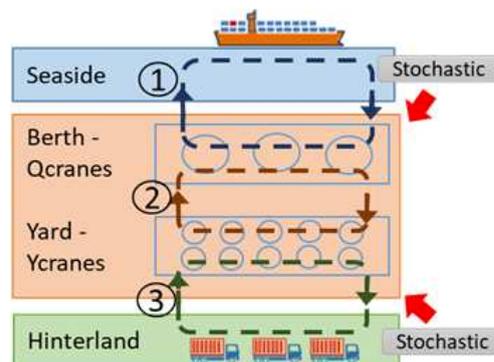


FIGURE 1.2 – Flows of containers on port operation

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 are 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 in the Figure 1.2) and the yard crane/stacker (Ycranes in the Figure 1.2). 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 caused 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 arrived the yard, it waits 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 complex. The port system is connected by resource sharing interdependently bonding the three container flows. When a resource proceeds a container, the others containers in the same flow or in the connected flow have to wait. When the resource is held, performance of the connected container flows are impacted. Specifically, the period that the port is influenced by disturbance or uncertainty impact of both internal or external, performance of the container logistics on the port can become vague due to the interdependency of operation. Due to the complexity of the operational system, this study is then explored into the planning of port resources to specify the critical point for monitoring the existence of uncertainty in the port operational system.

1.1.2 Maritime port resource management

Illustrated in the Figure 1.3, Bierwirth, Meisel proposed the flow of port resource management, three areas of a port are divided as seaside, yard and hinterland for resource management. The model defines the flow of operation planning in each port area under the limitation scoped by the physical layout, location and equipment at the strategic level. This implies differences of physical operation on each particular port such as route direction, container travelling distance and time. While, the operation planning of each particular port is generally in the same/similar sequence and dependence of procedure as defined in the model.

For the container service operation, the port plans the demand of container logistics service receiving from the seaside and the hinterland. Berth on the seaside and hinterland access gate are the first resource planned to handle container accesses from the external of the port. Then, the other port resources such as quay crane, yard crane and internal transportation are planned corresponding to the sequence of port operation flow.

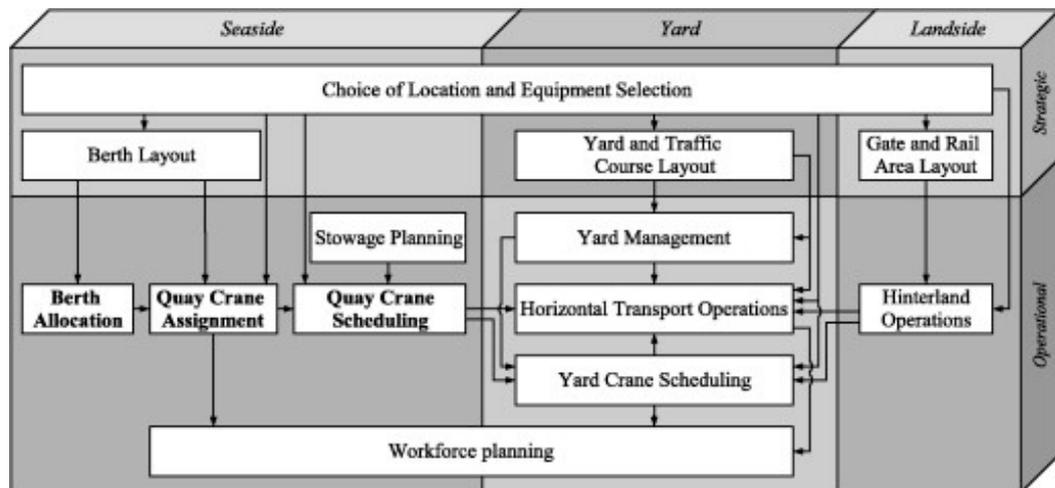


FIGURE 1.3 – Flow of port resource management, [9]

On the seaside, before a vessel visit, the vessel liner usually informs the weekly schedule to the port about three to seven days in advance for the first initial berth allocation. During the time, there can be changes in the visit time or number of containers, however, the vessel has to confirm its arrival information at least 24 hours before the visit. The information includes the estimated of vessel arrival time(ETA), the estimated of vessel departure time(ETD), number of containers and others vessel trip and container information. The port then considers the circumstance of berth and quay crane availability and agreements made to vessel liners to confirm the plan of berthing position and schedule.

On the hinterland side, external transportation such as the external truck and train accessing to drop off or pickup containers. The accessing of transportation from the hinterland side is related to the traffic of local road transportation. There are two general approaches for hinterland access management ; transportation access by schedule using reservation system or by stochastic arrival (no schedule). By the reservation, the information regarding the container pickup/drop off is submitted in advanced. The transportation can access the port at the appointed time, however, there are cases that the transportation does not arrive at the appointed time. For the stochastic arrival, the port services the arrival as first-come first-served (FCFS) basis. There are queues for documentation process, for the yard entrances and for the yard equipment to deliver operation service. The reservation approach offers resource utilization for the port while the FCFS handles containers in stochastic and the arrival of demand for port resources is uncertain.

In the yard, the port yard has to service container demands from both the seaside and the hinterland side by managing a limit set of internal yard transportation and yard cranes. Between the two sides, demand from the seaside is in a higher priority for holding port resources. Vessel liners are direct customers of the port. The port has a contractual agreement to the vessel liner in the service level e.g. the average

of container throughput (transferring rate for loading/unloading containers to the vessel). In addition, the volume of containers from a vessel is usually in a higher number comparing to containers from the hinterland side at a time. The port has to perform the operation as committed, otherwise, a penalty charge will be applied. Therefore, among the set of sharing resources, planning of resources on the yard is based on the priority of transportation. The lower priority transportation or even the maintenance of equipment has to queue up, however, a long time of transportation queuing can accumulate traffic inside the port and also the local road around the port.

Among resource managements in the port operation flow (Figure 1.3), the berth allocation is the critical point. It is the first operation on the port handling a large volume of container from the seaside which is in a higher priority in holding resources. A change to the berth allocation such as the time window of vessel visit, the others resources in the management flow are in a risk of losing balance of the operation performance as defined in the original plan. For example, on an uncertain event such as the delay of vessel, it directly impacts the starting time of berthing, however, remaining the ETD as the original plan is desired as the best case scenario. So, the vessel can continue its travelling to the next port as the vessel schedule. At the port operation, it might require an accelerating of operation. As a consequence, resources on the seaside through the yard operations are in priority to service the vessel. This can further impact to the land gate operation, especially the reservation system of the external truck visit.

In the other cases that the original ETD cannot be kept, the ETD must be extended and this leads to a question : **How much time that the vessel ETD will be extended ?** The answer of this question is used for further decision in the reactivity to the plans that are impacted by the ETD extension such as the incoming vessel berthing plans and port resource planning. However, the estimation of ETD

extension can be difficult due to the complexity of the port operation system with dependencies and combinations of various kinds of operation uncertainty.

1.2 Industrial issues

Uncertainty and resilience to changes has become a highlight in the industry perception [116]. Global supply chain consists of various kinds of risk events such as currency, transit time variability, accuracy of forecasts, dependency and etc. An interesting of these risk events is that they are linked to each other in complex patterns. For example, an error forecasting over an operation lead time causes a lost and the management tends to overreact in the next plan resulting over consuming of resources. Transportation transit time and prediction accuracy are in the top considerations of risks among global supply chain managers due to the high variability of operation lead time[69].

It is ambiguous to specify all factors relating the operation lead time, especially at the port. Vessel liners believe that 90% of their schedule unreliability sources is the unexpected waiting time and productivity at the port [81]. On the other hands, the vessel liners have influences to the variability of turnaround time as well. Port is the central spot switching containers among transportation modes on both seaside and hinterland side and it interfaces to various logistics service operators. Each operator has different perspective in keeping the schedule, some is oriented to the reliability while some is more resilience to delay. Therefore, not only the containers that the port has to handle with these operators but also uncertainty factors that made the actual operation cannot be performed as planned. In addition to the external uncertainties, inside the port itself, the operational uncertainty is also the case that the port has to handle.

1.2.1 Port uncertainties

Threat and uncertainty exist in the supply chain. The global supply chain network consists of various factors causing uncertainties. In the internationalization trading, the exchange rate, competition and trading barriers are the major factors causing uncertainties to demand, product pricing, costs and lead times. For the factors such as natural disasters and terrorist attacks cause uncertainties to the operation capability. The other factors such as health crises can influence the capability of operation workforce as well. In addition, the operation itself, unexpected events/disturbances can be exploded.

As well as the port, its challenge is to handle various of uncertainty factors which are random in occurrence. Consider the relationship of global uncertainty factors, operational uncertainty and the port operation as illustrated in the Figure 1.4,

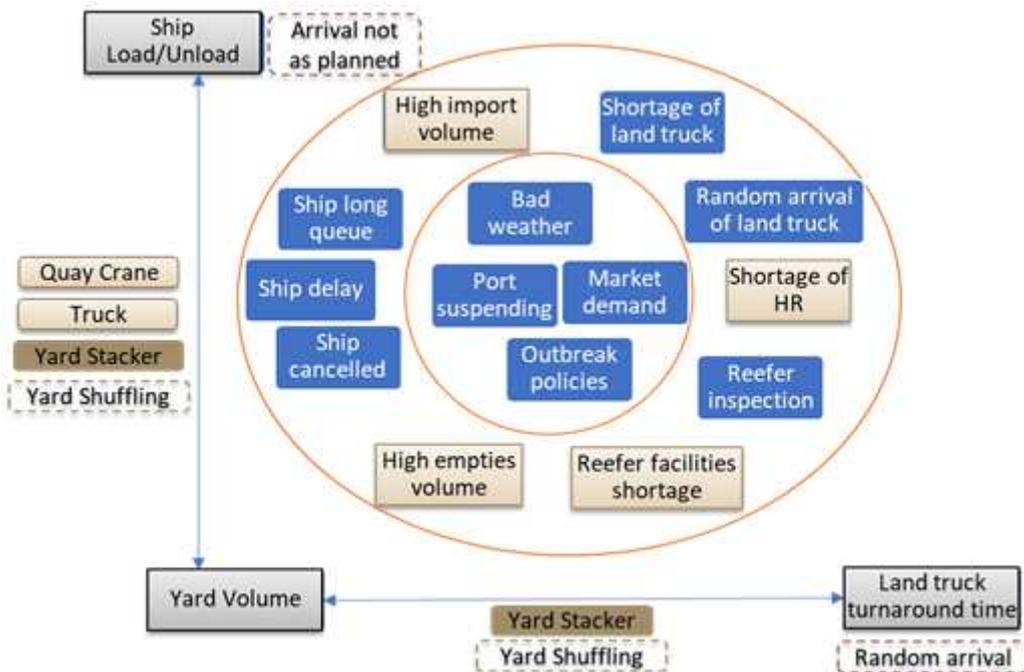


FIGURE 1.4 – Uncertainties and their impacts to the port operation

- Inner ring : represents uncertainty factors at the level of global event or port strategic/policy. These factors can cause operational uncertainties shown in the outer ring.
- Outer ring : represents operational uncertainty occurred in the chain of logistics. At the port viewpoint, an uncertainty factors can cause operational uncertainties in both the external uncertainty and the internal uncertainty. For example, on days with severe weather, vessels are delayed accumulating a long queue and few land trucks pickups the containers out of the port resulting a high volume of import containers in the yard.
 - The external uncertainty are uncertainty that occurs outside of the port such as in vessels and trucks.
 - The internal uncertainty are uncertainty that directly occurs inside of the port such as uncertainty in the practice of port operation, uncertainty in the number of containers holding on the port and uncertainty in the availability of port facilities.
- The flow of port operation : on an occurrence of uncertainty factors and operational uncertainties in logistics, the port has to hold these uncertainties in its operations.
 - The external uncertainty mostly involves the uncertain in the demand for the port service; the time and the amount container arrival. This kind of uncertainty arrives to the port operation via transportation access channels; seaside and hinterland side. Uncertainty via the vessel is such as the vessel arrival is different from the plan. Uncertainty via the external truck is such as the pattern of truck arrival is different from the normal situation.
 - The internal uncertainty is a more complicate in dependency involving several elements of port operation ; number of containers, availability of resources and operation practice. A different configuration of these three elements results a variability of port operation, especially the yard shuffling. For example,

the higher number of containers on the stack leads to a longer time to shuffle containers and retrieve the expected container.

Several of uncertainties and uncertainty factors can be exploded at the same time. Their impacts can disrupt the port infrastructure and the operation performance. The impacts can be remained/increased/decreased in the port operation for a during of time. The combination of these uncertainties accrues a more complex to estimate how much the uncertainties impact to the operation at a time.

1.2.2 Impact of uncertainties to the port operation

Researches in port resilience measured causes-effect of threats/uncertainty factors and assessed how these impacted to the port in the dimension of resilience capacity. Hossain et al. [40] assessed the cause-effect of tornado to the resilience of 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 Bayesian in order to suggest leading factors that potentially improve port flexibility in case of the tornado. Russell et al. [90] 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 a significant relation to the port operational uncertainty. However, these studies focused only on particular uncertainties. Further, the approaches in

quantifying and to handling uncertainty are in the strategic level while the management of uncertainty in the level of port operational system is rarely derived.

For researches that study in the port operational level with an interest in uncertainty, the studies somehow specifically focus on particular parts of port operation such how uncertainty impacts to the operation. Table 1.1 shows the summarized of the port operation in various functions based on the literature. Port operation performance is the major concern of these studies in uncertainties and their impact. For example, in the berth allocation and quay crane (QC) assignment, several studies consider the punctual of vessel arrival time since the vessel arrival affects the port in the actual start time for vessel berthing [125]. In addition, the variation of berthing time window can be affected by the traffic of internal truck operation [125], the container volume on the port [137] and/or weather condition [61]. In reverse, the internal trucks are affected by uncertainties in the queues of quay cranes and the yard cranes (YC) [42]. Further, the YCs are impacted by uncertainties from the stochastic arrivals of external trucks and from the variation of stowage planning quality [133].

As a summarize for the handling of port uncertainty based on the literature, uncertainty factors are studied to quantify port resilience capacity which are measured on particular factors in the strategic level. For the studies in operational level, uncertainties are measured on the impact to the operation performance, nevertheless, only some uncertainties are studied at a particular part of port operations. While the operation in the field consists of various types of uncertainties potentially affect through the chain of logistics including the port operations. Therefore, the quantified linkage of uncertainty impact from uncertainty factors to the port operation performance currently seems to be limited.

TABLE 1.1 – Port operations with uncertainties and their impacts

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

1.2.3 Knowledge limitation

Ports require to manage various kinds of unforeseen uncertainties to level up their performance to the position of competitive excellence. Regarding the question noticed in 1.1.2 that how much of the magnitude that uncertainties impact to the port operations. In particular, the case of berth allocation which seems to be complicated to quantify due to the number of uncertainty factors is enormous (some is unknown or not possible to know). Moreover, the linkage between uncertainty factors to the performance of port operation is ambiguous. Therefore, during the period of uncertain circumstance, the estimation of the vessel berth time in the actual operation can be difficult due to the lacking of knowledge of uncertain situation around the port.

In 2020, the coronavirus pandemic (COVID-19) brought several changes affecting maritime transport globally. Economic tensions drove the trade pattern to alternative markets and suppliers away from China e.g. South-East Asian countries. Then, flows of the container volume were changed as consequence to changes in demand, as well as the vessel capacity managed by vessel liners[116]. In addition, ports are directly impacted by the pandemic in the change of procedure that additional operation policies for the COVID-19 outbreak were applied costing more operation time [107]. Last, UK's ports were attacked by severe weather [106]. Both the pandemic and the additional factors of congestion such as adverse weather and industrial action(strikes) contribute congestion to port operation directly and indirectly during the pandemic period [35].

As a result of these threats, several UK's ports were suspended. Later, they faced to several operational difficulties which are high demand to process container volume, shortage of haulage, 140-minute average truck turnaround time and etc. [106]. After the situation had passed for a month, the status reports of the port showed declining of the traffic but the actual service time of vessels are still deviated from the estimated time to arrival (ETA) and the estimated time to departure (ETD) even the ETA-ETDs were rescheduled for a few times.

A port in Southampton also affected from the occurred events as stated. The port area is almost 1 square kilometers with 1.92 kilometers of deepwater quay and 17 super-post-Panamax quay cranes which are the largest modern type of crane. Even the port is a most productive container port in UK, the port still had a difficulty in estimating the ETA-ETD during the uncertain situation. As shown in the Figure 1.5, on Jan 12, 2021 at 14 :00, APL RAFFLES was estimated to depart on Jan 13, 2021 at 19 :30 but the estimation of ETD was delayed for 7 hours 40 minutes. Even the vessel was already in berthing for about one day but the ETD could not be certain due to the port congestion. So, we implied that the port was lacked of

information/knowledge to estimate an accurate operation time during the congestion circumstance. In addition, the situation combined with several uncertainty factors which are unusual and the port operators might not have been experienced before.

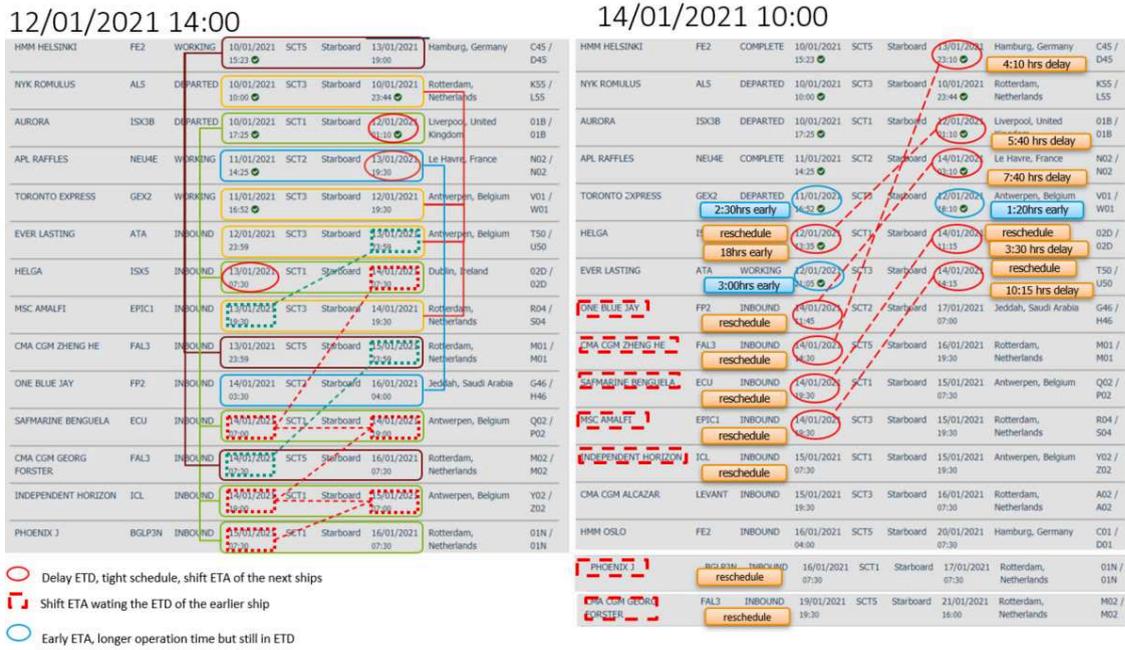


FIGURE 1.5 – Effect of uncertainty to the berth allocation of vessels

Once an unexpected event has destroyed the original plan, a new reactivity plan is then expected. As the example shown in the Figure 1.5, the incoming vessels were rescheduled with a longer wait for berthing. However, the reactivity should be estimated based on a more recent information to gain more accuracy since the berth allocation is the first port operation which has influenced to the planning of the others port resources, the incoming vessels and the others transportation. Therefore, the berth allocation planning (ETA-ETD) using updated information based on the knowledge of port operation with uncertainty impact seems to be an essential function supporting decisions in the planning of port resources.

1.3 Scientific problem

From the above of this chapter, we discuss the contexts and issues of the port operation in the industrial point of view. The following, viewpoints in scientific are explored and presented in the relationship between uncertainties and the port, current approaches for handling uncertainties and the research problem. Finally, the research questions for this thesis are presented.

1.3.1 Uncertainties in container port

1.3.1.1 Uncertainties in maritime logistics

In the 1.2.1, various kinds of uncertainties and uncertainty factors are presented. In the empirical literature, a number of uncertainties are studied in the maritime container logistics as shown in the table 1.2. The table illustrates the list of uncertainties involved with scientific issues in the maritime logistics. Information in the table is acquired by a systematic literature review from the main bibliography sources such Scopus and Web of Science. The data set is acquired by three group of search terms : 1) container, 2) logistics, supply chain, multimodal or intermodal, 3) uncertainty or delay. The search results 157 journal articles. Then, we review articles to filter the final list of 99 articles including the studies that handle uncertainties in the global containerized logistics. The excluded articles are such as uncertainty studies in the other activity of supply chain (e.g. manufacturing, packing, warehousing), in the other sector of logistics (e.g. logistics in general, logistics in the local area, humanitarian logistics), and etc. The final result set ranges from the year 2001 to 2019.

	Strategical		Tactical		Operational	
	Issue	Uncertainty	Issue	Uncertainty	Issue	Uncertainty
1. Global chain (e.g. shipper viewpoint)	(12)		(0)		(2)	
	Network	economic pressure, severe	-	-	Risk analysis: operation	security, time, cost
2. Ship Liner (21)	(6)		(13)		(2)	
	Competitiveness	demand uncertainty	Ship planning	demand uncertainty	Risk analysis: operation	delay
	Risk analysis: cost	disruption, policy			Arrival prediction	stochastic arrival
3. Port (27)	(11)		(10)		(6)	
	Competitiveness	demand uncertainty	Resource planning	external stochastic, operation time	Risk analysis: interdependency	lead time, delay, congestion
	port infrastructure	climate, waterlevel, demand			Risk analysis: breakdown	delay and cost
	Port resilience	hazardous/emergency events				
4. Intermodal Port/Hub (37)	(13)		(17)		(7)	
	Competitiveness	quality of connection, travel time, cost, throughput	Transit flow planning	traffic	Risk analysis: flow	flow time, delay, fault diagnosis
	Port Infrastructure	economic performance, congestion	Resource allocation	delay		
	Network flow	traffic congestion, disruption, transit time	Transport allocation	time-restriction, capacity, delay		
Tracking policy	delay, unexpected event					

TABLE 1.2 – Issues of maritime logistics related to uncertainties studied in the empirical researches

Each literature is then classified in two dimensional table by the actor viewpoint and the managerial level of the scientific issue. The first dimension of actor viewpoint separates stakeholders involving in the issue including 1)Global Chain, 2)Ship Liner, 3)Port : Fundamental and 4)Port : Intermodal. The second dimension is the managerial level of the issue that the literature is focusing on including strategical, tactical or operational. In each boundary area of table 1.2 presents the number of literature studied in the area, the list of interested issues and the list of uncertainties involved in the issue.

1. Global Chain - This research set focuses on the global viewpoint considering consider the overall performance and risks in the logistics network. The research result can supports decisions of various stakeholders in the logistics chain/network e.g. shipper/consignee, ship liner, port, government, etc. They can consider the vulnerability, capacity traffic and risks of the chain/network. About 71.4% of this research set supports the strategical decision and 28.6%

evaluates operational risks in global logistics. There are no studies on the tactical level due to there is no owner that manages problems at the chain level.

(a) Issues at the strategical level : The problems majorly concerns in the change of network stability as follows :

- Network vulnerability : influenced by severe threats such as economic pressure, terrorism, natural disasters, security and safety of the route. The studies only assess the impact of these uncertainties influencing to the network, however, the treatment or improvement of resilience depends on individual logistics agent.
- Network capacity flow : due to the uncertainty of demand, the change of capacity results the container traffic that can influence the service capabilities and competitive advantage of both transport carriers and port [38, 54, 105]. For the shippers, traffic is analysed to identify the potential changes in the flow such as disruptions, security, the transferring between each logistics agents [48].

(b) Issues at the tactical level : Not available due to no managerial ownership in a global issue.

(c) Issues at the operational level : The uncertainty during the operation in global view is identified to analyse the impact in time, cost and security. For example, Arıkan et al. [6] analysed impact of transportation lead-time variability to economic and environmental performance.

2. Ship Liner - the carrier who has to deliver demand of containers to ports by the schedule. Profit and cost of Ship Liner are based on economies of scale. Change of market and demand uncertainty is the major uncertainties influencing its decisions on both strategical and tactical. About 28.6% of Ship Liner research set supports strategic decisions in routing and pricing, 61.9%

manages the demand of container capacity with the optimized vessel space and 9.5% studies in the delay of the vessel operation.

- (a) Issues at the strategical level : For carriers to develop shipping network, pricing scheme and future investment, the market and logistics demand are estimated to get the optimal economic advantage [52, 83]. Furthermore, in order to maximize the profit, the others factors causing addition cost are considered to prevent/control on the selected routing such as port choice selection [132], port perturbation [1] and fuel cost [49].
 - (b) Issues at the tactical level : The demand uncertainty is also the main influence to the planning of ship liners. In order to maximize the profit, the demand capacity and the ship space should be in equal. Therefore, the planning of ship size, a sequence of sail timing on the route, allocation of container space on the ship (both full and empty container), and etc. include the demand uncertainty into the planning model [22–24, 60, 123].
 - (c) Issues at the operational level : Shippers expect the shipping liner to maintain the schedule reliability. Base on the result set of this study, Only two researches study in the delay of the vessel, predicting the probability of vessel delay [91, 109].
3. Port : fundamental - the port who fundamentally operates the container transferring between the port and vessels by considering the schedule of vessel is the major priority. Demand uncertainty also influences to the port similarly to the ship liner and together with the stochastic arrival of transportation. Even with several kinds of uncertainties, port requires to deliver the container transferring speed as contracted with the ship liners. Therefore, a major challenge for the port is the operation time under various uncertainties.
- (a) Issues at the strategical level : Coping with the capacity uncertainty to improve stability for port service as follows :

- Port competitiveness and connectivity : a port with stable processing time and network connectivity for cargo distribution can attract shipper/ship liners. In order to improve its competitiveness, the assessment of container flow proposed to handle with the uncertainty of congestion and demand [28, 112].
 - Port infrastructure : port service can be interrupted by the change of climate, water level, demand. These uncertainties are considered in the port infrastructure to improve flexibility of port service [98, 114, 131].
 - Port resilience : hazardous and emergency events can harm port security and cause disruption to the port. Safety policy and transportation network proposed to reduce the vulnerability [15, 108].
- (b) Issues at the tactical level : As mentioned that port operation time is a significant index, therefore, the planning of the port involves the port resource management synchronizing to meet the service level agreement. The problems are such as berth allocation [26, 58, 117], crane scheduling [2], container yard storage planning [74, 130]. These operations handles with stochastic arrival of containers and reducing delay either from the vessel or from the hinterland transportation [26, 72, 76].
- (c) Issues at the operational level : Port operation is analysed to identify risk and impact such as the lateness of container [103], the closure of port-of-entry [59] and machine breakdown [70]. The impact results mainly in time dimension.
4. Port : intermodal connectivity - the port who extends its functions to control the flow of containers for various kinds of scheduled/non-scheduled transportation such as truck, train or airplane. This logistics role is the most interest area in handling uncertainty. Quality of connectivity, transit time and cost are priorities.
- (a) Issues at the strategical level

-
- Port competitiveness : researches analyse the risk in the quality of connection to hinterland e.g. port throughput, travel time and cost [27, 36, 99].
 - Port infrastructure : the infrastructure models propose to cope with congestion, transshipment time/delay, capacity expansion, etc. [7, 97, 111].
 - Network flow : uncertainty in traffic congestion, disruption and transit time are analysed to improve the hinterland network flow [8, 71, 86].
 - Tracking policy : technology such as RFID proposes the visibility to shipment delay and unexpected events in terminal operation [5, 16, 77].
- (b) Issues at the tactical level : Concerning in the uncertainty of delay in transferring, several studies propose models for the transferring under the uncertainty of time and capacity, to allocate resources(staff, facilities, inter-terminal transportation) [21, 68, 135, 136], to allocate transportation slot [45, 65, 102, 120], to allocate space in real-time [25, 87] or to plan the container move based on traffic flow [41, 101, 128].
- (c) Issues at the operational level : The operation of container flow propose to analyse flow timing [3, 57, 110], the delay and missing of transshipment[18], port operation handling time [53, 67] in order to understand the time constraint and minimize transfer time/delay.

Considering the number of studied literature, the trend increases from the upstream actors to the downstream actors. The lowest is in the global chain viewpoint at 14 studies and the highest is in the port :intermodal viewpoint at 37 studies. Among actors in the chain, from the global shippers to the port, the port is more interesting for the further study into the problem according to the number of impact as reflected.

Further exploration into the list of issues and uncertainties, the uncertainty of the upstream actor can cause the issue of the downstream actor at a higher managerial

level. For example, delay time and stochastic arrival are uncertainties of the ship liner at the operational level, however, these uncertainties becomes the causes of uncertainty in planning the port resources at the tactical level. Furthermore, these uncertainties in the operation time extend their impacts to the port intermodal connectivity at the strategical level. The quality of connection, traffic flow and delay become the major focus to improve the port strategy, however, uncertainty is a major cause of these strategic index which occurs in the operational level. In the other words, in order to improve the connectivity of the port, uncertainties should be monitored and detected at the very early stage. Therefore, the port is the point of interest to handle uncertainties occurred in the operation of maritime logistics.

1.3.1.2 Uncertainties in port operational functions

Further study into the current approaches how ports handle operational uncertainties, it is rarely found the literature that includes operational uncertainty through the chain of port operation even if there are some studies concerning in the operation dependency. Table 1.3 shows the list of port decisions for resources management that involves with the operational uncertainties.

At the berth, the planning of berth and quay crane are the core resource facility of this area. The berth allocation plans the time window for vessels coming to the berth for container loading/unloading. On the allocation decision, some works consider an individual resource type separately; the planning of berth[55, 118, 126] and the planning of quay cranes [2]. Some solutions combines the berth together with other resources in the consideration regarding that the performance of the berth has a relationship with these resources; with quay crane assignment [37, 64, 94] and with yard allocation [66]. With a forethought of uncertainty the decisions include the uncertainty in vessel arrival [37, 55, 66, 118, 126], the uncertainty of quay crane

Port Operational Decisions		Sea	Port				Land
		Ship	Berth	Quay	Yard	InT	ExT
Berth Management	• Berth allocation	Y	Y				
	• Berth allocation and quay crane assignment		Y	Y			
	• Quay crane scheduling			Y	Y	Y	
	• Berth and yard allocation	Y	Y		Y		
Yard management	• Yard congestion template	Y			Y	Y	
	• Yard truck scheduling and storage allocation			Y	Y	Y	
	• Yard crane - storage allocation	Y			Y		Y
	• Yard reshuffling	Y			Y		
	• Yard reshuffling with truck appointment				Y		Y
Gate Entrance	• Hinterland transport scheduling	Y					Y

TABLE 1.3 – Area of information supporting port operational decisions

productivity [2, 64, 94] and the uncertainty of operational travelling distance between the berth and the yard [66].

At the yard, there are two areas of decision for yard functions; the first is the container travelling route to/around the yard and the second is the container storage space. Yard congestion and operational interdependency with interruptions from external trucks are major concerns in these areas.

For the yard traffic, studies decide on the travelling distance between the vessel and the yard by considering the yard template in order to minimizing the travelling cost/time and the congestion [46, 47, 138, 139]. Some studies considers the flow containers in between port operations. Niu et al. [79] manages uncertainty in the operational interdependency by minimizing total delay for all schedule jobs of quay

crane, yard crane and truck. Cavone et al. [13] optimizes container transferring speed with the maximized container flow and minimized residual fluid container.

For the yard storage, yard crane is the main resource to stack/retrieve containers at the allocated stack position. Several kinds of tasks hold the usage of yard crane ; 1) to service containers from vessels, 2) to service containers from hinterland truck, 3) to reshuffle containers preparing for fast retrieval while the crane is idle from the service calling and 4) to maintain the yard crane.

- Servicing containers from vessels and hinterland trucks - container liners are customers of the port. Motor vessel is usually in priority to hold resources for container transferring within the vessel handling time. However, hinterland trucks waiting for yard crane service can increase traffic in the yard. Moreover, vessel arrival can be delayed and truck arrival is generally stochastic. Lin, Chiang [62] proposes to minimize the potential number of yard crane movements by integrating tasks of the vessel handling with the possibility of tasks of container retrieval for hinterland truck.
- Yard Reshuffling - containers are reshuffle on stacks to organize sequences for the vessel loading, however, vessel can be delay or information of container sequences is uncertain. Gharehgozli et al. [32] proposes to include the probability of vessel delay to the reshuffling algorithm. Le, Knust [56] minimizes the number of used stacks for containers with unsure information. Covic [19] includes the appointment of hinterland truck into the sequencing of reshuffle function in order to reduce the number of shuffle moves.
- Yard crane maintenance - this task is in a lower priority comparing to the others tasks of crane. The maintenance schedule is frequently shifted due to uncertainties. Lacking of maintenance can lead to a problem during the operation.

At the Hinterland entrance gate, the gate is the checkpoint registering the external transportation. Generally, the hinterland transportation arrives the port in random as a stochastic service. Several studies proposes the queuing system or the appointment system to manage the arrivals. Chen, Jiang [14] proposes the truck scheduling by time windows with the consideration of vessel arrival time. [55] points to minimizing the waiting time of the transportation. Roy et al. [89] uses truck queue to control the flow of traffic from the external which minimizes the external truck turnaround time in the port.

From decision functions along the chain of port operation described above, uncertainty is scattered in every part of port functions. Uncertainty of each operation section is handled separately. Several studies integrate multiple objectives into an optimization for scheduling/allocation solution but not all tasks are integrated. In addition, scheduling/allocation tasks of port resources are interdependent to each others. Therefore, solutions currently proposed in the literature mostly focus on the optimization of a particular task with particular uncertainty types. However, due to the operation interdependence, optimizing a task may induce additional uncertainty in the others task. Then, for considering the operational uncertainties on the port in another systematic viewpoint, we proposes the classification of uncertainty types in the following section.

1.3.1.3 Types of uncertainties in containerized logistics operation

At the operational level, in order to estimate the impact of uncertainty factor, currently the estimation considers only some kinds of uncertainty as shown in the table 1.3. However, measuring and considering the impact of all kinds of operational uncertainties that are effecting the port operations is not rarely found in the literature. Therefore, this study classifies types of port operational uncertainty based on the

flow of relationship among uncertainty factors, operational uncertainty and port operation functions as described in the section 1.2.1, in the Figure 1.4 and above in this section 1.3.1. Three types of operational uncertainties in the containerized logistics operation are as follows :

1. **Uncertainty in demand** : includes any possible changes of container capacity from the external to be serviced by the port, specifically the uncertain to the number of container arriving/departing the port and their arrival/departure time. This type of uncertainty effects the capacity load of containers, balance of network flow and competitiveness of all logistics agent. It affects the strategy of logistics agent to acquire the capacity load to gain profit from the market. Then, it affects the tactical planning to allocate adequate facilities for the logistics.
2. **Uncertainty in resource availability** : considers the change in the capability of port facilities performing the operation, e.g. breakdown, in maintenance and etc. This effects the rate of container throughput serviced by the facility.
3. **Uncertainty in operation interdependency** : includes any situation circumstance effecting the cooperation of several facilities in the port operation network. An uncertain effecting an operation can spread its impact to the others operations. This type of uncertainty occurs in daily stochastic during the operation resulting an uncertain to the operation performance in meeting the planned time and cost.

Instead of estimating each uncertainty factor one-by-one, this classification aims to measure the impact of all uncertainty factors flowing at the operational level in the port network. Generally in the operation, container throughput (number of proceeded container per a time unit) is measured as an index of operation performance and uncertainty is carried with the containers as an effect in the time unit. Therefore, the

impact of uncertainties and the operation performance are reflecting in each other. Uncertainty in demand represents uncertainty travelling with containers from the external into the port operation. Uncertainty in resource availability represents the capability rate of port facilities that process the container flow. Uncertainty in operation interdependency represents the transferring of performance and uncertainty between the link of a couple of operations. These three types of uncertainties are also connected in the container operation flow, therefore, measuring the operation performance at the point of interest on the port reflects the performance calculated based on all uncertainties influencing the port under the consideration of these three uncertainty types.

An example map of port operations as shown in the Figure 1.6 presents the relations of the three types of uncertainty. The dashed arrows represent the uncertainty in demand from the external of port system. Uncertainty in demand enters into the port through the container entrance channels such as vessels, the hinterland gates and etc. Inside the port system, several port operation functions perform to transfer containers from one to one another. The operation function requires resources for container transferring, however, performance of each operation is depended on uncertainty in resource availability as presented in the dashed circles. In addition, the transferring of containers between each two operations is interdependence which is represented in the dashed line of uncertainty in operation interdependency. These three types of uncertainties are interconnected and influenced to one another. Thus, the more complex of relationships, the more occurring of experiences and knowledge to solve for supporting decisions. Further, the knowledge of relations among these uncertainties is rarely found to be explored or to be measured in numerical.

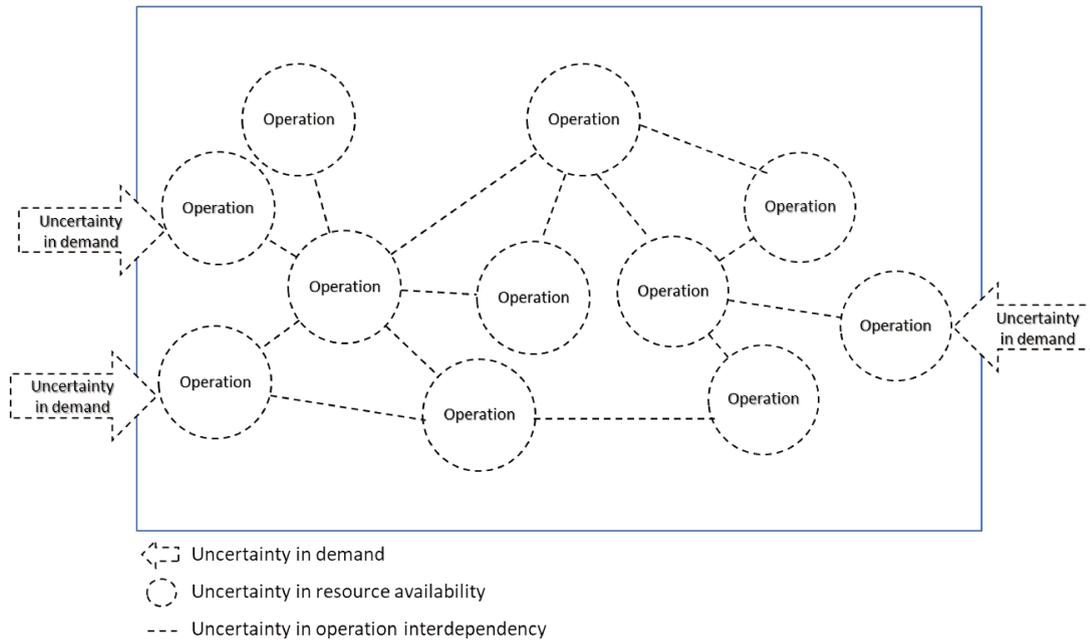


FIGURE 1.6 – Map of port operations with uncertainties

1.3.2 Decision toward uncertainty

After an occurrence of event caused by uncertainty, a period of time is taken to aware insights about the event becoming available. Later, the analysis into the event is conducted and further measurement is performed collecting information to support decision. On a decision of optimization problems, Robustness and Reactivity are two major strategies used to handle with uncertainty in the problem.

The 1st strategy – Robustness

The robustness approach considers the solution based on a set of selected criteria in the efficiency of the operation performance(cost, time, sustainability) and service performance (delay, goods quality).

1. **Cost** - the operational cost is a main part of organization capital cost. Minimizing the cost of operation benefits value to the business.

-
2. **Time** - the supply chain concerns the planning of warehouse, production and time to market so the arrival time of material, parts or product effects to the plan and value of the product. The estimated time of arrival (ETA) and the estimated time of departure (ETD) are specified in every sector of supply chain planning. Controlling the operation time as in the plan is efficient, not to cause an extra cost.
 3. **Sustainability** - every operation consumes fuel and emits pollution. This raises the chance of higher cost in the future. Minimizing the emission in the production is an approach for reducing the cost.
 4. **Robustness in delay** - this criteria applies a configuration to the solution preventing the chance of delay to impact the production. For example, a buffer time is added in addition to the operation lead time. Then, the plan of operation is minimized in chance and in the impact from delay.
 5. **Robustness in goods quality** - this criteria applies to minimize the risk that can damage goods and its value.

These criteria normally are a drawback to each other. Specifically, the case of handling delay by the robustness, the additional of buffer time can reduce chance of penalty cost caused by a delay once in a while. However, it increases an addition lead time in a regular basis which produces zero productivity. Moreover, in case that the delay reaches over the buffer time, a reactivity to the impact of delay is necessary to take into consideration.

The 2nd strategy – Reactivity

To enhance the drawback of the first strategy, this strategy aims to improve the operation performance by minimizing the impact caused by uncertainty. On an event occurs, the following procedure is conducted.

1. Detection - a notification of event occurrence should be detected. Data/information signaling to the event should be observed and monitored.
2. Diagnosis - the root cause of the event should be diagnosis as information for supporting the reactivity decision.
3. Prediction - the impact of event to the plan/operation should be specified in order to make a decision on the reactivity planning precisely.
4. Reactivity - a decision is made to choose a reactivity that minimizes the disruption impact.

1.3.2.1 The case of berth allocation with uncertainty

Berth allocation models also make decisions in the uncertainty handling in two approaches. First, the proactive planning is planned ahead of the actual berthing. The planning approaches are such as rolling-time horizon and robust buffer time which are used to reduce/prevent the chance that the operation has to confront to an uncertain circumstance. The rolling-time horizon plans the regular berth allocation for vessels in a short period of time e.g. weekly under the basis that the shorter of time the more certain of information [137]. The robust buffering allocates extra time window in addition to the vessel handling time as a buffer. In case that the berthing requires more time due to uncertainty, the delay is then not interfere plan of the next vessel berthing [44].

Second, the reactive planning is conducted after an incident has disrupted the original plan. For example, on the vessel arrival delay, [Xiang et al.](#) proposes an approach searching the re-planning solution that minimizes the total impact of changes of all effected vessels in delay time and recovery cost comparing to the baseline. However, the information supporting the reactivity decision seems to be insufficient in the

knowledge about uncertainty. Tool for observing uncertainty from the recent operation is also limit. Therefore, the information about uncertainty type and its impact is hardly assessed. Reactive planning currently uses the static set of data from the historical statistic which is not compliance with the nature of dynamic uncertainty.

A determination set of uncertainty parameters such as vessel arrival time, handling time of loading/unloading containers and/or the other specific uncertainty are commonly used in berth allocation models. The others unspecified uncertainty which may also impact the berthing operation are not included in the planning models. In several models, these uncertainty parameters are left as independent inputs assuming that the information is precisely known in advance. The port operators have to estimate based on their existing information and experiences in the situation which may be erupted from others new factors. Some other models use the probability distribution as input parameter based on the past data which is static in range while the magnitude of uncertainty can be evolved by the time and may exceed the range of the static set. These uncertainty sets can be effective for the planning of regular daily operation. However, in an abnormal situation such as the congestion which is unknown in dynamic of uncertainties, it can be difficult to estimate the operation performance purposely to support decisions on planning.

Few studies addressing the use of dynamic characteristics of uncertainty in the berth allocation model. For the parameter of vessel arrival, [134] predicts uncertainty from data mining to learn the ship arrival based on dynamic tracking of vessel AIS data. For the vessel handling time is still limited in data range. [117] used a finite set of dynamic model which has not yet reflected the actual operation situation. [12] uses the actual states of vessel arrival and operational status concerning uncertainty in the operational constraints but the collected dataset is still limit in a range of time. In addition, as mentioned in the section 1.1.2 , each port operations cooperates

in interdependency procedure and the trace of uncertainties are connected in the operational performing.

The estimation of handling time is limit, [117] used a finite set of dynamic model which has not yet reflected the actual operation situation. [12] uses the actual states of vessel arrival and operational status concerning uncertainty in the operational constraints but the collected dataset is still limit in a range of time. In addition, as mentioned in the section 1.3.1.2, the port operation functions cooperate and are interdependency. The trace of uncertainties are connected in the operational performing.

The proposed approaches in literature integrate only some parts of uncertainties. Given numbers of uncertainties presented above, it is 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.

The incapacity to apply the current planning is the barriers to trigger event for the reactivity. Our goal is to predict this incapacity as early as possible.

The usage of knowledge experiences to support the situation prediction is useful, especially in a complex relationships of uncertainty impacts and port operation functions. However, most literature are introduced just the statistics as the tools to estimate uncertainties but have no linkage to apply knowledge (information) nor considering in an overall impact to the system.

To conclude, the port decision toward operational uncertainty such the case of berth allocation seems to be limited in knowledge about uncertainty for estimating the situation. Port managers consider the scenario individually based on their reasoning, experience and received information. Literature researches propose the use of statistics in uncertainties, however, the uncertainty statistics are measured at a specific point which is represented as one uncertainty source. Meanwhile, uncertainties are

from various sources and influence to the chain of operations. The usage of knowledge experiences to support the situation prediction is useful, especially in a complex relationships of uncertainty impacts and port operation functions. However, most literature are introduced just the statistics as the tools to estimate uncertainties but have no linkage to apply knowledge (information) nor considering in an overall impact to the system. Therefore, this study is interested in extracting knowledge from activities of port operation functions for predicting situation based on the changes of uncertainties.

1.3.3 Research questions

Based on the context and issues described in the Chapter 1 , the main research question and sub-questions are as follows :

Main Question : How to predict the port operation performance under uncertainty by integrating the knowledge base ?

Current knowledge of uncertainty used for the port operation planning is such as the statistics of vessel delay time. Knowledge of uncertainty is collected as one kind of operational uncertainty. Moreover, the distribution statistics is a static finite set of historical data used as a representative of uncertainty in a future time while the uncertainty can be changed. Last, the interdependency of operations is not included to the port planning model, therefore, the linkage between knowledge of uncertainty and the port operation is not explored.

To answer the main question, the following sub-questions are considered in the source of knowledge, the process and the tool construct the knowledge :

Sub-question 1 : Which data to be collected from the physical port to support the prediction of port operation performance ?

This sub-question is for considering the source of knowledge which is eligible to support the prediction of port operation situation ; by considering in the variability and nature of uncertainties, the interdependency of port operations and the availability of data and information in the physical port system.

Sub-question 2 : How to acquire the data with operational uncertainty to support the prediction of port operation performance ?

In the real-world operation in a period of time, the operation might face to a number of uncertainties. However, sources of uncertainties tends to be unknown. The data collection collected from the physical port is limit in terms of uncertainty variability cases. Therefore, this sub-question specifies the approach for collecting data with various kinds of operational uncertainty to construct the knowledge base.

Sub-question 3 : What is the appropriate tool for learning the data collection with uncertainty to predict the operation performance ?

In order to construct the knowledge base for predicting the port operation performance, this sub-question considers the tool for learning the collected data which contains behavior of the port operation and operational uncertainties for transforming data and constructing the knowledge base for prediction.

1.3.4 Conclusion

By the maritime industry, UNCTAD highlights uncertainty and resilience to changes in year 2020 due to its impact linked to the global network in complex pattern. Port is a global network unit with high variability of uncertainty factors. Port challenge is to handle various random kinds of uncertainty. Operation is changed by unknown of uncertainty magnitude, by the taken reactivity and by operation interdependency, so it is ambiguous to specify relationships between the operation lead time and

impact influenced from all uncertainty. In addition, the uncertainty magnitude and the operation lead time are changed overtime.

By the scientific literature, two structural literature reviews are conducted illustrating that kinds of uncertainty are exploded and transferred through the chain of maritime logistics, container carriers and port operational functions. They are interrelated and uncertainty results in the performance of port operation functions. However, researches study in the scope of particular port operation functions. Some researches study in the scope of particular uncertainty sources. While the operation in the field consists of various kinds of uncertainty affecting through the flows of port operations. The quantitative relationships between uncertainty and the operation lead time are, therefore, limited.

The case of UK port congestion during the pandemic period in 2020 shows difficulties in estimating the operation lead time caused by uncertainty. Dealing with various uncertainties e.g. vessel traffic, container volume, haulage shortage and etc., the estimation of vessel lead time such as the ETAs and ETDs were recurrently scheduled. According to the issue and limitations in literature as described, it seems that the information and knowledge for supporting the estimation is limited.

The ability in estimation of port operation lead time to support decisions in port resource management is critical, especially the berth allocation. The ETA and ETD should be estimated at an accuracy, otherwise, the planning of the others resources in the operation flows requires updates in accordance to the changes of ETA and ETD. So, we are interested to use the knowledge of port operation with uncertainty to support the reactivity decision for berth allocation as the case study.

Acquiring knowledge of port operation under uncertainty to construct a knowledge base for later supporting the decisions of port operation is the key of this research to solve described issue. Therefore, this research aims to answer the main question

of 'How to predict the port operation status under uncertainty by integrating the knowledge base?' with three sub-questions to support the answering of the main question :

1. Which data to be collected from the port to support the prediction of port operation performance ?
2. How to integrate uncertainty into the operational data to support the prediction of port operation performance ?
3. What is the appropriate tool for learning the collected operational data with uncertainty to predict the operation performance ?

Chapitre 2

State of the Art

2.1 Knowledge for port decisions

The port operation performance depends on the relationships between the port operation and the event caused by uncertainties. However, due to the complexity of port operation network and various kinds of operational uncertainties, their relationships are dynamically changed by the circumstance of the port at the consideration time. Therefore, estimating the operation performance for the operation planning in advance is a challenge and the knowledge of port operation relating to uncertainties is required.

2.1.1 Conceptual of knowledge for dealing with uncertainty

Uncertainty is a topic for the debate in epistemology since the ancient Greek. In modern history, a number of literature describes the definition of “uncertainty” as inadequacy of knowledge. Knight [51] states how “uncertainty” is different from “risk” by discussing in the field of science and economics. Uncertainty is broader than

risk. Risk is calculable in terms of probability and impact loss so it is controllable even it is unknowable. Uncertainty is in the remaining area that is incalculable and uncontrollable. Risk can be a kind of uncertainty at a lower level which is quantified by impact losses and probabilities. This definition is further adopted for the field of decision making. Uncertainty is relevant not only to the future context but also to the result of behavior after the decision is applied [85].

Model of uncertainty proposed by Van Asselt, Rotmans [119]

Van Asselt, Rotmans [119] points that uncertainty is not simply the lacking of knowledge based on the pluralism. Knowledge is not the truth or certainty. Uncertainty still exists even information and knowledge is available. New information can increase or decrease uncertainty. New knowledge may reveal the existence/behavior of uncertainty that were unknown/misestimated. The author classifies two high-level sources of uncertainty, variability and limited knowledge, with sub-level sources of uncertainty on each. The typology is illustrated as in the Figure 2.1.

Uncertainty due to variability refers to factors that cause the behavior/value of the system/process acting differently. It is also mentioned as primary uncertainty, objective uncertainty, external uncertainty, stochastic uncertainty or random uncertainty. Sub-levels of variability considers dynamic and diversity of things including the system/process itself, the nature/environment, human/social/culture and the relevant to the context such as economic/technology.

Among the variability, lacking of resources/tools to observe and gather empirical information leads to unpredictability as another source of uncertainty; limited knowledge. Limited knowledge is inherited from variability, however, deterministic knowledge can be incomplete that uncertain can be further explored. The continuum of limited knowledge is then ranged from inexactness to irreducible ignorance.

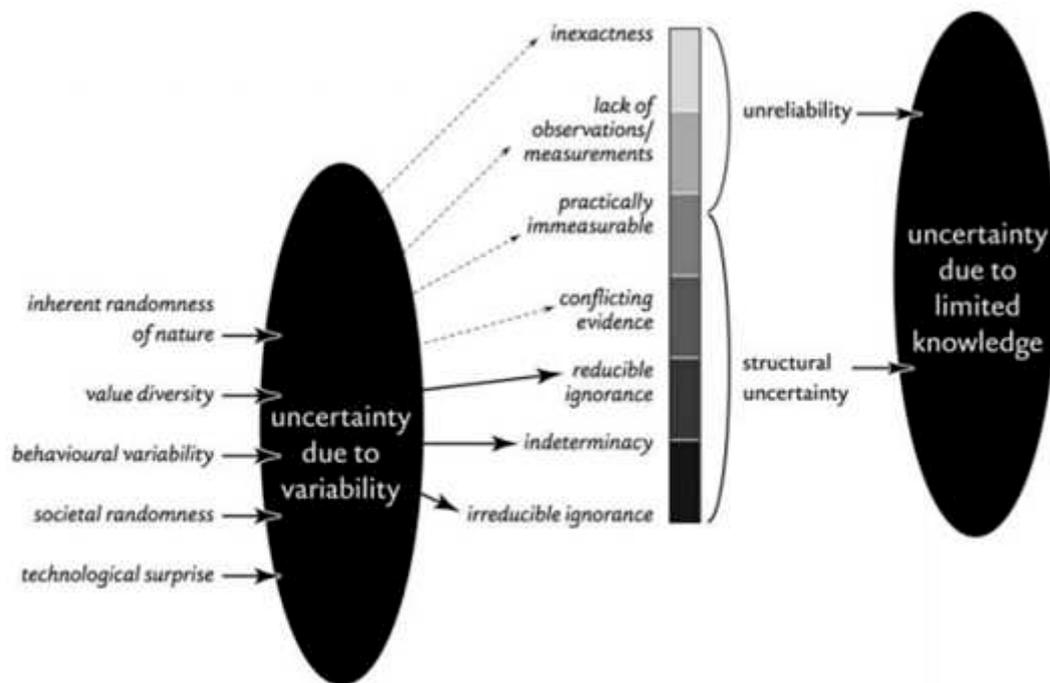


FIGURE 2.1 – Typology of sources of uncertainties

- **Inexactness** : refers to “the roughly known” that every physical quantity is measured but can be affected by measuring errors of a random character.
- **Lack of observations/ measurements** : refers to the lacking data that “could have been collected” but have not.
- **Practically immeasurable** : refers to the lacking data that can be measured in the principle but not practical in the field. At this level, it is “known what is not measured”.
- **Conflicting evidence** : refers to sets of data that are different which requires an interpretation. It is “unsure/uncertain in what is known”.
- **Reducible ignorance** : refers to processes that are not observed by the current theory but may by the future, considered as “inability to observe now”.
- **Indeterminacy** : refers to processes that is known by principles and laws but can never been fully determined. It is considered as “will never know”

such as weather dynamics.

- **Irreducible ignorance** : refers to processes or interactions between processes that is ambiguous to determine by human. It is considered as "cannot know".

Uncertainties in the unreliability group are measurable or calculable from an understood system/process. They can be described by a principle in quantitative with margins/patterns even the best end can somehow be as the roughly known. For uncertainties in the group of structural uncertainty, they are more radical that their existences can be perceived by the conflicting evidence, reducible ignorance, indeterminacy and irreducible ignorance regarding the uncertainty due to variability [119].

Model of uncertainty proposed by Walker et al. [122]

Another perspective to uncertainty proposed by Walker et al. [122], the authors applies concept of uncertainty specifically for decision making in complex system. They define uncertainty as “*any deviation from the unachievable ideal of completely deterministic knowledge of the relevant system*”. Based on this definition, four involved elements are the system, uncertainty, outcome, and knowledge . A conceptual model is proposed to represent a system treating uncertainty that is driven by cause-effect relationships of subjective components within the system. Existing knowledge is used to determine decision focusing on the system performance in the future context.

The conceptual model of uncertainty is proposed in three dimensions; Location, Level and Nature.

Location of uncertainty : involves uncertainty, outcome and the system. The conceptual model represents uncertainty in the location of uncertainty. In other words, once the location of uncertainty is specified, it can somehow be changed due to an extent of uncertainty. Uncertainty driving the system is located in the following parts of the system (consider with the Figure 2.2) :

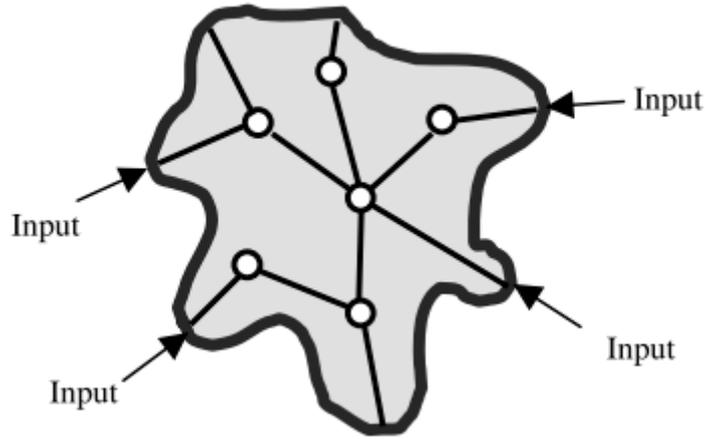


FIGURE 2.2 – Model illustrating location of uncertainty [122]

1. context boundary - scope of the interested system.
2. model structure - including system elements, behavior, cause-effect interrelationship among elements and uncertainty correlated with relationships among inputs, variables, outputs, behavior functions, system boundary, assumptions and even mathematical algorithms.
3. input - referred to uncertainty driving force as input into the interested system. Uncertainty force can be from both external input and internal system data.
4. calibrated parameters - constant values of the model structured in the chosen context and scenarios based on historical data. They represents relationship between input and outcome of the model.
5. outcome - the estimated outcome resulted from the accumulation of all uncertainties stated in 1) to 4).

Value/specification of uncertainty on each location can be changed and inevitable for the outcome. The predicted outcome and the true value outcome can be a gap

due to several uncertainties. The prediction error should be validated by comparing values of these two outcome.

Level of uncertainty : To handle with uncertainty, the ultimate goal is to reduce the surprise of unexpected impacts. Level of uncertainty is classified into a spectrum of knowledge level ranging from the determinism to the indeterminacy of total ignorance as illustrated in the Figure 2.3. This spectrum represents the continual degree of knowledge available for decision making between the well known and the not known about the future situation or about the outcomes from changes.

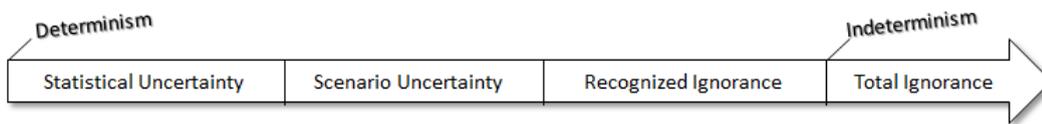


FIGURE 2.3 – Spectrum of knowledge level [122]

- Level 1 : Statistical Uncertainty At any location of the model structure uncertainty, the outcome can be measured or described in statistics including probabilities in the stochastic model.
- Level 2 : Scenario Uncertainty Scenario is used as an analytical tool to describe uncertainties and unknown(able) future. A scenario determines key relationships of system elements and driving factors based on a coherent and consistent set of assumptions. The alternative scenario can be in the form of alternative formulations and/or sets of input data. The prediction cannot specified exactly what will happen ; rather it estimates what might happen.
- Level 3 : Recognised Ignorance System functions and mechanisms are studied in fundamental but lacking of knowledge for developing scientific, statistics or scenarios.
- Level 4 : Total Ignorance This uncertainty is at a deep level. The source or impact of this uncertainty is inconsiderable.

Discussion : knowledge for dealing with uncertainty in the port operation

Model of Van Asselt, Rotmans [119] and model of Walker et al. [122] classified uncertainty into 2 major groups of uncertainties, uncertainty in the problem context with variability and uncertainty in the knowledge level for dealing with uncertainty. The models are presented differently.

In the problem context, [Van Asselt, Rotmans](#) describes the source of uncertainty as factors while [Walker et al.](#) describes uncertainty at more fundamental perspective considering uncertainty as forces that locate and influence to elements around the system. The perception of the first model is similarly to the approach that current literature of port operations reviewed in [1.3.1.2](#) considers the problem context toward uncertainty, a limited kinds of uncertainty is included in the concern. The structure of the latter model is consistent to the structure of uncertainty in the physical port operation as discussed in [Section 1.3.1](#) and as shown in [Figure 1.6](#). Even the [Walker et al.](#)'s model is specifically proposed for decision making in strategical policy problems, however, its concept for modelling uncertainty in the system structure seems to be compatible with the complex system of port operation with uncertainty.

1. context boundary - the port operation system is the scope.
2. model structure - the port operation system consists of several operations as system elements. Each operation interacts to the others operations and has interrelationship among operations in terms of operation performance and uncertainty.
3. input - uncertainty input as the driving force of changes to the system is from both the external partners such as vessels or from the internal operations such as machine breakdown.
4. outcome - the estimated outcome, this research assumes that the result of port operation performance as the outcome of all uncertainties.

5. calibrated parameters - constant values representing relationship between input of port operation uncertainty and outcome of port performance can be specified by the calibration using historical data.

In the knowledge for dealing with uncertainty, at a first glance when forces of uncertainty is affecting, the first step is to understand the context by estimating how much the forces is going to affect the system and later to decide how to react to the situation. [Van Asselt, Rotmans](#)'s model classify uncertainty by the availability of knowledge such how much the context can be perceived, is it possible to be observed or measured or is there a tool for the observation/measuring. While [Walker et al.](#)'s model classifies the level of knowledge by the knowledge form such as in statistical, in scenario, in theoretical or inconsiderable. Both approaches are interested to distinguish levels of knowledge for the port uncertainty.

2.1.2 Source of knowledge for dealing with operational uncertainty

Acquiring knowledge of uncertainty in the context of port operation is complicated due to uncertainty involves in several operations and moreover they are interconnected among operations in the system. Generally, the context of knowledge is discussed as a resource of human while the knowledge as a part of system process is rarely discussed.

The resource-based approach considers knowledge in the viewpoint that knowledge is a resource remained and transferable among human such as SECI model [80]. The learning of knowledge is via the transforming between tacit and explicit knowledge and transferring from a person or a group of people to the others. Socialization, Externalization, Combination, Internalization are activities that transform knowledge.

The model justifies that human first learns new tacit knowledge from the interaction with other people via the socialization activity. However, in the context of uncertainty, a person can learn by the self analysis/synthesis, not limit to the learning from others.

For the port operation during a new uncertain situation, port operators respond to uncertainty based on their own tacit knowledge with/without discussion with the port manager. Somehow, decision of port manager is also majorly based on own tacit knowledge. To manage the organization knowledge, knowledge extraction can be conducted in order to clarify for a better understanding into the situation of how input of uncertainty forces affects the port operation and results the outcome of operation performance. The extraction should transform the tacit to explicit knowledge from the group of staff who involved in the situation due to an action/decision of individual has an direct/indirect effect to the others. However, the knowledge extraction from several people takes time, especially in case that there is a conflict. The situation can be concluded in the level of scenario. Statistics of operation performance such as container throughput is normally measured but it is not identified the relationships with uncertainty or with the others port operation. Moreover, these relationships are too complex to be expressed by human using resource-based approach.

Another viewpoint of knowledge proposed by Spender [100] considers the knowledge in dynamic process-based approach. Body of organization knowledge aligns in the activity system which includes individual and collective knowledge, as well as explicit and tacit knowledge similarly to the resource-based approach but the process-based approach extends form of knowledge dynamically, not only from human. Activity resulted in the system is produced by the combination of the learned such as tacit and explicit knowledge and the unlearned such as some part of environment including

uncertainty which is exist but not yet aware by human. Similarly to the transformation of human tacit to explicit, some area of the system which is autonomy by the nature and unexplained, techniques, tools or technologies are used in somehow to extract and transform tacit to explicit to gain more understanding in the system context.

Technology regarding the socio-technical perspective is at first brought to change the industrial practice by increasing knowledge and also improving work situations for employees. The socio-technical involves the process and the principles of humanistic that are associated to change and technology [75]. However, the technical should not be limited only to serve on some specific tasks but also broaden to unexpected cases as stated by Spender [100]. Such as examples of technology usage for extracting knowledge, connectomic big data is used to represent brain connectivity networks using graph theoretical approach. Also, using machine learning and statistical analytic to gain knowledge of brain functional architecture within the network. Xia, He [124] uses big data of spatial and/or temporal precision, large and long-term sample size recorded from brain activities along with other biological variables and findings to acquire new knowledge of brain mechanism functions in various situations e.g. normal functional, aging functional, disorder functional and etc. In the area of environmental science, Passalacqua [84] proposes the Delta Connectome as a network-based framework to understand the formation and evolution of river deltas processes and to response to perturbations. The network connects nodes of physical attributes with the linkages of process coupling with the function of coastal systems ; by the support of technology to collect data such as satellite image, remote geomorphic sensing tools and etc. The exchanges of energy and information are continuously observed for the evolution over time .

For the context of port operation, the activity of each operation function and its performance result can be perceived and considered as knowledge of the organization

even some uncertain area behind it is unknown. Force of uncertainty is the input to changes in the outcome of port operation performance. Connectivity among all port operation has a kind of relationship which is currently complicate to be expressed by human cognitive due to the unknown force. The uncertainty structure proposed by Walker et al. classifies components involved with uncertainty in the system. The model is adopt in this research to structure components of the port operation in order to explicitly extract relationships of uncertainty and port operation based on the system activities. Traceability data is collected as the dataset representing activities in the port system.

2.1.3 Data of activity system

Uncertainty is dynamically evolved by the time. Collecting data of activity system for chain/network analysis, continual of data is mandatory to retrieve the evolution of uncertainty impact at each point of interest in the system. Traceability data is generally used to control the quality of operation and logistics for organizations in the supply chain. For this study, traceability data is collected during the operation in the field in order to identify risk/event.

Traceability data

ISO 9000 :2015 defines traceability as “ability to trace the history, application, or location of an object” while “object” means “anything perceivable or conceivable” such as product, process, service, person, system, organization, or resource. Traceability of a product or a service can also include the processing record, the distribution and location after delivery [43]. In supply chain, traceability is distinguished by the partnership as internal traceability and chain traceability. Internal traceability collects data within an organizational internally e.g. batch processing. Chain traceability

collects data from continuous productions from several partners along the supply chain; from materials or resources, productions, distributors and/or others [73].

Data of chain traceability can be collected in two approaches as shown in the Figure 2.4.

1. Local collection - An identity(ID) such as barcode, QR code or RFID is attached on the tracking product. Only the information of product ID is passed through operations in the chain. ID data is collected in event-based by a reader. Data is collected and stored separately based on the event type of operation activity. Activities information of a product requires a cooperation of involved organizations to aggregate pieces of product data through the chain.
2. Unitary collection - The product has an ability to collect data and store on the centralize data storage. In another words, activities information of each product is attached to the product and visible through its travelling. Data such as status of the product can be collected in periodic-based and/or event-based depending on the configuration of data collection in the platform.

Currently, the local collection is the common approach for the chain traceability such as the practice of Electronic Product Code Information Services (EPCIS). EPCIS is the only global standard which uses barcode and/or RFID technologies to perform four major activities for the traceability : (1) to identify traceable items, (2) to capture events (date-time, location, event-type e.g. arrival, transfer, etc.) separately by each partner using their own barcode or RFID reader, (3) to share business-critical information with involved partners and (4) to trace the product flow among trading partners [31]. However, the frequency of event capturing limits the visibility of event-based. The tracing status in between reading points during logistics is invisible which further restricts the awareness of uncertain situation. Moreover, due to the scattering of data storage owned by different stakeholders, it requires extra efforts to qualify

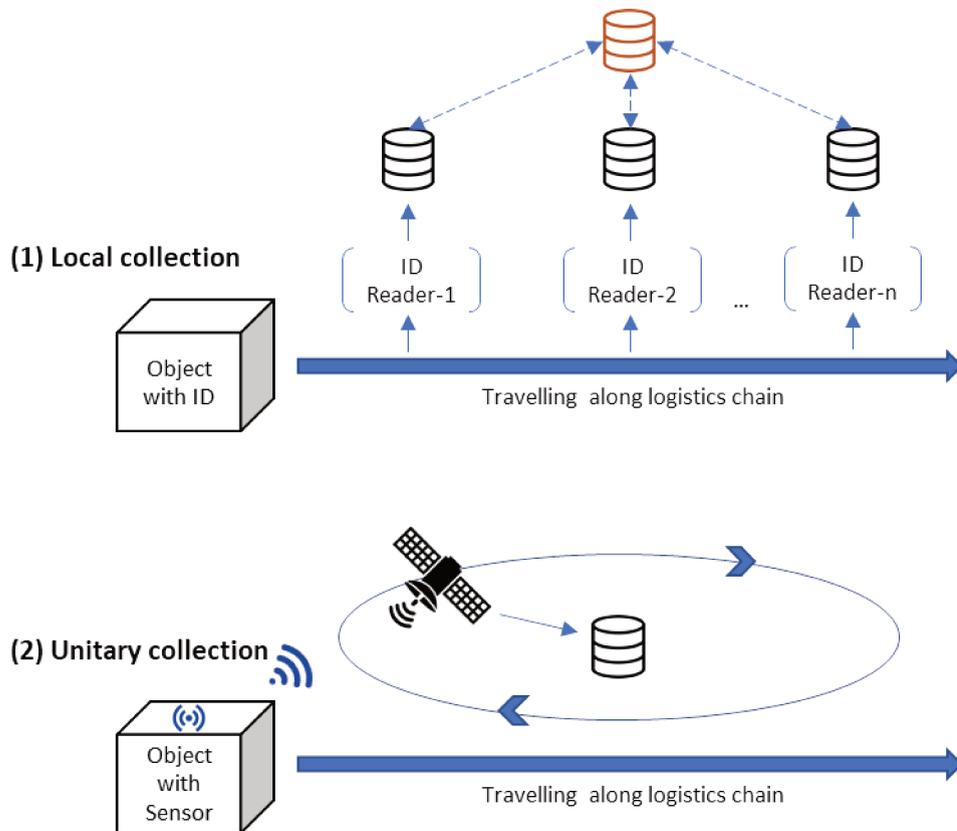


FIGURE 2.4 – Approaches for traceability data collection

chain data. The additional technical implementation such as the data crawling to fulfil requirements of the chain collaboration.

Soon, the unitary collection is possible to acquire from the unitary traceability object(UTO) within the Industry 4.0 environment. Even now it is scarce to adopt the technology due to the difficulty attaching data on an object during the travel, in the future, the collection becomes possible for the case of smart container using as the UTO. UTO is the object which can perform unitary collection. Traxen container solution proposes to sense the actual status of the tracing object (e.g. position, temperature, container's status, etc.) and collect these data to one global data storage in near real-time, not limited to the event-based. Traxens also offers data service platform for clients to monitor smart container and related data in real-time [113].

The visibility is then extended through the chain during transportation in real-time by technologies of the Internet of Things (IoT), also the analysis of operation chain which is currently limited.

Once the operational data is available, in order to explore the potential of how current data is used to support decision in the activity system of the supply chain and logistics, a study is conducted to observe the use of the traceability data to support decisions of the supply chain. A literature review is conducted within main bibliography sources ; Scopus, Web of Science and IEEE. First, major related keywords are searched, “traceability” and “data”, and “supply chain” or “logistics”, and “decision” or “performance”. After merging results from all databases to remove duplicated papers, there are 142 publications from the year 1996 to 2017. Then, papers are reviewed to exclude studies which have no usage of traceability data or the usage is only for tracking and tracing or high-level usage concept without data parameters, for example, studies of methods for tracing resource originality, studies of stakeholder’s perspective based on survey, studies that adopt technologies such as RFID for traceability, conceptual papers and etc. The remained 31 publications are reviewed again in detail and information is structured using mind mapping. The classifications on mind map are structured in three major axes.

1. Acquisition of traceability Data : containing a list of data parameter and type of the data (e.g. master data, transport condition, business transaction), the acquisition tools and the frequency of traceability data acquisition : real-time/ event based/ batch/ offline.
2. Usage of Traceability Data for Decision Support : the use of traceability data is classified into three levels : operational, tactical and strategical. The impact of the decision is also classified into activities of the supply chain process with supported data attributes.

-
3. Issues : presenting issues of technical and business perspectives caused by implementing current traceability system.

As results, 31 publications study in the use of traceability data are classified into three axes as follows :

1. Acquisition of traceability data

Traceability data can be classified into three types by its characteristics as master data, transaction data and condition status. Master data contains permanent or not subject to frequent change data such as identifications, product information, location information, etc. Transaction data contains events captured during the flow of tracing object e.g. shipment information (date of dispatch/arrival, to/from, delivery operator). Condition Status captures parameters related to the tracing object such as the status of surrounding environment e.g. temperature, humidity, position, etc. or the status of tracing object's component e.g. nutrients of food product occurring during the production in the field.

In the data acquisition, the availability of data and information is the major factor for visibility of physical activities occurred in the process flow. Data acquisition can be conducted by different tools e.g. RFID, sensor, GPS, Laboratory or Manual. Data is captured in different frequency : real-time, batch or event-based. For the real-time capturing, data is detected and transmitted immediately and continuously to the information system. For the batch capturing, data is collected once in a time interval or once in a production lot. For an event-based, data is collected by an event action such as product arrival/depart time, recall, etc. The classification of data acquisition of traceability data is as presented in Table 2.1 (note : one research can acquire more than one type of traceability data).

On a traceability system, a combination set of various data types is used. Master data is mandatory that every product tracing defines for the production in the field.

Data Acquisition	Transactional	Conditional Status					
		Temperature	Humidity	Position	Gas	Object's component	Others
Classification by Acquisition tool							
RFID/ Barcode	51.61%			19.35%			
Sensor		35.48%	16.13%		3.23%		3.23%
GPS				9.68%			
Manual/ Laboratory	9.68%	3.23%				9.68%	6.45%
Classification by Acquisition frequency							
Real-time		25.80%	12.90%	9.68%	3.23%		
Batch of production or Time interval	3.23%	12.90%				9.68%	6.45%
Event-based	67.74%	3.23%	3.23%	19.35%			3.23%

TABLE 2.1 – Classification of traceability data acquisition

For the transaction data and condition status data, about two-third of 31 reviewed researches makes use of these data types in different approaches. It is noticed that most of transaction data which can be referred to system activities are recorded in event-based by RFID or barcode. While the condition status which can be used for decision support such as data of temperature, position and humidity are used at 38.71%, 29.03% and 16.13%, respectively. Most of the condition data is detected by sensors in real-time except the data of position which can be collected by the event-based RFID or the real-time GPS.

2. Usage of traceability data

Acquired data is used to support activities of the supply chain process including the decision. The classification of traceability data usage is presented in decision levels e.g. operational, tactical and strategical. First classification by the frequency of data analysis is conducted to obtain the decision behavior in the supply chain, how frequent the traceability data is used to support decisions. Second classification by impacted activities is conducted to specify which activities in the supply chain are interested to use traceability data for decision support. The data usage is mapped to the 9 activities of supply chain process defined by Grant et al. [33]. The classification

result of traceability data usage is as shown in Table 2.2 (note : one research can used more than one area of analysis/activity).

Usage of data	Decision Support Level		
	Operational	Tactical	Strategical
Classification by frequency of data analysis			
Real-time	32.26%	9.68%	
Event-based	25.80%	9.68%	6.45%
Batch of production	9.68%	3.23%	
End of cycle		3.23%	9.68%
Series of process cycle		3.23%	6.45%
Classification by Impacted activities			
1. Customer service and support	3.23%	3.23%	19.35%
2. Demand forecasting and planning		6.45%	19.35%
3. Purchasing and procurement		6.45%	3.23%
4. Inventory management		6.45%	3.23%
5. Order processing and logistics communications	29.03%	12.90%	6.45%
6. Material handling and packaging	6.45%		6.45%
7. Transportation	45.16%	16.13%	6.45%
8. Facilities site selection, warehousing and storage	32.26%		6.45%
9. Return goods handling and reverse logistics	6.45%		

TABLE 2.2 – Classification of traceability data usage

— Decision functions in operational problems

Traceability data is most used to support real-time analysis of operational problem at 32.26%. By the process of supply chain, it is most used in the operation of transportation activity at 45.16%. Decision functions that apply in the operation level generally concern the awareness of uncertainty before it became as an event such as anomaly prediction, pre-warning prediction, food shelf-life prediction and fault diagnosis. Real-time analysis is then important for decisions during the operation. Noted that every researches that analyse

the operational and tactical problems in real-time as shown in the Table 2.2 uses the real-time data acquisition as shown in the Table 2.1.

— Decision functions in tactical problems

'Position' parameter plays an important role in supporting the planning and scheduling of the manufacture [29, 50, 140] and to improve collaboration among partners [4, 82, 88, 121]. The 'position' can be used for acknowledging the position of a sharing object or can be mining for the knowledge of object trajectory to support plan optimization.

— Decision functions in strategical problems

Traceability data is used as secondary information to support the strategical decision. Operational data is modelled to illustrate the big picture of the process. The first usage is to measure the performance of the operation process. A method is by integrating the Business Process Management Notation (BPMN) to the process interaction model. KPIs are measured and analysed for each activity performance along the chain process [30]. In the case of environmental performance, traceability graph is mapped to environmental KPIs e.g. CO₂, CH₄, N₂O etc. [10, 95, 96]. The second usage is to model process from historical data for simulating the process re-engineering. The process model is constructed for the experiment of process change before the actual implementation [63].

Overall, the usage of real-time data is important for the decision in operational and tactical levels.

3. Issues of chain traceability implementation

Challenges which are preventing the estimation of operational uncertainty impact by using the traceability data in current solutions are as follows :

1. Traceability data sharing

Regarding that global traceability of event-based approach, only the relevant data captured by each partner should be shared while respecting confidentiality of all partners [88]. Only necessary interfaces among partners are limited. However, partners are still lack of willingness to share due to concerning in data security and reliability [30, 121] and some partner can choose not to share access code of EPC on their sites [88].

Moreover, in addition to the selected 31 papers studying the use of traceability data, it is interesting that there are 14 papers which propose data models to aggregate data of the chain. These models tend to improve visibility and consistency for real-time tracing, collaboration, and decision-making. By the number of these studies, it is about half compared to the selected dataset. It is assumed that currently there are requirements to improve the linkage of data and information for sharing in the chain level.

2. Changes in business

There can be changes in business which cause uncertainty to practice, process model [121] and decision-making procedure [82]. A dynamic information system which is flexible to changes and enables real-time feedback for precise adaptive decision is required [82].

To consider which approach of data acquisition is practical for using as data of activity system for constructing the knowledge base of port operation with uncertainty. The unitary collection of UTO offers the continual of near real-time data visibility through the chain while the local collection is limited in terms of data sharing and acquiring information of uncertainty from the external partner.

According to Walker et al.'s model of uncertainty structure, data of port system activities and uncertainty information from the external adjacent is essential as an input for the knowledge base construction. UTo offers the real-time through the operation chain which eliminates the process to collect external data. Further, several

usage techniques of traceability data are beneficial for modelling the uncertainty structure using UTO data. First, 'position' and 'time' parameters extends the data integration with the external related data such as operation position, operation performance, planning of the operation, weather and etc. The knowledge base for prediction can be more informative. Second, the traceability data can also be used to formulate the operation process model for simulating and predicting situation in the future. Third, UTO allows the recursive monitoring in real-time. On any change due to uncertainty, a reactivity decision or a business/process adjustment, UTO is the microscopic element in the system which its acquisition process is not altered by the operation changes. Inversely, all information of those changes in the operation is embedded into UTO data of 'position' and 'time' parameters. Therefore, UTO is a robust tool for observing operational data from the chain of port operation as the activity system. The acquisition of UTO data is then be used in the next step of prediction modelling.

2.2 Prediction based on port activity system

2.2.1 Knowledge Engineering

The knowledge-based system (KBS) consists of two main parts : the knowledge base and the reasoning engine. Even, any normal software system can be considered as a knowledge-based system since an extent of knowledge exists in every system, however, knowledge of the knowledge-based system should be able to present explicitly. [92]. The mandatory capability of knowledge-based system is that knowledge of the system should be explicitly represented.

Process of Knowledge-Engineering consists of five major activities :

1. Knowledge acquisition

Knowledge is generally acquired from the knowledge sources such as human experts, documents, books, sensors and computer files. The knowledge may be general knowledge (e.g. about business), or may be specific to the problem/solving procedures, or may be the knowledge about knowledge (metaknowledge).

2. Knowledge representation

Once the knowledge is acquired, it is organized and prepare as a knowledge map to use for the encoding to the knowledge base.

3. Knowledge validation

This activity involves the validation and verification for ensuring the knowledge quality that they are accuracy and acceptable.

4. Inferencing

The inferencing involves the logical of software design enabling inferences to the knowledge stored for the specific problem.

5. Explanation and justification

This activity involves the explanation to the capability of how the knowledge base answer questions.

First, the knowledge from sources are collected in the knowledge acquisition stage. Then, the acquired knowledge is coded into a scheme representing for knowledge base construction. Once the knowledge base is created, it is verified and validated by test cases or experts. Finally, it can be used as a knowledge-based system for solving problems defined in machine inference and to explain the output recommendation [115].

The process of knowledge engineering illustrated in 2.5 is adapted from Turban et al. [115]. Regarding that the port operation activities can be changes by various

sources of uncertainty and decisions from port planner. Moreover, these changes can be acquired through port system activities which data can be collected by the UTOs as a dynamic input to the source of knowledge. Then, the KE model is adapted to align with the dynamic of port operation system and the knowledge base is modelled for continual learning.

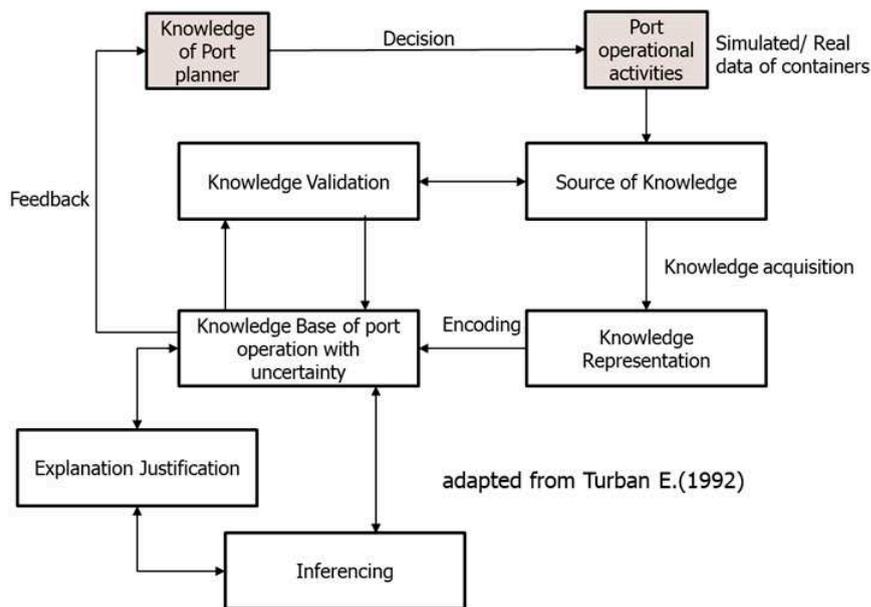


FIGURE 2.5 – Process of knowledge engineering in the port activity system

The activities of KE model are defined in the conceptual perception for knowledge base construction. For the system perception, the flow of data and information for machine learning is applied in the digital twin concept. Even the use of the UTOs to directly collect data of system activity from the port operation, however, still a limitation that all uncertainty cannot be directly observed from the real operation in a short time. Thus, regarding to our research aim for predicting the incapacity to apply the planning, the study proposes to apply a digital twin(DT) allowing to generate in an accelerated way a sufficient volume of data to apply machine learning

for predicting the port performance. Based on the behavior of port operation functions extracted from the collectible set of system activity data, input of uncertainty can be configured to observe the performance of port operation functions.

2.2.2 Digital twin

The term Digital Twin (DT) is defined as the mirroring space model or mirroring product in the context of product life management (PLM) by the University of Michigan in 2002 [34]. The model represents the visual of 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 a risk in operation. The model 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 similarly 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. [39] proposed a DT to support truck dispatching operator. The IoT platform acquired input data for the database. The simulate-based DT was then updated and provided information of current system status to the integrated algorithm. The algorithm evaluated and suggested the dispatching solution for the operator. [141] 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. It is not yet found the study of digital twin of the port operation system during the confronting to uncertainty factors. Therefore, we are interested to apply the digital twin by enabling the scalability of the real-world port performance and executing the operation with interdependency and configured uncertainty several in times of operation execution with interdependency and configurable uncertainty.

The digital twin enables to operate the port system for several of times. In addition, performance with the with accelerate

2.2.3 Machine Learning

Machine learning is a area of Artificial Intelligence (AI) development. AI consists of concepts and ideas from various domains to develop the intelligence system in various areas. It focuses on the thought processes and it behavioral performance. Intelligence systems are proposed to learn human thought process and duplicate the thought process into the machine to solve the problem. The machine intelligence then applies the thinking process for solving the problem with the change of environment or dataset. The machine accelerates the logical thinking at a fine computation even that human has never experienced the solving process with those changed environment or dataset. It is defined as "activity devoted to making machines intelligent, and intelligence is that quality that enables an entity to function appropriately and with foresight in its environment." [78].

Characteristics of the port operation

The problem of port operational with uncertainties concerns changes in the port operation environment impacted by various kinds of uncertainties. This research aims

to predict the port operation performance under uncertainties. According to the literature discussed in the subsection 1.3.1 that the performance of port operation is influenced by kinds of uncertainties. Three types of uncertainties in containerized logistics operation summarized and classified in the subsection 1.3.1.3 leads to the following three main characteristics of port operation which conveys a part of thinking process for the machine to learn the changes of port operation performance due to uncertainties.

1. **Time dependent** - due to operations on the port are interdependency to each others, this causes an amount of uncertainty force from an operation to the adjacent operation. Even if no major change occurs in the port operation environment, the port operation performance could be fluctuated by the time.
2. **Resource dependent** - flows of containerized operation on the port require resources for the logistics activities. Changes in resource capacity result some changes in performance in the logistics flow.
3. **External transportation dependent** - port operation activities are majorly motivated by demand from the external transportation. Port has to deal with stochastic of the arrival time and the amount of containers to handle at a time. The rate of operation performance is then depended on the service demand from the external transportation. Additional concern to this point, the pattern and the period of changes caused by vessels are considered. In 2018, [Sea-Intelligence Maritime Analysis](#) reports the statistics of global container vessel schedule reliability during the year 2012-2018 as shown in the Figure 2.6. Each year, the average of schedule reliability seems not aligning in the same pattern. In some period such as Mar-June 2018, the change of reliability pattern continues for a few months, coherently to the pattern of average delay for late vessel arrival. While some others period, the changing patterns are fluctuate in monthly. In addition, some trade lanes such as Asia to North

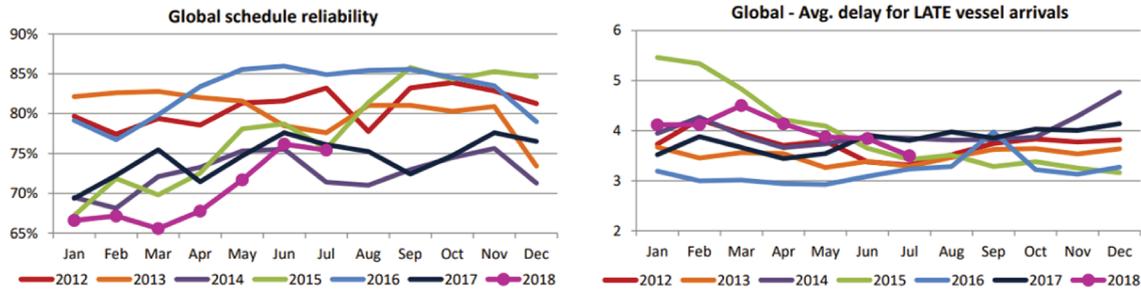


FIGURE 2.6 – Reliability of container liner schedule during 2012 to 2018, globally,
Source : [Sea-Intelligence Maritime Analysis](#)

America East Coast and Asia to North Europe have seasonal patterns that almost every year the schedule reliability tends to drop during January to February due to the Chinese new year [93]. This shows that in the environment of uncertain changes, there are patterns and trends of vessel arrival which by chance to be changed in weekly, monthly, a few months or annually.

Based on these three characteristics as the core of thinking process for the machine to learn how the port operation performance changes when uncertainties are taken into the port operation system, together with the dataset of port system activities and uncertainty information from the external adjacent as discussed in the section 2.1.3 are considered to choose the machine learning approach for constructing the knowledge base of port operation.

2.2.3.1 Machine learning approaches

The machine learning performs functions to learn to identify deep hidden patterns in the dataset or to learn for searching the specific features in the dataset for the specific responses or outputs. De Spiegeleire et al. [20] defines a typology of 5 Schools of Thought for distinguishing the AI machine learning by the field of science.

-
1. Connectionists - based on the neuroscience, the learning of how neurons work to encode knowledge. The backpropagation is developed as the neural-net algorithm to learn from the sample dataset. Inputs are fed into layers of artificial neuron network until the output is emitted. The final output is compared to the output in the training data to validate the correctness.
 2. Evolutionists - based on the evolutionary biology, despite of the connectionists which the mimicry of non-human intelligence to structure in human neural architecture is limit, the genetic algorithms is proposed to emulate and speed up the natural selection. The algorithm is generally used for adaptive systems.
 3. Bayesians - based on the computer science and logic, the algorithm works with statistics on the Bayesian network by estimating the encoded probabilities for several competing hypotheses. When a new information is available, the probabilities is updated under a respective believe. It enhances the ability and transparency of the decision making of the neural network.
 4. Symbolists - the classic strand of knowledge-based AI. General-purpose learning algorithm freely combine rules and knowledge components. The learning aims to mimic scientist's thought process to formulate hypotheses and deduce new knowledge.
 5. Analogisers - based on human psychology, the algorithm searches for the most similar situation encountered in the past to apply for solving problems in the new cases.

The genetic algorithm of evolutionists appears to be used in the port operation problems in optimization such as berth and quay crane allocation. Bayesian network is also used to solve the analysis of structure interdependency among port operations to specify lateness in the operation [104]. For the problem of predicting the port operation performance, the learning aims to recognize the relationship patterns among port operations and uncertainties over the time period. The learning is then from

the dataset of port operational activities in temporal. Connectionists tend to be the learning approach for this problem. AI neural network is the mathematics-based model capable to model the prediction with continuous and complex data pattern.

2.2.3.2 Time-series prediction

In time-series forecasting domain, the parametric models such as ARIMA which are based on linear statistical method has influenced for long time, however, they are not well-adapted to stochastic applications. The others nonlinear time-series models such as autoregressive conditional heteroscedastic (ARCH), the bi-linear model and the threshold autoregressive model are proposed to deal with stochastic data. Recently, the black-box data driven models such Artificial Neural Network(ANN) which are also the nonparametric nonlinear models are in the highlight to learn stochastic dependency from the past to the future. Only the historical data is required for the extraction of nonlinear relationships between input and output of the black-box. ANN outperforms the classical statistic approaches such as linear regression and not require the mathematics expressions as generally used in the others time-series models.

ANN is based on the neuroscience that mimic the behavior of the human brain. The biological neurons which send signal to one another is transformed to artificial nodes and layers of nodes as illustrated in the Figure 2.7. The ANN network comprises of input layer, hidden layer(s) and output layer. Each node connects to nodes in the next layer with associated weight and threshold. Once an individual node is activated by the input and the weight and reached the specified threshold, the node then transmits data to the node in the next layer. ANN models of Multilayer Perceptrons(MLP), Long Short-Term Memory Networks (LSTM), Gated Recurrent Unit Networks (GRU) are discussed.

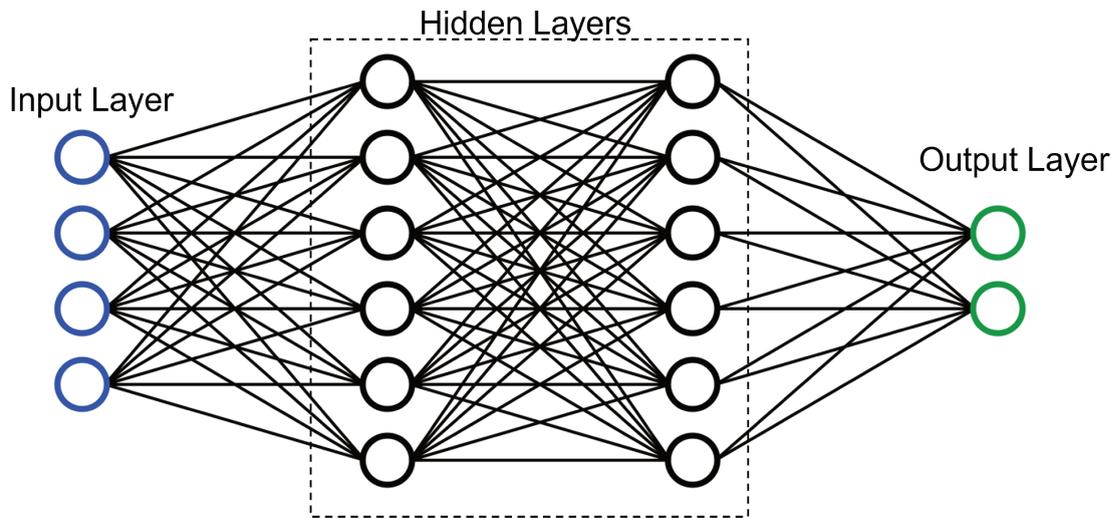


FIGURE 2.7 – ANN architecture

Multilayer Perceptrons (MLP) is a feedforward neural network with the backpropagation algorithm. The data flows in the forward direction from the input layer to the output layer. The weights, biases and activation function of the neuron determine its output passing to neurons in the next layer, repeatedly until it reaches the output layer. The network output is compared to the expected output and the error is computed for each output nodes on the network. In order to maximize the learning performance, error of the neural network should be minimized. Error signals are transmitted backwards to each network nodes from the output layer to the hidden layers which contribute a trace of error to the network output. The backpropagation algorithm searches for the minimum value of the error function to adjust the weights and the biases of neurons using gradient descent. The weights and biases that minimize the error function is then considered to be the solution. Use cases are such as pattern recognition, classification, optimization and prediction. MLP is also used for time-series prediction as shown in the Figure 2.8. The input of historical data observed in $t-1, t-2, \dots, t-n$ to predict output for the time periods $(t, t+1, t+2, \dots, t+h)$.

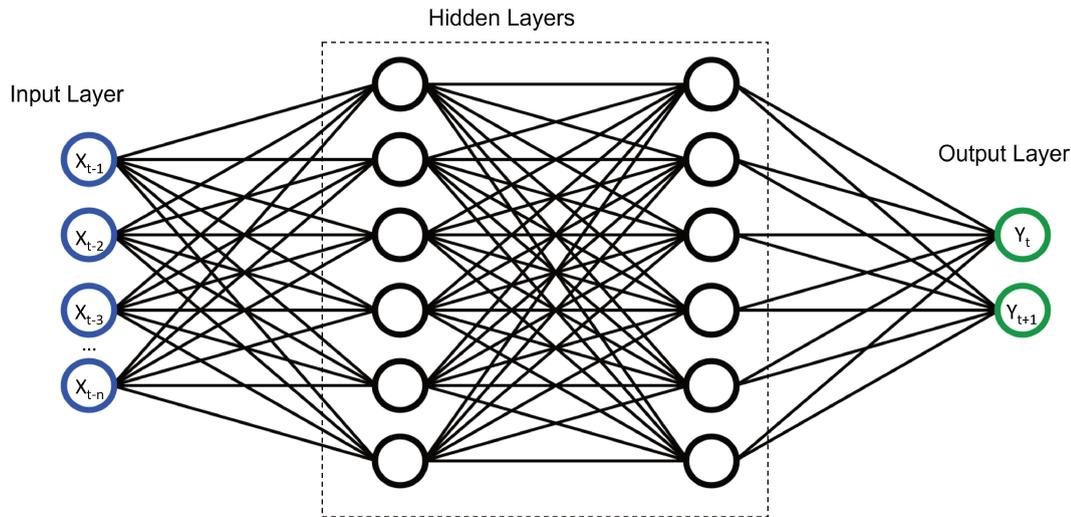


FIGURE 2.8 – MLP time-series prediction

Long Short-Term Memory (LSTM) network is a type of Recurrent Neural Network (RNN) which is a feedback network. RNN has the same architecture of core layers as the other neural network but it has feedback paths in addition. Feedback flows back to the network NN using loops as shown in the Figure 2.9 allowing the network NN dynamically learning from both input signal and feedback signal. As consequence, weights and biases of the network NN are changed continuously. Unfolding the loop, the network is visualized in series of time steps. The feedback of the current time step is signaled to the next time step processing. Hence, the information of previous learning is forwarded to support the following steps of solving consideration with the updated dataset.

LSTM is different from the classic RNN model that the RNN has a problem of gradient vanishing with long-term data dependencies. The gradient descent algorithm of the backpropagation requires to update the weight of all neurons far back through time in the network. This results the vanishing/exploding of weight value and the network is not trained properly. The LSTM proposes the architecture with mechanics to regulate the information flow including input gate, forget gate, output gate

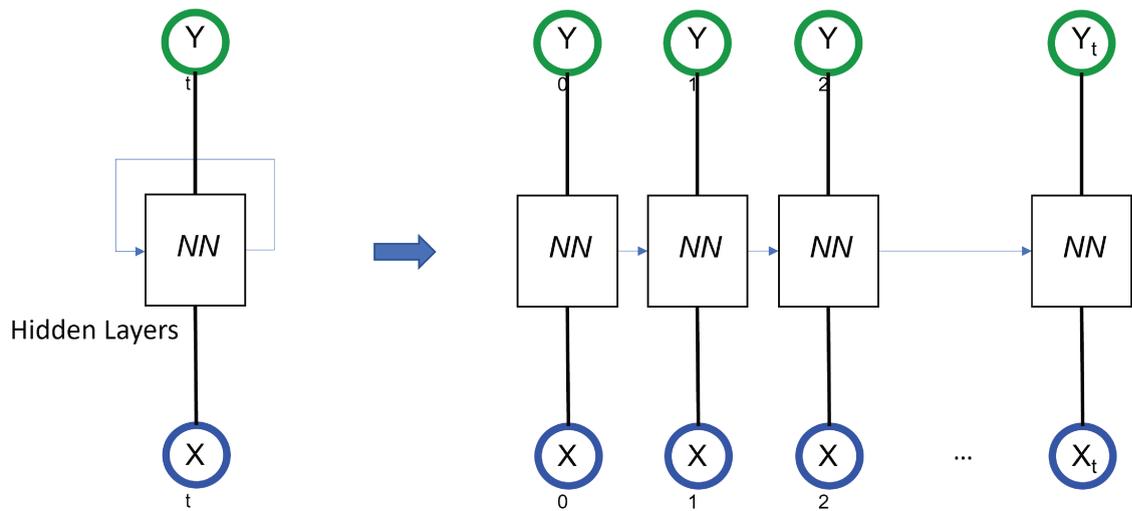


FIGURE 2.9 – Feedback network architecture

and memory cell. The forget gate is used to control the gradient by eliminating some information overtime preventing the problems of gradient vanishing/exploding [17]. LSTM in particular provides additional ability to learn the relevant information from the past and eliminate the irrelevant information allowing the learning information for long periods of time with the preservation of information dependency.

Gated Recurrent Unit Networks (GRU) is similar to the LSTM. GRU network is proposed based on RNN with gate mechanic to regulate the long-term information but with a simpler mechanic. The memory cell as LSTM is removed. GRU consists of reset gate and update gate. The reset gate is responsible for the short-term memory deciding whether to combine the current state with the previous information for current learning. The update gate is responsible for the long-term memory similar to the input and forget gates of LSTM deciding to remember or to forget the previous information in the hidden state.

Applying a time-series machine learning for port operation prediction, additional challenges such the multivariate dependency and the multi-step input and output should be considered for the context.

In predicting the port operation performance, recognition of pattern that variables are dependent in time is expected to learn from the time-series neural network. In addition, the recognition of dependency pattern among port operations with the flowing of uncertainty forces is also expected. Xu et al. [129] proposes a recurrent network to predict the number of taxi calling in each local area with a condition that each local area is dependence to one another e.g. If the number of taxi in a zone is high, the nearby zone tends to be high as well. The study applies the multivariate LSTM time-series model to recognize the dependency of taxi calling in each area. The work shows that LSTM offers ability to learn dependency from both horizontal and vertical variables, similarly require for the prediction problem of port operation performance but the port problem has more variety of data type and ranges of data value while the work of Xu et al. uses the number of taxi calling of each zone as the main variables with a few additional factors such as weather, day of the week and number of drop-off.

In addition, the time-series dataset contains sequence of historical data collection of an observed feature in equal time intervals. It is used to learn knowledge of the past in order to predict the future. [11] emphasize the size of prediction steps that a single-output model overlooks dependency among future values while the *the multi-step forecasting* causes the accumulation of errors, uncertainty and reduced accuracy. In the context of port prediction, the learning and predicting tends to be the multi-step model due to the period of operation learning and the period of performance predicting are in the different ranges. The learning period length should be in a shorter period adequately for the machine learning to perceive the changes in operation states on each learning sequence. The predicting period length is usually expected a farthest period at an acceptable accuracy. Therefore, at a learning sequence, the number of input learning steps and output predicting steps should be explored.

2.3 Conclusion

This chapter, literature reviews are conducted to justify the research approaches in order to define the structure of the knowledge model for port operation with uncertainties, to specify the knowledge source and to specify the approach to construct the knowledge.

To define the knowledge structure of port operation under uncertainty, two conceptual models of uncertainty proposed by Van Asselt, Rotmans [119] and Walker et al. [122] are reviewed. Both models define their models in two parts; the modelling of uncertainty context and the modelling of knowledge for dealing with uncertainty.

Walker et al.'s model is adopted in the port of uncertainty context due to its consistent to the physical port operation with its uncertainty. The model describes uncertainty as the fundamental forces travelling around the system.

For the part of knowledge for dealing with uncertainty, Van Asselt, Rotmans mentions the availability of knowledge to be observed/measured by available tool. Walker et al. classifies knowledge level by its form; in statistical, in scenario, in theoretical or inconsiderable.

Body of knowledge for dealing with port operational uncertainty is aligned in dynamic process-based approach such the activity system [100] than the human resource-based approach such the SECI model [80]. Due to the operational uncertainty dynamically flows in the environment in autonomy by the nature and unexplained, human instant perception is limited.

The next step is to consider how to acquire knowledge from the port activity system. Generally, traceability data is used to track activities of systems. A structural literature review of traceability data is analysed in acquisition approaches, data usages and issues. As a result, the unitary traceability data (UTO) offers capability as the

real-time microscopic data that allows visibility of operation movements through the system. UTO is the eligible tool to acquire data for modelling the [Walker et al.](#)'s uncertainty structure.

Knowledge Engineering (KE) is studied in the conceptual process to transform data of activity system to construct the knowledge base of port operation with uncertainties. Along with, Digital Twin(DT) is used to define the system implementation process to transform data of activity system to construct the knowledge base in practicable. DT offers the generation of a sufficient volume of data with configurable cases of uncertainty scenarios.

Chapitre 3

Methodology

3.1 Conceptual framework

3.1.1 Current limitations

Estimating the port operation performance interfered by uncertainty is in difficulty due to limitations as follows :

1. **Lacking of chain analysis** - due to the research scope of literature (as reviewed in [1.3.1](#)) focus on a specific area of problems or uncertainty type, this limits the analysis of uncertainty through the chain of port operation functions. As a result, impact of uncertainty or the result of reactivity made after the decision are not studied how their impact forces disperse to the rest of port functions out of the scope.
2. **Limited of human knowledge** - human has a limitation in perceiving all details of the happening around the environment. According that, uncertainty and its impact can be noticeable or unnoticeable. Therefore, knowledge about

force of uncertainty relating to the port operation functions is difficult for human to specify in the level of statistical/numerical knowledge without a tool.

3. **Limited of knowledge level** - human knowledge about uncertainty is limited to the level of scenario. Statistical information such as the deviation vessel arrival is frequently used in mathematical optimization formulas. The statistical information is represented as a finite set of uncertainty occurred in the past. However, the relationship of uncertainty information to the others parameters such port operations are rarely constructed in the knowledgeable method due to the equation formulas defines parameters in static relations. Genetic algorithm is used in some studies to construct a knowledge base but relationships of parameters are constructed by the random approach.
4. **Inaccessible of all uncertainty** - the variability of uncertainty is unlimited. Constructing knowledge requires the dataset containing various scenarios for knowledge learning, however, collecting data from the real-world activity system in a short time for the research experiment is inadequate.
5. **Unknowable of uncertainty** - Even the knowledge of port activity is constructed, the input forces of uncertainty is continuously changed by uncertainty force or by the activity made to the system after the decision. Therefore, the estimation should be based on the updated information of port activities. Data for constructing knowledge related to uncertainty should be collected continuously.
6. **Few use of updated data about uncertainty in decision support** - current solutions of port resource planning such as the berth allocation usually apply historical statistics which can be deviated by the time inducing a decrease in the planning performance. Genetic Algorithm(GA) is proposed to integrate status of updated port condition into the planning. The GA

mutation is based on the random approach to search for the optimal solution, however, GA is limited in constructing a knowledge base.

The root problem is that the relationships between uncertainty and port system components are not examined so the prediction of port situation under an uncertain circumstance is limited. Extracting the relationships requires data of operational activities for continual machine learning. The data extends the construction of knowledge about uncertainty which can be further used to support decisions in the chain analysis of port operation functions.

Conceptual of smart container discussed in [2.1.3](#) offers capabilities to be used as a tool for collecting port system activities. Port functions performance can be acquired continuously in temporal and dynamically. So, the status of each port functions can be captured explicitly at the same time for further examining the relationships among port functions and uncertainty at the time.

3.1.2 Knowledge base framework

This research aims to overcome the limitations and constraints discussed above by conducting experiments based on the following conceptual framework (Figure. [3.1](#)). The main goal of framework is to dynamically manage the flow of port knowledge sourcing from port activity system with forces of uncertainty. Knowledge Engineering(KE) is used to control the process of knowledge construction. Digital Twin (DT) supports the generating of synchronized temporal data of all activity instances. Machine Learning (ML) then transforms the data to construct relationships among instances which represents the knowledge of port activity system under uncertainty

forces. The deviation time from the initial operation plan is then predicted to support decision of the port. With/Without changes from the port decision, the framework can continually captures recent port activity influenced by others operational uncertainties to proceed the prediction repeatedly.

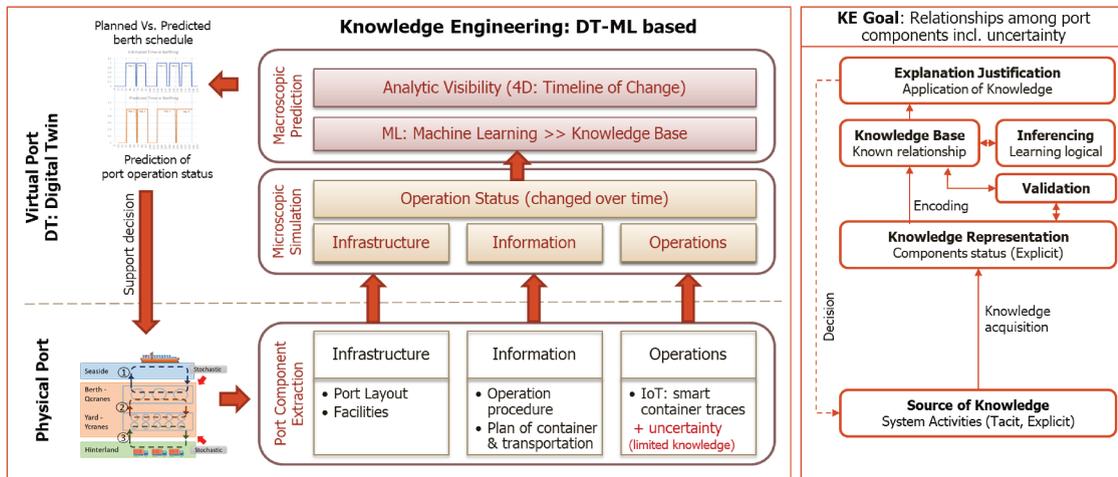


FIGURE 3.1 – Conceptual Framework

3.1.2.1 KE goal

The framework consists of three stages; Port component extraction, Microscopic simulation and Macroscopic prediction. The port information passes through these three stages in the DT cycle with the main purpose to construct the knowledge base of continual machine learning. The knowledge model is based on Walker et al. representing the context of uncertainty in nodes of port functions and relationship links among them.

Starting from the physical port that operators perform operation activity according to the plan. Port Component Extraction distinguishes components that are mainly used for building the virtual of digital twin to execute the port operation. The virtual model also requires including components for Walker et al.'s uncertainty

model which is later constructed as the knowledge base by the machine learning model. Information of these components are acquired from several sources not only from the operation activities but also from the primary and secondary sources ; both tacit and explicit.

The second stage of Microscopic Simulation has the role to transform the physical port operation into the DT virtual port operation. Due to uncertainty in the real-world operation occurs in occasions limiting the size of dataset with traces of uncertainty for building knowledge. Therefore, the virtual port is built from components extracted from the previous stage. With the 3 kinds of classified uncertainties influencing the port system ; uncertainty in demand, uncertainty in resource availability and uncertainty in operation interdependency, are simulated in the virtual port to generate microscopic changes in port operations over the time. Also, the synchronized temporal data of each port operation states and the external transportation states are explicitly generated as the nodes of [Walker et al.](#)'s model and as the knowledge representation of port operation activities embedded with forces of uncertainty. Then, these nodes are input for the next stage to explore the relation linkage among the nodes.

The third stage of Macroscopic Prediction has the major role in machine learning to construct the knowledge base of port activity system for the use of prediction. Based on the input of temporal data nodes, data on each node presents a change of its operation function by the time which might be related to the change of the others nodes. The inference in the changes of operation activities over time and the deviation time from the initial plan are applied for the machine to learn the operation logic and find inter-linkage among the nodes of port operation functions. The knowledge base learns logical changes from the microscopic dataset of all port operations to predict the macroscopic outcome representing port operation performance. The deviated time of operation activity in the coming hours visually presents how

much uncertainty interferes the operation. The deviated time can be used to support decisions of port reactivity plan on how much the deviated time will interfere the next phase operations.

After the decision is applied to the system or not, activities of the system are still continually changed and can be further used for continual learning and dynamic prediction based on the flow of knowledge engineering.

3.1.2.2 Digital twin

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. This research studies the case of berth allocation on the port. Uncertainties are applied to observe their impact on the berthing time; specifically in the deviation of vessel berthing time and the deviation of vessel departure time.

The digital twin proposes abilities to visualize the port operation, to apply scenarios of uncertainty forces to the operation, to generate operational data and to estimate the operation performance. These abilities not only perform in the real-time manner, but the information further promotes an accuracy of the operation estimation in a nearly coming time.

Modelling of digital twin

The virtual system of the DT generally represents the visual of physical object(s) similarly to the simulation. However, in addition to the simulation capability, the

virtual system must have the same behavior as the real system. The physical and the virtual systems 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.

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. After the Port Component Extraction extracts port physical objects and operation procedure to sync with the Microscopic Simulation, the simulation model is validated to ensure that the simulated output has the same behavior as the physical port operation and is valid for knowledge construction by the machine learning.

On the second synchronization of virtual-to-physical, the Macroscopic Prediction model generates the output of berth handling time and vessel departure time in the future hours. They can be compared to the resource plan to specify the deviation time 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 impact of recent uncertainty factors into consideration.

3.2 Port Component Extraction

Components of port operation for implementing in the simulation does not serve the physical-virtual replication of DT model. The output of the simulation must be aligned with the Walker's uncertainty model for knowledge structure. Data at certain

locations of uncertainties must be available for collecting. Further, the rational of uncertainty and operation activities must be included in the simulation data as well. Therefore, extracting components for the port system has to adequately serve the usage in three purposes; 1)to replicate DT modelling, 2)to be knowledge representation applied with Walker's uncertainty structure and 3)to use for reasoning the prediction model using machine learning.

3.2.1 For modelling the Digital Twin

On the first purpose for modelling DT, to simulate the port operation behavior to be as same as the physical port operation. The simulation can modelled in three methods by the level of problem abstraction; macro, meso or micro level. The macro level simulates minimum details of the problem in high abstract level such as the system dynamics model using seasonal/annual statistics of vessel visits to estimate container productivity. The meso level simulates in the intermediate abstraction combining both the high level statistics and the low level of physical simulation. Since this research is interested in constructing knowledge based on system activities which can be collected from the UTOs such as smart container, therefore, the smart container is the macro element interacting in the port system. The simulation is then chosen to be developed in the micro level. Containers are simulated as the major element with some statistical data which is currently limited in the acquisition such as the statistics of external truck arrival.

To model the microscopic simulation to observe movements of containers in the virtual world requires knowledge and information about the port infrastructure and facilities, the port procedure, the plan of container arrivals and data of the smart containers as the Unitary Traceability Object (UTO).

3.2.2 For structuring the knowledge

On the second purpose for structuring the knowledge of uncertainty as knowledge representation. To be more specific in the required data from the simulation, the knowledge model is described based on the concept of activity system and uncertainty modelling.

Knowledge structure

According to 2.1.2, data from the activity system can facilitate the construction of knowledge for dealing with the operational uncertainty. By the consistence, the structure of port activity system (Figure 1.6) has a similarity to Walker et al.'s model which defines uncertainties in the component structure. The Walker et al.'s model is adopted in the context of port operation activities as follows :

1. context boundary

The boundary of this uncertainty knowledge model is in the context of port operation activity system. It includes container logistics operations that use port resources to facilitate the transferring from/to the external transportation or the container movement within the port.

2. model structure

Port operation services consist of vessel berthing (BTH), quay crane loading/unloading (QC), internal truck transferring (ITT), yard crane stacking (YC), external truck gate entrancing (GATE). Each service can have several stations/units. Each operation unit is considered as an uncertainty node with its own attribute(s) which is evolvable by the interdependency linkage to the others nodes or by the input force of uncertainty. Therefore, the value of node attributes and linkages are dynamically changed by the time. Figure

3.2 shows an example case of uncertainty structure of port system. The type and number of port resources can be different on each port.

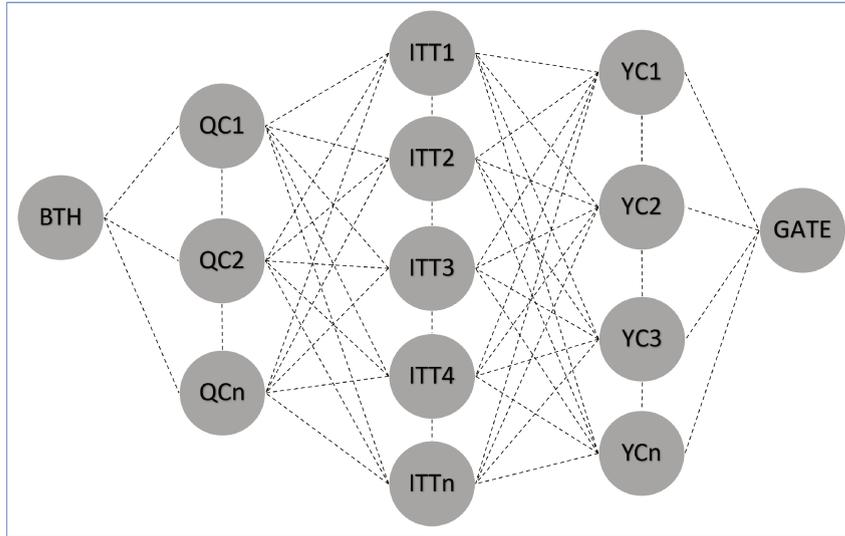


FIGURE 3.2 – Structure of uncertainty nodes with linkages of interdependency

3. input

Uncertainty input is the driving force of changes to the system from both external and internal such as uncertainty in demand from the external transportation and uncertainty in resource availability e.g. machine breakdown. In addition, these input forces can be carried to the others nodes via the operation linkages. Figure 3.3 shows an example of uncertainty input influencing port operation nodes. The input force can occur at any point inside/outside the system boundary.

4. outcome

Uncertainty outcome is the impact result of all kinds of uncertainty to the interested node. For the study case, the vessel berthing time and the vessel departure time are measured and estimated for the next hours outcome as an example shown in the Figure 3.4.

5. calibrated parameters

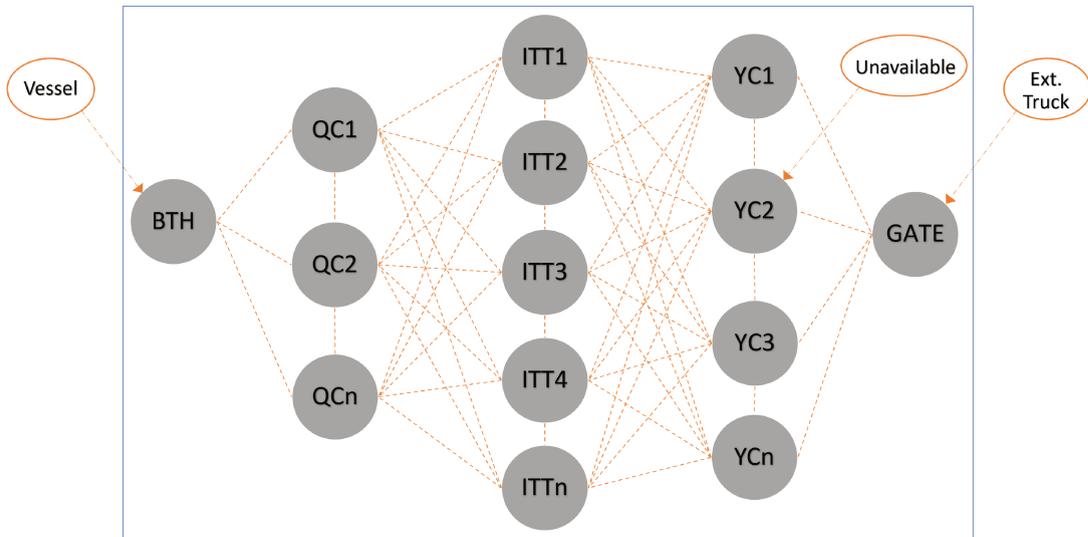


FIGURE 3.3 – Example of uncertainty input forces

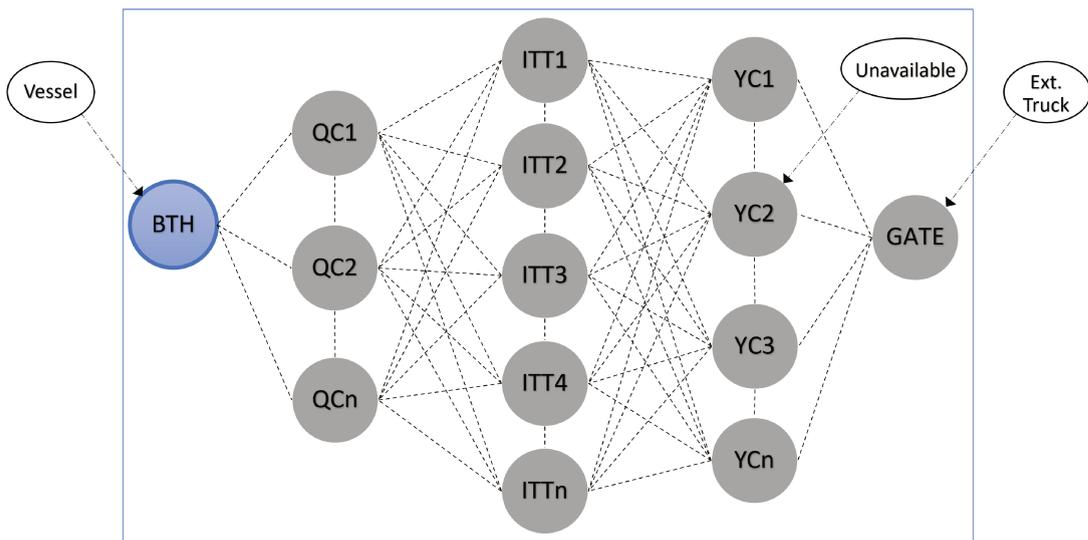


FIGURE 3.4 – Outcome of

In the principle of uncertainty, the set of parameters that shows the relationship between the input and the outcome cannot always be true due to the parameters are calibrated from historical dataset. Their relationship can be changed in the future. Therefore, the knowledge for predicting the uncertainty outcome should consider the number of parameters based on complexity of the system. The more complexity with information variation requires the

more parameters to fit the calibration. Otherwise, using fewer parameters leads chance of deviated prediction from the real value [122].

To construct the knowledge structure of port activity system, each node of the operation service defined in the model structure should capture its value in the form of **performance capacity** in temporal collection. The nodes when integrate with input forces, they reflect the integrated results via the performance capacity of the nodes as well. By the simulation, the input forces such as vessel arrival/truck arrival/ machine breakdown can be configured and generate the dataset of performance capacity of operation nodes. The internal port operation nodes are stated in performance capacity such the number of proceeded containers while the external input forces are stated as the number of queuing containers for BTH/GATE nodes. The dataset is adequate for constructing the knowledge of port activity system by the concept.

However, in the problem of prediction, the machine requires to learn logical of operation activities in order to explore the change pattern of activity occurrence for estimating situation in the near future. The relationships of activities among port operation nodes and the relationship of external activities and the port are different. Especially, the vessel arrival which is the main input force arriving into the port system in stochastic as regular arrivals. Therefore, the prediction using machine learning requires another set of data components that state the happening of external transportation activities (input forces).

3.2.3 For reasoning the machine learning

For the third purpose of prediction modelling using machine learning, the study focuses on predicting the uncertainty outcome which are the vessel berthing time and departure time. The knowledge structure defined above locates the port operation

nodes which generate data parameters for the machine learning. Walker et al.'s model does not specifically define the evolving of the structure change, however, the machine learning has the role to learn the logical of activity changes through the input dataset. This part defines changes of port operations through the dependency among port operations as shown in the Figure 3.5.

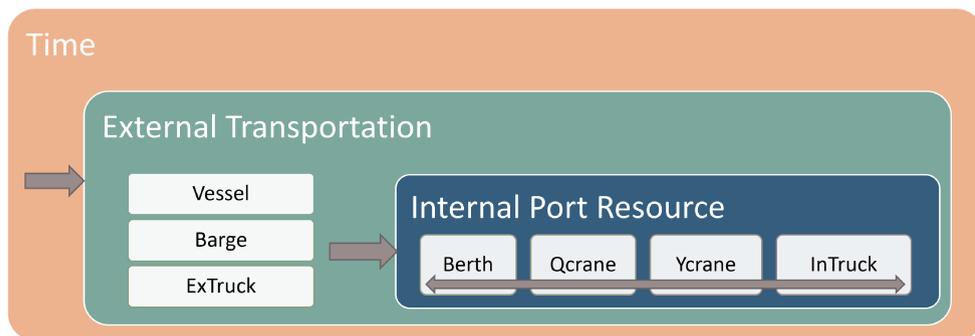


FIGURE 3.5 – Changes of the port operation

1. Dependency to internal port resources

Due to resources are shared among all containers, the change in an operation decision or policy can have an effect to the others operations in the port system. The relationships of activities among port operations are in sequential transferring containers. A bottleneck at an operation leads to an idle at the others operation. This kind of operation relationship, the machine can learn from the changes of performance capacity.

2. Dependency to external transportation

Transportation carries containers into and out of the port and they are considered as an uncertainty input of the port activity system. The arrival/departure of containers require the performing of operation resources so the port operation capacity is changed due to the external transportation. The relationship between external transportation and the port system is in stochastic. Vessels plan the visit through the agreement of berth allocation with the port, however, various factors causes the vessel berthing deviated from the plan.

The stochastic of vessel arrival is ranged by various root factors which may not be identified or quantified the impact at the operation time. The deviation of berthing arrival can be by individual of the vessel itself or by pattern of deviated vessel series e.g. a broken at the other port causes delay to vessels. This kind of stochastic relationship, the machine can learn the evolving from the changes of deviation to the arrival plan.

For the barge and the external truck, they visit the port based on the berthing plan of their contact vessel. Each transportation visits the port in particular random time. Most of visit is ranged in 1 week before/after the vessel berthing. On the arrival, the barge is queued for berthing activities and the external truck is queued for loading/unloading service. The queue is in first-come-first-serve. Statistic is used to support stochastic analysis, therefore, the arrival rate is used to specify the relationship between the port and the external transportation. On some ports, the appointment system is applied to control the arrival rate of external truck visit reducing the stochastic. The machine can learn this kind of stochastic relationship with the port system by the evolving of the visit rate.

3. Dependency to time

Even there is no significant event happening to the port operation, the operational activities are eventually changed by the time. As the time pass, the matter of all uncertainties that is influencing the port operation are evolved dispersing/reducing on the port operation nodes by the time.

Theses changes are required as the signal to inform the machine learning how much the operation is changed during the time. The required data/information is as follows :

- the performance capacity of each operation
- the berthing plan of vessels

-
- the berthing activities of vessels
 - the berthing activities of barges
 - the arrival rate of external trucks

Port components

Constructing the knowledge base for predicting the operation capacity should include components to serve the three purposes as discussed above. Three dataset of components are required as shown in the framework 3.1 ; infrastructure, information and operation.

Infrastructure dataset is for constructing the virtual port operation environment including, the physical layout, the number of port facilities, their capabilities and operation policy.

Information dataset is the information for configuring the virtual port operation such as procedure, policy, uncertainty and vessel arrival plan.

Operation dataset requires two set of data. One is generated from the virtual operation with configured environment. This dataset is used as input for the machine learning to construct the prediction knowledge base. Another operation dataset captured from the UTOs is used in two roles, as input for the simulation and as baseline for the simulation validation.

In the next stage, these components are extracted to construct the simulation, to feed as the simulation input and to validate the simulation behavior.

3.3 Microscopic Simulation

The Microscopic Simulation is required to implement all components that is defined from the stage of Port Component Extraction in order to generate a series of simulation output. The output represents as data nodes of the port uncertainty knowledge base for further learning by the Macroscopic Prediction model. AnyLogic is selected as the simulation tool. The approach for modelling the simulation starts with the data acquisition

Simulation tool selection

Various simulation tools are used to simulate the port situations with uncertainty such as Arena, AnyLogic, Flexim, Flexterm and etc. The tool selection is based on the criteria that is matched to the purpose of the framework. Table 3.1 presents the comparison of simulation tools. The criteria includes the ability that the simulation can read the input for the operation execution and can generate and write the output. In addition, it should be able to configure stochastic uncertainty such as delay and facility breakdown. The simulation should also have library of container that its movement flow can be individually configured replicating to the real-world movement.

Tool	Data Collection	Stochastic Delay	Stochastic Breakdown	Container Configurable
AnyLogic	read/write	✓	✓	✓
Arena	read/write	✓	✓	n/a
FlexSim	bitnami cloud	✓	✓	n/a
FlexTerm	read/write	✓	✓	n/a

TABLE 3.1 – Comparison of simulation tools

As a result, AnyLogic is the only tool that meets all criteria. AnyLogic provides the development of simulation model in the microscopic level. The object-based simulation considers port components as objects which can be configured and programmed.

The simulation is modelled in the following steps :

1. Data acquisition
2. Simulation modelling
3. Simulation validation

3.3.1 Data acquisition

Constructing the Microscopic Simulation uses data from both primary and secondary sources as shown in the Figure 3.6. As the primary, core of the port system such the port infrastructure and operation procedure are collected from the interview with port operator. Others specific details for configuring the simulation are collected via the secondary sources such as physical layout specification is measured from the Google Earth. Types of the known uncertainty are aggregated and classified from the literature. The information of operation plan can be acquired via the port community system or the port website. Data of the vessel plan is captured by the scheduled cron job from the port community system or the port website. The last dataset of port system activities such as vessel berthing, external truck arrival and activities of port operations are observed and transformed from the UTOs data.

3.3.2 Simulation modelling

The main role of the simulation is to generate the simulation data of port activities for knowledge base construction. The simulation is modelled in the following parts :

	Source	Method	Tool	Acquired Data/Information
Infrastructure	Google Earth	Measurement	Google Earth	- Port layout - Locations of port operations/ facilities
	Port operator	Interview	-	- Transportation routing directions - Specification of facilities - Port operation procedure and policy
Information	Literature	Review	-	Types of known uncertainty
	Port community system/ Port website	Observation	Monitoring cron job	Berthing plan of vessels
Operation	Operation in the field	Observation	UTO	- Berthing activities of vessels - Arrival rate of external trucks - Performance capacity of operations with trace of uncertainty

FIGURE 3.6 – Sources of port components

1. Environment infrastructure and procedure of port operation

To set up the operation baseline of the port system, infrastructure dataset is used to initial the replicated DT virtual in the simulation. They include the specification of the physical port. Also, the information dataset of port procedure and policy are programmed.

- Port physical layout : to draw the transportation routing map and location of port operations at the same scale as the physical port. Then, the travel time of a container between operation-to-operation reflects the real-world value.
- Port facility : to define 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. Information for uncertainty configuration To execute operation scenarios with uncertainty, the known uncertainty can be configured as uncertainty input to the container flows.

- Transportation input : consists uncertainty in the arrival time and the number of containers. The arrival of motor vessels are 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.

— Availability of port resource : consists uncertainty in the performance capacity. The availability/capability of port facility is configured by the number decreasing/increasing. While the operational interdependency depends on the whole operation condition, no direct configurable.

3. Operation output To collect generated data from each port operation, the core of the container flow starts from the transportation arrival plan (vessel or external truck) which contains uncertainties. Containers pass through facilities under the port environment with additional configured of uncertainty. Finally, results of performance capacity on each port operations are captured and exported to the file.

3.3.2.1 Usages of UTO operational dataset

UTO data represents the container transaction interact with operation activities in the physical world. Changing of 'position' and 'time' of UTOs parameters can be mapped with port operation position (Figure 3.7) to specify the container status related to its position (arrival, waiting and departure) and further to the operational status (ATA, waiting queue, ATD and productivity rate). On the leave of an operation to another operation and the speed of movement can also be specify, however, the move status is not applied in the proposed framework.

UTOs data from the real-world can be transformed and applied to the DT virtual in 2 ways.

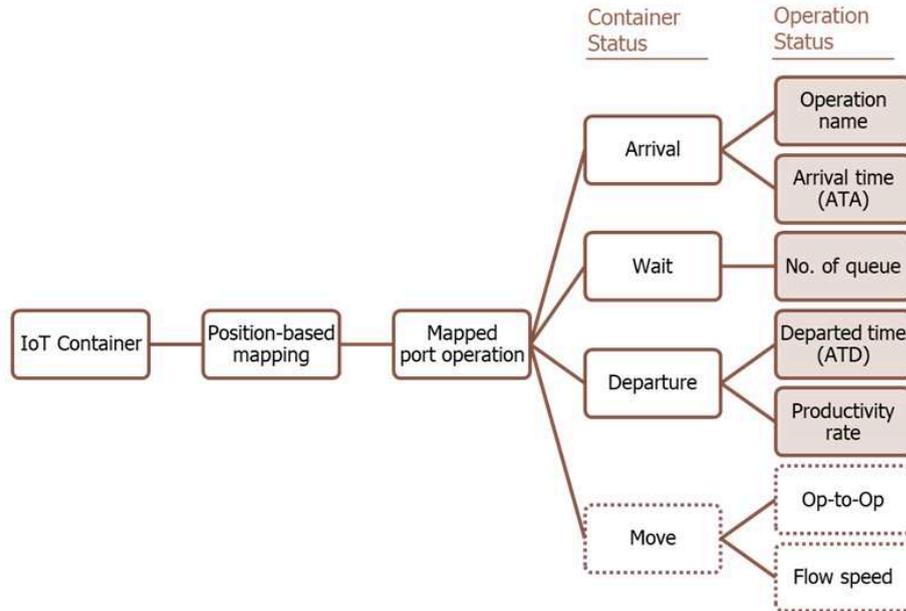


FIGURE 3.7 – Mapping of smart container data to operation attributes

- as uncertainty of transportation input : UTOs data of vessel berthing activities and external truck arrivals can be configured to introduce containers into the simulation. Then, each internal operation continues to handle containers with simulation results as performance capacity of each operations.
- as DT validation baseline : in order to ensure that the real-world physical and DT virtual have the same behavior, the performance capacity captured from UTOs dataset such as the productivity rate can be used to compared to the performance capacity generated from the simulation.

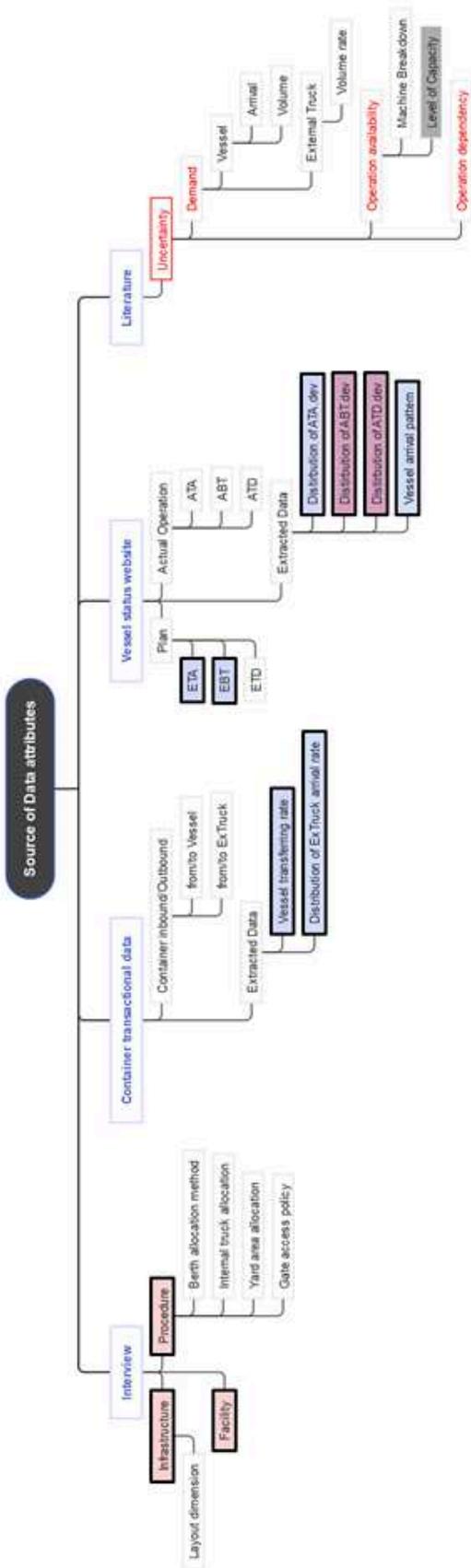


FIGURE 3.8 – List of data elements captured for the simulation

3.3.3 Simulation validation

Since the Microscopic Simulation is in the middle stage transforming data from the physical port to the virtual port. On the last step of simulation modelling, the simulation is then validated to ensure that the model of virtual port has the same behavior as the physical port and the simulated data is valid for knowledge construction.

According to two physical-virtual synchronizations mentioned in the framework, 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 model applying DT, simulated output is used to compare with the output of physical system under a 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 analytic 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 aware the upcoming of uncertainty impact beforehand, the simulated output should be executed continually in advance. Periodical data is chosen.

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.

3.4 Macroscopic Prediction

Figure 3.9 shows the process to model the knowledge base for prediction. The prediction model receives input from the Microscopic Simulation to construct/update the knowledge base of port operation system. The generated data from the simulation is in the format of text, numerical and Boolean value. It requires a pre-processing to prepare data type and format ready for the machine learning. Then, the machine learning splits the input dataset for the training dataset and the testing dataset. The training dataset is to train the machine learning in the inference of port activity system. Once the prediction model is train, the testing dataset is used to verify the accuracy of prediction.

3.4.1 Inference for prediction modelling

As mentioned earlier in this chapter, the reasoning of port activity system involves three kinds of dependency; dependency to time, dependency to internal port resources and dependency to external transportation. The first two kinds of dependency are presented through the temporal data of each operation capacity. While the last kind of dependency, especially the relationship between the vessel activity and the port activity is more complicate due to the stochastic in vessel arrival. Therefore, this study defines parameters of vessel berthing activities for the machine learning to perceive in temporal data approach.

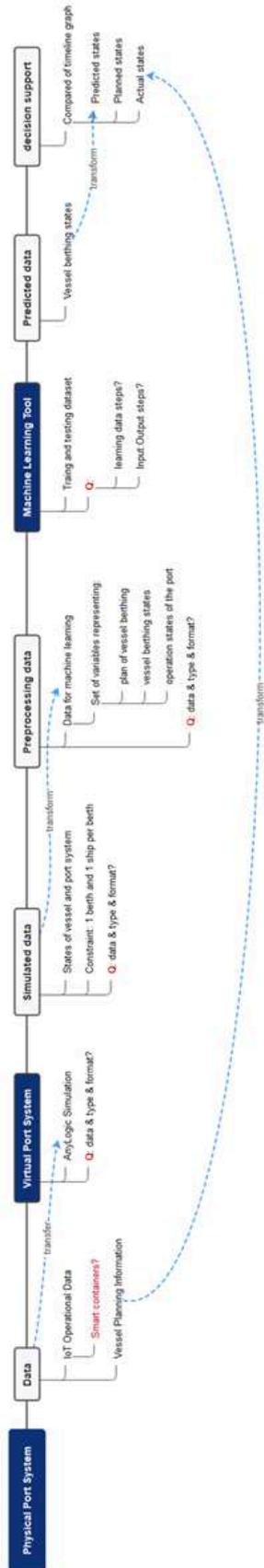


FIGURE 3.9 – Methodology for prediction modelling

Vessel berthing activities

Table 3.2 shows activities and data attributes on each phase of vessel berthing. There are two zones for vessels; the waiting zone(WZ) and the berthing zone(BT). On the first phase of vessel arrival, the vessel waits at the waiting zone until the port confirms to enter into the berth. Then, on the second phase of vessel berthing, the loading and unloading of containers are handled. The vessel handling time should be within the allocated berthing plan. On the last phase, the vessel depart the port Once the vessel handling is complete.

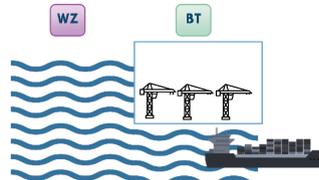
Vessel Berthing Activities	 Vessel arrival into the port wait zone	 Vessel arrival into the berth	 Vessel departure from the berth
Vessel Berthing Conditions	- several vessels can wait in the wait zone at a time. - several vessels can be expected into the wait zone at a time.	- one berth limits to one vessel. - several vessels can be expected into the berth at a time.	
Vessel Plan attributes	<p>ETA_WZ expected time of arrival into the wait zone</p> <p>expnum_WZ expected number of vessels in the wait zone</p> <p>expname_WZ name list of expected vessels in the wait zone</p> <p>box_tounload number of containers planned to unload</p> <p>box_toload number of containers planned to load</p>	<p>ETA_BT expected time of arrival into the berth</p> <p>expnum_BT expected number of vessels in the berth</p> <p>expname_BT name list of expected vessels in the berth</p>	<p>ETD_BT expected time of departure from the berth</p>
Vessel Actual Event attributes	<p>ATA_WZ actual time of arrival into the wait zone</p> <p>shipnum_WZ actual number of vessels in the wait zone</p> <p>shipname_WZ name list of actual vessels in the wait zone</p>	<p>ATA_BT actual time of arrival into the berth</p> <p>shipname_BT name list of actual vessels in the berth</p>	<p>ATD_BT actual time of departure from the berth</p>
Resource attributes	<p>crane_states number of containers queue</p> <p>intruck_time in-truck process time</p>	<p>box_toupload status of containers remaining to upload</p> <p>box_toload status of containers remaining to load</p> <p>crane_states number of containers queue</p> <p>intruck_time in-truck process time</p>	<p>crane_states number of containers queue</p> <p>intruck_time in-truck process time</p>
Ex-Truck attributes	<p>extruck_states number of containers access</p> <p>extruck_time ex-truck process time</p>	<p>extruck_states number of containers access</p> <p>extruck_time ex-truck process time</p>	<p>extruck_states number of containers access</p> <p>extruck_time ex-truck process time</p>

TABLE 3.2 – Data attributes relating to vessel berthing activities

On each phase of vessel berthing activities, there are attributes stating status of vessels, port operation resources and external truck. Vessel activities are stated in temporal signal attributes (0=no, 1=yes). Attributes of vessel plan inform the machine learning about the expectation of incoming vessels regarding the schedule; ETA_WZ = expected to arrive in WZ, ETA_BT = expected to arrive in BT, ETD_BT = expected to depart from BT. Attributes of vessel plan can be compared with attributes of vessel actual event for the machine learning to be notified the delay of arrival/departure. Attributes of vessel actual event also inform the temporal signal to the machine learning about the actual arrival/departure of the vessel; ATA_WZ = actual arrival in WZ, ATA_BT = actual arrival in BT, ATD_BT = actual departure from BT.

In addition to the vessel berthing states, the number of container boxes to load and unload are informed for the machine learning to estimate the uncertainty impact in the quantified of incoming/processing containers. Also, the states of others port operations and external trucks are provided along the berthing activities as well.

These data attributes are feed into the machine learning in temporal time-series as shown in the examples in the figure 3.10 and the figure 3.11. On the left side of the prediction line, at each time temporal, the prediction model learns data attributes related to the phase of vessel berthing. Both planning of activities and actual activities of vessel and others operations are feed as recent historical data. The prediction model learns the inference of these activities and predicts the berthing time of vessels in the near future.

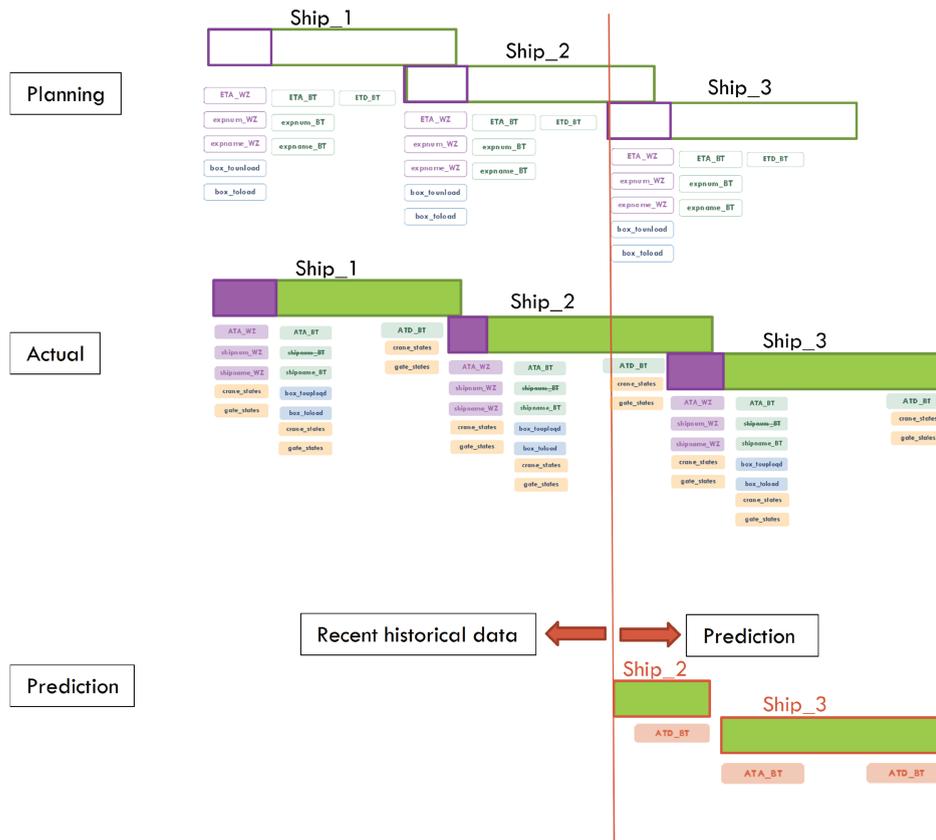


FIGURE 3.10 – Evolving of port data attributes for model training

3.5 Validation Scenario

3.5.1 Case of Thailand port

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 10 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

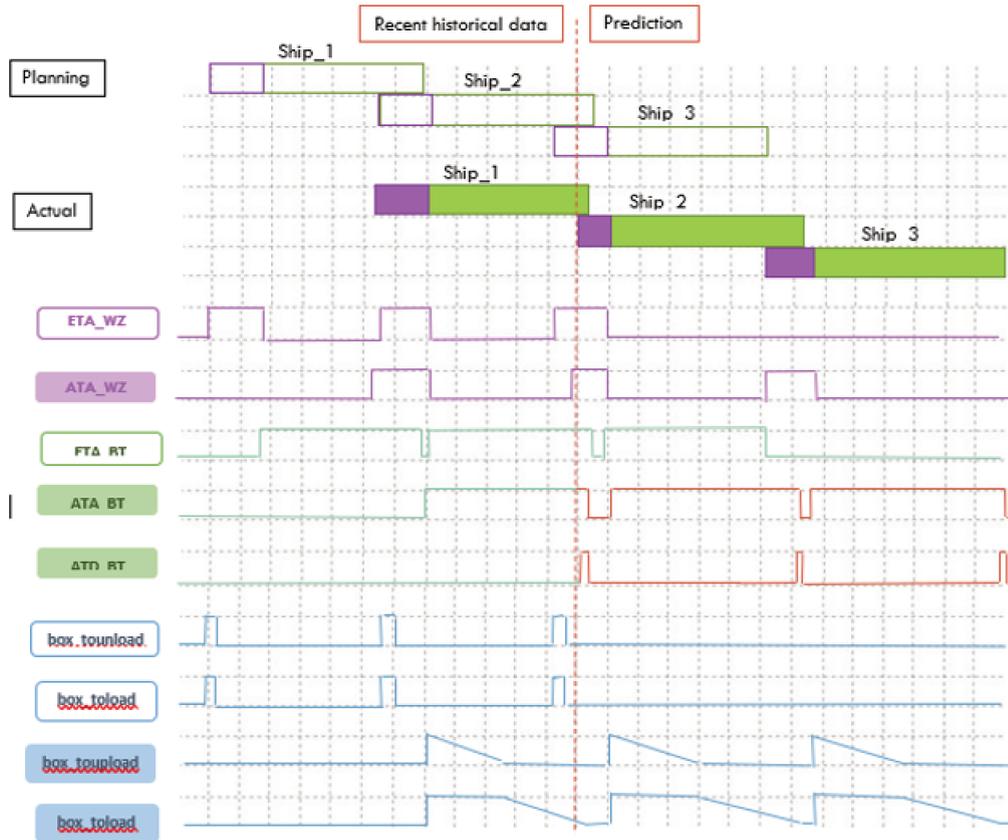


FIGURE 3.11 – Signal of Data attributes for model training

truck for transferring containers between the berth quay and the yard via a 3,000-meter connecting bridge. On the land connecting side, 5 entrances and 3 exits are for external truck carriers of export containers. 3 entrances and 3 exits are for external truck carriers of import containers.

3.6 Conclusion

This chapter proposes the framework consisting of three stages; Port Component Extraction, Microscopic Simulation and Macroscopic Prediction. On the first stage, Port Component Extraction should specifies components that requires for building

the virtual port of the Digital Twin. We analyse the requirement in the use of data components for the proposed framework. Port components are used for modelling the Digital Twin, for structuring the knowledge of port uncertainty and for reasoning the machine learning. The required components are classified as Infrastructure, Information and Operations. Data of port components are collected from the real-world port system via the primary and secondary sources. Port manager of the case study port in Thailand is interviewed. The case also provides historical data of container transactions which is further used to extract the operation statistics such as vessel transferring rate, visiting rate of external truck, the duration of container storage at the yard and etc. The information of vessel berthing plan and berthing activities are collected from the port website.

Chapitre 4

Microscopic Simulation

The main roles of the Microscopic Simulation is first, to replicate the real-world operation to operate the port activities in the DT. DT operation environment is programmed using the AnyLogic simulation. Second, to integrate the cases of uncertainty to the operational environment preparing for the knowledge base construction since current data of the real world is limited in cases of uncertainty. Last, to generate the operational data in terms of performance capacity of each operation nodes in parallel synchronizing with the data of external transportation activities (e.g. vessel berthing). The simulated data is then as the input for the knowledge learning by the Macroscopic Prediction model.

The DT is modelled in microscopic discrete event-based simulation by considering containers as the microscopic object. Due to the research is interested in the lacked knowledge of linkages among operation nodes which are related by movement behavior of containers. Therefore, when the Microscopic Simulation transfers containers between two operation nodes, it creates the relationship of operation time between the two nodes. This operation-to-operation link is then bonded in a numeric form of state-and-time changing.

Further, the simulation applies the configuration of uncertainty as an event interfering the operation time. As a consequence, it is assumed that the container is a carrier transmitting an impact of uncertainty to operation nodes by changing state-and-time of the operation. Then, by operating various of containers, performance capacity of the operation reflects an evolving by uncertainty impact through a time period.

Last, the performance capacity of every port operation is captured at the same time in a series of time steps as representative values of uncertainty nodes in the knowledge structure. The representative values of uncertainty nodes are then eligible to explore the evolving of node relationships by the machine learning in the next framework stage of Macroscopic Prediction.

For the case study of berth allocation problem, the performance capacity is measured in terms of the operation time and the departure time of vessel comparing to the berth plan. The deviation time delayed from the plan represents as an uncertainty impact from the accumulated travelling of containers through the port uncertainty structure.

4.1 Simulation modelling

According to the framework illustrated in the Figure 3.1 and the methodology of data acquisition in the section 3.3.1, data and information are acquired from major sources supporting in different purposes. 1)Literature review is the first study source for exploring the port operation functions and port operational uncertainties in general approaches as discussed in Chapter 1 and Chapter 2. 2)Interview of port management is conducted to refine the specification of port functions for to configure the simulation particularly for the case study of a port system in Thailand. Last,

3) Observation of operations in the field is to collect the precised operational data for the simulation to replicate the port operation behavior based on the real-world operation activities.

Modelling the Macroscopic Simulation uses data elements extracted from the physical port components such infrastructure, information and operational data which are collected from various sources. Information collected from the literature review and the interview are applied directly to the simulation. The data source of 3) Observation of operations in the field should be collected from the UTOs. However, due to the limitation of UTOs data availability, currently we cannot access those data. Therefore, the historical data of container transactions is used to extract the statistical of container movement behavior for configuring in the simulation.

4.1.1 Infrastructure

The simulation is first implemented with the port infrastructure. The information is from the interview of port management used as the primary information. The secondary is collected from the Google Earth for precisising the port scale. The infrastructure includes components as follows :

1. **Port layout** - The physical dimensions such as distances among port operations are measured by the Google Earth as shown in the Figure 4.1. In addition, the port management system (Navis) which the port uses to manage container stacking in the yard. We uses its layout comparing to the physical layout for implementing in the simulation. The Figure 4.2 shows the layout of port yard configured on the port application (left) and the physical yard layout (right).

Then, the physical port layout is scaled as the draft of port layout for the simulation as illustrated in the Figure 4.3. Finally, the layout is transformed

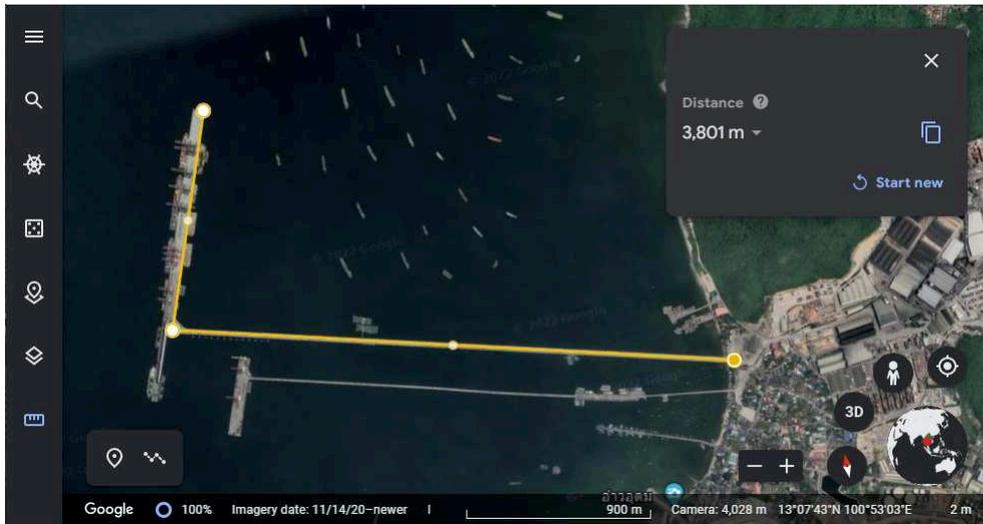


FIGURE 4.1 – Port measurement via Google Earth



FIGURE 4.2 – Port yard layout

to fit in the grid-based layout of AnyLogic simulation in the same scale as shown in the draft.

2. **Facility specification** - Once, the port layout has allocated the areas for operation facilities, then instances of facilities are specified into the simulation. The number of facilities, capabilities of facilities and operational policy are provided by the port management as shown in the Table 4.1

Quay	Number of cranes (for container)	10 units
	Crane moving speed on rail	2,716.2 metre per hour
	Crane container moving speed	number of container 20-25 move per hour
Yard	Number of cranes	RTG 24 units,RS 25 Unit
	Crane type	Rubber-tyred gantry crane
	Crane moving speed on rail	5,400-7,800 metre per Hour
	Crane container moving speed	number of container 18 move per hour
	Container Stack - Number of blocks	ICD1 23 Block,ICD2 21 Block
	Container Stack - Number of rows	6 rows
	Container Stack - Number of stacking height	5 Tier
Truck	Number of Kerry trucks	131 units
	Approx. driving speed	30 Km. per hour
Barge	Number of cranes (for container)	1 units
	Crane container moving speed	number of container 20 move per hour
Gate	Number of entrance gate	8 units
	Number of exit gate	6 units
	Approx. average process time - entrance	2 minutes per truck
	Approx. average process time - exit	1 minutes per truck

TABLE 4.1 – Specifications of port facilities

(study case records : year 2018) that records inbound/outbound time, inbound/outbound transportation, type of container and status of container is used to extracted statistic information related to the port procedure. In addition, types of uncertainty should be able to configured as the interference to the operation.

To enable the operation procedure as stated to the simulation requires the information of port procedure, the planning of vessel arrival and information about uncertainty.

1. **Port procedure** - The information from literature review and the interview of port case about port procedure are collected. A procedure handling containers via the process of vessel unloading is shown in the Figure 4.6.

Microscopic Simulation is modelled according to the collected information of procedure flows. However, the implementation can be programmed in an extent of port function. Due to the trade-off of simulation tools and its execution performance, some fining detail of operation could not be implemented and some should not be implemented. For example, the allocation of yard

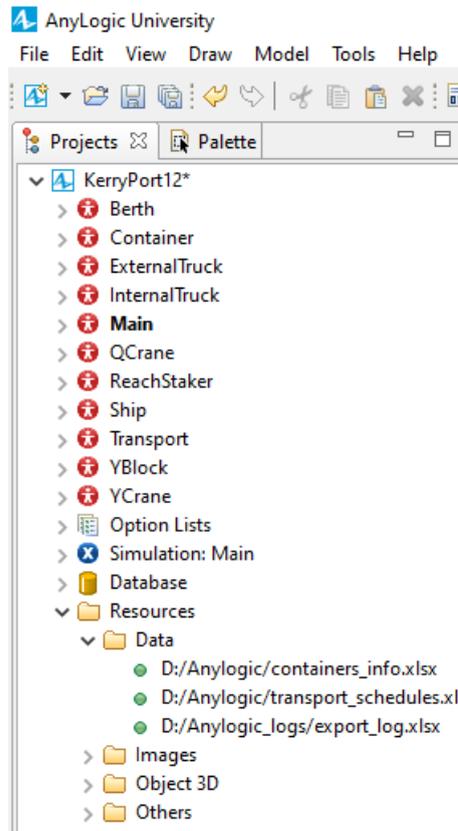


FIGURE 4.4 – Simulation : components

stacks for particular ship liners cannot be implemented due to limit of information. The reshuffling of containers requires the departure time of each container and the reshuffling algorithm. Implementing the function consumes both memory and computing which loads the execution of simulation. In addition, the port operations consists of several computational functions. Therefore, the procedure of port functions is implemented in both deterministic and stochastic.

Discrete events of container operation activities are implemented in four major operation flows :

- Vessel unloading to import/export yard (SHUL)
- Vessel loading from export yard (SHLD)

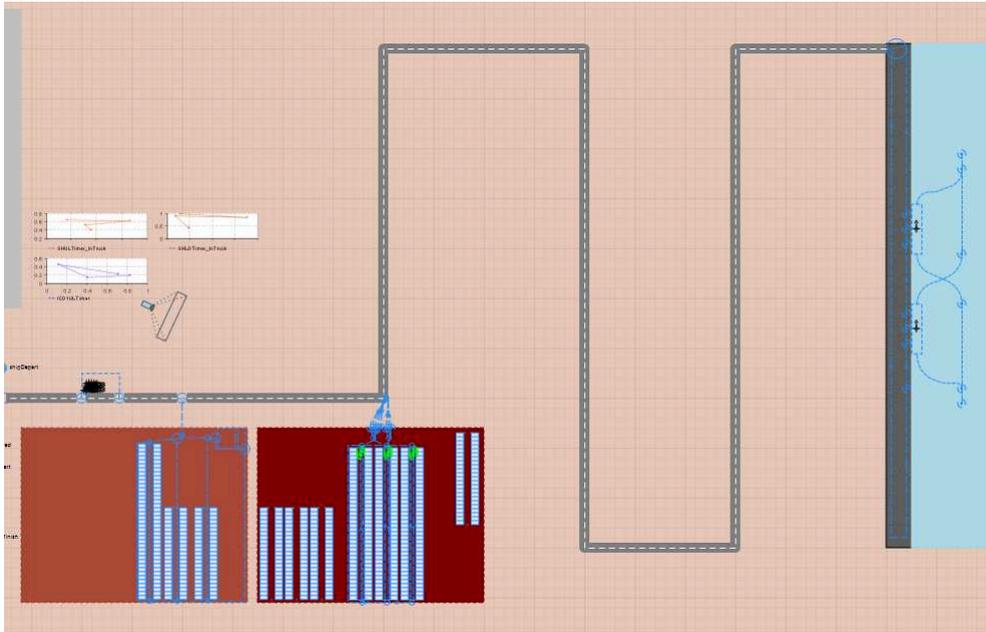


FIGURE 4.5 – Simulation : layout map

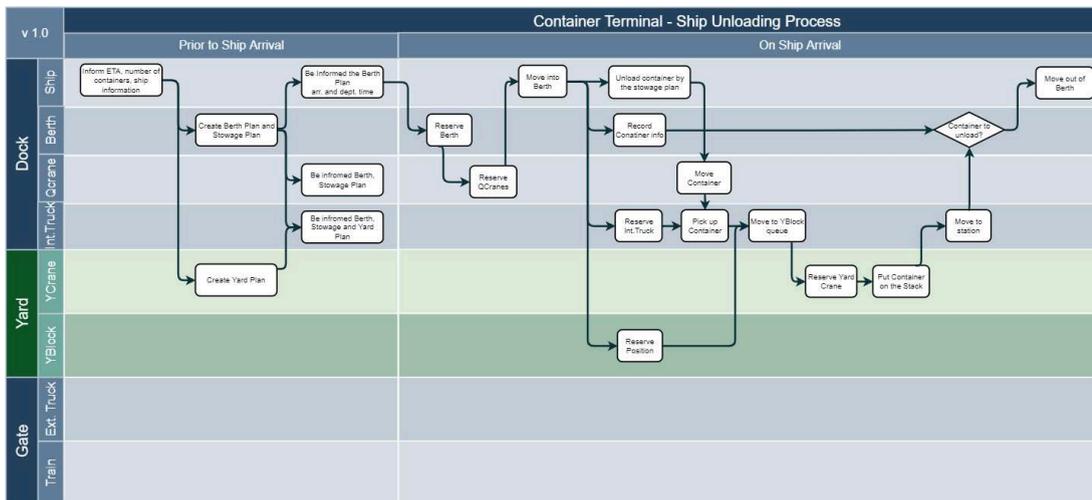


FIGURE 4.6 – Port procedure - vessel unloading

- External truck unloading to export yard (EXUL)
- External truck loading from import yard (EXLD)

On the arrival of vessel, the historical data of vessel arrival which includes both the planning schedule and the actual arrival time is used as input for the simulation. The stochastic of vessel arrival is then based on the historical.

Each vessel carries different numbers of containers for the import and export, however, the historical data of vessel arrival does not specify the number of containers.

The historical data of inbound/outbound container transaction received from the port case is used to extract the number of import and export container of vessels. First, the transaction data is extracted to specify the number containers in each transportation mode as shown in the Figure 4.7 and 4.8. Then, the proportion of containers for loading and for unloading are specified for Motor vessel (MV) and Local barge (LT) which is 1.11 : 1 for MV and 12.5 :5 for LT, accordingly.

IMPORT	Total	From truck	From vessel
To barge	3,538	0	3,538
To Truck	48,469	0	48,469
To Yard	327	0	327

FIGURE 4.7 – Proportion of import containers on each transportation mode

EXPORT	Total	From truck	From barge
To Vessel	58,138	49,410	8,728
To Truck (cannot load)	2,234	2,225	9
To Yard	1	1	0

FIGURE 4.8 – Proportion of export containers on each transportation mode

After that, the total number of containers for each ship is calculated based on the historical ship rate. The ship rate calculates the period of time taken for the port to handle containers on the vessel. The ship rate of MV and LT is as shown in the Figure 4.9 and 4.10.

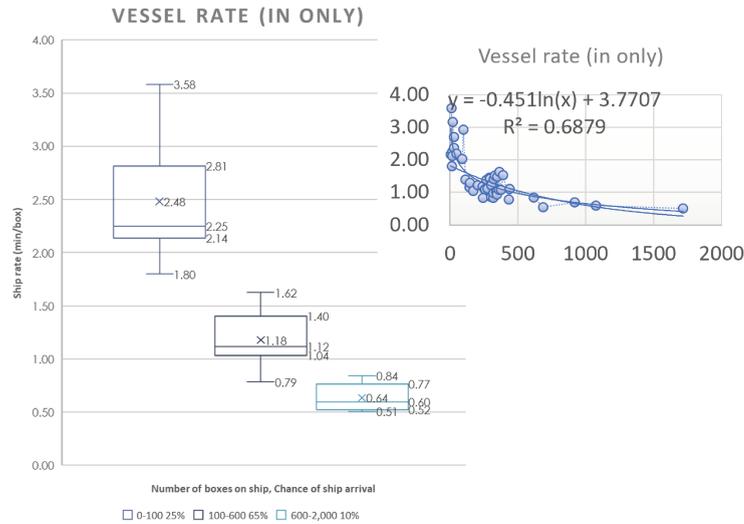


FIGURE 4.9 – MV vessel rate

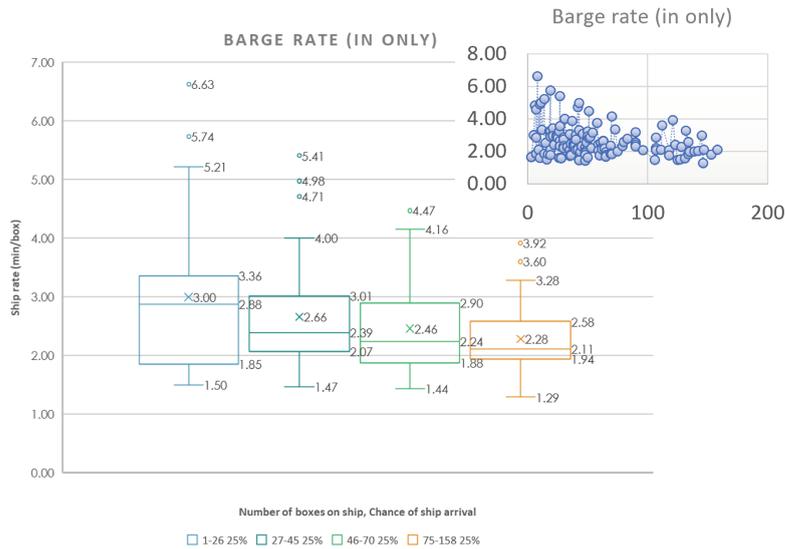


FIGURE 4.10 – LT vessel rate

Once the vessel gets into berth, the internal truck arrives at the quay crane to pick up container to the yard area for the import or for the transshipment depending on the destination of each container which is pre-configured in the containers_info.xlsx

On the other side of external truck arrival, each port handles the arrival

rate differently. For the Thai port case, the arrival rate is extracted from the historical data. The arrival of external truck for import and export containers are shown in the Figure 4.11 and 4.12. The data is classified by the SPSS TwoStep to separate peak and off-peak hours. Then, each clustered dataset is fitted to specify the proper distribution model. The Figure 4.13 shows the example of distribution model fitting for external truck arrival rate, the Weibull distribution is selected for the dataset. Finally, the selected distribution models are specified to generate the external truck of each hour.

	average	min	max	Arrival Hour	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	
Sunday	180.28	1	1047	Sunday	1	4	5	5	5	2	2	5	4	8	15	15	18	7	11	12	9	11	17	9	5	4	3	2	2
Monday	99.19	1	592	Monday	2	1	1	1	2	2	2	2	4	5	7	7	6	4	6	6	6	6	7	5	5	5	6	4	4
Tuesday	129.60	1	690	Tuesday	3	2	2	3	3	3	3	3	4	7	7	7	5	6	5	7	7	8	9	6	9	7	7	5	
Wednesd.	133.86	1	911	Wednesd.	4	3	3	3	3	3	4	3	4	6	5	9	6	8	7	10	8	8	7	8	7	6	5	4	
Thursday	115.34	1	723	Thursday	5	3	2	3	3	3	3	3	3	5	6	6	7	7	8	8	6	6	6	5	5	5	4		
Friday	128.75	1	777	Friday	6	4	4	3	3	3	2	4	4	7	8	6	6	11	9	9	5	6	8	6	5	4	3		
Saturday	133.68	1	803	Saturday	7	3	3	3	3	2	3	4	5	7	10	9	5	8	9	11	8	7	8	6	7	4	3	3	
Total	920.70	1	1047																										

FIGURE 4.11 – Arrival rate of external truck for import containers

	average	min	max	Arrival Hour	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	
Sunday	343.33	137	519	Sunday	1	12	11	12	10	11	14	16	13	17	16	17	15	17	17	18	18	19	18	15	13	14	12	8	
Monday	521.46	4	866	Monday	2	8	6	6	6	8	13	18	14	17	13	19	22	29	28	32	34	36	37	33	26	35	31	26	24
Tuesday	687.46	36	993	Tuesday	3	26	18	20	17	17	23	26	22	29	26	25	23	27	32	34	38	38	41	41	28	42	32	37	26
Wednesd.	834.67	192	1136	Wednesd.	4	31	28	23	22	20	29	33	33	36	28	33	30	34	36	40	41	43	45	46	33	43	50	43	35
Thursday	671.77	425	1089	Thursday	5	28	28	24	22	21	24	31	26	33	25	26	24	27	28	32	34	32	35	32	26	33	33	26	24
Friday	490.67	205	984	Friday	6	27	25	22	16	19	21	25	17	19	22	22	24	24	19	25	20	23	23	16	19	16	13	13	
Saturday	375.92	221	607	Saturday	7	16	14	14	12	10	15	16	13	18	14	12	14	15	17	22	19	18	24	20	11	17	17	12	
Total	3,925.28	4	1136																										

FIGURE 4.12 – Arrival rate of external truck for export containers

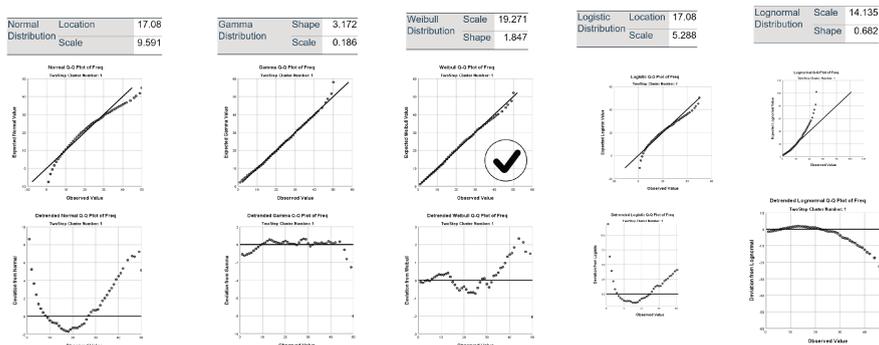


FIGURE 4.13 – Example of distribution model fitting for external truck

The Figure 4.14 shows the implementation of discrete events of the four flows in the simulation. The simulation is defined with data list, variables and functions (Figure 4.15). Each event and function are programmable to control the process of operation handling containers in the flows (Figure 4.16).

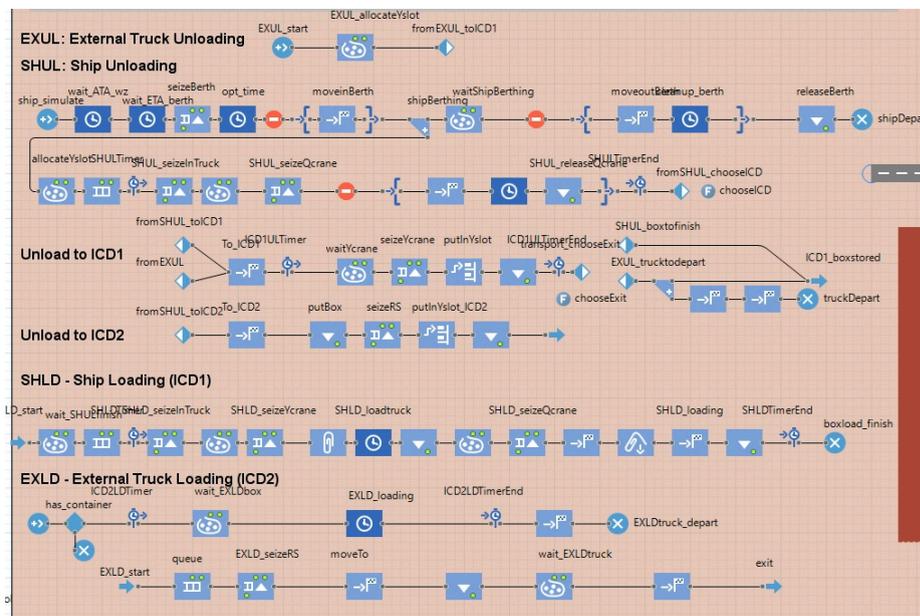


FIGURE 4.14 – Simulation : Event-based container flows in the port operation

2. **Planning of vessel arrival** - The port procedure is executed by the movement of containers. Major volume of containers arrive/depart via vessels which is planned on the berth allocation before its visit. The berth allocation usually specifies the time window (arrival and departure) of each vessel visit. The information of vessel berth plan and vessel berthing status is captured from the port website of the case study. The example of port berth information on the website is shown in the Figure 4.17. The port updates the berth plan on the changes of planning or berthing status of each vessel.

In every hour, port berthing data on the website is collected. Chrome browser is scheduled by the Task Scheduler on Windows10 to access the website. Then, the data is collected by Table Capture extension on Chrome to capture table

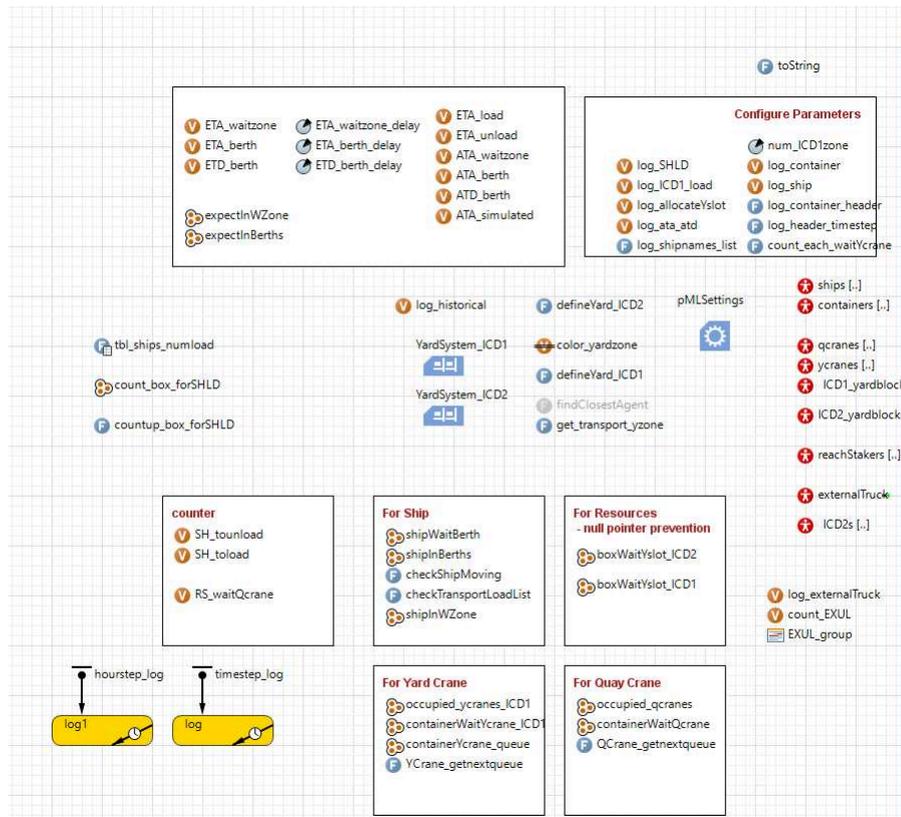


FIGURE 4.15 – Simulation : defined variables and functions

data on the website to excel file. The data is collected during 12-22 February 2021 as in the Figure 4.18 (note : due to technical problem, data of some hour is not collected).

The Task Scheduler on Windows10 is scheduled to execute the Chrome browser every hour to access the port website. Then, the Table Capture extension on the Chrome is used to capture data on website table of the port vessel plan and status to the excel files. Further the dataset is sorted and filtered to acquire the transition change of vessel plan and vessel status as shown in the Figure 4.19. Finally, the schedule of vessel berthing is acquired to show the transition difference between the planning period and the actual berthing period (Figure 4.20).

```

Function body
List<Container> allqueue = findAll(containerWaitYcrane_ICD1,
    p -> p.reserved_ycrane.equals(agent.reserved_ycrane));

int priority ;
priority = uniform(<0.7 ? 3 : (uniform(<2/3 ? 2 : 0));

//NOTE:to give priority to containers on the ealier ship
List<Container> priorityqueue = findAll(containerWaitYcrane_ICD1,
    p -> p.reserved_ycrane.equals(agent.reserved_ycrane)
    && p.priority >= priority);

//NOTE:trying to give priority to the ealier ship
//issue:deadlock on truck and crane resources
//List<Container> shippriority = findAll(queue,
//    p -> shipInBerth.getFirst().equals(p.transport_in) ||
//    shipInBerth.getFirst().equals(p.transport_out) );

Container c;

//if(shippriority.size() > 0) { c = randomFrom(shippriority); }
//else
if(priorityqueue.size() > 0) {
    c = randomFrom(priorityqueue);
}
else if(allqueue.size() > 0) {
    c = randomFrom(allqueue);
}
else{ return; }

switch(c.process_state) {
case SH_UL: waitYcrane.free(c); break;
case SH_LD: SHLD_waitYcrane.free(c); break;
case EX_UL: waitYcrane.free(c); break;
default: traceToDB("ycrane next queue - no state");break;
}

containerWaitYcrane_ICD1.remove(c);
    
```

FIGURE 4.16 – Simulation : an example of custom function

Vessel	Vessel Name	VY Flag	CYB Flag	Phase	ETA	ATD	ATD	Berth No.
470	MS YCROTE	GR	GR	Waiting	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	10
4700	ET PANTERA MARINA 2	GR	GR	Waiting	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4701	MS YC AQUARUS	GR	GR	Waiting	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	12
4702	MS YC ANTONIO	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4703	ET SAPHIR MARIT 2	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4704	ET SAPHIR MARIT 1	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4705	MS YC ANTONIO	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4706	ET SAPHIR	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4707	MS YC ANTONIO	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4708	MS YC ANTONIO	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4709	MS YC ANTONIO	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4710	MS YC ANTONIO	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4711	MS YC ANTONIO	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4712	MS YC ANTONIO	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4713	MS YC ANTONIO	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4714	MS YC ANTONIO	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4715	MS YC ANTONIO	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4716	MS YC ANTONIO	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4717	MS YC ANTONIO	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4718	MS YC ANTONIO	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4719	MS YC ANTONIO	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4720	MS YC ANTONIO	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4721	MS YC ANTONIO	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4722	MS YC ANTONIO	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4723	MS YC ANTONIO	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4724	MS YC ANTONIO	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4725	MS YC ANTONIO	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4726	MS YC ANTONIO	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4727	MS YC ANTONIO	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4728	MS YC ANTONIO	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4729	MS YC ANTONIO	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4730	MS YC ANTONIO	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4731	MS YC ANTONIO	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4732	MS YC ANTONIO	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4733	MS YC ANTONIO	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4734	MS YC ANTONIO	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4735	MS YC ANTONIO	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4736	MS YC ANTONIO	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4737	MS YC ANTONIO	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4738	MS YC ANTONIO	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4739	MS YC ANTONIO	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4740	MS YC ANTONIO	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4741	MS YC ANTONIO	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4742	MS YC ANTONIO	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4743	MS YC ANTONIO	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4744	MS YC ANTONIO	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4745	MS YC ANTONIO	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4746	MS YC ANTONIO	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4747	MS YC ANTONIO	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4748	MS YC ANTONIO	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4749	MS YC ANTONIO	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9
4750	MS YC ANTONIO	GR	GR	Arrival	25/02/2021 19:00	25/02/2021 19:00	25/02/2021 19:00	9

FIGURE 4.17 – List of vessel berthing on the case study’s website

In the simulation, the acquired vessel plan information is used as the simulation resource data using Excel as in a list shown in Figure 4.4.

In addition to the vessel berthing arrival and departure time, the number of containers for loading and unloading is also the necessary for the vessel

	A	B	C	D	E	F	G	H	I	J	K	Y
	I/B Vyg	Vessel	Vessel Name	O/B Vyg	Phase	ETA	ETD	ATA	ATD	Berth		
1		17Feb0400										
2												
3	S024JBAW	S024	JBAW	M.V.BELAWAN	N024	Working	16/2/2021 21:00	17/2/2021 9:00	16/2/2021 21:48			12
4	0067-024ACLRT	0067-024A	CLRT	M.V.GREEN CLARITY	0067-024A	Working	16/2/2021 13:00	17/2/2021 7:00	16/2/2021 13:30			10
5	0068-018ACSTT	0068-018A	CSTT	M.V.EVER CAST	0068-018A	Inbound	21/2/2021 0:01	22/2/2021 9:00				
6	0147-017SCORE	0147-017S	CORE	M.V.EVER CORE	0147-017N	Inbound	22/2/2021 1:00	23/2/2021 6:00				
7	21049OPK3	21049	OPK3	L.T.O.P.K.3	21050	Inbound	17/2/2021 4:00	17/2/2021 12:00				6
8	0066-020BCLST	0066-020B	CLST	M.V.GREEN CELESTE	0066-020B	Inbound	19/2/2021 8:00	20/2/2021 3:00				10
9	0065-025BCLBT	0065-025B	CLBT	M.V.GREEN CELEBRITY	0065-025B	Inbound	17/2/2021 3:00	18/2/2021 1:00				10
10	153NBMY	153N	BMY	M.V.BUXMELODY	153N	Inbound	22/2/2021 23:54	23/2/2021 15:00				12
11	S033CBED	S033	CBED	M.V.BOX ENDURANCE	N033	Inbound	22/2/2021 0:01	22/2/2021 14:00				--- (OPTION NO LONGER
12	0505MUU	050S	MUU	M.V.MOUNT GOUGH	050S	Inbound	20/2/2021 0:01	20/2/2021 20:00				10
13	0067-024BCLRT	0067-024B	CLRT	M.V.GREEN CLARITY	0067-024B	Inbound	24/2/2021 15:00	25/2/2021 14:00				--- (OPTION NO LONGER
14	S025JBAW	S025	JBAW	M.V.BELAWAN	N025	Inbound	1/3/2021 0:06	1/3/2021 14:00				--- (OPTION NO LONGER
15	0148-023SCOPE	0148-023S	COPE	M.V.EVER COPE	0148-023N	Inbound	26/2/2021 0:01	26/2/2021 20:00				--- (OPTION NO LONGER
16	3NP5	3N	PT5	M.V.PORTO	3N	Inbound	24/2/2021 7:00	25/2/2021 7:00				--- (OPTION NO LONGER
17	050NMMU	050N	MUU	M.V.MOUNT GOUGH	050N	Inbound	18/2/2021 4:00	18/2/2021 17:00				12
18	21022SNPL3	21022S	NPL3	LT NP LOVEGISTICS 3	21023N	Inbound	18/2/2021 13:00	18/2/2021 19:00				10
19	102EGNHR	102E	GNHR	M.V.GREEN HORIZON	102W	Inbound	17/2/2021 22:00	18/2/2021 6:00				12
20	1133NPACA	1133N	PACA	M.V.PACAO	1134S	Inbound	18/2/2021 23:54	19/2/2021 5:00				8
21	21MB111WMTBT	21MB111W	MTBT	M.V.MTT BINTULU	21MB112E	Inbound	19/2/2021 18:00	20/2/2021 10:00				8
22	21006NVKPA	21006N	VKPA	M.V.VEGA KAPPA	21006N	Inbound	25/2/2021 8:00	25/2/2021 23:00				6
23	HN107AMLID	HN107A	MLID	M.V.MSC LIDIA	HN107R	Inbound	20/2/2021 1:00	21/2/2021 2:00				10
24	HO105RMIMM	HO105R	MIMM	M.V.MSC IMMA	HO105R	Inbound	17/2/2021 7:00	17/2/2021 16:00				12
25	250NYING	250N	YING	M.V.YM INAUGURATION	250N	Inbound	19/2/2021 21:00	20/2/2021 12:00				10
26	144ESOK	144E	SOK	M.V.SANTA LOUKIA	144W	Inbound	20/2/2021 13:00	20/2/2021 22:00				8
27	21025KPO	21025	KPO	M.V.KMTC POHANG	2102N	Inbound	17/2/2021 10:00	18/2/2021 16:00				8
28	210225TGX	21025	STGX	M.V.SITC GUANGXI	2103N	Inbound	21/2/2021 16:00	22/2/2021 8:00				10
29	187NSUT5	187N	SUT5	LT SUNTAD SAMUT 5	187S	Inbound	18/2/2021 16:00	18/2/2021 22:00				0 (OPTION NO LONGER E

FIGURE 4.18 – Vessel berthing information displayed on the port website

berthing time. However, information of the vessel plan announced on the website does not state the number of containers. Therefore, this information is calculated based on the historical data which we will discuss later in the part of Operation component.

3. **Uncertainty** - based on the literature, we classified three types of uncertainties according to the Section 1.3.1.3. Variations of uncertainty are configured in the simulation for executing each scenario differently.

- Uncertainty in demand : variations of container arrivals from vessels and external trucks. The variation of vessel arrival time is collected from the vessel plan discussed above.

There are 6 different patterns of vessel arrival :

RecordId	VesselName	Phase	ETA	ETA	ETD	ETD	ATA	ATA	ATD	ATD	Berth	Status	Berth-Id	Berth-Id
1	13Feb_1700	21003NSZNB	Inbound	12/02/2021 20:00		13/02/2021 05:00						6 Visit	B6	
1	13Feb_1400	21003NSZNB	Working				12/02/2021 20:42	0-0:42:00	13/02/2021 15:00	0-10:00:00		6 Visit	B6	
1	14Feb_0000	21003NSZNB	Data-DEL									6 Visit	B6	
5	11Feb_1700	212NYITA	Inbound	12/02/2021 18:00		13/02/2021 06:00						8 Visit	B8	B8
5	13Feb_1400	212NYITA	Arrived	13/02/2021 08:00	0-14:00:00	14/02/2021 03:00	0-21:00:00	13/02/2021 14:36	0-20:36:00			8 Visit	B8	B8
5	14Feb_0000	212NYITA	Working				13/02/2021 14:42	0-6:42:00				8 Visit	B8	B8
5	14Feb_0600	212NYITA	Data-DEL									8 Visit	B8	B8
6	11Feb_1700	234SYIRM	Inbound	13/02/2021 22:00		14/02/2021 08:00						8 Visit	B8	B8
6	13Feb_1400	234SYIRM	Working	14/02/2021 09:00	0-11:00:00	14/02/2021 19:00	0-11:00:00					8 Visit	B8	B8
6	14Feb_1200	234SYIRM	Working				14/02/2021 09:42	0-0:42:00				8 Visit	B8	B8
6	14Feb_1800	234SYIRM	Working				14/02/2021 09:42	0-0:42:00				8 Visit	B8	B8
6	15Feb_0000	234SYIRM	Data-DEL									8 Visit	B8	B8
7	11Feb_1700	21019SNPL3	Complete	11/02/2021 12:00		11/02/2021 18:00		11/02/2021 12:06		11/02/2021 17:00		10 Visit		
8	11Feb_1700	205OU1	Inbound	12/02/2021 03:00		12/02/2021 18:00						10 Visit		
8	13Feb_1400	205OU1	Complete				12/02/2021 04:06	0-1:06:00	13/02/2021 12:00	0-18:00:00		10 Visit		
8	14Feb_0000	205OU1	Data-DEL									10 Visit		
9	11Feb_1700	HN106AMLID	Inbound	12/02/2021 19:00		13/02/2021 23:00						10 Visit		
9	13Feb_1400	HN106AMLID	Working	12/02/2021 23:59	0-4:59:00	14/02/2021 12:00	0-13:00:00	13/02/2021 13:00	0-18:00:00			10 Visit		
9	14Feb_0000	HN106AMLID					13/02/2021 13:54	0-13:55:00				10 Visit		
9	14Feb_0600	HN106AMLID					13/02/2021 13:54	0-13:55:00				10 Visit		
9	14Feb_1200	HN106AMLID					13/02/2021 13:54	0-13:55:00	14/02/2021 13:00	0-1:00:00		10 Visit		
9	14Feb_1800	HN106AMLID	Data-DEL									10 Visit		
10	11Feb_1700	S024JBAW	Inbound	15/02/2021 00:06		15/02/2021 14:00						10 Visit		
10	13Feb_1400	S024JBAW		17/02/2021 20:00	2-19:54:00	18/02/2021 08:00	2-18:00:00					10 Visit		
10	14Feb_1800	S024JBAW		17/02/2021 21:00	0-1:00:00	18/02/2021 08:00	0-0:00:00					10 Visit		
10	15Feb_1200	S024JBAW	Berth-cha	16/02/2021 21:00	1-0:00:00	17/02/2021 09:00	0-23:00:00					12 Visit		
10	16Feb2300	S024JBAW	Working				16/02/2021 21:48	0-0:48:00				12 Visit		
10	17Feb0000	S024JBAW					16/02/2021 21:48	0-0:48:00				12 Visit		
10	17Feb0100	S024JBAW					16/02/2021 21:48	0-0:48:00				12 Visit		
10	17Feb0200	S024JBAW					16/02/2021 21:48	0-0:48:00				12 Visit		
10	17Feb0300	S024JBAW					16/02/2021 21:48	0-0:48:00				12 Visit		
10	17Feb0400	S024JBAW					16/02/2021 21:48	0-0:48:00				12 Visit		
10	17Feb0500	S024JBAW					16/02/2021 21:48	0-0:48:00				12 Visit		
10	17Feb0600	S024JBAW					16/02/2021 21:48	0-0:48:00				12 Visit		
10	17Feb0700	S024JBAW					16/02/2021 21:48	0-0:48:00				12 Visit		
10	17Feb0800	S024JBAW					16/02/2021 21:30	0-0:30:00				12 Visit		
10	17Feb0900	S024JBAW					16/02/2021 21:30	0-0:30:00				12 Visit		
10	17Feb1000	S024JBAW					16/02/2021 21:30	0-0:30:00				12 Visit		
10	17Feb1100	S024JBAW					16/02/2021 21:30	0-0:30:00				12 Visit		
10	17Feb1200	S024JBAW					16/02/2021 21:30	0-0:30:00				12 Visit		
10	17Feb1800	S024JBAW	Data-DEL									10 Visit		
11	11Feb_1700	0066-0208CLS	Inbound	19/02/2021 13:00		20/02/2021 14:00						10 Visit		
11	16Feb1000	0066-0208CLS		19/02/2021 09:00	0-4:00:00	20/02/2021 03:00	0-11:00:00					10 Visit		
11	16Feb1500	0066-0208CLS		19/02/2021 08:00	0-1:00:00	20/02/2021 03:00	0-0:00:00					10 Visit		

FIGURE 4.19 – Transition of vessel status (after filtering of raw data)

Pattern 0 - On time arrival of MV vessel : ATA and ATD is similar to the ETA and ETD. The arrival of vessel sequence is the same as the vessel plan.

Pattern 1 - Delay of a MV with shifted queue of several LTs : the shifted of LT queues is considered as FIFO priority

Pattern 2 - Delay of several MVs with shifted queue of LTs to the end : On the delay of the first MV, LT cannot be serviced in the remaining time gap. LT is in the less priority than the second MV. After all MVs are finished, LTs get into the berth. (This pattern is not implemented in the simulation due to the switching sequence of vessels is not fitted with the machine learning inference of this study.)

Pattern 3 - Several LTs arrivals before the MV

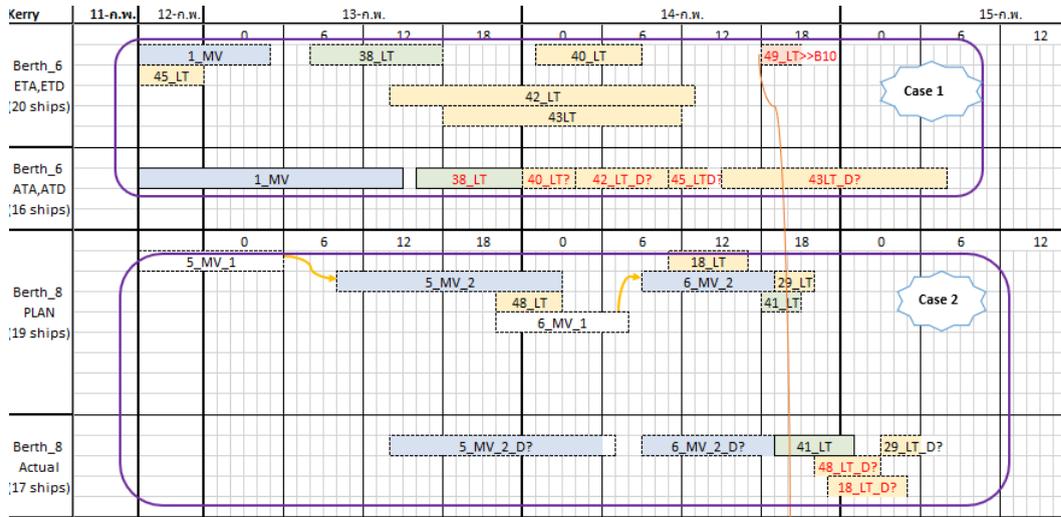


FIGURE 4.20 – Schedule of vessel berthing

Pattern 4 - Rushed MV operation with series of delayed LTs : on some delay of MV arrival, the loading/unloading operation is accelerated to finish by the allocated departure time. As an effect, the LTs are not in berthing service right away after MV is departed. They are delayed for a while. (This pattern is not implemented in the simulation due to inadequate information of the reason and pattern of LT delay.)

Pattern 5 - Tight schedule of several MVs : some MVs is delayed on ATA extending berthing hours and further delay the next MVs.

For the uncertain arrival of external trucks is calculated based on the historical data which we will discuss later in the part of Operation component.

- Uncertainty in resource availability : there is uncertainty in the level of resource capacity due to resource breakdown or the configuration of operation facilities. In the simulation, we configure the resource capacity by the change in percentage from 100% of full capacity, 75%, 50% and 0% of breakdown service.
- Uncertainty in operation interdependency : this kind of uncertainty is

already in the simulated operation regarding that we implement the infrastructure, operation procedure and operational activities based on the real-world operation. Therefore, the operation interdependency of the virtual DT is assumed to be replicated from the real-world.

4.1.3 Operation

Once the simulation is developed with port infrastructure and operation procedures are defined. On execution of port activities, it starts by the arrival of external transportation (vessels and external trucks) to drop or to pick up the containers. Then, the activities of the internal operation are executed as the consequence of the implemented procedural flows.

Based on the proposed framework, data of operational activities should be retrieved from the UTOs, however, currently UTOs data is inadequate for the implementation. Instead, historical data of vessel and external truck are collected and manipulated to acquire the necessary data for implementation. Historical of container transaction data is provided from the port case. 135,278 transaction records are extracted from the year 2018, January to December in one week of each month. The historical data is extracted for port activity statistical as follows :

1. Container input for the port operation : the port connects external access to the seaside and to hinterland trucks. The information related to the flows of containers are extracted e.g. the ratio of each container types, the number of import/export container accessing on each transportation modes, frequency of transportation arrival/departure and etc.

Additional information of vessel visit 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 4.21.

Further, the input number of container 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.

2. Uncertainty factors triggering the operation : the vessel arrival pattern shown in the Figure 4.21 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.

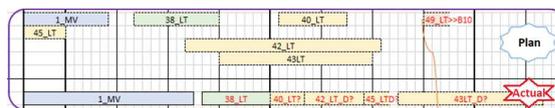


FIGURE 4.21 – Comparison of the plan and the actual pattern of vessel visits

3. 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 4.22) for later to compare with the virtual operation output.

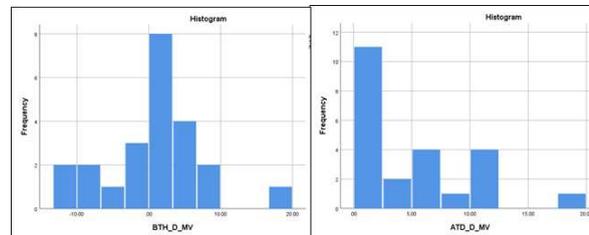


FIGURE 4.22 – Deviation of vessel operation time (left) and deviation of vessel departure time (right)

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 4.23 shows the 3D model of port operation simulation.

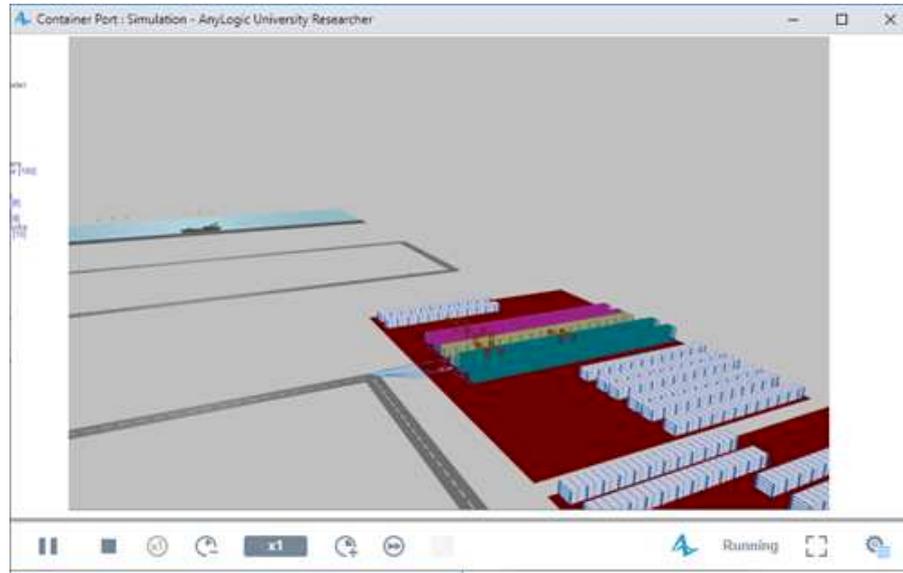


FIGURE 4.23 – Simulation of port operation

4.2 Simulation calibration

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 are complete and vessel departed, the actual departure time was recorded as the example shown in Table 4.2. 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 4.2 – Simulated result 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

4.3 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, 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 4.24.

Different for 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 4.25, 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

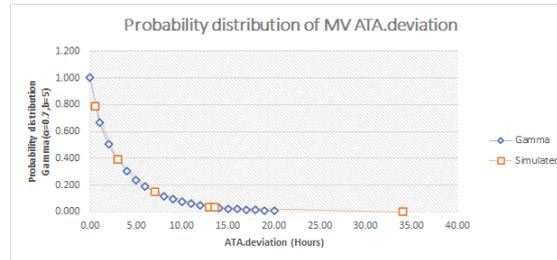


FIGURE 4.24 – Input validation of vessel arrival deviation

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 4.25.

4.4 Discussion and Conclusions

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

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 excepts in the case of high volume of container arrival. The expansion of difference in the two system 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.

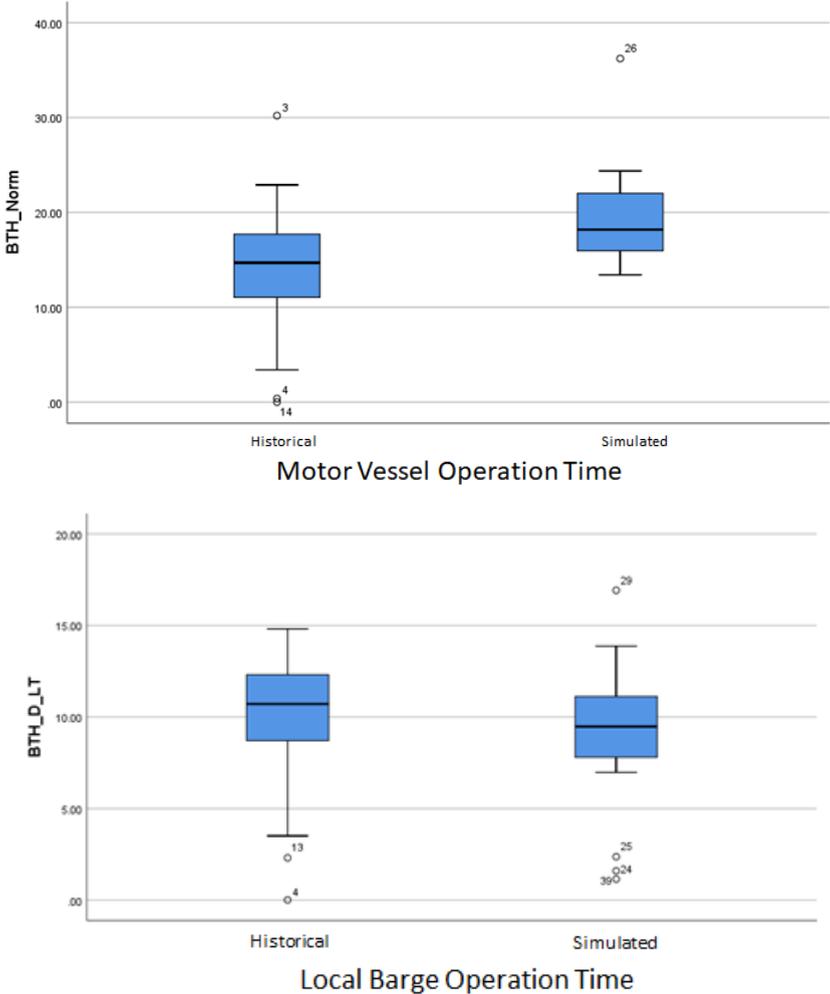


FIGURE 4.25 – Output validation of vessel operation time

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

Chapitre 5

Macroscopic prediction

The Macroscopic Prediction is the last stage in the proposed framework. Earlier stage, the Microscopic Simulation executes the movement of containers at the microscopic level. The results of all port operation nodes are collected as input for the Macroscopic Prediction to learn and construct the knowledge base. The multivariate LSTM is used to model the machine to learn the port operation activities under forces of uncertain changes and then to predict performance of the interested operation as discussed in the section 2.2.3.2. Dataset receiving from the Microscopic Simulation is transformed to be prepared for the input of machine learning as the inference proposed in the section 3.4.1. The learning aims to construct the knowledge base of the port operation with uncertainty as defined based on the uncertainty structure of Walker et al. for performance prediction. The result of prediction is finally presented.

5.1 Prediction modelling

The main purpose for prediction modelling is to predict the interested operation state which is the vessel operation time (from the arrival time to the departure time) for this study case. The predicted value is further used to support port manager's decision. The Macroscopic Prediction receives temporal dataset from the Microscopic Simulation. The simulation generates a temporal dataset of port operational states aligning with the berthing plan from microscopic point of view. The dataset of operational states is the knowledge representation of uncertainty evolving among the port operations, however, the relationships of operation nodes that transfer the magnitude of uncertainty are not constructed. The machine learning of multivariate LSTM is proposed to recognize the correlations among port operations through the parameters of the dataset with multi-input multi-output (MIMO) steps. Once the knowledge of the port operation with uncertainty is constructed via the multivariate LSTM neural network, the interested operation state which we would like to estimate can be predicted as the macroscopic result computing from the LSTM network of port operation nodes. The Figure 5.1 shows the process for modelling the Macroscopic Prediction to support port manager's decision.

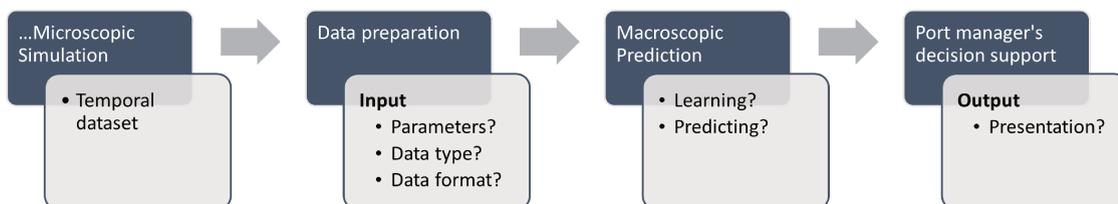


FIGURE 5.1 – Process of prediction modelling

5.1.1 LSTM Architecture

LSTM is in the form of chain of neural network modules connected to pass the information of the previous states and output to the next step. The Figure 5.2 illustrates the architecture of LSTM network. The top horizontal arrow represents the memory of the network storing as cell states. Information of the previous steps and the current step can be added or omitted from the memory. The bottom horizontal arrow represents output of the current step. The architecture inside each module consists of 3 gates with 4 neural networks. Considering the module at the time step (t).

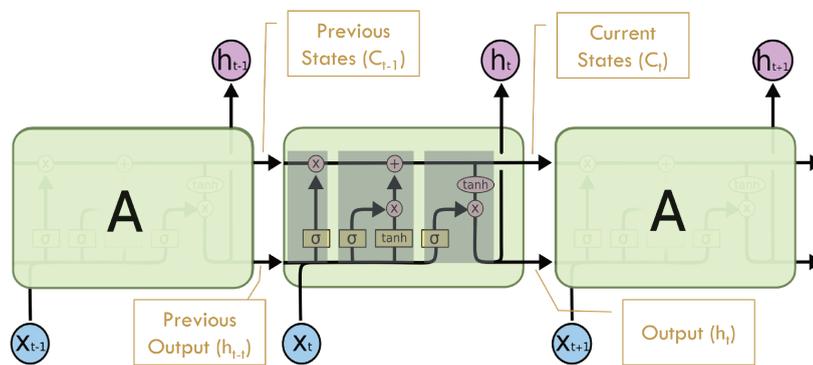


FIGURE 5.2 – LSTM Architecture

1. Forget gate - the first gate that the information passes to consider which previous information is going to forget or to keep. The selection is committed by the sigmoid neural network from the data of previous step output $h(t-1)$ and the input of current step $X(t)$. The output(0 or 1) is then multiplied with the previous states $C(t-1)$ in the memory. 0 is to omit and 1 is to keep.
2. Input gate - the second gate to consider which new information is going to be added into the memory. The consideration uses two neural networks of sigmoid and tanh. The previous step output $h(t-1)$ and the input of current step $X(t)$ are the input of the gate. The output of the selected information is then added into the memory as updated cell states $C(t)$.

3. Output gate - the last gate to decide output using all information of previous step output $h(t-1)$, current step input $X(t)$ and updated cell states in the memory $C(t)$. The sigmoid neural network chooses which parameters are the output. Then, the result is multiplied with the tanh of historical information to identify the relevant among current information and the previous information.

5.1.2 LSTM for knowledge learning

Based on the uncertainty structure proposed by [122], the knowledge of port operation with uncertainty should be constructed from uncertainty nodes of both the internal operations and the external operations. Therefore, the machine learning of LSTM should learn multiple data nodes at a time. Then, the multivariate stack LSTM as shown in the Figure 5.3 is used to learn the operation states of all nodes that happening at the same time in all at once. In addition, by this model approach, the dependency of operation nodes is in the consideration [129]. In the next time step, the LSTM learns the evolving of all nodes in all at once through the historical memory storing information of nodes as well. In another words, by the multivariate stack LSTM offers the port operation learning with data dependency in both the horizontal dependency among port operation nodes and the vertical dependency between port operation nodes and uncertainty changes through the time in short term and long term.

The Figure 5.4 illustrates the example of multi-input and multi-output steps (MIMO) of 3-step input and 2-step output. Each column represents the data collected at *timestep-n*. At a timestep data of all features are collected at once. On the first learning step, data of timestep-1 to timestep-3 are fed as input to predicts future

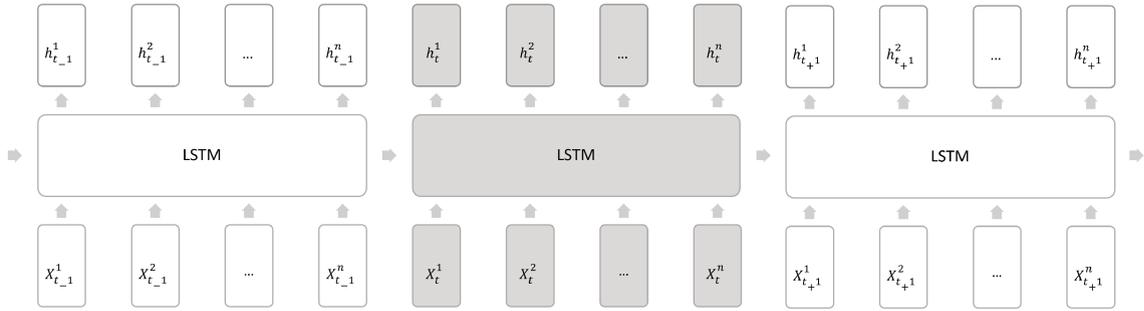


FIGURE 5.3 – Multivariate LSTM

states of all features which are at timestep-4 and timestep-5. On the second learning step, input dataset is shifted to timestep-2 to timestep-4 to predict the output of data states at timestep-5 and timestep-6. The learning is continuous, also the continuous predicting to the future time until the input dataset is not fed. On each learning step, the LSTM considers the correlation among current input dataset, the correlation between current input dataset and previous hidden states, the correlation among candidate output dataset and the correlation between candidate output dataset and hidden states. Along the learning steps, input of the current state is used as prediction feedback to the previous state e.g. timestep-4 as input of the second learning step validates timestep-4 as output of the first learning step. The neuron weights of network neurons are adjusted through the backpropagation.

	Timestep									
	1	2	3	4	5	6	7	8	9	10
Feature1	0.5	6.4	1.7	1.7	1.7	1.9	2	1.9	2.1	2.6
Feature2	0	0	0	0	0	0	0	0	0	0
Feature3	4.8	4.7	4.7	4.7	4.6	4.6	4.6	4.4	4.5	4.5
Feature4	0	0	0	0	0	0	0	0	0	0
Feature5	2	2	0	1	2	0	1	2	0	2
Feature6	0	0	0	0	0	0	0	2	1	1
Feature7	0	0	0	0	0	0	0	31	0	0
Feature8	0	0	0	0	0	0	0	77	0	0
Feature9	274	256	243	213	183	153	123	93	63	35
Feature10	336	336	336	336	336	336	336	336	336	336

	Timestep									
	1	2	3	4	5	6	7	8	9	10
Feature1	0.5	6.4	1.7	1.7	1.7	1.9	2	1.9	2.1	2.6
Feature2	0	0	0	0	0	0	0	0	0	0
Feature3	4.8	4.7	4.7	4.7	4.6	4.6	4.6	4.4	4.5	4.5
Feature4	0	0	0	0	0	0	0	0	0	0
Feature5	2	2	0	1	2	0	1	2	0	2
Feature6	0	0	0	0	0	0	0	2	1	1
Feature7	0	0	0	0	0	0	0	31	0	0
Feature8	0	0	0	0	0	0	0	77	0	0
Feature9	274	256	243	213	183	153	123	93	63	35
Feature10	336	336	336	336	336	336	336	336	336	336

FIGURE 5.4 – LSTM learning sample using 3-step input and 2-step output

5.1.3 Data preprocessing

The Microscopic Simulation executes the simulation and captures the temporal dataset every 10 minutes consisting vessel berthing plan, vessel states and port operation states. The simulated dataset consists 5 sets of information with the total of 22 parameters. Some parameters are in String format while the learning of LSTM works with the metric of numerical data. Therefore, those features requires a transformation to numerical format and the formatted dataset should be consistent to the learning inference. The list of simulated data features is as follows :

SET1 - Vessel berthing plan guiding LSTM

vessel_initial - The incoming vessel initiated to the simulation prior to its ETA
expected_tounload - Number of expected containers to unload from initialed vessels
expected_toload - Number of expected containers to load from initialed vessels

SET2 - Vessel states representing the berthing activities

ata_wz - The vessel that arrives into the wait zone
ata_berth - The vessel that arrives into the berth
atd_berth - The vessel that departs from the berth

SET3 - Vessel states representing expected and arrived queues

shipnum_exp_wz - Number of vessels expected to arrive in the wait zone
shipname_exp_wz - List of vessels expected to arrive in the wait zone
shipnum_exp_berth - Number of vessels expected to arrive in the berth
shipname_exp_berth - List of vessels expected to arrive in the berth
shipnum_wz - Number of vessels arrived in the wait zone
shipname_wz - List of expected arrived in the wait zone
shipnum_berth - Number of vessels arrived in the berth
shipname_berth - List of vessels arrived in the berth

SET4 - Operation states representing performance of facilities

Qcrane_time_SHUL - Avg. of Qcrane operation time to unload a container
Qcrane_time_SHLD - Avg. of Qcrane operation time to load a container
ICD1_Ycrane_time - Avg. of Ycrane operation time to process a container

ICD2_Turnaround_time - Avg. of truck turnaround time to process a container

SET5 - Operation states representing number of handling containers

count_EXUL - Number of external truck to unload container

count_EXLD - Number of external truck to load container

SH_tounload - Number of containers to unload from the berthing vessel

SH_toload - Number of containers to load from the berthing vessel

The simulation records activities of port operations every 10 minutes. These parameters specifies states of activities occurred during each time step.

SET1 is the information of vessel berthing plan. Since the vessel arrival is in stochastic even with the plan, the actual arrival can be deviated in early arrival or delay arrival. This set of information has a purpose to reduce stochastic of the arrival by informing the LSTM in advance that soon a vessel is visiting. The simulation initiates the vessel instance three hours in advance of the vessel ETA. Early of vessel instantiation is for adhering to the next record of vessel actual arrival either early or delay arrival. *vessel_initial* specifies the incoming vessel name. *expected_tounload* and *expected_toload* specify the number of incoming containers to unload and to load.

SET2 information is used to inform the LSTM about the actual occurrence of vessel berthing activities during the time step. *ata_wz*, *ata_berth* and *atd_berth* records the vessel name on its wait zone arrival, berth arrival and berth departure, respectively. The information notifies the LSTM when the berthing activity of the vessel is occurred. In addition, the deviation of vessel arrival from the plan can be implied from the difference between time steps of SET1 and SET2 information.

SET3 information is to track the changes of vessel status. The vessel lists are updated when a vessel changes its berthing activity. For example, when the vessel is initiated, it is added to *shipname_exp_wz* and *shipname_exp_berth* lists implied that the

vessel is expected to arrive to the wait zone and the berth in three hours. On the arrival to the wait zone, the vessel is then removed from *shipname_exp_wz* and added to *shipname_wz* notifying the change of activity. When the vessel moves into the berth, the vessel is shifted from the *shipname_wz* to the *shipname_berth*. The *shipname_berth* presents the vessel status when the vessel arrives or departs the berth so this parameter is also used for the prediction output.

In addition to the information that parameters of SET1, SET2 and SET3 inform the LSTM about the plan and the actual occurrence of berthing activities, the evolving of data also shows the period of time between activity transitions. For example the vessel arrival as a change of berthing activity, the deviation from the ETA is believed to be implicated via the difference of time steps between *vessel_initial* and *ata_wz* parameters. Further, the trend of vessel arrival is believed to be explored by the LSTM.

SET4 is the information of performing time of port operations during the collecting time step. The parameters shows changes of operation state in regard to the container demand from both the vessel and the external truck. *Qcrane_time_SHUL* measures the time from the container since it starts waiting for the quay crane on the vessel until it is unloaded to the internal truck. *Qcrane_time_SHLD* measures the time from the container since it starts waiting for the internal truck to pick up from the stack until it is loaded to the vessel. *ICD1_Ycrane_time* measures the time that a truck waits for the yard crane to pick up the container and place on the stack at the ICD1 export yard. *ICD2_Turnaround_time* measures the time that the external truck waits to pick up the container from the ICD2 import yard.

SET5 is the information to show how much containers that the port is operating during the collecting time step. *count_EXUL* and *count_EXLD* shows the number of external truck visiting to unload and to load containers, respectively. *SH_tounload*

and $SH_tounload$ shows the number of containers to unload and to load, respectively from the berthing vessel.

The Table 5.1 shows the sample of simulated data illustrating the transition of vessel berthing activities. ETA of the vessel MV_1 is planned. Before the ETA time for 3 hours, MV_1 is instantiated at the data record of timestep 1. The number of expected containers to handle for MV_1 are specified in the $expected_toload$ and $expected_tounload$. MV_1 is also added to the list of $shipname_exp_wz$ and $shipname_exp_berth$ as it is expected to arrive in both areas soon. As well as the expecting of LT_45 in the timestep 2, LT_45 is added to the same lists as MV_1.

Timestep	vessel_initial	expected_toload	expected_tounload	ata_wz	ata_berth	atd_berth	shipnum_exp_wz	shipnames_exp_wz	shipnum_exp_berth	shipnames_exp_berth	shipnum_wz	shipnames_wz	shipnum_berth	shipnames_berth	Qcrane_time_SHUL	Qcrane_time_SHLD	ICD1_Ycrane_time	ICD2_Turnaround_time	count_EXUL	count_EXLD	SH_tounload	SH_toload
1	MV_1	303	336				1MV_1	1MV_1	1MV_1	1MV_1	0	0	0	0	0	4.96	0	3	0	0	0	
2	LT_245	27	68				2LT_45,MV_1	2LT_45,MV_1	2LT_45,MV_1	2LT_45,MV_1	0	0	0	0	0	5.02	0	2	0	0	0	
3							2LT_45,MV_1	2LT_45,MV_1	2LT_45,MV_1	2LT_45,MV_1	0	0	0	0	0	5.02	0	1	0	0	0	
...																						
23				MV_1			1LT_45	2LT_45,MV_1	1MV_1	1MV_1	0	0	0	0	0	4.95	0	2	0	0	0	
24					MV_1		1LT_45	1LT_45	1LT_45	1LT_45	0	1MV_1	0.54	0	4.82	0	2	0	274	336		
...																						
54							2LT_40,LT_45	2LT_40,LT_45	2LT_40,LT_45	2LT_40,LT_45	0	1MV_1	3.66	91.3	9.96	35.8	3	1	0	260		
55							2LT_40,LT_45	2LT_40,LT_45	2LT_40,LT_45	2LT_40,LT_45	0	1MV_1	3.66	91.3	6.59	33.7	4	1	0	255		
...																						
115						MV_1	2LT_40,LT_45	2LT_40,LT_45	2LT_40,LT_45	2LT_40,LT_45	0	0	3.66	91.5	4.8	2.5	3	0	0	0	0	
...																						

TABLE 5.1 – Example of simulated data : vessel berthing transition

Later, MV_1 has actually arrived the wait zone at the timestep 23. ata_wz records the arrival activity. MV_1 is removed from the list of $shipname_exp_wz$ to the list of $shipname_wz$. Then, MV_1 moves into the berth at the timestep 24 due to the berth is available. ata_berth is notified. MV_1 is removed from the list of $shipname_exp_berth$ and $shipname_wz$ representing that it is not expected anymore nor not in the wait zone. Instead, MV_1 is added to $shipname_berth$ list. Quay crane starts unloading from the vessel as shown in $Qcrane_time_SHUL$ and the

number of containers in $SH_tounload$ and SH_toload are updated. MV_1 continues its unloading and loading with the continual changes of others vessel activities and port operation activities as shown in timestep 54 and 55. Until, the $SH_tounload$ and SH_toload are zero and the MV_1 is departed at the timestep 115. atd_berth is notified and MV_1 is removed from the $shipname_berth$.

The parameters of vessel lists such $shipname_exp_wz$, $shipname_exp_berth$ and $shipname_wz$ store data in String. They cannot be used as input for LSTM model. Therefore, they are simplified by splitting the list to multiple parameters. Each parameter contains only one vessel status. Based on the historical data, at a particular time, the vessel list does not exceed 5 vessels. Therefore, one vessel list is split to five parameters for LSTM parameters. For example, $shipname_exp_wz$ is split to X_exp_wz , $X+1_exp_wz$, $X+2_exp_wz$, $X+3_exp_wz$ and $X+4_exp_wz$. Value 1 represents a vessel in the sequence and 0 represents no vessel in the sequence. Simulated data of Table 5.1 is transformed to Table

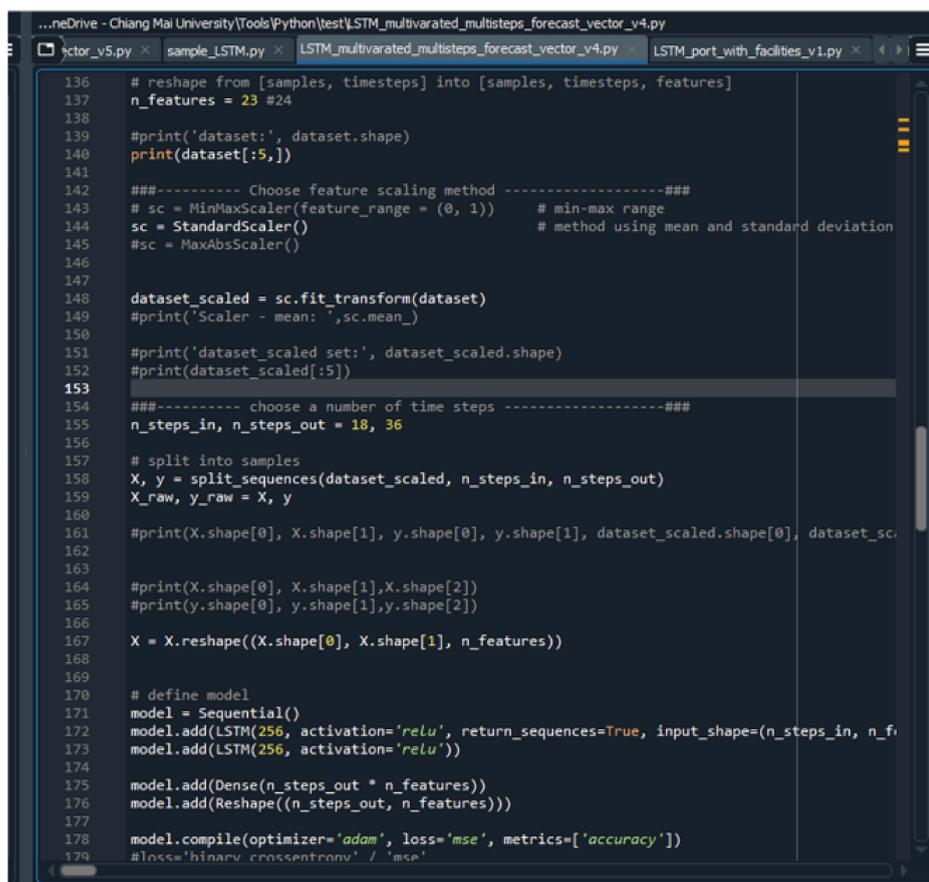
Berthing activity	Timestep	vessel_initial	expected_tounload	expected_toload	ata_wz	ata_berth	atd_berth	shipnum_exp_wz	X_exp_wz	X+1_exp_wz	X+2_exp_wz	X+3_exp_wz	X+4_exp_wz	shipnum_exp_berth	X_exp_berth	X+1_exp_berth	X+2_exp_berth	X+3_exp_berth	X+4_exp_berth	shipnum_wz	X_wz	X+1_wz	X+2_wz	X+3_wz	X+4_wz	shipnum_berth	Ocrane_time_SHUL	Ocrane_time_SHLD	ICD1_Ycrane_time	ICD2_Turnaround_time	count_EXUL	count_EXLD	SH_tounload	SH_toload		
MV_1 is expected	1	1	303	336	0	0	0	1	1	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
LT_ is expected	2	1	27	68	0	0	0	2	1	1	0	0	0	2	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
...	3	0	0	0	0	0	0	2	1	1	0	0	0	2	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MV_1 arrives wz	23	0	0	0	1	0	0	1	1	0	0	0	0	2	1	1	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MV_1 arrives berth	24	0	0	0	0	1	0	1	1	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	1	0.54	0	4.82	0	2	0	274	336		
...	54	0	0	0	0	0	0	2	1	1	0	0	0	2	1	1	0	0	0	0	0	0	0	0	0	1	3.66	91.34	9.96	35.79	3	1	0	260		
...	55	0	0	0	0	0	0	2	1	1	0	0	0	2	1	1	0	0	0	0	0	0	0	0	0	1	3.66	91.34	6.59	33.71	4	1	0	255		
MV_1 departs berth	115	0	0	0	0	0	1	4	1	1	1	1	0	4	1	1	1	1	0	0	0	0	0	0	0	0	3.66	91.5	4.8	2.502	3	0	0	0		
...	

TABLE 5.2 – Example of preprocessed data : split of vessel lists

Finally, the dataset is preprocessed to 33 parameters for the LSTM training and prediction.

5.1.4 Prediction model

The LSTM is modelled on the platform of Anaconda Python package with Tensorflow environment. The neural network library is Keras API. The program is coded in Python as shown in the Figure 5.5.

A screenshot of a code editor window showing a Python script for a multivariate LSTM model. The script includes comments and code for data preprocessing, model definition, and compilation. The code is as follows:

```
136 # reshape from [samples, timesteps] into [samples, timesteps, features]
137 n_features = 23 #24
138
139 #print('dataset:', dataset.shape)
140 print(dataset[:5,])
141
142 ###----- Choose feature scaling method -----###
143 # sc = MinMaxScaler(feature_range = (0, 1)) # min-max range
144 sc = StandardScaler() # method using mean and standard deviation
145 #sc = MaxAbsScaler()
146
147
148 dataset_scaled = sc.fit_transform(dataset)
149 #print("Scaler - mean: ",sc.mean_)
150
151 #print('dataset_scaled set:', dataset_scaled.shape)
152 #print(dataset_scaled[:5])
153
154 ###----- choose a number of time steps -----###
155 n_steps_in, n_steps_out = 18, 36
156
157 # split into samples
158 X, y = split_sequences(dataset_scaled, n_steps_in, n_steps_out)
159 X_raw, y_raw = X, y
160
161 #print(X.shape[0], X.shape[1], y.shape[0], y.shape[1], dataset_scaled.shape[0], dataset_sc
162
163
164 #print(X.shape[0], X.shape[1],X.shape[2])
165 #print(y.shape[0], y.shape[1],y.shape[2])
166
167 X = X.reshape((X.shape[0], X.shape[1], n_features))
168
169
170 # define model
171 model = Sequential()
172 model.add(LSTM(256, activation='relu', return_sequences=True, input_shape=(n_steps_in, n_fi
173 model.add(LSTM(256, activation='relu'))
174
175 model.add(Dense(n_steps_out * n_features))
176 model.add(Reshape((n_steps_out, n_features)))
177
178 model.compile(optimizer='adam', loss='mse', metrics=['accuracy'])
179 #loss='binary_crossentropy' / 'mse'
```

FIGURE 5.5 – Multivariate stack LSTM

Before the network training, features of the dataset is normalized using Standard-Scaler which rescales the data distribution using mean and standard deviation.

The LSTM is defined based on the Sequential neural network model. LSTM layers are stacked in sequential allowing LSTMs work with data in sequence. The LSTM

is then able to learn the port operational dataset in both vertical and horizontal by using 3D data input.

5.2 Prediction result

Experiments on prediction model are conducted with purposes as follows :

1. to verify that the proposed inference with features derived from port operation activities are eligible for the LSTM prediction modelling
2. the LSTM prediction model is capable to predict the state of port performance using the dataset of real-world case of port operation with uncertainty
3. to explore how the behavior of prediction is changed due to the configuration of MIMO steps

5.2.1 Scenarios

Experiments are conducted in 2 phases. The first phase is to use the mocked up data and a simple simulation model to proof the concept of modelling approach. The second phase is to use the dataset based on the real-world port activities to verify the capability of the proposed model in prediction accuracy.

5.2.1.1 Set 1 : Mocked up data

The first set of experiments, the simple simulation model executes the mocked up data of 5 vessels. Each vessel arrives to the port according to the plan. The external trucks arrive the port at a fixed rate. It captures data of operation states in 10-minute interval, so it generates 255 temporal data records. The dataset is split to 175 samples for LSTM training and 44 sample for the LSTM validation.

The configurations of MIMO steps are applied on each LSTM execution. The results are as shown in the Figure 5.6.

The prediction results are more accurate on the shorter steps of prediction output. In addition, it is noticed that on the transition of the previous vessel departure to the next vessel arrival, the prediction is more accurate when the time space between the two vessel is wider.

For this dataset that seems not containing various impact from uncertainties, the model is capable for predicting the port operation for 18 steps or 3 hours. At MIMO steps of 36-36 or 6-hour input and output, the prediction tends to be impracticable for distinguishing the arrival and the departure of vessels.

5.2.1.2 Set 2 : Real-world port data

The second experiment is conducted using data based on real-world port operation generated from the configured digital twin. The DT simulation executes 30 vessels. It generates 2,510 temporal data records. The dataset is split to 2,003 samples for LSTM training and 507 sample for the LSTM validation. This dataset contains the real-world stochastic of vessel arrival uncertainty as classified in the patterns of vessel arrival and the stochastic of external truck arrival as discussed in the section 4.1.2.

The configurations of MIMO steps are applied on each LSTM execution. The prediction results are as shown in the Figure 5.7 with the graph of model accuracy (Figure 5.8) and the graph of model loss (Figure 5.9).

The prediction model can learn and well predict the result with the MIMO : 1-1 step configuration (accuracy=87.38%). Even it is impractical for the prediction time range, however, the result shows that the implication of proposed inference is applicable for LSTM learning and construction of real-world port operation knowledge.

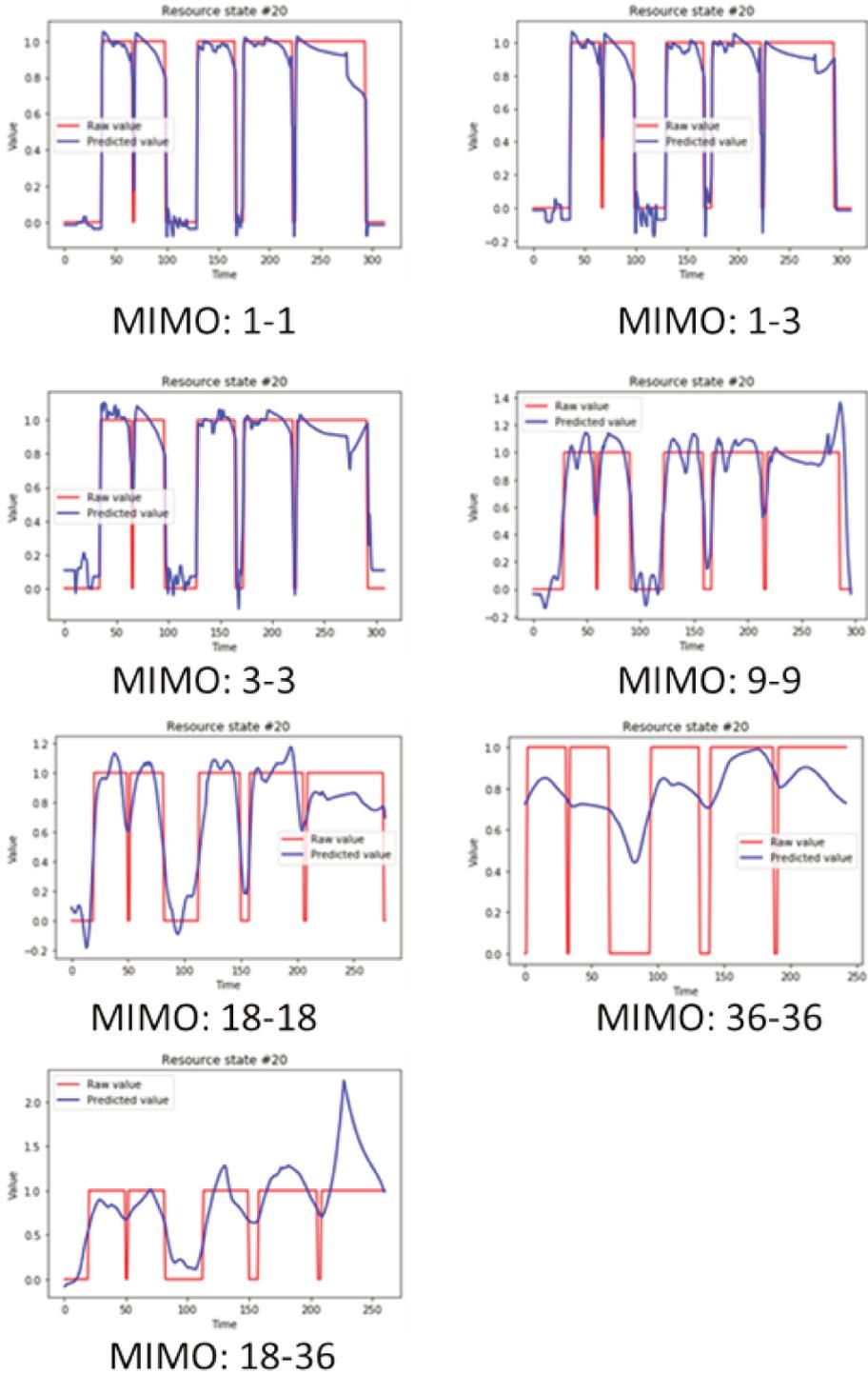
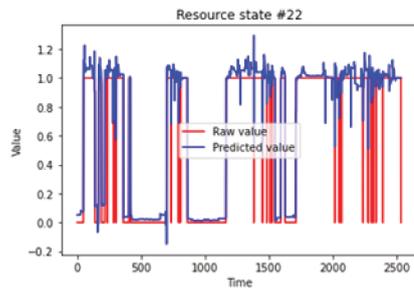
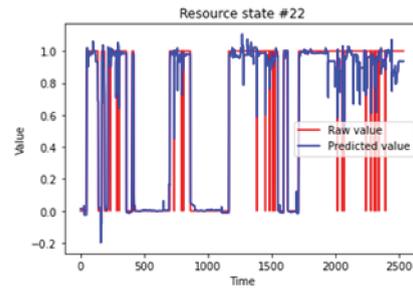


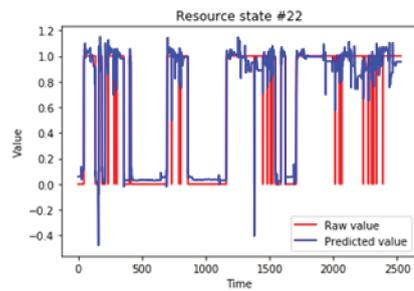
FIGURE 5.6 – Prediction results of dataset 1 : mocked up vessels



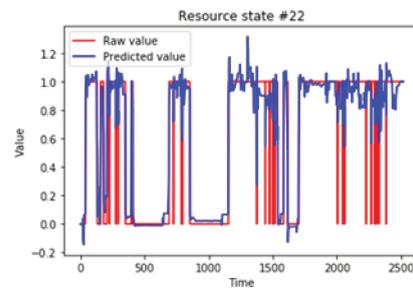
MIMO: 1-1



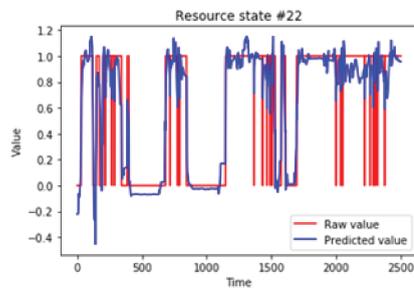
MIMO: 1-3



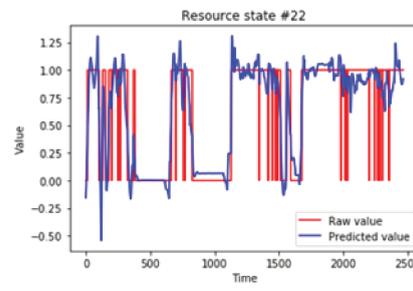
MIMO: 3-3



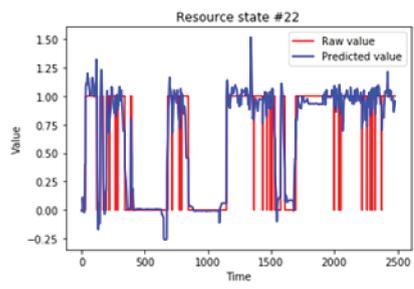
MIMO: 9-9



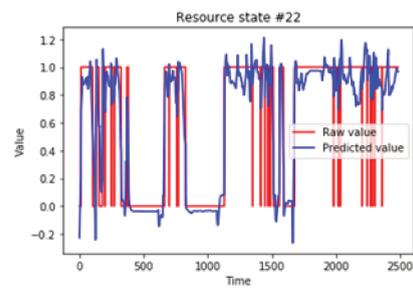
MIMO: 18-18



MIMO: 36-36



MIMO: 18-36



MIMO: 36-18

FIGURE 5.7 – Prediction results of dataset 2 : real-world port

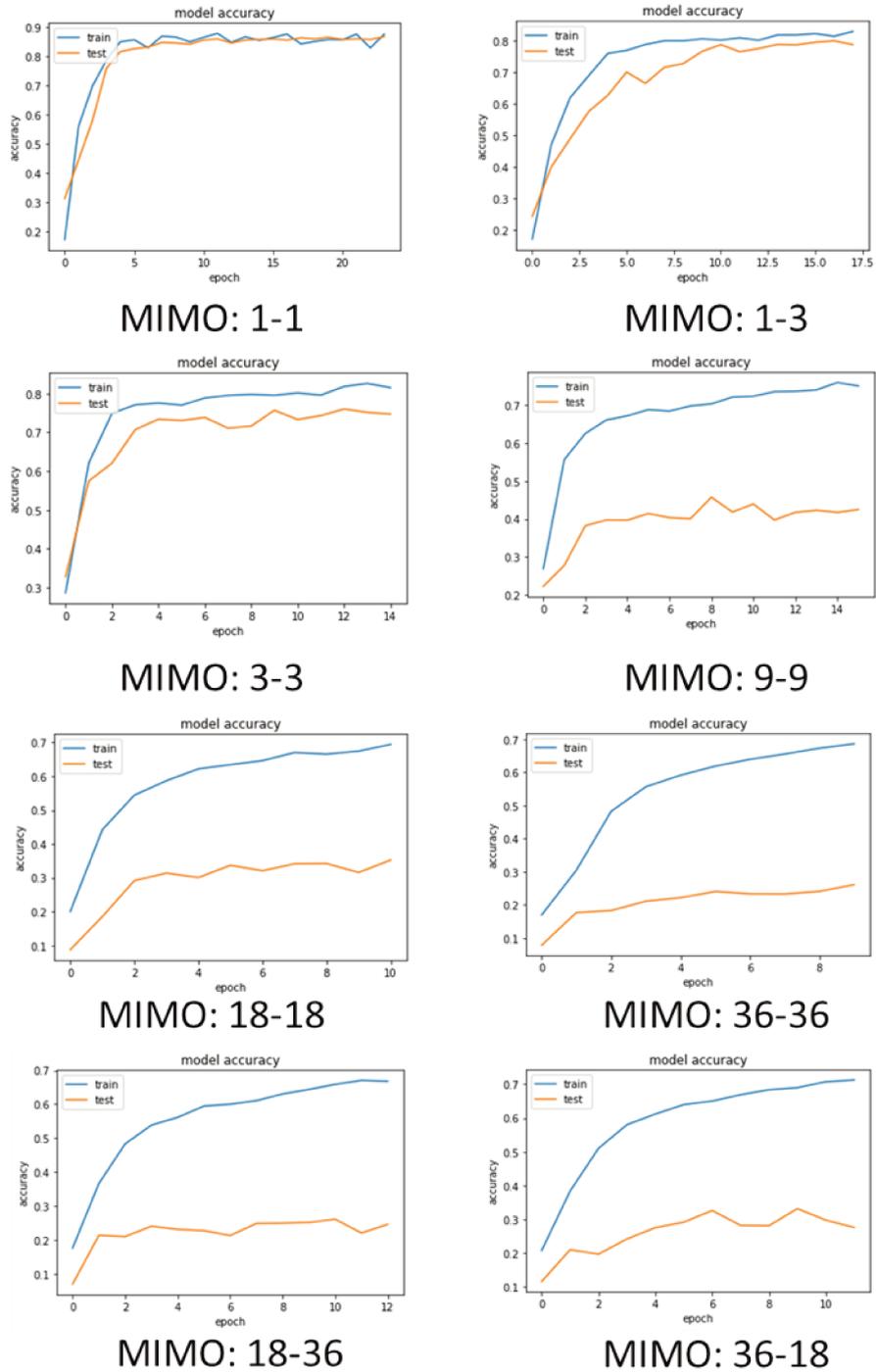
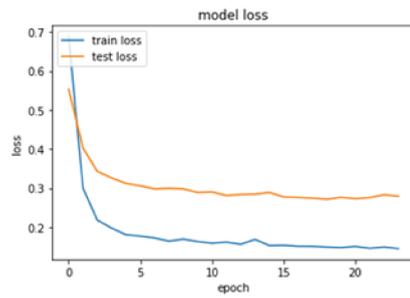
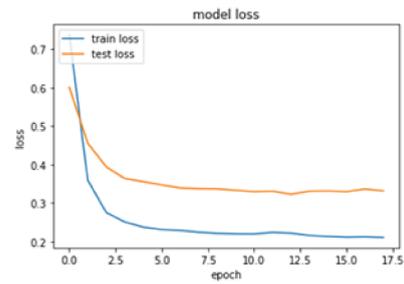


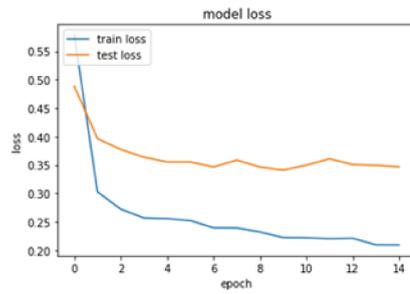
FIGURE 5.8 – Model accuracy of dataset 2 : real-world port



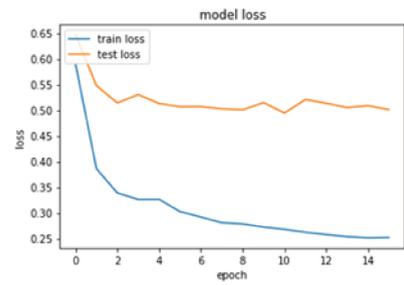
MIMO: 1-1



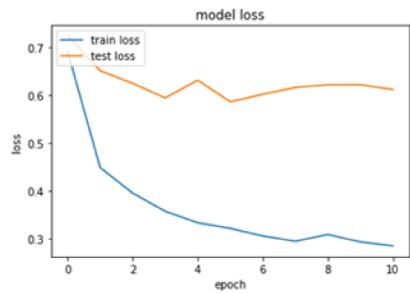
MIMO: 1-3



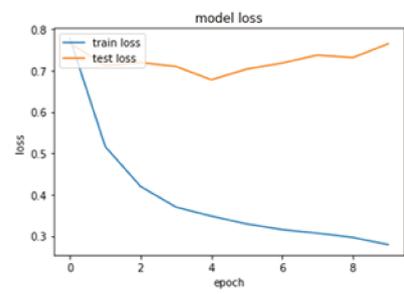
MIMO: 3-3



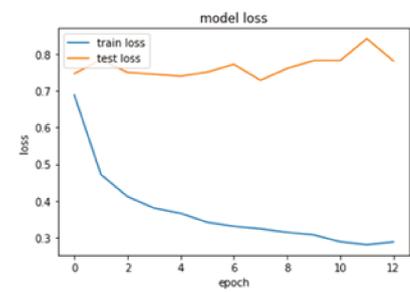
MIMO: 9-9



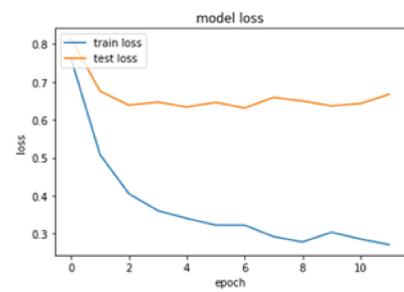
MIMO: 18-18



MIMO: 36-36



MIMO: 18-36



MIMO: 36-18

FIGURE 5.9 – Model loss of dataset 2 : real-world port

For the dataset of this scenario is capable for predicting the port operation for 3 steps or 30 minutes which is far less than the set1 scenario of mocked up data. The reason could be the stochastic in the operation resulting the variation of pattern in the dataset. Notice the Figure 5.8 and 5.9, at MIMO 9-9, the testing accuracy is dropped dramatically, also the testing loss. The gap between the training data loss and testing data loss are expanded between these two lines, this is interpreted that the more dataset is required for the model training, as well as, the others longer prediction period.

5.3 Conclusion

Once the operational dataset is generated by the simulation, In the chapter 5, the Macroscopic Prediction models the knowledge base based on the dataset using the LSTM network. The LSTM is modelled as the multivariate stacked in order to be conformed with the characteristic of port uncertainty. The port uncertainty is horizontally interdependence among operations and the is vertically changed by the time. 3D temporal dataset is pre-processed by transforming simulated String data to the binary format. Five sets of information which are inferred to port operation activities, vessel berthing activities and vessel berthing plan are also the elements of uncertainty structure. Two experiment sets are conducted to observe the fitting accuracy of the dataset with the configuration of input learning steps and output prediction steps. Results shows that the proposed inference and data features can be trained by the LSTM to construct the knowledge base for port operation with uncertainties. Even the prediction result of the current real-world dataset with uncertainty forces cannot accurately predict the operation for long hours but training the longer period of dataset might improve the prediction accuracy. Further, the

testing of MIMO step is suggested for modelling the port operation prediction since it would help verify the sensitivity of dataset to the operation change.

Conclusion and Outlook

Contribution

By the maritime industry, UNCTAD highlights uncertainty and resilience to changes in year 2020 due to its impact linked to the global network in complex pattern [116]. Port is a global network unit with high variability of uncertainty factors. Port challenge is to handle various random kinds of uncertainty. Operation is changed by unknown of uncertainty magnitude, by the taken reactivity and by operation interdependency, so it is ambiguous to specify relationships between the operation lead time and impact influenced from all uncertainty. In addition, the uncertainty magnitude and the operation lead time are changed overtime.

By the scientific literature, two structural literature reviews are conducted illustrating that kinds of uncertainty are exploded and transferred through the chain of maritime logistics, container carriers and port operational functions. They are interrelated and uncertainty results in the performance of port operation functions. However, researches study in the scope of particular port operation functions. Some researches study in the scope of particular uncertainty sources. While the operation in the field consists of various kinds of uncertainty affecting through the flows of port operations. The quantitative relationships between uncertainty and the operation lead time are, therefore, limited.

The case of UK port congestion during the pandemic period in 2020 shows difficulties in estimating the operation lead time caused by uncertainty. Dealing with various uncertainties e.g. vessel traffic, container volume, haulage shortage and etc., the estimation of vessel lead time such as the ETAs and ETDs were recurrently scheduled. According to the issue and limitations in literature as described, it seems that the information and knowledge for supporting the estimation is limited.

The ability in estimation of port operation lead time to support decisions in port resource management is critical, especially the berth allocation. The ETA and ETD should be estimated at an accuracy, otherwise, the planning of the others resources in the operation flows requires updates in accordance to the changes of ETA and ETD. So, we are interested to use the knowledge of port operation with uncertainty to support the reactivity decision for berth allocation as the case study.

In the Chapter2, literature reviews are conducted to justify the research approaches in order to define the structure of the knowledge model for port operation with uncertainties, to specify the knowledge source and to specify the approach to construct the knowledge.

To define the knowledge structure of port operation under uncertainty, two conceptual models of uncertainty proposed by Van Asselt, Rotmans [119] and Walker et al. [122] are reviewed. Both models define their models in two parts ; the modelling of uncertainty context and the modelling of knowledge for dealing with uncertainty. Walker et al.'s model is adopted in the port of uncertainty context due to its consistent to the physical port operation with its uncertainty. The model describes uncertainty as the fundamental forces travelling around the system. For the part of knowledge for dealing with uncertainty, Van Asselt, Rotmans mentions the availability of knowledge to be observed/measured by available tool. Walker et al. classifies knowledge level by its form ; in statistical, in scenario, in theoretical or inconsiderable.

Body of knowledge for dealing with port operational uncertainty is aligned in dynamic process-based approach such the activity system [100] than the human resource-based approach such the SECI model [80]. Due to the operational uncertainty dynamically flows in the environment in autonomy by the nature and unexplained, human instant perception is limited.

Next, shows the consideration of how to acquire knowledge from the port activity system. Generally, traceability data is used to track activities of systems. A structural literature review of traceability data is analysed in acquisition approaches, data usages and issues. As a result, the unitary traceability data (UTO) offers capability as the real-time microscopic data that allows visibility of operation movements through the system. UTO is the eligible tool to acquire data for modelling the Walker et al.'s uncertainty structure.

Knowledge Engineering (KE) is studied in the conceptual process to transform data of activity system to construct the knowledge base of port operation with uncertainties. Along with, Digital Twin(DT) is used to define the system implementation process to transform data of activity system to construct the knowledge base in practicable. DT offers the generation of a sufficient volume of data with configurable cases of uncertainty scenarios.

Chapter 3 proposes the framework consisting of three stages ; Port Component Extraction, Microscopic Simulation and Macroscopic Prediction. On the first stage, Port Component Extraction should specifies components that requires for building the virtual port of the Digital Twin. In the chapter 3, we analyse the requirement in the use of data components for the proposed framework. Port components are used for modelling the Digital Twin, for structuring the knowledge of port uncertainty and for reasoning the machine learning. The required components are classified as Infrastructure, Information and Operations. Data of port components are collected from the real-world port system via the primary and secondary sources. Port

manager of the case study port in Thailand is interviewed. The case also provides historical data of container transactions which is further used to extract the operation statistics such as vessel transferring rate, visiting rate of external truck, the duration of container storage at the yard and etc. The information of vessel berthing plan and berthing activities are collected from the port website.

In the chapter 4, the Microscopic Simulation constructs the digital twin model based on data and information extracted from the physical port. The physical-virtual synchronization run was executed using historical data as input to the model. The Results of the virtual and the physical system have similar behavior excepts in the case of high volume of container arrival. The expansion of difference in the two system 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 application can be explored. We aim at using periodic data of port facility status to observe the ability in maintaining the berth planning by predicting the estimated time to departure (ETD) of vessel in the future time horizon.

Once the operational dataset is generated by the simulation, In the chapter 5, the Macroscopic Prediction models the knowledge base based on the dataset using the LSTM network. The LSTM is modelled as the multivariate stacked in order to be conformed with the characteristic of port uncertainty. The port uncertainty is horizontally interdependence among operations and the is vertically changed by the time. 3D temporal dataset is pre-processed by transforming simulated String data to the binary format. Five sets of information which are inferred to port operation activities, vessel berthing activities and vessel berthing plan are also the elements of uncertainty structure. Two experiment sets are conducted to observe the fitting

accuracy of the dataset with the configuration of input learning steps and output prediction steps. Results shows that the proposed inference and data features can be trained by the LSTM to construct the knowledge base for port operation with uncertainties. Even the prediction result of the current real-world dataset with uncertainty forces cannot accurately predict the operation for long hours but training the longer period of dataset might improve the prediction accuracy. Further, the testing of MIMO step is suggested for modelling the port operation prediction since it would help verify the sensitivity of dataset to the operation change.

Future work

The outlook of this research could be subjected in short term, middle term and long term.

The digital twin on our experiment is developed based on the real physical port system with real-world data input that stimulate uncertainty into the port system, however, the acquisition of data is limit. It requires to collect data from various sources and requires data manipulations.

Therefore, in short term, to improve this research. First, scaling up the data volume would support the prediction modelling. The validation of prediction model would be more precise. Second, the proposed pre-processing of data features is based on one implication approach, the technique of feature selection could be applied. Once the prediction model is solid, it further would be deployed in the real port with the verification of decision support by the port manager.

In the middle term, the study may extend the experiment in the whole cycle of digital twin. This research focus in the initializing of knowledge based prediction model by using simulation to generate uncertainty and using data from several sources. If

data is accessible directly from the real operation, the whole cycle of digital twin that performs the real-time prediction to support the port manager. In addition, the other techniques of prediction modelling such as the combination of recurrent model with the other deep learning algorithm is also interested to improve the fitting of port operational dataset.

Last, in the long term, it is interested to extend the operation dataset with the surrounded environment such as weather and traffic. The data is available to aggregate from the GPS. It would comprehend the operation situation.

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