Global tank container asset management

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The degree of Doctor in Philosophy

By

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Abstract

Growth in the petrochemical industry has fuelled demand for 3rd party logistics services provided by tank container operators (TCOs), who strive to maximize profit through the integration of global tank container (TC) operations with the job 'quotation-booking' process. However, TCOs face challenges not faced by general shipping container operators, including process uncertainties arising from TC cleaning, the use of freight forwarders (FFs), and customers over-holding TCs due to the special storage needs of chemicals. These challenges have received little attention in the academic literature. This thesis addresses this gap by aiming to help TCOs with better decision-making at different planning levels under various uncertainties.

To provide an understanding of container asset management, this thesis presents a literature review for both general container operations research and TC operations specific research. The key issues and existing approaches are not only categorised, but also linked to the foundation of asset management to articulate the framework of this research and its objectives. Following this, two main research goals are addressed.

First, a simulation-based two-stage optimisation model is developed to address the operational level challenges. The first stage focuses on tactical decisions in setting inventory levels and control policy for empty tank container repositioning. The second stage integrates the dynamic job acceptance/rejection decisions in the quotation-booking process with container operations decisions in the planning and execution processes, such as job fulfilment, container leasing terms, and choice of FFs considering cost and reliability, and empty tank container repositioning. The solution procedure uses the simulation model combined with heuristic algorithms including an adjusted Genetic Algorithm, mathematical programming and heuristic rules. Numerical examples based on a real case study demonstrate the effectiveness of the model.

Second, a math-heuristic based two-stage optimisation model is developed to address the strategic/tactical level challenges. This upper level aims at optimising TC fleet size and customer holding polices to create a more effective TC flow at the lower level based on a time-space TC flow network. To solve the model, a GA-based solution and two Progressive Hedging Algorithm based math-heuristic solutions are introduced. Using numerical experiments, the merits of the different solutions are investigated and some significant findings obtained.

Remarks of this thesis

By the time of submitting this thesis, Chapter Four has already been converted to two working papers. One is titled as "*Tank container asset management with uncertainties in booking-quotation and container cleaning*", accepted and presented on LRN 2017. The second paper is titled "*Tank container operators' profit maximization through dynamic operations planning integrated with the quotation-booking process under multiple uncertainties*", and now it is accepted subject to making the experiment data publicly by European Journal of Operational Research. In addition, Chapter Five is being transformed to a working paper and it is planned to be submitted to Transportation Research Part B by the end of this year or beginning of next year.

Acronyms

TC – Tank Container

DC – Dry Container

TCO – Tank Container Operator

DCO – Dry Container Operator

ETCR- Empty Tank Container Repositioning

ECR – Empty Container Repositioning

FFs – Freight Forwarders

RAIL – Regional Average Inventory Level

GA – Genetic Algorithm

AGA – The Adapted Genetic Algorithm

HSM – The Heuristic Search Method

LCCNO – Largest Consecutive Container Net Outflow

CCNO – Continuous Container Net Outflow

LIL – Least Inventory Level

LBO – Largest Backlog Order

LRA – Largest can be Repositioned Amount

MIL – Most Inventory Level

SAA – Sample Average Approximation

PHA – Progressive Hedging Algorithm

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1. Introduction

1.1 Background and research motivations

The petrochemical industry has been growing steadily over recent decades, and up to 2014 the size of the global petrochemical market reached 490.5 million tons and is forecasted to grow at a Compound Annual Growth Rate (CAGR) of 5.1% from 2015 to 2022 (Grand View Research, 2016). As the biggest consumer, China accounted for 26.7% of global consumption in 2014 and is expected to witness growth of 6.2% from 2015 to 2022 (ibid). In terms of market value, 419.4 billion US dollars were traded in 2015, and the high demands are majorly coming from the automotive, textile, construction, industrial, medical pharmaceuticals, electronics and consumer goods industries. With the growth in the petrochemical industry, associated transport demands are also growing. As one of the key transport modes in this industry, Tank Containers (TCs) play an important role due to their convenient handling, safety, and environmental friendly features. Similar to Dry Containers (DCs), they are designed for intermodal transport, so they can be moved easily by truck, train and ship. According to the International Tank Container Organisation (ITCO, 2016), the global fleet size of TCs was estimated as 458,200 units in 2016, and it is maintaining a steady growth rate of 10% per year. Erera et al. (2005) concluded that the major advantages of TCs that have resulted in this growth are:

i. they are safer and produce less leakage during transportation and handling;
ii. they provide better space utilization compared to other modes, e.g. 43% more volume than drums stowed in DCs;
iii. no additional specialized port-side infrastructure is required when handling both DCs and TCs;
iv. they can be used to provide a reliable liquid storage device, particularly at the customer-end post-transport.

Although the physical features of TCs are similar to DCs, so that they are compatible with standardized cargo handling equipment and intermodal transport, their operations are quite different due to the special features of this industry. Dry Container Operators (DCOs) are normally shipping companies, who manage their own containers or long-term leased containers (can be regarded as self-ownership) with their own liner service. In contrast, Tank Container Operators (TCOs) offer a complete logistics service to customers in the petrochemical supply chain, but do not own ships, and their customer demands are satisfied by a so-called "*quotation-booking*" process (Erera et al. 2005). DCs are used in much higher volumes, creating large regular flows, through aggregation, that the large shipping companies can then match with regular routes and their own ships. It makes business sense for the shipping companies to own and manage DCs as it fits with their economies of scale business model. TCOs in contrast are used in much smaller volumes to provide far more specialist services, often with irregular flows. This is a low-volume high variety market less suited to the large shipping companies to own and manage TCs themselves. Instead, smaller specialist petrochemical logistics companies offer TC logistics and then piggyback on the container ships of the larger shipping companies. As a result, TCOs tend to emphasize profit (or revenue) maximization instead of cost minimization. As an asset compares to DC, TC is five times more expensive than DC (IICL, 2010) and TC is the core asset that differentiates TCOs from one another (i.e. the business design is thoroughly surrounding TCs), therefore, maintaining good performance of TCs' profitability and utilisation is the key to TCOs' business success. However, due to the characteristics of TCs and the industrial practice in TC market, conducting good TC asset management is never an easy task.

First, the "*quotation-booking*" process in this industry is that customers book logistics services from TCOs with expected itinerary and execution time. TCOs need to respond quickly by developing a quotation through negotiation with external resource providers and analysis of their own resources. In this process, TCOs are challenged by how to deal with the uncertainties arising from the time gap between quotation development and service delivery. In particular, the time gap between demand receipt and execution has not been modelled appropriately. As the customer request for a price quotation is often received well in advance of the demand execution time, so TCOs have to decide whether to issue a price quotation without accurate information on TC availability at the demand execution time. In addition, the demand receipt is revealed gradually over time. Erera et al. (2005) emphasized the "*quotation-booking*" process in TC management, but assumed all demands are known and deterministic in the planning horizon. Hence, TCOs are lack of support in determining precisely how to service individual demands, calculating expected costs and subsequently maximizing profits through the quotation process. This problem becomes even more complex with the option to lease containers, which can take the form of planned leasing or spot/emergent-leasing, in more real-time, with their different costs. Furthermore, the high reliance on external resources magnifies these uncertainties. Because, TCOs normally don't own vessels, third parties are thereby needed for transporting TCs for the seaborne journeys. In turn, TC asset management for this part cannot be controlled by TCOs but relies on freight forwarders (FFs) and shipping companies with significant uncertainties. Also, it can place great difficulties for TCOs coping with unbalanced global flows of loaded containers, because empty tank container repositioning (ETCR) is more expensive to be carried with more uncertainties. The planned and forecast execution of booked customer demands in the future may influence the volume of ETCR at the present time, but something unforeseen in the future may make the current ETCR ineffective. Therefore, it is worth constructing a reliable tool that can support decision-makings to "quotation-booking" process and enhance the corresponding performance.

Second, in this industry, TCs are known as safe and reliable equipment for cargo transporting and storage purposes. When customers book transportation service from TCOs, they also will be granted a free period of time to return TCs to the designated locations. However, since setting up dedicated storage facilities in petrochemical industry is expensive plus the market demand is quite fluctuated in short (e.g. the U.S. Benzene imports statistics in Figure 1.1), TCs are normally used by customers as temporary storage equipment for their production purpose. Consequently, the prevalent TC overholding issue causes difficulties for TCOs in controlling their over TC flows. On the one hand, due to the high cost of TC overholding, it generates great profits for TCOs, but on the other hand, such customer behaviour has significantly delayed TC flow efficiency and negatively influences TCOs' performance in service new customer demands. Especially, when TCOs are lack of visibility from customers' side, effective mechanisms repositioning their own TCs or not enough TC fleet sizes, they will face problems of losing jobs, higher operational costs and poor customer satisfaction. What's worse is, due to the benefits brought by TC overholding (i.e. high profit at the current moment), this problem is commonly ignored by the industry and no effective solutions to evaluate, control and optimise this problem. From an asset management viewpoint, it is questionable whether a maximised overall profitability of TCs is achieved with the consideration of all the pros and cons brought by TC overholding phenomenon. In turn, it is practically meaningful to obtain the evidences that can raise industry's awareness toward TC overholding issue as well as to seek the solutions to leverage its pros and minimise its cons to enlarge TCs' asset value.

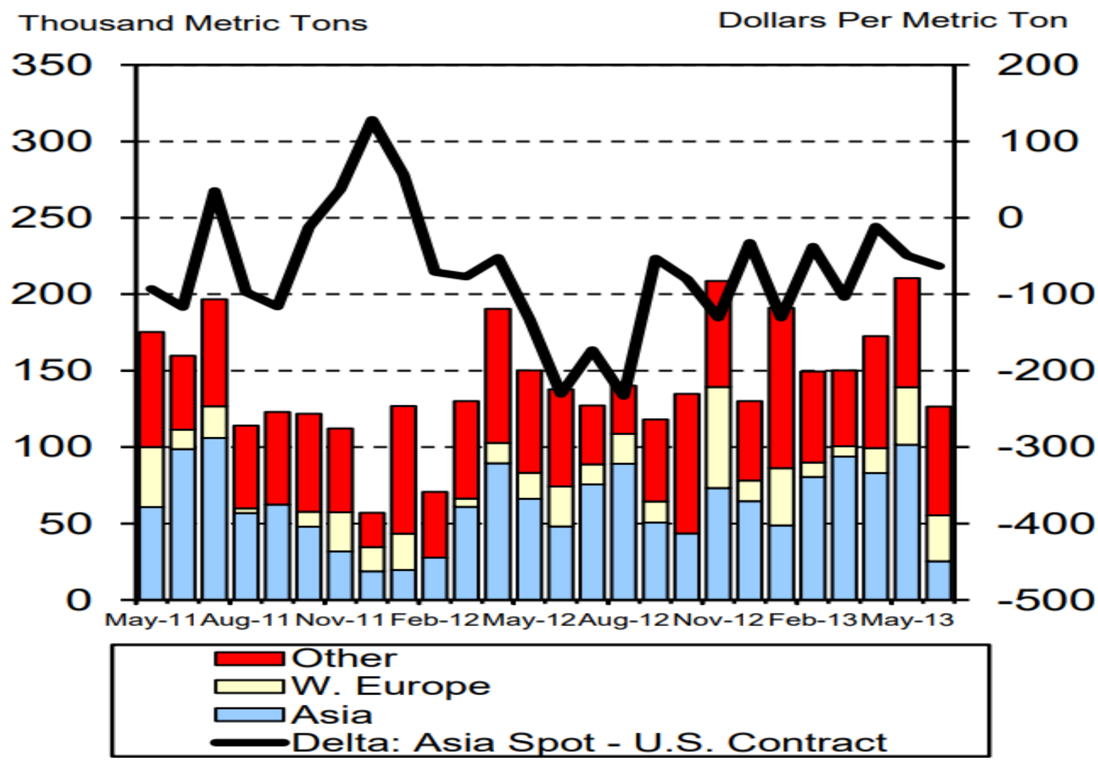

Figure 1.1. the U.S. Benzene imports from 2011 -2013

Source from: Macquarie Capital (2013)

Third, TC flows are also greatly distorted because of uncertain TC cleaning process. As the transport mean for liquids especially petrochemical products, the cleaning procedures for TCs vary largely and should fully recognise the chemical properties of the previous cargo such as the volatility, solubility in water, viscosity, colour, drying cargo, polimerisable cargo or strong absorber etc. (Panaitescu et al., 2018). Consequently, it is always hard to predict the exact cleaning duration for each job but can only roughly estimate each with a certain range (i.e. 3-7 days). In reality, this can place great uncertainties in operations such as inventory controlling, job planning or repositioning scheduling. As an asset, TCs' profitability level can be driven down greatly as the underlying uncertainties could increase operational cost or opportunity cost. And if taking the TC overholding and complex "*quotation-booking*" into account, the underlying uncertainties can further compound the negative effects of those challenges. Meanwhile, other features of TCs such as they are heavier, more diversified with container types and scarcer to the market can bring in new issues and new requirements for the management of TCs asset. Hence, the industrial and characteristics related uncertainties need to be comprehensively understood in terms of evaluation, controlling and mitigation.

By appreciating all the mentioned aspects, the overall goal of this research is **to build up a panoramic view of TC asset management that can support decision-making, comprehensive evaluation and effective planning with thorough consideration of TCs' features and uncertainties**.

To achieve above research goal, the following research objectives are proposed to be achieved:

1. To build the comprehensive understanding of the container asset management domain;

2. To pin down the key issues for tank container asset management at the operational level and develop effective tools for tank container operators for better decision-makings under various uncertainties;

3. To pin down the key issues for tank container asset management at the strategic/tactical level and develop effective tools for tank container operators for better decision-makings under various uncertainties;

In addition, there are several potential contributions that wish to be achieved by the end of this research. First, this research would like to draw research attention and fill up gaps both academically and industrially. Due to lack of research about TC industry, more effective practices are necessitated to better address its special features and various dynamic traits from its market. This PhD will contributes to building the cornerstone of strategic TC asset management and inspiring future research into this domain. Second, this research wish to contribute to the improvements of some modelling and solution methodologies with addressing TC industrial features. Particularly, it wishes to incorporate features such as plan-leasing, choice of FFs and two-week look ahead etc. features into existing ECR or container-based network flow simulations or models. Also, it wishes to find more effective way of obtaining optimality (or near-optimality) solutions under the TC stochastic environment. Finally, this PhD thesis would also like to provide the simulation tool, evaluation tool and optimisation tool for industrial practitioners from the underlying industry. With the help of the research outcomes, it is expected to allow the current TCOs applying the simulation and optimisation techniques out of this research into their operational and strategic use. It can also help TCOs further develop operational measurements, management insights and continuous improving solutions regarding TC asset management.

1.2 Outline of Methodologies

Guided by the proposed research aim and objectives, the whole research will systematically apply different methodologies for the corresponding sections. In order to build the knowledge base of the container asset management domain, literature review will be firstly conducted. In particular, existing studies from both general container and tank container industry will be reviewed and discussed. Through a systematic literature review process, it helps this research conceptualise research frameworks, construct knowledge hierarchy, identify research gaps and further clarify the research objectives. Followed, operations research-based modelling and optimisation techniques and mechanisms are applied to formulate the identified research problems, solve the problems and achieving the target for help tank container operators with better decision-makings at different operational planning levels. Specifically, both simulation-based and mathematical-based modelling techniques will be used for formulating different research problems. To solve and optimise the constructed models, mechanisms including linear optimisation, mixed-integer optimisation, sample average approximation and heuristics such as progressive hedging algorithm and genetic algorithm will be implemented. In the end, to maintain the credibility of this research from how it is conceptualised until how the research outcomes are obtained, methods for research validation and verification (V&V) are applied as well. This includes the V&V for data processing, V&V for model formulating and V&V for model solution and optimisation. By doing so, the intended research objectives are achieved with more credits and it is more confident to demonstrate the potential research findings as well.

1.3 Thesis structure

Next, the rest of the research will be organised as follows. Chapter 2 will explain in detail of the relevant literature review and the research gaps will be identified. In Chapter 3, the methodologies for problem modelling and solution will be critically discussed and the selected mechanisms and techniques are clarified. Also, methodologies that will be used for the validation and verification will be introduced. Chapter 4 will firstly address TC asset management issues from operational and tactic levels. It includes the formulation of the underlying problems, design and execution of model solutions, and a series of experiments will be carried to demonstrate the research outcomes and insights. Likewise, Chapter 5 addresses TC asset management issues from tactic and strategic levels. The same steps taken in Chapter 4 will be go through again, so that the overall results can complete the full a picture to answer the research subjective raised by this PhD thesis. In the end, Chapter 5 is going to give a panoramic view of this PhD research, in particular, the main findings from different level of studies will be summarised, in the meanwhile, limitations and what is missing from this research will be also pointed out, so it can imply the further research opportunities and directions.

2. Literature Review

This chapter will conduct a broad review of studies that are relevant to the target domain. Especially, with the guide of designed literature review method, the whole chapter will be comprised by background of DC and TC market, literature review frameworks, operational level research reviewing, tactical/strategic level research reviewing, research gaps discussion and research objecting proposing six main sections. Next, the implementation of literature review method is firstly introduced and then the rest of the contents will be following its guide accordingly.

2.1 Methodology of this chapter

In order to achieve the underlying research objectives, this chapter will firstly explore the industry backgrounds for both DC and TC markets to give the industry highlights as well as the difference between the two markets. Then surrounding container asset management, subtopics that are going to be reviewed are framed and studies about DCs are used as the reference point for identifying the research gaps for TCs with consideration of TCs' features. Reasons of this arrangement are two folds. First, researches directly investigate issues in TC industry are scarce. To the best of the authors' knowledge, searches have been carried for TCs management in several databases (e.g. Web of Science, Science Direct) with changing the terminologies of TCs (e.g. ISO tanks, tank containers etc.) from year 1990 to now, there are only two papers found (see Erera et al., 2005; Karimi et al., 2005) in the relevant domain. The special features about TC and TC operation have been sufficiently discussed and summarised by these two studies, yet their proposed models and solutions have left some issues unaddressed. Two, similarities shared by DCs and TCs enable the studies about DCs to be used as the theoretical foundation for this research. Because, as an asset, both TC and DC share similar asset life cycle. They both start with similar processes of asset acquisition (i.e. container purchasing), asset operation (e.g. job assignment) and maintenance (e.g. cleaning and repairing) and asset disposal (e.g. used container market). Activities throughout above journey are similar to both containers. For example, they both can be handled and stored with the same facilities; they both can be transported through the same multimodal options; and they have similar supply chain configurations (e.g. consignors, consignees, carriers, service providers etc.). Hence, studies about DCs management are reviewed the most to identify the research gaps.

Next, how to select the candidate papers for this literature review is carried as follow. Web of Science is the major academic source used by this PhD thesis, and it allows the author to try different key words and key words combinations to search for the most relevant literatures. Followed, through the reviewing of searched papers, more key words can be inspired, and the searched results can be further modified and supplemented. Meanwhile, some important articles which contains none of the searched key words would be added in as well. At last, the same processes will be go through again with Science Direct and Google Scholar in case of the resource difference due to different databases.

For each subtopic, the total reviewed papers are obtained through adjusting the keywords, searching multiple resources and defining the research scope. For example, in order to narrow down the relevant literatures for ETCR issue, we applied the keyword rule as: "empty container movement" and/or "container repositioning" not "terminal", because our study do not focus on terminal operations. Followed by this rule, 1,250 papers are firstly obtained. To further process the results, patent papers are excluded, and the remaining document types are majorly articles, meeting proceedings, books or book chapters and etc. Then the results are further narrowed to 128. Moreover, through the abstract reviewing of all the 128 papers, only English papers and empty container repositioning relevant are kept for further in-depth reading, therefore the amount of left papers is 96 in total. Moreover, on top of the obtained 96 papers, some other techniques are incorporated to further expand the overall literature pool of this topic. First, with reviewing the obtained literatures, some other key words or key words combination are used. For example, "container network optimization", "ocean container/marine container reposition/movement" are being used, and/or "empty container" is substituted by "empty equipment", "container repositioning" is replaced by "container allocation", "container assignment" or "container distribution" etc. More specifically, the different spellings between American English and British English are tried as well, such as "optimisation" and "optimization". Second, different resources are being searched. As we mentioned before, apart from Web of Science, Science Direct and Google Scholar are also tried the same key word(s) to capture the missing relevant articles. Third, with reviewing the relevant literatures, especially the literature reviews or literature survey papers regarding to container network designing or optimization (i.e. Tran and Haasis, 2015; Braekers et al., 2011; SteadieSeifi et al., 2014), some missing articles are being added as well. To illustrate the overall process of conducting the literature review, figure 2.1 below includes a flow chart to present it. As a result, 29 additional papers were included, which ultimately made the overall amount of reviewed papers as 125.

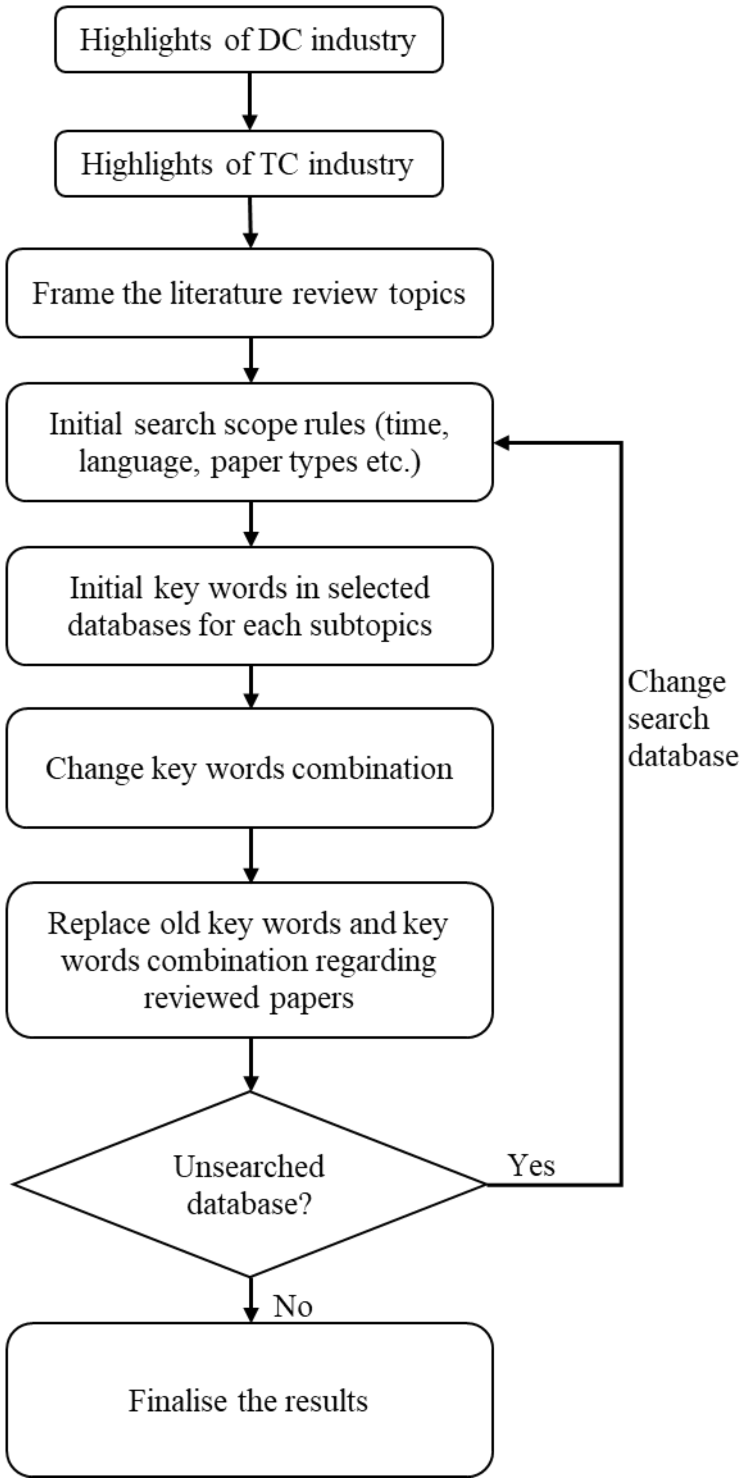

Figure 2.1 flow chart of literature review search method

2.2 Overview of the general container and TC container market

2.2.1 The general container market

With the international trade booming, the world seaborne trade embraces a stable growth for the past decades. As data in figure 2.2 revealed (UNCTAD, 2017), the global seaborne trade volume increased nearly 5 times since 1975, which plays the major contribution to the growth of global trade.

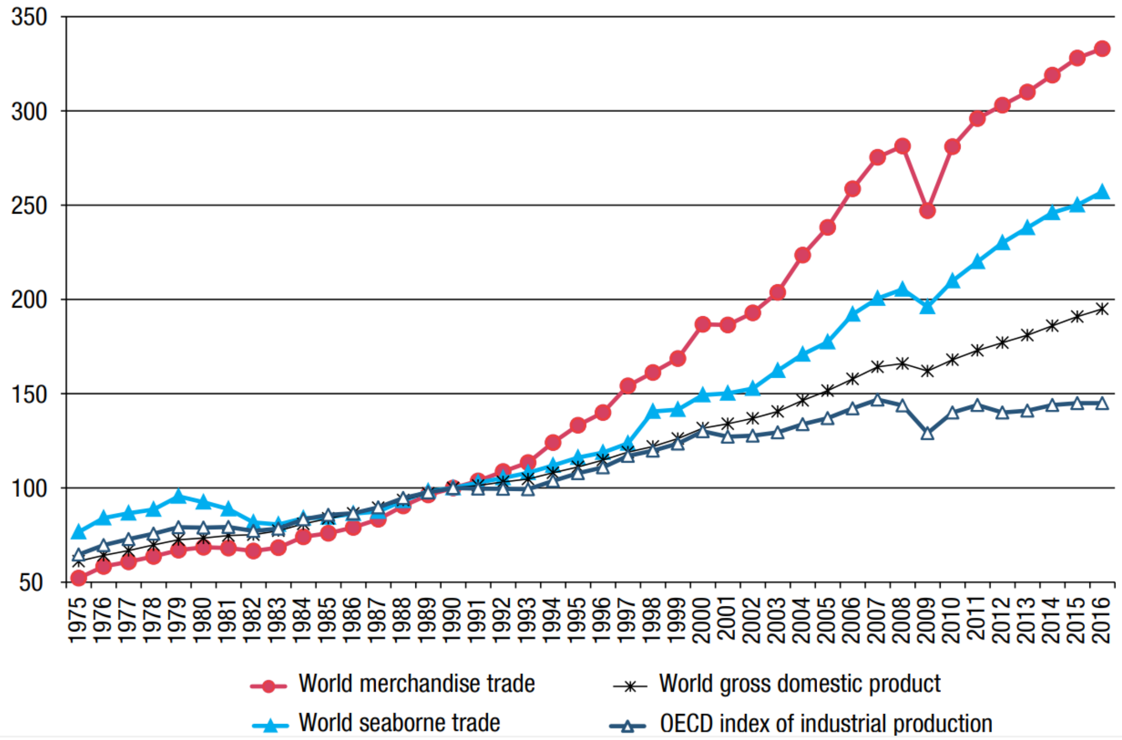

Figure 2.2 the growth indices for world trade, seaborne shipments, and gross domestic product, 1975-2016

Source from: UNCTAD (2017)

As a result, containerised trade expanded heavily due to its important role in world seaborne trade, Considering the value of traded cargoes, global seaborne container trade is believed to be accounted for approximately 60 percent of all world seaborne trade, and was valued at around 5.6 trillion U.S. dollars in 2010 (Statista, 2015). While the quantity of goods carried by containers has risen from around 100 million metric tons in 1980 to about 1.5 billion metric tons in 2013, the capacities of vessels are also increased (ibid). Between

1980 and 2015, the deadweight tonnage of container ships has grown from about 11 million metric tons to around 228 million metric tons. According to the data provided by UNCTAD (2015), the containerised trade is keeping on increase since 1996 up to 2015 (except a slight decrease in 2009 after the 2008 economic crisis) (fig. 2.3). See in the figure below, after the economic crisis, around 5% increase pace is kept in terms of containerised trade, which has also made the global containerised trade reached more than 140 million twenty-foot equivalent units (TEUs) in 2017. In the study of Song and Dong (2015), the continuous development of containerised trading market (even during the post-economic-crisis period) is driven by two major reasons. One, during the last two decades, goods are becoming more containerised, which are not only the majority of manufactured goods, but also commodities such as coffee and refrigerated cargos (e.g. meet and fruits). Second, for the consideration of energetic efficiency, economics of scales and green supply chain initiatives, containerships are built larger and larger over the past years, and relatively more containers are therefore being moved globally.

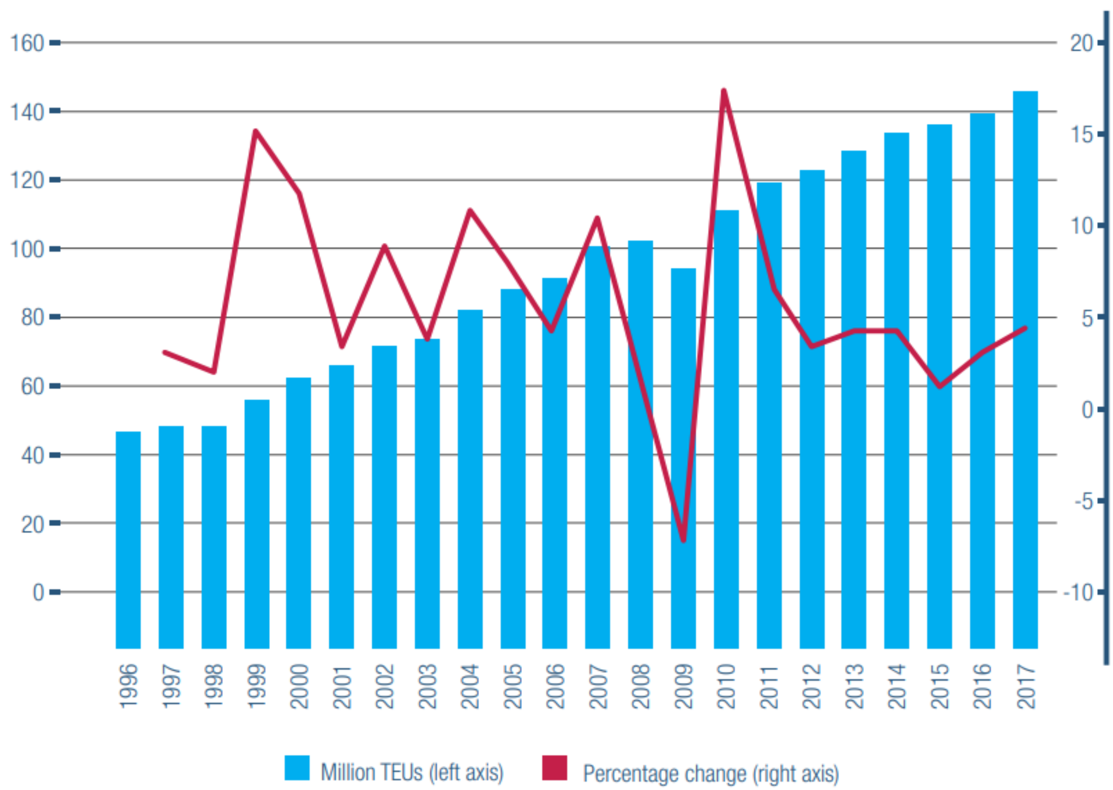

Figure 2.3 Global containerised trade, 1996-2017 (million TEUs and percentage annual change)

Source from: UNCTAD (2017)

In this industry, a containerised trade involves participation of several parties, and collaboratively, they formed the supply chain configurations of this market (Figure 2.4). In particular, containers are first needed to be prepared at the right place and right time with right volumes in order to ensure cargoes sent by shippers can be fully loaded; Followed, effective operations should be conducted to transport, charge/discharge and store containers to ensure cargoes can be delivered to consignees timely and cost effectively. In the end, containers should be emptied, cleaned or maintained (if necessary), and returned to appropriate locations in order to serve next transport tasks.

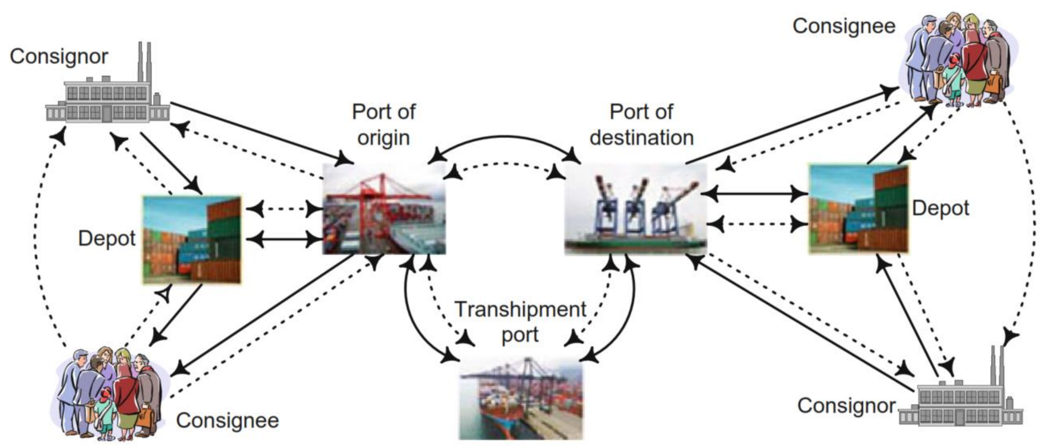

Figure 2.4 container shipping supply chain

Source from Song and Dong (2015)

To complete above cycle, maritime containers are one of the key assets that forms the backbone of the overall supply chain. It is the general form of material flow throughout most of the supply chain, and it also determines what services can be designed alongside this supply chain. As a result, containers are essential to their owners and need to be taken good care of. According to Consultantsea (2016), the estimated world global container fleet size is about 43 million shipping containers or equivalent to 72 million TEUs. But unfortunately, since (a) the large amount of shipping container factories with various and dynamic production rates; (b) container fleet owners refuse to publish their fleet TEU sizes;

(c) the existing of some un-standardised containers (e.g. 30ft or 10ft etc.), there is no exact records about how many containers existed in the world. Data from IICL (2010) illustrated, the world container fleets are generally owned by shipping companies or container lessors, and as the biggest owner of this industry, 60% of the global container fleet is owned by shipping companies. Regarding the recent price for a 20ft container new purchase (Alibaba, 2018), there are more than $108 billion container globally owned by shipping companies. For such a great investment, containers are essential assets that shipping companies need to maximise their profitability the lifecycle. Apart from the actual value of containers as an asset, they are important because (1) service about moving cargoes is the core business for shipping companies. Within the scope of this business, container is the only asset reaches almost everywhere of this business. Failing to conduct good container care and container exploitation may directly result in high business costs, poor customer satisfactory and failure in meeting market demands. Hence, performing better container management can lead to better performance of shipping companies' core business; (2) Data from UNCTAD (2017) illustrated, it is highly fluctuated (from -46.5% to 68.2%) for container freight market from 2009 to 2016 across different lines (e.g. Trans-Pacific, Intra-Asian) for different type of container units. Maintaining a good cost control for container operation enables shipping companies a good level of flexibility in dealing with the freight market dynamics. In addition, a shipping container is normally only in service for 12-14 years (Consultantsea, 2016), therefore, it will further limit shipping companies maximising their return on investment from containers during the freight market ups and downs; (3) The current shipping market is extremely competitive and overcapacity (Lopez, 2017), and earnings for container industry are squeezed to be very tiny nowadays (see figure 2.5). As a result, cost control becomes the essence for shipping companies to be survival in the market, therefore, as one of the major assets, container management takes the priority of overall cost control.

Figure 2.5 the container industry market earnings 2002-2013

Source from: BSIC (2016)

Of course, for shipping companies, they normally own both containers and vessels to operate with. But for these two assets, their different features determine their management agendas are different from each other. First, container management is normally associated with large volume but in service different customers whereas vessel management is more likely to focus on only one or a few vessels but aggregates large demands. Two, containers have longer journey which involves more players along the supply chain and multimodal options while vessels are only operated on sea or river. Third, even though vessels have higher unit price, they also have longer life time (24-30 years vs. 12-14 years) and higher residual value when the life cycle ends (Dinu and Llie, 2015). Overall, for the management of shipping companies, vessels represent stable, levelled and big volume value streams while individual container is used to satisfy dynamic individual demands. Therefore, vessel management is more into satisfying a large sum of customer demands and minimising the total cost while management for containers throughout their journey is about choosing effective modes connections to satisfy individual customer's needs with better profit opportunity.

However, even for containers themselves, different management agendas are required due to different types of containers. As we discussed in introduction chapter, the most common container type is dry containers (DCs) which could be different due to sizes (e.g. 20ft and 40ft) and different features (e.g. open top, double doors, and flat rack etc.). Also, due to the special characteristics of the carrying products, container types include Refrigerated ISO containers (e.g. foods and medications etc.), thermal containers (e.g. products with long distance movement), tanks (e.g. petrochemical products) and so on. Figure 2.6 below gives a more detail information regarding different container types.

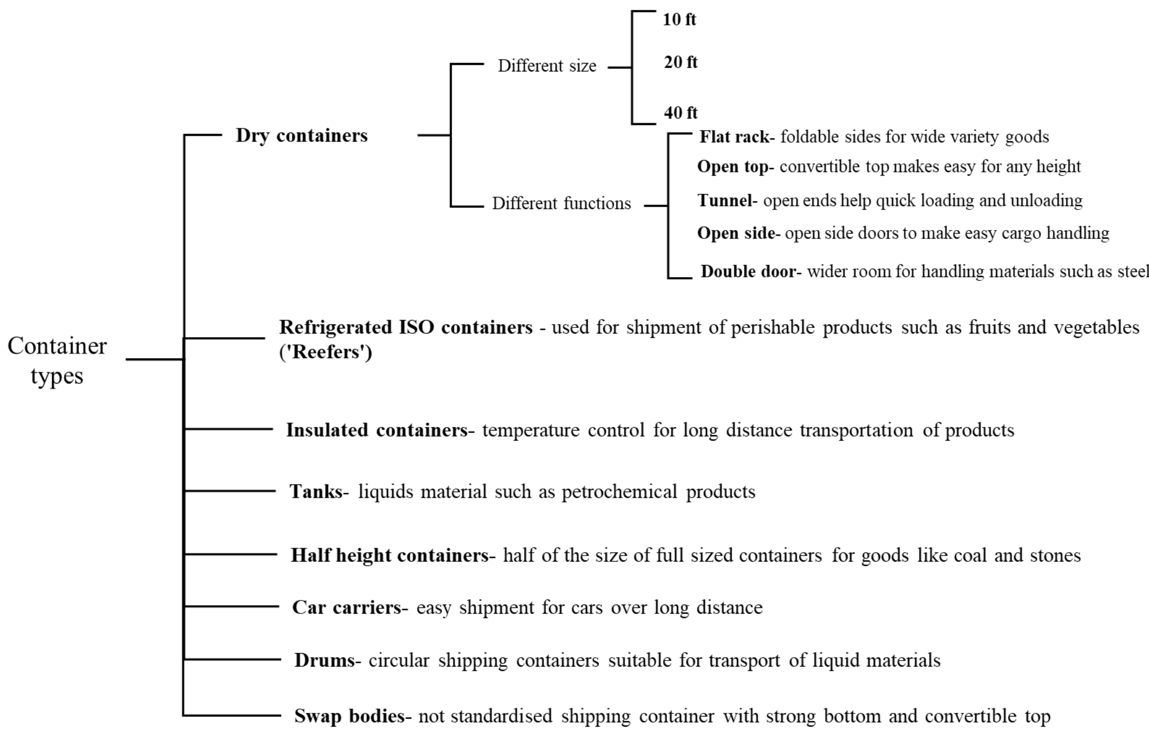

Figure 2.6 container types

Source from: Marine Insight (2017)

They different types of containers have their unique characteristics designed for different purposes and as a result, they need special care and are associated with different management requirements. As one of the specialised containers, the background of TC and how it is different from DC are going to be reviewed in detail.

2.2.2 Overview of TC market

As a specialized branch of the containerized shipping industry, the tank container market continues to grow steadily. According to ITCO (2015), the world's tank container fleet grew by 12.6 per cent last year, with the figure now standing at some 440,220 units. In this industry, tank containers (TCs) are highly regulated and required to meet stringent standards of operation, including statutory periodic inspection and renewal of test certification. Due to different delivery cargoes, TCs have different types specialised for liquids, liquefied gases, powders, swap tanks and specials (ibid). Base on different customers' requirements, various types of TCs can be provided from two main resources. The first one is TC operators. They are third party logistics companies that provide a door-to-door service to shippers and others that require transport of bulk liquids, powders or gases. The fleet listing for each company includes all TCs operated by that company, regardless of whether the TCs are owned outright, managed, leased or any other financial structure used to acquire the asset. Another supply resource is coming from TC lessors. TC lessors provide TCs to operators, shippers and others, usually on a contractual term basis, where the lessee takes quiet possession and operates that TC as if it were owned. Lessor fleet listings include all TCs within the leasing company fleet including owned outright, managed on behalf of investor owners and any other financial means of acquisition.

Similar to shipping companies in the DC market, TCs are critical assets to both TC operators (TCOs) and TC lessors. According to ITCO (2015), there are 194 TCOs and 33 TC lessors, and the world tank container fleet sizing is more than 500,700 (305,700 from operators and 195,000 from lessors). An average price for 20-feet new-build TCs listed by Alibaba is $8,500 (price for 2016), therefore value of $18,751,000 assets is being fully/partly owned by each TCOs/ TC lessors, and being operated. If we take a look of the largest TC operator in terms of fleet size registered on ITCO 2015, Stolt Tank Containers operates 32,000 TCs which are worth $272,000,000. More detail of the overall tank container market can be seen as below (table 2.1):

Company Names	Country	Container fleet size
Stolt Tank Containers	United Kingdom	32000
Hoyer Group	Germany	29110

Bulkhaul Ltd	United Kingdom	20500
Newport (Sinochem)	Netherlands	15000
Bertschi Group	Switzerland	13000
Interbulk Group	Netherlands	11200
China Railway Tielong Logistics	China	10640
VOTG Tanktainer	Germany	7580
Suttons International	United Kingdom	7500
Den Hartogh Logistics	Netherlands	7250
Interflow Tank Systems	United Kingdom	6000
Intermodal Tank Transport (ITT)	United States of America	5500
Nichicon Tank	Japan	5500
Eagletainer Logistics	Singapore	5400
M&S Logistics	United Kingdom	4700
R.M.I Global Logistics	Netherlands	4600
Fourcee Infrastructure Equipment	India	4500
Spectransgarant (Railgarant)	Russia	4010
GCA Trans	France	4000

Table 2.1 Top 20 tank container operators around the world

Source from ITCO (2015)

In the UK, there are 13 tank container operators in total, and their container fleet size information is as below (table 2.2):

Company Names	**Country**	**Container fleet size**
Stolt Tank Containers	United Kingdom	32000
Bulkhaul Ltd	United Kingdom	20500
Suttons International	United Kingdom	7500
Interflow Tank Systems	United Kingdom	6000
M&S Logistics	United Kingdom	4700
Braid Logistics	United Kingdom	1760
Paltank Ltd	United Kingdom	1350
Argon Isotank	United Kingdom	610
Bulkglobal Logistics Ltd.	United Kingdom	500
Cassilon Liquid Logistics	United Kingdom	450
Huktra UK	United Kingdom	450
Tankspeed Fraikin	United Kingdom	150

Seabrook Tank Services	United Kingdom	130

Table 2.2 the UK tank container operators

Source from ITCO (2015)

As above figures indicated, the overall market shows a great net worth for the total TC fleet size, and similar to what we discussed for DCs and shipping companies, TCs are intrinsic assets to TCOs which need take good care of. However, due to some significant differences between TCs and DCs, their operations are different. In next, the major differences of their operations are going to be discussed in detail.

2.2.3 The difference between TCs and DCs

Although TCs and DCs share some physical similarities, the special features associated with TC operation made it is never the same the operations in DC industry.

First, since TCOs don't own vessels, a special "quotation-booking" process is carried to satisfy customer demands in TC market. This process is comprehensively introduced by Erera et al. (2005) that TCOs maintain contracts with both inland and sea leg transportation service providers (e.g. shipping companies, trucking companies, railroads etc.) and combine these legs into itineraries to develop price quote to customers for any origin-destination pair request. Depending on how fast the delivery is expected to be completed, the charges are varied accordingly. Once a quote is agreed between a customer and a TCO, the logistics service should be executed as how it is planned on its executing date. However, since there's time delay involved between this "*quotation-booking*" process and demand execution, several challenges are involved.

a. Once the quotation is agreed between customers and tank container operators, it shall not be changed, but if the situation is not as expected on the demand execution date, any associated upsurge costs or operation risks are covered by TCOs only. For example, a quotation is accepted and planned to be served with self-owned TCs. But there might be not enough self-owned TCs in stock on the execution day, so leasing containers will be required which are normally more expensive than using self-owned TCs;

b. Tank container operators are serving a niche market, and consequently, they can more often reject some customer demands if they can help for seizing more profitable opportunities, and they will have less influence on their future business because of TCOs' selling power. However, since the market is small, the reject decisions should be taken very careful as it will hamper tank container operators' reputation. Considering the dynamic process of "*quotation-booking*", deliberate job rejection provides tank container operators more profit improvement opportunities, but the difficulties are increased as well;
c. Different uncertainties need to be focused on in TC "*quotation-booking*". Mentioned by introduction chapter, significant uncertainties existed during the container return journey. Since TC can be used for different type of liquidified commodities, it requires thoroughly cleaned process each time before it becomes available for next time use. Regarding to the commodities it moved, the cleaning procedures are varied, and tank container operators always hard to predict the actual cleaning duration. Moreover, since TC provides a safety, reliable and economic effective way for storage, it is very common that customers over-held TCs as their temporary storage equipment and used for satisfying their production purposes.

Two, similar to DC market, the global trade pattern is highly imbalanced for TC market as well. Empty container repositioning (ECR) seems an effective way of mitigating the imbalanced trade caused container flow inefficiency, but for TCOs, empty tank container repositioning (ETCR) is not all the same.

a. As we mentioned before, tank container operators don't own any transportation resources for executing seaborne transport. When cross-ocean ETCR needs occurred, they cannot exploit their own available capacities, and it is thereby a more costly decision-making. Therefore, ETCR is normally taken intra-regionally, and the effects of ETCR in countering the global imbalanced flow is constrained;
b. Followed, when TCOs search for external transportation resources, FFs are normally involved. With different cost level of FFs, the reliability level of them are different. Particularly, a more reliable FF charges higher service cost. For meeting customer demands, TCOs will always pick the most reliable FF to combine the itineraries, but for ETCR movements, relaxation on the FFs' reliability may reduce

TCs’ cost without compromising the operational effectiveness. Especially, thanks to TC inventory, a certain proportion of unsuccessful ETCR shipments will not be influenced in a short-term. Therefore, ETCR plan is different from ECR in DC market because it includes the selection of FFs as well;

c. As the industrial practitioners revealed, a two-week time prediction is commonly used as the practice for guiding their daily operations. They can be very confident with the two-week time look ahead but they are lack of mechanisms or solutions to better integrate the two-week time prediction with “quotation-booking” process and ETCR decision-making.

Three, similar to demurrage and detention (D&D) behaviour in DC market, TC overholding refers to the delay of container return during the container flow journey at seaport and onward inland, but difference from three aspects distinguished TC overholding from the former ones:

a. D&D are two distinctive periods coupled by the time point when container left sea terminals, while TC customer overholding could occur from any point since TC arrived at sea terminal until it returns to TCOs. As Fazi and Roodbergen (2018) defined, a container is to be in demurrage when it is positioned at a seaport and is to be in detention when it has left the seaport to hinterland until it returns to shipping companies (normally the dry container operators) or to an agreed seaport terminal. Throughout the two periods, two different bodies that shippers will dealt with. When containers are in demurrage, shippers will be penalised with a daily demurrage fee by port operators if their containers exceeded the pre-granted free demurrage period. While if the same situation occurred during detention, such cost is paid to the owner of the containers (i.e. shipping companies). Likewise, shippers will be granted a period of free days of holding TCs and they have to pay extra fees if the free days are exceeded, namely when TC overholding occurs. But differently, TC overholding could happen when TC still at seaport, during the hinterland transport, at shipper’s site or on the way back to TCOs. And the associated cost only flows to TCO’s account. Therefore, on the one hand, TC overholding is more likely to be planned and controlled than delays associated with D&D, because the later ones involve multi-channel scheduling, but on the other hand, TC overholding has more chance to create higher profits for TCOs, which drives TCOs become reluctant to make changes. Particularly, TCs are scarcer than DCs so that the overholding cost rate is normally more expensive; TC overholding is more common and the delay time is normally longer; and since TC overholding covers the whole journey of D&D, delays happened at seaport can also benefit TCOs while D&D cannot. Hence, it traps TCOs with dilemma and they are less motivated to make any changes for this issue.

b. as Veenstra (2015) and Ypsilantis et al. (2014) assert, shippers would always like to run out the free days during demurrage, so more flexibility can be obtained during the detention period, and in turn, exceeding the detention period is comparatively low with shorter days. While differently, since there is no clear boundary for customer holding period in TC market, the overholding could start from any time point or spread out through different stages after TC arrives at a sea terminal. Therefore, it is more difficult for TCOs predicting the container return date, and hard to plan the overall TC flows.

c. when the containers return to operators, both DC and TC need to go through a thorough container cleaning process, but the difference of the cleaning for the two types of containers makes great difference over the planning for D&D and TC customer holding. As the industrial practice indicated, the cleaning process associated with DC is much more standard with more stable duration and simpler steps, but cleaning for TCs is associated with complex procedures and special facilities which are largely varied with respect to the types of commodities that have been delivered. As a result, the TC cleaning is more dynamic, and it can further worsen the result caused by TC overholding and makes TCOs hard to control and improve the asset management performance associated with TC return.

To sum up, TC operation is unique to the DC sector due to above aspects. Specifically, compare to DC sector, TC operation has a complex "*quotation-booking*" process with different uncertain attributes, and it is also significantly influenced by a special customer behaviour. Therefore, to manage TCs with better profitability and asset utilisation, different issues need to be addressed. On day-to-day basis, the "quotation-booking" process in TC operation requires better decisions-making support which can mitigate influences of the time delay and the underlying uncertainties and contributing to better self-owned TC profitability. In a long-run, they need better strategies and policies that can manipulate unwanted market behaviour and improving the overall network efficiency. With appreciating the differences of the operations between TCs and DCs, how existing literature (especially about DC operations) can be used for conceptualising research frameworks, identifying research gaps and achieve underlying research objectives is going to discussed in next section.

2.3 Framework of TC asset management

Regarding all the discussions above, asset is one of the key words mentioned frequently. It is a form of value that costs company's resource to own and keep for business purposes (BSI, 2008). Since the core of commercial business is about exploiting limited resources to create maximal values, as a type of companies' resources, assets need to be properly managed and exploit for more profitable opportunities. This brought in the concept of asset management, according to BSI PAS 55 (BSI, 2008), asset management is '*the systematic and coordinated activities and practices through which an organization optimally and sustainably manages its assets and asset systems, their associated performance, risks and expenditures over their life cycles for the purpose of achieving its organizational strategic plan*'. A good asset management requires well integration of effective process across all aspects of a business to ensure business objectives are aligned over both short term and long term with the needs of all stakeholders (Lloyd, 2010). According to different level of objectives, implementation of asset management includes various activities that support both short-term and long-term level goals (ibid). In short term, the major activities comprising asset management include asset operating, maintaining, repairing, and replacing. Those activities normally need to be deployed quickly with respect to day-to-day dynamic information and they aim at maintaining good asset performance on a daily basis. In long term, the major tasks for asset management are asset acquisition, designing, procedure & policy making, and disposal. They normally associate with consuming large resources, generating long-term and wide influences, and executing constantly for long while. Regarding such methodology, asset management about TCs can be comprehensively mapped out and conceptualised hierarchically. Particularly, in line with the features of TC planning (from TCOs' perspective) discussed in section 2.2.2, different activities in TC domain can be grouped by different levels of asset management.

In short, activities associated with TC planning are mainly focusing on fulfilling the daily operational duties (operational level planning). TCOs need to decide how to effectively utilise available TCs to meet market demands, maintaining good condition of TCs and scheduling TC flows. To meet customer demands, activities such as TC assignment planning, demand forecasting, and quotation developing etc. They aim at exploiting TCs to yield the maximal return in terms of profit and customer satisfaction. To maintain good TC conditions, TCOs need to carry effective maintenance planning, executing, monitoring and improving. For contaminated TCs, they need to be properly cleaned in a timely manner and for broken ones, they need to be promptly repaired or replaced. By doing so, uncertainties can be mitigated to minimise the negative influence over asset profitability. Also, TCs are ensured the maximal service lifetime for better return on assets. To maintain more effective and efficient TC flows, TCOs need to carry activities including inventory planning and controlling, ETCR, transport optimisation and intermodal planning. Activities in this category hold the goal of integrating both internal and external resources to enable TCs more profitable opportunities.

In long run, TCs are managed to align different strategic objectives with the needs of stakeholders in this market. From TCOs' perspective, planning activities for TCs in this group need to ensure tactics of TCOs are executed effectively and strategic goals of TCOs are served well, so that TCOs' competitive positions are maintained. In particular, those activities are ranging from TC fleet sizing, design for location networks or commodity flow networks, contracting & pricing, and supply chain reconfiguration etc. Some of those activities are implemented for serving self-interests in a long-term while some of those activities are deployed to cope with external environment or parties. Regardless the purposes, all these activities can influence daily operations but are rather at a higher level that aim at creating platforms, improving relationships and providing wider and longer time effects. To summarise all above discussed TC asset management activities, figure 2.7 below present them with a hierarchical view.

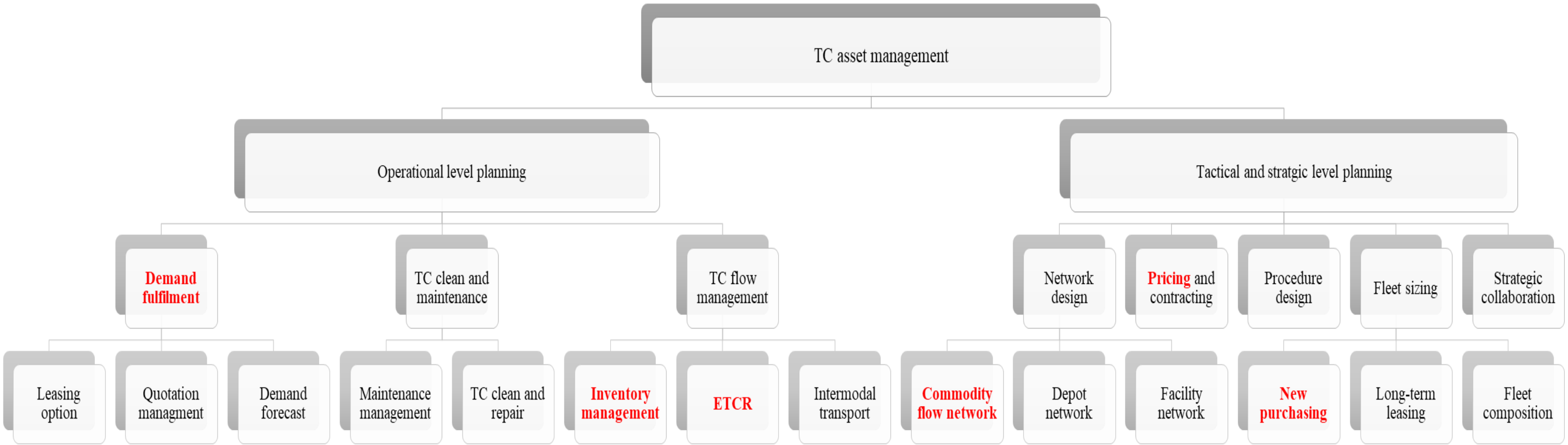

Figure 2.7 the hierarchical structure of tank container management

Next, with above framework, the rest of the chapter will go through existing literature to form the fundamental knowledge base of this study and identify research gaps. Due to time limit, the proposed research goal(s) and available information, only the topics in red are going to focused by this research.

2.4 Studies about operational level TC asset management

At the operational level, ECR is the key word that is highly connected to most of the decisions and activities in maritime container industry. As some published literature surveys indicated (e.g. SteadieSeifi et al., 2014; Song and Dong, 2015), ECR is one of the most extensively studied topics in container operation management researches, while other issues we framed above (e.g. demand fulfilment, container inventory control etc.) are jointly discussed in the context of ECR studies. This is because ECR has significant meaning in controlling and managing container flows by container operators. Therefore, it can be related to many other container operational management topics. For example, container flow is the dynamic input and output of container inventory, so influence caused by different ECR planning activities will be passed onto container inventory dynamics and affects inventory management. Hence, to investigate the highlighted issues about operational TC asset management, ECR planning and optimisation will be the core to carry the literature review of this section. According to whether the system is focusing on ECR only or it has combined ECR with other optimisation issues, maritime container researches for this planning level can be split into ECR-oriented and ECR-joint optimisation with other topics (*with network design*, *with sustainability* and *with inventory control-based* policies).

In addition, even though ECR problem an operational issue, it can be interactively investigated with approaches that are accommodated in a mid-term or even longer or researched jointly with other issues which belong to tactical or strategic planning level. From this viewpoint, some ECR related studies may be beyond the realm of operational planning. Nevertheless, the main purpose of this section is to identify the research vacuum of the underlying problem, especially to critique the application of existing literature in TC context. Therefore, the following reviewed papers are not filtered by the planning level of them but by the relativeness of their nature to ECR problems.

2.4.1 ECR-oriented studies

With the development of ECR related studies, different initiatives are carried to make ECR planning activities can be more practical and effective. In order to move the emphasis of ECR research from technical aspects to business aspects, Shen and Khoong (1995) construct a decision support system to solve a large-scale planning problem concerning multiperiod distribution of empty containers with the consideration of container leasing decisions. Also, unmet demands are considered by tweaking the model with constraint relaxation and solved heuristically, however the detail of the model formulation is only briefly introduced. Likewise, Long et al. (2013) developed a decision support tool to help the liner operator in managing their maritime container with deterministic setting. An elaborated mathematical model is presented with the consideration of multi-depots, multi-services and multi-commodities. Instead of focusing on increasing scale of ECR problems, some studies consider the idea of "street turns" or "container reuse" to reduce hinterland transportation, mitigate environmental influence and increase profits (Song and Dong, 2015). Jula et al. (2006) modelled the empty container reuse in the Los Angeles and Long Beach port area. They have specifically designed the empty container reuse methodologies with "street turn" and "depot-direct", with the help of current and projected future data, various realistic case studies highlight the significance of empty container reuse on both local economy and environment. In order to better implement the street turn methodology, Lei and Church (2011) built three strategic-level models to explore the effectiveness of locating away-from-port storage yards for empty shipping containers. Furio et al. (2013) built two mathematical models to optimise land empty container movements among shippers, consignees, terminals, and depots.

Also, there are some other new components are introduced by different studies. The application of foldable and standard containers is discussed (e.g. Shintani et al. 2010; Myung and Moon, 2014). As a substitution of the standard containers, foldable containers have lower unit cost when transported in empty. Hence it provides the potential cost saving opportunities for manage ECR activities. As the results of the case studies (Shintani et al., 2010; Myung and Moon, 2014) illustrated, the use of foldable containers does provide cost saving opportunities. However, its cost saving effects are limited by strict conditions such as the distance of the reposition transport, the distribution pattern of the deficit and surplus depots. Since TCs are normally repositioned intra-regionally, and hard to produce such analogous foldable equipment, such practice is not to be applied. Belayachi et al. (2017) studied the cost minimisation for empty container return at some ports of maritime transport network to satisfy the demands of clients. In the study of Sun et al. (2009), a deterministic mathematical model is constructed to represent the use of sea-rail transport to alleviate ECR problem and increase the ECR efficiency. Model proposed by Olivo et al. (2013) evaluated the effectiveness of involving the flexible leased containers into their time-extended optimisation model to support the decision-making process on ECR arrangements and substitution options between different container types. The leasing account clauses imposed by container lessors are taken into account as well. As a result, the model presented is able to determine the flows of empty containers and set demand and supply values at each depot for different container types. However, since this model is constructed under a deterministic environment, it may find difficulties in applying to a stochastic environment, or at least, require efficient solutions to solve the model.

Further, container coordinating and sharing initiatives are incorporate to improve ECR planning. In the study of Kopfer and Sterzik (2012), a mathematical programming model is construct to demonstrate the advantages coming from multi-depot container truck transportation problem with container sharing over no sharing scenarios. Further on, Sterzik et al. (2015) elaborated the two scenarios of container sharing for the seaport hinterland transportation. With the help of realistic-sized examples, benefits obtained from container sharing and truck routing optimisation is proven to be remarkable. In addition, they have also pointed out the main barriers that prevent container carriers from sharing their assets are concerns of losing asset control and revealing business secrets. With different transport mode, Zheng et al. (2015) studied the possibility of exchanging empty containers among liner carriers to mitigate the influence of the unbalanced trade pattern to all the carriers. They proposed a two-stage optimisation model and the inverse optimisation technique is used to determine a centralized empty container sharing and allocation to solve

ECR problems. Furthermore, they have also investigated the perceived value of empty containers at each port, which can be used later on to compare with the leasing price at each port to support the pricing strategy for container lessors. In general, container coordination and sharing among the industry aims at creating a container fleet pool where a more centralized planning can be deployed. Apart from pooling the container fleet among carriers, researches such as Vojdani et al. (2013) formulated a space-time network model to explore the economic benefits from pooling container fleet from container carriers and leasing companies. Song and Carter (2009) evaluated four strategies for ECR on three major routes mathematically. They pointed out that even though container sharing and coordination solution can alleviate the ECR problems, it cannot eliminate the needs of ECR.

To enhance the practical meaning of ECR studies, there is another group of literature has accommodated ECR research with uncertainties. Cheung and Chen (1998) applied a rolling horizon fashion to construct a two-stage stochastic programming model that address empty container allocation problem with uncertain environment at the operational level. Li and Han (2009) applied chance constrained programming to transform the constraints that contain stochastic parameters. Specifically, they gave a confidence level which is supposed as the target level that the random parameter is ranged by it.

Different to finding the optimal plans to all scenarios under stochastic setting, some researches are looking at the recourse to worst case scenarios. Erera et al. (2009) used the adjusted robust optimisation framework for dynamic empty repositioning when demands and future supply of empty containers are uncertain. Specifically, decisions and plans in this model are recoverable when feasibility can be reestablished for any outcome in a defined uncertainty set. Gavranovic and Buljubasic (2011) construct a time-space networks to formulate a robust optimisation ECR problem and solved with linear programming methods. With the help of a so-called constraint generation linear programming approach, the computation ability of the model is demonstrated by solving real-time cases with hundreds of millions of additional linear constraints.

The robust optimisation demonstrated the ability in coping with uncertain environment, however, as above researches illustrated, the viability of robust optimisation model is limited by predefined uncertain set, also the robust optimisation result doesn’t guarantee a better result for parameters with known probabilities. Also, it is still associated with heavy computation workloads, especially when it comes down to adjusted robust optimisation problems.

To have a clearer view of studies in this group, table 2.3 is created by showing some key features of those papers. In particular, they are compared by different research objectives (functions), different way of formulating researched questions, and different research context settings to demonstrate the significant contributions of each paper, what are commonly used when study the underlying research problem and where are less studied after reviewing those papers (research vacuums).

Author	Year	Optimisation type	Methodology	Multi-commodity	Multi-port	Leasing option	Trans. Mode	Multi-service	Penalty	Uncertainties
Long et al.	2015	Cost Min.	SAA based	DCs with different sizes	√		Sea	√		Demand, supply, ship capacity
Di Francesco et al.	2013a	Cost Min.	Rolling horizon for scenario based		√		Sea			Supply and handling capacity
Di Francesco et al.	2013b	Cost Min.	Rolling horizon for scenario based		√		Sea			Demand
Gavranovic and Buljubasic	2011	Cost Min.	Robust optimisation		√		Sea			Supply
Di Francesco et al.	2009	Cost Min.	Rolling horizon for scenario based	Different types of containers	√		Sea			Demand and supply
Li and Han	2009	Cost Min.	Stochastic programming	Different types of containers		√	Sea			Demand and supply
Cheung and Chen	1998	Profit Max.	Stochastic programming		√	√	Sea			Demand and supply, ship capacity
Erera et al.	2009	Cost Min.	Robust optimisation		√		Sea			Demand and supply

Zeng et al.	2010	Profit Max.	Robust optimisation		√		Sea			Demand
Belayachi, et al.	2017	Cost Min.	Tabu search		√		Sea			
Zheng et al.	2015	Profit Max.	Two-stage linear programming		√		Sea	√		
Sterzik et al.	2015	Cost Min.	Mixed-integer linear programming		√		Hinterland			
Myung and Moon	2014	Cost Min.	Mixed-integer linear programming	Standard and foldable DCs	√		Sea			
Olivo et al.	2013	Cost Min.	Time-space mathematical programming	DCs with different sizes	√	√	Inland			
Long et al.	2013	Cost Min.	Mixed-integer linear programming	DCs with different sizes	√		Sea	√	Demand unmet	
Kopfer and Sterzik	2012	Cost Min.	Integer programming		√		Inland			

Lei and Church	2011	Distance Min.	Mixed-integer linear programming				Inland	
Shintani et al.	2010	Cost Min.	Mixed-integer linear programming	Standard and foldable DCs	√		Intermodal	
Cai and Ting	2010	Cost Min.	Mixed-integer linear programming with GA		√	√	Intermodal	
Sun et al.	2009	Cost Min.	Linear optimisation		√		Intermodal	
Song and Carter	2009	Cost Min.	Linear optimisation		√		Sea	√
Jula et al.	2006	Cost Min.	Integer programming		Two depots		Inland	
Karimi et al.	2005	Cost Min.	Linear optimisation		√	√	Intermodal	
Bell et al.	2013	Cost Min.	Linear optimisation		√		Sea	√
Al-Rikabi et al.	2014	Cost Min.	Linear optimisation		√	√	Sea	√

Choong et al.	2002	Cost Min.	Linear optimisation		√	√	Inland	
Shen and Khoong	1995	Cost Min.	Mixed-integer linear programming with Heuristic		√	√	Intermodal	Demand unmet
Change et al.	2008	Cost Min.	Mixed-integer linear programming with Heuristic	DCs and reefers with different sizes	√		Intermodal	
Furio et al.	2013	Cost Min.	Integer programming	DCs with different type	√		Inland	

Table 2.3 papers for ECR-oriented studies

As above table shown, most of the models are built for seeking cost reduction. Whereas profit maximisation is not commonly tried to achieve in above papers. Then leasing option is another potential gap here. According to Dong and Song (2012), lease options can be classified as spot-leasing or long-term leasing depending on the contract length. Yet there is only spot-leasing or flexible leasing (e.g. Olivo et al. 2013) incorporated, while long-term leasing (e.g. Karimi et al. 2005; Choong et al. 2002) is normally regarded as company's own containers and the associated decision-making is equivalent to new purchasing. At last, since the common practice in DC market is meeting customers' demands by all means, job rejects are barely considered. For the studies considered job rejects, they either treat them as backlog orders or just linked with penalty cost, whereas no independent decision-making process involved. Also, the current random parameters are majorly surrounding demand and supply, but insufficient in discussing other aspects. The maritime industry is highly volatile which is associated with uncertainties coming from all kinds. As Seatrade Maritime News (2013) reported, different uncertainties could cause unpredicted market demand, container supply, ship and terminal capacity, voyage time, container demurrage and detention, repair and cleaning, and clearance and inspection etc. Therefore, exploring more different uncertainties could be beneficial both academically and practically. Moreover, markets such as TCs are unique with their own operation process and asset features, the uncertainties existed in DCs might less severe comparing to the others, hence the associated studies should be designed specifically, and different uncertain elements need to be considered.

Next, papers that jointly investigated ECR with other management issues are going to be discussed.

2.4.2 ECR with network designing problems

As we discussed, ECR will directly influence container flow condition, therefore ECR can be jointly discussed with other topics that are highly affected by how containers are flowed.

The maritime network design studies include subjects such as selecting calling ports and calling sequences, optimising shipping routes (and route structure), service frequency and ship deployments etc. The rationale of jointly optimising container network design with ECR issue is because, from a long-term perspective, decisions about the network design will become constraints for container flow later on, so as to the ECR arrangements. For example, the determined the ports calling and the sequence will influence where, when and how much of the ECR activities taken place on an operational basis. Also issues such as ship fleet size and capacities would determine the flexible capacity for conducting ECR daily and so influence the effectiveness and efficiency of ECR activities. Therefore, it worth including the investigation of ECR issue when making decisions about network design problems at the higher level.

From the seabourne side, some studies look at building the container network design with more effective and efficient container flow (e.g. Meng and Wang, 2011; Wang et al., 2013; SteadieSeifi et al., 2017 etc.). The ultimate goal of them is designing the liner shipping service network with proper typologies and operations that allows the most efficient and effective container flows. Then some research developed network design problem to be more complicated with the consideration of other elements.

Shitani et al. (2007) proposed a two-stage model that addresses the shipping service network problem, ship deployment and ECR simultaneously. With the help of a GA based heuristic algorithm, the model is able to find a set of calling ports with optimized calling sequence, the number of ships by size category with determined cruising speed and the optimal empty container allocation that jointly yield the maximized profits. However, as Chen (2009) pointed out, due to a lack of cargo traffic demand fluctuations and cargo flow distributions among ports in their experiments, the obtained ship-slot allocations show the flaws. Therefore, in a similar approach of his research, a periodic fluctuations of cargo traffic demand with freight rates are considered for the experimental tests. In the study of Mittal et al. (2013), scenario-based analysis is used for solving an inland-empty-container depot locations problem with stochastic demand. A two-stage stochastic model is proposed to achieve cost reduction. Likewise, Perez-Rodriguez and Holguin-Veras (2014) addressed the empty container issue in urban planning and policy making with the consideration of stochastic empty container demand and supply. Wang (2013) provided a holistic network design, fleet deployment and ECR solution with the consideration of ship availability, service frequency, ship capacity, transshipment, slot purchasing and ship repositioning. Further, Huang et al. (2015) have added the cargo routing consideration simultaneously with network design, ship deployment and ECR optimisation. Zheng et al. (2016) have added the exploration of perceived leasing price at each port by a so-called inverse optimisation technique. As a result, it helps operators with better freight price strategy and make better decisions when have the options for leasing and ECR.

Also, there are some researches only address one specific network-design based issue with the consideration of ECR. Lu et al. (2010) addressed a slot allocation planning problem with ECR for multi-commodity containers and in a short sea liner service. Lu and Mu (2016) studied ship slot capacity management with ECR optimisation. It considers the adjustment of shipping schedules caused ship slot reallocation. Song and Dong (2012) consider the problem of joint cargo routing and ECR at the operational level for a shipping network with multiple service routes, multiple deployed vessels and multiple regular voyages. Some other cargo allocation with ECR researches can be found in Wang et al. (2014) and Brouer et al. (2011). And some research investigated the ship deployment with ECR simultaneously (e.g. Zhang and Wang, 2017; Shitani et al., 2007).

From the inland side, the research focus is moved to vehicle deployment related, or barge vessel deployment and depot location problem with ECR consideration. Different from the underlying problems addressed in the sea leg, this context has its special features due to the difference in between vessel and vehicle (e.g. single unit vs. bulk delivery, see Cheung and Chen, 1998), flexibility of services (e.g. fixed schedule vs. flexible schedule, see Cheung and Chen, 1998; Erera et al., 2005) and geographic difference (e.g. longer distance and less route options vs. shorter and more route options, see Song and Dong, 2015). Crainic et al. (1989) construct a model discussing vehicle depots location with interdepot balancing requirements. It provides multimode transportations and aims at minimising various operational costs.

More complicatedly, some studies address the network-design based problem with ECR consideration in an intermodal context. In this sense, the proposed models need to achieve an overall optimisation by considering the characteristics of the logistics network from both sides of shore. In addressing the significance of TC operation process, Erera et al. (2005)

proposed a time-space network flow model to arrange TC allocation with given shipping network and inland transportation network. Bandeira et al. (2009) integrated the distribution of both empty and full containers in an intermodal network and optimised the distribution strategy with a proposed heuristic. Braekers et al. (2013) presented a decision support model for service network design in intermodal barge transportation. In a dynamic setting, Crainic et al. (1993) proposed a two-stage network flow model with the consideration of uncertainties in demand and supply uncertainties. In the deterministic part, both single and multi-commodity cases are considered while for the stochastic part, only the single commodity is presented. Although the study didn't discuss in detail of solutions to the proposed model, stochastic quasigradient methods are suggested to obtain the optimality as it can exploit the network structure of the problem. Song and Dong (2011) studied the ECR problem for a general shipping service routes. With the application of different inventory control policies, this research is evaluated under different deterministic and stochastic environments. Dong et al. (2015) built a two-stage stochastic model that jointly optimising service capacity planning, dynamic container routing in liner shipping with uncertain demand. Table 2.4 below summarise the major papers that fall into this category.

Author	Year	Optimisation type	Methodology	Multi-commodity	Multi-port	Leasing option	Trans. mode	Multi-service	Penalty
Jeong et al.	2018	Cost Min.	Linear programming		√	√	Sea		
Lu and Mu	2016	Profit Max.	Integer programming	DCs and Reefers	√		Sea		
Huang et al.	2015	Cost Min.	Mixed-integer linear programming		√		Sea	√	
Xu et al.	2015	Profit Max.	Game Theory		Two ports		Road		
Wang et al.	2014	Profit Max.	Mixed-integer linear programming		√		Sea	√	
Song and Dong	2013	Cost Min.	Three-stage optimisation		√		Sea	√	
Wang	2013	Cost Min.	Mixed-integer linear programming	DCs and Reefers with different sizes	√		Sea		Reposition rejection
Braekers et al.	2013a	Distance and number of trucks Min.	Mixed-integer non-linear programming with annealing solution		Two ports		Road		
Braekers et al.	2013b	Profit Max.	Integer programming		√		Water		
Wang et al.	2013	Cost Min.	Mixed-integer linear programming with heuristic	DCs and Reefers with different sizes	√		Sea	√	Unmoved container

Moon et al.	2013	Cost Min.	Integer programming with heuristic	Standard and foldable DCs	√		Sea		
Song and Dong	2012	Cost Min.	Two-stage short-path based and two-stage heuristic-rules		√		Sea	√	
Dong and Song	2012	Cost Min.	Event-evolution based with GA solution		√	√	Sea		
Bell et al.	2011	Sailing time and dwelling time Min.	Frequency-based method		√		Sea	√	
Meng and Wang	2011	Cost Min.	Mixed-integer linear programming		√		Sea		
Brouer et al.	2011	Profit Max.	Integer programming with linear relaxation and column generation	DCs with different types	√	√	Sea	√	Unmet demand
Liu et al.	2011	Profit Max.	Mixed-integer linear programming		√		Sea	√	
Wong et al.	2010	Cost Min.	Immunity-based evolutionary algorithm		√		Sea		Unmet demand
Braekers et al.	2010	Profit Max.	Mixed-integer linear programming		√	√	Hinter -land		

Zhou and Lee	2009	Profit Max.	Game theory		Two ports		N/A		
Chandoul et al.	2009	Cost Min.	Mixed-integer linear programming				Road		
Chen	2009	Profit Max. and Cost Min.	Mixed-integer non-linear programming		√	√	Sea		
Tuljak-Suban and Twrdy	2008	Cost Min.	Vehicle Routing Problem with Pickup and Delivery		√		Water		
Shintani et al.	2007	Profit Max.	Mixed-integer linear programming and GA solution		√	√	Sea		Penalty is used to represent ECR and leasing
Erera et al.	2005	Cost Min.	Mixed-integer linear programming		√	√	Inter-modal	√	
Jansen et al.	2004	N/A	Decision support system		Two hubs		N/A		
Lu et al.	2010	Profit Max.	Integer programming	DCs and Reefers with different types	√		Sea		
Crainic et al.	1989	Cost Min.	Integer programming	Vehicle commodity with different types	√		Inter-modal		

Imai and Rivera	2001	Cost Min.	Simulation	DCs and Reefers	√	√	Sea		
Imai et al.	2009	N/A	Mixed-integer linear programming	No	√	√	Sea	√	
Moon et al.	2010	Cost Min.	Mixed-integer linear programming with GA	DCs with different size	√	√	Sea		
Takano and Makoto	2010	Profit Max.	Linear programming with GA	No	√		Sea		Reposition rejection
Hjortnaes et al.	2017	Cost Min.	Mixed-integer linear programming	DCs with different size and with damages or not	√		Sea		
Zheng et al.	2016	Cost Min.	Mixed-integer non-linear programming	Standard and foldable containers	√	√	Sea		
Chen et al.	2016	Profit Max.	Game Theory		√		Sea		
Monemi and Gelareh	2017	Profit Max.	Mixed-integer linear programming with branch-and-cut, bender decomposition		√		Sea	√	
SteadieSeifi et al.	2017	Cost Min.	Mixed-integer linear programming with		√		Multi-modal		

			adaptive large neighborhood search					
Zhang et al.	2017	Profit Max.	Dynamic programming			√	√	Sea
Bandeira et al.	2009	Cost Min.	Mixed-integer linear programming			√	√	Inter-modal

Table 2.4 Papers for ECR with network design related studies

2.4.3 ECR with sustainability problems

Apart from network design related ECR planning, some researches have also incorporated sustainable consideration. Topics such as slow steaming, technologically advanced hull coatings, ECR management shows the essence in contributing to both sea and inland environments. Song and Xu (2012) develops an operational activity-based method to include the carbon emission as one indicator for evaluating ECR performances. The activity-based method is a simulation-based model that integrate the operations from port and shipping company with proper interfaces to various data. Through two case studies, how ECR management and port handling capacity jointly influence carbon emission is well presented. Lam and Gu (2016) proposed a market-oriented approach for achieving a bi-objective goal including cost and transit time minimization with constrained carbon emission. Specifically, such approach stands from customers' viewpoint and develops transport planning by integrating customer needs and infrastructure settings. As the two papers show, the green initiatives are directly addressed from carbon emission aspect, whereas other environmental issues such as noise, land use or product spillage are either briefly mentioned (e.g. Shintaini et al., 2010) or not addressed, at least, not properly formulated mathematically. In the study of Li et al. (2015), the sustainable efforts that can be achieved from ECR or empty container reuse is indirectly illustrated. Since the model and case studies have included considerations such as revenue, size of commodities, transit time, and delivery delay etc., the green contributions can be indirectly summarised from how much profit improvement can be achieved by reusing empty containers, how much space could be saved from ECR and container reusing, and how much congestions could be reduced etc. But again, it didn't explicitly and directly include more green considerations as one component from the model formulation process. Hence, there is an absence of modelling green impacts (apart from emissions) on ECR planning. Moreover, operational process perspective, the green consideration adds more constraints to planning but it doesn't change the nature of process itself. Therefore, the application of the existing researches to industry (e.g. TC industry) with different process focus may not be viable.

In addition, ECR issues are also often discussed with other topics such as container fleet sizing problem or pricing strategies. Since those topics will be reviewed comprehensively in later of this chapter, to avoid repetition, they will only be listed in the following table but not discussed. Similar to the pervious category, table 2.5 details the papers of this group.

Author	Year	Optimisation type	Methodology	Multi-commodity	Multi-port	Leasing option	Trans. mode	Multi-service	Penalty
Li et al.	2015	Profit Max.	Linear programming		√	√	Sea	√	
Wang et al.	2014	Profit Max.	Mixed-integer linear programming		√		Sea	√	
Wang et al.	2013	Cost Min.	Mixed-integer linear programming with heuristic	DCs and Reefers with different sizes	√		Sea	√	Unmoved container
Moon et al.	2013	Cost Min.	Integer programming with heuristic	Standard and foldable DCs	√		Sea		
Song and Xu	2012	N/A	Operational activity-based		√		Sea		
Shintani et al.	2007	Profit Max.	Mixed-integer linear programming and GA solution		√	√	Sea		Penalty is used to represent ECR and leasing
Shintani et al.	2012	Cost Min.	Integer programming	Standard and foldable containers	√	√	Sea		
Lam and Gu	2016	Cost Min.	Mixed-integer linear programming		√		Road		

Table 2.5 Papers for ECR with suitability

2.4.4 ECR with inventory based-policies

Different from above studies, some researches set up inventory control policies to address ECR problems. As Song and Zhang (2010) claimed, such policy has the advantages of being easy to operate and easy to understand, as well as being near optimal or even optimal sometimes. Specifically, despite the highly volatile environment, approaches of this kind tend to direct the ECR decisions with a series of decision-making rules associated with system dynamic states such as inventory levels of empty containers. To compare with mathematical-based ECR models, the practical ability of the mathematical ones is highly constrained by computational complexity as they are attempt to find a series of values that describe how many empty containers should be moved from which ports to another across whole network structure and time; while the inventory control-based mechanism only finds the optimised inventory control policy in advance, not all the value-based decisions. For example, Li et al. (2004) has incorporated (U, D) policy to manage empty container repositioning. Its rule is repositioning in empty containers up to U when the number of empty containers in a port is less than U, or repositioning out empty containers down to D when the number of empty containers is larger than D, doing nothing otherwise. Therefore, once the parameters and the rules of the policy are set up, such policy can be applied to make the ECR decisions involving whether to reposition empty containers, to or from which ports, and in what quantity.

Lai *et al.* (1995) considered the ECR problem from mid-east port to far-east ports. They used a simulation model to evaluate different container allocation policies, which were characterized by a safety stock level, critical allocation point and port priority. Their study is a major milestone in the development of simulation model for container fleet sizing problem with inventory policies. Du and Hall (1997) utilized inventory and queuing theory and proposed a single threshold policy to redistribute empty containers in a hub-and-spoke system with random demands and deterministic travel times.

Several researchers tend to explore the inventory-based mechanism in addressing ECR problem in the stochastic systems. Li *et al.* (2004) formulated the one port containerization problem as a non-standard inventory problem with positive and negative demands. They showed that the two-level threshold policy was optimal for the single port system and a value iterative algorithm was proposed to calculate the optimal threshold values. Song and Zhang (2010) also considered ECR problem for a single port. Song (2005) and Song and Earl (2008) considered the empty vehicle redistribution problem in a two-depot system with continuous-reviewed. As they had mentioned, a vehicle may be defined as a reusable resource for realization of a given kind of transportation, such as ECR in shipping business. Song (2007) considered the similar problem with Song (2005) with periodical-reviewed. Song (2007) proved that optimal empty repositioning policy was also of threshold control structure in such system and a value iterative algorithm was applied to find the optimal threshold values. These studies demonstrate that the optimal repositioning policies are of threshold-type, which are characterized by a set of parameters and a set of rules, in some situations such as one-port and two-port systems. Once the parameters and rules are designed in advance, such threshold control type policies are easy to operate. Dong and Song (2012) proposed an event-driven simulation model which formulated the container fleet sizing problem and container allocation problem under uncertain customer demands and stochastic inland transport times. Rule-based policies are designed, optimised with respect to states of inventory and every individual container.

Further works are extended to focus on the implementation of the threshold-type control policies for ECR problem in more general systems. Li *et al.* (2007) extended the study by Li et al. (2004) to a multi-port system. Song and Carter (2008) further extended works by Song (2005) and Song and Earl (2008) to a hub-and-spoke system, in which only the demands between the hub and spokes were considered. Song and Dong (2008) applied the threshold policy for empty container management in a cyclic shipping route problem and demonstrated that the threshold policy significantly outperformed the heuristic policies with simulation results. Moreover, Yun et al. (2011) applied the (s, S) policy-based inventory control for driving empty container repositioning activities. It was implemented in an inland area between customers and terminals with random demands for empties. The near optimal (s, S) value is acquired through a simulation-based optimization. Further, Dang et al. (2013) extended the above work to a port area with multiple depots considering three types of decisions: repositioning empties from overseas ports, inland repositioning between depots and leasing from lessors.

In addition, threshold-based control policies are not the only application in inventory-based model for ECR problems. Lai et al. (1995) incorporated an optimized safety stock to conduct the ECR decisions. Feng and Chang (2008) formulated the ECR problem for intra-Asia liner shipping as a two-stage problem. The value of safety stock in each port was estimated as an average of difference in known inbound containers and outbound containers for two weeks. Epstein et al. (2012) introduced a decision support tools for company CSAV make ECR decision and safety stock holding optimization in a stochastic environment. Chou et al. (2010) proposed a fuzzy backorder quantity inventory model for solving the decision-making of optimal quantity of empty containers at one port.

Followed, table 2.6 below is created to elaborate the reviewed papers of this group.

Author	Year	Optimisation type	Threshold type	Multi-commodity	Multi-port	Leasing option	Trans. mode	Multi-service	Penalty	Uncertainties
Wong et al.	2015	Profit Max.			√	√	Sea			
Wang et al.	2015	Profit Max.			√		Sea			
Dang et al.	2013	Cost Min.	Double		√	√	Road			Demand
Ng et al.	2012	Cost Min.			Two ports		Road			Demand and supply, ECR lead-time
Dang et al.	2012	Cost Min.	Double		√	√	Road			Demand and supply
Epstein et al.	2012	Cost Min.	Safety stock	DCs with different types	√		Sea			ECR lead-time
Dong and Song	2012	Cost Min.	N/A		√		intermodal	√	Loss of sales	Demand and travel time
Song and Dong	2011	Cost Min.	N/A		√		Sea		Loss of sales	
Song and Zhang	2011	Cost Min.	N/A				Sea			Demand
Chou et al.	2010	Cost Min.	N/A	DCs with different sizes	√	√	Sea			Demand and cost

Song and Zhang	2010	Cost Min.	Four			√	Sea		Demand
Dong and Song	2009	Cost Min.	Double		√	√	Sea		Demand
Song and Zhang	2009	Cost Min.	N/A			√	Sea		Demand and supply
Song	2007	Cost Min.	Double		Two terminals	√	Sea		Demand
Lai et al.	1995	Cost Min.	Safety stock	DCs with different sizes	√	√	Sea		Demand
Yun et al.	2011	Cost Min.	Double	DCs with two sizes		√	Road		Demand
Du and Hall	1997	Cost Min.	Double				Road		Travel time
Li et al.	2007	Cost Min.	Double		√	√	Intermodal		Demand
Li et al.	2004	Cost Min.	Double			√	N/A		Demand
Lee et al.	2011	Cost Min.	Single		√	√	Sea		Demand
Lee et al.	2012	Cost Min.	Single		√	√	Sea		Demand
Song and Dong	2008	Cost Min.	Double		√		Sea	Loss of sales	Demand
Song and Earl	2008	Cost Min.	Double		Two depots	√	Road		ECR time and loaded

									vehicle arrival
Song	2005	Cost Min.	Threshold policy with Markov Process		Two depots	√	Road		Demand and travel time

Table 2.6 Papers for ECR with inventory control-based policies

For papers above discussed about ECR with other operational issues, two distinct gaps are identified. One, multi-commodity issue is narrowly studied. Even though, some papers are carried under multi-commodity context, they majorly focused on DCs with different sizes or types. Yet, multi-commodity issue can be different type of containers and it will bring in more questions that are not addressed so far (e.g. thermal containers, TCs or reefers). Two, there are lack of studies examining wider range of uncertain issues when it comes to more realistic research background. In particular, if the features of TCs are taken into account, the reviewed studies are hard to be directly applied.

First, due to the complex operation for TCs and its uncertain environment, the associated inventory control level should consider not only the overall net import or net export situation of each depot on each demand coming period, it also should take the demand coming and demand actual execution into account. Specifically, the existing inventory control-based models are designed to keep the optimised amount of inventory level that can meet the customer demands generated and satisfied at the same period of time. While for TC operation, the common practice is that demands are always generated prior to their execution date, in this sense, the designed inventory level of TC depot should consider the ability and flexibility in satisfying current demand execution as well as preparing for demands received on the same day but to-be-executed in the near future. It is the time delay in between demand receiving and demand execution makes the process much more complex, so same complexity should be applied to its inventory control logics.

Two, the most studied uncertainties for all reviewed papers are no more than uncertain demand, supply, ECR lead-time or travel time. However, within the TC context, some other uncertainties can be significant due to two features from the industry itself. Similar to non-vessel operating common carriers (NVOCCs), who organise shipments for customers' goods delivery through contracting with different logistics modes (Guo and Li, 2015). Hence, without actually owning transport resources (no vessels for TCOs), NVOCCs and TCOs are facing uncertain reliabilities from using external resources. But differently, when managing cross-ocean transport, NVOCCs normally keep direct communication with shipping carriers while TCOs need FFs to be the intermediation. Therefore, the different choice of FFs is associated with different reliability levels, which will further compound uncertainties and difficulties of the associated operation. Even though some existing studies have considered uncertain container supply, it is more caused by uncontrollable reasons such as uncertain customer return or uncertain travel time, but not FF related uncertainties. Hence, different model formulation and solution techniques are required. Next, the commodity that TC carries is different from DCs', and the high standard requirements and various processes for TC cleaning leaves significant uncertainties. Since TC cleaning can be highly varied to different types of products that the TC moved as well as different types of TCs are used, it then requires new investigation of its influence on overall operation and associated solutions. Meanwhile, it can further complicate the problem by linking it with multi-commodity research context which is seldom studied as above table illustrated.

2.5 Tactical and strategic level TC asset management

Tactical and strategic planning activities are designed for long-term objectives. In container asset management domain, tactical and strategic planning activities aim at maximising the overall values that can be contributed from containers throughout a long period of time. Some researchers tried to achieve the tactical and strategic goals with container asset management by optimising network designs. For example, Jeong et al. (2018) presents an investigation in a two-way four-echelon container supply chain to design direct shipping service routes so that container operational cost can be significantly reduced in a long run. Vilhelmsen et al. (2014) investigated the tramp ship routing and scheduling network analysis to maximise the total profit for tramp ship operators. Also, some studies about tactical and strategic asset planning are focusing on optimising assets value through collaboration and competition with players along their supply chains. For example, Heaver (2002) indicated the different cooperative agreements in shipping companies and illustrated the potential benefits for maximising asset return. Maloni et al. (2016) investigated the share of vessel strategy among shipping lines to gain better market position for shipping companies with their assets. Moreover, there are studies investigating asset maintenance and security related policies and procedures (e.g. Ramirez-Mar-quez, 2008; Boros et al. 2009; Kantor and Boros, 2010) which look at maintaining good condition of assets with cost effective strategies; service design issues (e.g. Balci et al., 2018; Lim, 1998) which look at how shipping companies differentiate their core services with available assets. Nevertheless, due to the reasons mentioned in seiction 2.4.1.2, this research will only focus on fleet sizing and pricing issues. Therefore, the following subsections are developed surrounding these two directions only.

2.5.1 Container fleet sizing

In maritime industry fleet sizing problem is often associated with vessels or containers. Since our main focus is to link this topic with TC industry, yet TC operators have no vessel fleet to worry about, only the container fleet sizing problem is thereby discussed. As an essential decision for maritime decision makers, container fleet sizing influences how customer demands are satisfied (job fulfilment) and determines what service level can be achieved, but on the other hand, the associated investment and operating costs will create a dilemma for its decision-making (Dong and Song, 2012). Since the direct link and influence of container fleet sizing decisions is on operational-level planning, the underlying problem is normally jointly studied with various operational maritime issues.

For normal DCs, Turnquist and Jordan (1986) have firstly develop a model to decide the optimal container fleet size when container travel times are stochastic with inland transport and deterministic production cycle. The proposed model and tests have presented the dynamic relationship of production cycles, travel time uncertainty and number of plants with total container equipment requirements. As the results illustrated, optimising the container fleet size can effectively reduce freight equipment requirements as well as empty equipment redistribution costs. However, how specific container travelling deployments, job fulfilments and ECR decisions etc. are not explicitly optimised after the decision of container fleet sizing. In studying the influence of network structure design over container flow, Imai et al. (2009) have taken the container fleet sizing optimisation into account. Two typical service networks with different ship sizes are tested and the overall model is comprised by the network design and container distribution two stages. With the consideration of ECR, different scenario analyses are given to present the insights of container fleet sizing and ECR strategies when different network structures are applied.

In order to align container fleet sizing problem with everyday operation. Some researchers investigated the impacts of container fleet sizing problems over operational container distribution and job fulfilment strategies within different environments or systems. Du and Hall (1997) have pointed out the high interrelationship between container fleet sizing and empty equipment reposition. However, the model is not considered with uncertainties in transportation nor demand. In order to obtain the optimal inventory policy for driving ECR activities with uncertainties, Song (2007) considered the container fleet sizing decision in a Markov decision process model and the container distribution operation is carried in a periodic-review shuttle service system. Dong and Song (2009) have jointly studied the container fleet sizing and ECR problem in multi-vessel, multi-port and multi-voyage systems with dynamic and imbalanced customer demands. Similar research is conducted by Lee et al. (2012) while the optimisation process is completed by a non-linear programming and a gradient search approach.

To expand the scope of the container fleet sizing problem in the maritime operational research area, some studies have specifically looked into fleet sizing problem with different types of containers. Imai and Rivera (2001) carried the research to design strategic fleet size planning for maritime refrigerated containers. First an analytical model is discussed to determine the optimal size of self-owned DC fleet and then it is extended to reefers. Next, a simulation model is developed to provide decision support for practitioners when they are in the presence of new container investment options and leasing in conjunction with container allocation. Since the reefer industry is featured by extremely imbalanced trade, the proposed model is proven to provide effective decisions support. And with scenario analyses, the different scale of self-owned reefer fleet sizes is recommended when cargo trend varies. List et al. (2006) have explicitly studied container fleet sizing problem with radioactive wastes travelling problem. A complicated realistic problem is addressed by this study, which optimising the container fleet size with purchasing decisions and the transportation of wastes with defined rate and uncertainties are taken into account. A robust optimisation model is constructed to explore the effects of uncertainty on the purchasing strategy, meanwhile, the container movements over the networks are optimised as well. Shintani et al. (2012) have studied the container fleet management for standard and foldable containers in liner shipping networks. The model is formulated analytically by integer programming and it aims to find the proper combination of both standard and foldable container fleet sizes with given cost structure and trade patterns. As the case study results illustrated, only with strong imbalanced trade pattern environment, the mix of foldable containers with standard ones is able to generate substantial savings, while the high exploitation costs are the main issue that constrained the use of foldable containers.

Further, to summarise all the reviewed papers within the area, table 2.7 below incorporated some common metrics for benchmarking.

Author	Year	Optimisation type	Formulation and Solution highlights	Multi-commodity	Multi-port	Leasing option	Penalty	Uncertainties	Highlights
Dong and Song	2012	Cost Min.	Event-driven modelling, GA, GS and SA		√		Unmet demand	Demand and travel time	Fleet sizing with travel time impacts
Dong and Song	2009	Cost Min.	Simulation-based modelling, GA		√	√		Demand	Fleet sizing and inventory policy
Song	2007	Cost Min.	Markov Decision Process		Two terminals	√		Demand	Fleet sizing with different ECR policies
Du and Hall	1997	Cost Min.	Queueing model, Monte-Carlo simulation and decomposition approach					Travel time	Fleet sizing and container redistribution
Imai and Rivera	2001	Cost Min.	Analytical modelling and Simulation	DCs and reefers	√	√			Multi-commodity fleet sizing
Imai et al.	2009	Cost Min.	Time-space network and multi-dimensional comparison		√	√			Fleet sizing and network design
Lee et al.	2012	Cost Min.	Non-linear programming and gradient search		√	√		Demand	Fleet sizing and inventory control

Song and Earl	2008	Cost Min.	Queueing model and analytical solution		Two depots	√		Reposition time and loaded vehicle arrival	Fleet sizing and inventory control
Shintani et al.	2012	Cost Min.	Time-space network and linear optimisation	Standard and foldable containers	√	√			Multi-commodity fleet sizing
Turnquist and Jordan	1986	N/A	Mathematical programming		Multi-plants				Fleet sizing and travel time
List et al.	2006	Cost Min.	Two-stage stochastic optimisation	√	√				Product amount, production rate and container supply

Table 2.7 overview of studies with container fleet sizing problem

To sum up for this group of studies, the core of container fleet sizing is the decision that how can operators meet customer demands under various constraints and uncertainties with limited financial resources in a long run. The existing studies we reviewed have incorporated this issue along with other different operational planning. Apart from the specific research absence or limitations we covered above, table 2.5 also illustrated that, as tactical/strategic planning activities, container fleet sizing problem only jointly optimised with network flow designing and inventory policies. And the majority of all the studies are still focusing on evaluating the impacts of them on different operational decision-making. However, as a tactical/strategic decision-making, there are other issues (e.g. pricing and contracting) that lie on the same level could interrelate to it. This is important to TC industry, as they contain more opportunities to jointly influence asset profitability as whole. Therefore, incorporating those absences could largely fill up the academic gap as well as provide more insights in supporting better container asset management in a long-run.

2.5.*2* Pricing strategy

Due to the competitive nature of the freight transportation industry, pricing strategy plays a critical role in maintaining effective revenue management. Since price can directly determine companies' competitive positions, influence demand patterns and alter operation procedures (Xu et al., 2015), pricing strategy is well studied in the maritime industry for the past decades. According to whether the pricing strategy is used for coping with external environment or enhancing internal operations, the reviewed papers in this section are categorised into two groups.

i. Freight price and competition among carriers and logistics providers

Maritime industry is known for its complex and intensive competition due to the large number of different participants and their dynamic relationship network (Oliveira, 2014). Alongside this supply chain, competition is not only occurred at the end-market where different shipping companies struggle to expand their shares, but between carriers and customers, carriers and freight forwarders, competition is also severe in different way.

Since pricing strategy is the key component of revenue management, and the later one is essential to keep company financially stable and competitive, the impacts of pricing strategy on achieving better competence are well studied from various angles.

To study the pricing strategy and competition in freight transportation and logistics, Wan and Levary (1995) studied the procedure for shippers to obtaining the lowest adjusted price for a given shipping route with least period of time. They proposed a linear programming model to work on behalf of shippers. Zhou and Lee (2009) studied the pricing strategy of two competing firms between two locations with the consideration of ECR costs. With the realised demands, the price decision of both firms is reflected, and a mathematical model is built to look the insights of the interrelation between pricing and competition. As the results indicated, the optimal pricing strategy is either to seek the balanced realised demands or to treat two transportation directions as two separate markets. In addition, how carriers' profit is influenced by the competitive market environment is analytically represented. Similar to this study, Chen et al. (2016) explored pricing strategy and competition among carriers between two locations but with the consideration of waste shipments. Both a monopoly and duopoly model are built to find the optimal pricing strategy for carriers while the ECR cost is taken into account. As the cast study illustrated, the competitive environment can be significantly magnifying with the transportation of waste and scrap, profit of carriers may be reduced under some circumstances. But with the proposed optimisation approach, even for the most imbalanced shipping routes, profits can still be improved under competition through strategic pricing. Same to the pricing and competition research for carriers, Wang et al. (2014) discussed the topic when the context is defined in a new emerging liner container shipping market. Three game-theoretical models are developed to analyse the competition and then to maximise the total payoff through optimal freight rate and a combination of service frequency setting and ship capacity setting. This research jointly optimised several strategic/tactical level decision-making, and with the help of case study analysis, advices for these strategic/tactical level planning are pointed out with respect to different circumstances. Also, some studies have included the competition between other participants within this supply chain. Chen and Yu (2017) created a Stackelberg game model to explore the contract design for carrier and the pricing strategy of freight forwarders. Through the analyses on both symmetric and asymmetric demand information cases, how to design the optimal contract for carriers and how to tweak the price for freight forwarders are discussed in detail. Some studies (e.g. Tezuka et al., 2012; Yin et al., 2017) considered the competition among several participants and the corresponding pricing strategy are developed as well.

Different from the direct application of pricing strategy to enhance the competitive position for shipping companies, some studies incorporated different financial concepts jointly with pricing strategy to help with company's competence as well as address maritime management issues. Yin et al. (2010) proposed an option-based dynamic pricing model with American call/put options for shipping company under the existing legal regime. With respect to different types of options, different mechanism including option premium, strike price, expected instantaneous rate of return of underlying assets, the instantaneous standard deviation of return of underlying assets and non-risk rate of discount are derived to address the research objectives. Bu et al. (2012) stood on freight forwarders' interests to conduct a theoretical analysis which investigated freight forwarders' option ordering, pricing policies and with the consideration of ECR and option trade. It also illustrated the effectiveness of the model in improving freight forwarders' total revenue with optimising the option trade decisions and the unit cost of freight. Zheng et al. (2017) incorporated the idea of risk-aversion effects on carriers' pricing strategy and a game model is proposed to evaluate the optimal pricing decision for two carriers with different attitude of reducing the negative impact of uncertainty. Under uncertain demand and different conditions, the impact of price sensitivity and competition intensity parameters are analysed and the different optimal prices and the dynamic behaviours for the two competing carriers are well presented.

Link above addressed problems and approaches to the research problems of this thesis, the focus of deciding appropriate price policy for more effective container flow and better asset profitability are hard to be fully responded. Even though some of those researches have considered the ECR problem and demand uncertainties, their focus is on achieving optimal equilibrium with varying different parameters, while this research is interested in optimising the pricing strategy to obtain detailed container allocation and distribution plans. In another word, the exploration should not only stand at the tactical/strategic level, the followed operational planning need to be elaborated as well.

ii. Pricing and enhanced operational level planning

To develop the optimal pricing strategy for operational level planning, some research chose the port terminal operation as the focus. Laih et al. (2007) studied the queueing pricing strategy for container ship arrival decisions. They designed an optimal step toll scheme by cost equilibrium approach, which is aiming at finding the cost equilibrium for queueing cost and operating cost under such scheme. By doing this, container arrival schedule can be planned with less waiting at the queueing port. Likewise, Yu et al. (2015) designed an inbound container storage pricing schemes for terminal operators. Considering both free-time contract system and free-space contract system, a two-stage pricing game model is developed to derive the optimal decisions for both terminal operators and ocean carriers. Later Xiao and Ha (2018) have included unloading pricing together with storage pricing for inbound containers at terminals. With a novel model formulation, the two strategies are jointly determined to conduct the corresponding port operations and then maximise the total profit for terminal operators. The results shed light on how these price strategies can be determined jointly to balance the trade-off between profit extraction and storage cost efficiency, in addition, how the followed container unloading, transporting and storing planning at the port is presented. Rather than the inbound containers oriented, Woo et al. (2016) studied the pricing storage for outbound containers in container terminals. A price scheme is developed which includes both the free-time limit and storage charge per day for storing a container beyond the free-time limit. In order to achieve profit maximisation, a mathematical model is proposed based on the parameters with container operations in terminals. The results indicated that different practices of finding the optimal price policy is highly related to the distribution behaviour of the dwell time at port.

Rather than focusing on port-based policing strategy, some researches evaluated the pricing impacts over container allocation and distribution operations from shipping companies' viewpoint.

Gorman (2002) proposed a Monte Carlo simulation to capture uncertain market conditions and to optimise freight price with the consideration of ECR costs. A heuristic is developed to improve the profitability of price policies. In the study of Xu et al. (2015), a sea-cargo service chain with one carrier and two forwarders system is explored. By optimising the pricing policy, the cargo demands can be deliberately balanced which can further increase the efficiency of container flow and reduce the needs of ECR. Also, since the research found the benefits of ECR sharing between carriers and freight forwarders, a ECR sharing model is further studied to help with contracting problem between both forwarders and carriers. Liu and Yang (2015) examined the slot allocation problem with dynamic pricing strategy under sea-rail multimodal transportation. A two-stage model is developed where the first stage contracting the slot allocation and ECR availability with market, and the second stage takes dynamic pricing strategy and inventory control mechanisms to achieve overall revenue maximisation. To cope with the stochasticity of demand for the multimodal network, the model is convert to a deterministic one with chance constrained programming and robust optimisation. As the results revealed, optimising price strategy dynamically with respect to the fluctuation of container flows can significantly contribute to overall revenue management. Yin and Kim (2012) suggested quantity discounted pricing for freight forwarders, so that shipping companies can maximise their expected profit with increased sales. An analytical model is proposed, and the freight model is depicted by features such as price-break points, discounted freight rates, and penalties for unsold space.

Moreover, some researches have incorporated the leasing consideration with the pricing problem. Wang et al. (2015) construct a profit-based container assignment (P-CA) model while the customer demand is dependent on freight rate and both laden and empty container leasing cost is considered. With a tactical level P-CA design, the overall liner shipping network can be evaluated and improved, and then the operational level P-CA is addressed by adjusting freight rates to achieve maximised profit. The model is solved by both theoretical convergent trail-and-error approach and practical trail-and-error approach. Jiao et al. (2016) have explicitly studied pricing problem for stochastic container leasing system. Due to the difference comparing to consumer product pricing problem, the study examined the pricing problems in static and dynamic environments. Zheng et al. (2016) stood from the shipping companies' interests and evaluated the perceived container leasing prices to develop better container network design and reduce ECR. Specifically, the perceived leasing cost is defined by calculating the costs of using shipping companies' self-shipping network for ECR activities. Hence, this information can be used to take decisions on container leasing strategies at different places for shipping companies. Followed a two-stage network-based model is proposed. The first stage is aiming at completing the overall network design with ECR, and the second stage is used for finding the perceived leasing price. Foldable containers and mutual substitution between empty containers are considered.

Also, the context of reverse logistics is incorporated for pricing strategy in some papers. Huang et al. (2008) discussed the integration of inventory and pricing model to deal with inventory control, production scheduling and pricing decisions for the management of refillable containers. The objective of this study is finding the optimal policy at profit optimisation way that defines the procurement frequency, cycle time and pricing decisions simultaneously. Atamer et al. (2013) carried the study to focus on pricing and production decisions with reusable containers in a manufacturing system with stochastic customer demand. Two supply options in parallel are provided to customers with different price settings and the goal of the study is deciding the optimal price and production decisions to maximise the manufacture's profit with the combination of the two supplies. In addressing container return issue, Fazi and Roodbergen (2018) studied different price regimes for D&D issue with the goal of minimising costs incurred during the underlying period. Particularly, both separate and combined D&D regimes are evaluated, and their different applications are discussed respectively. The research is conducted under a deterministic setting and it is designed to fully fit DCs operation. Standing from Seaport terminals' perspective, Yu et al. (2018) utilise a two-stage game model that optimises free detention time with consideration of empty containers in the hinterland transportation system. Ndikom et al. (2017) investigated different demurrage policies and charges with selected shipping companies and their implications in Nigeria. The research conducted a survey model that tries to reveal the insights with a statistic manner. With the proposed literature review methods, only these three papers are found that discuss about pricing policies regarding D&D issue.

Since the variations for all the papers in this section are great in terms of the addressed issues, model context and methodologies, the table benchmarking is not going to be used here but only a qualitative conclusion is given. For above reviewed pricing strategy related studies, the following absence is spotted in considering our proposed research questions.

First, none of the papers reviewed for the tactical/strategic level planning (including fleet sizing problem) have jointly considered container fleet sizing and pricing strategy. Only network design as the high-level planning is frequently incorporated with these two, but the joint optimisation of these two decision-making seems scarce.

Two, as all the pricing strategy studies illustrated, demand is term that most researches wish to control when they manipulate price mechanisms. In the maritime logistics field, demand is always interpreted as how many containers or commodities will be purchased and this is the main content when it comes to logistics service. However, there are some other demands they are not necessary to the overall logistics service, but their existence can largely influence the overall efficiency. For example, customer pay premium for fast delivery or the charges for detention and demurrage etc.

2.6 Research gaps

To finish up the literature review chapter, all the research gaps after reviewing above studies are summarised as below.

2.6.1 Research gaps at the operational level

First, compared to inventory control-based ECR models, Although mathematical models can precisely plan container flow related activities, the complexity and high requirements on information visibility reduce their robustness in coping with uncertainties. Also, the computation complexity problem limits its application for operational level planning within a more realistic setting. However, for the existing inventory control-based models, gaps still exist when they are put into TC market context. For example, the types of operational uncertainties are still not broad enough in existing literature. It is widely appreciated that, apart from uncertain demand and supply, uncertain travel time, uncertain container charging and discharging, uncertain berthing, cleaning and return, and freight changing etc. can largely influence daily operation as well. Especially, in TC industry, special features from the moving commodity, market characteristic and "*quotation-booking*" process can bring more uncertain elements for TC travelling and return.

Therefore, to be more adaptable in addressing TC asset management, the current existing practices need to be changed and improved.

Second, the time gap between demand receipt and execution has not been modelled appropriately. As the customer request for a price quotation is often received well in advance of the demand execution time, so TCOs have to decide whether to issue a price quotation without accurate information on tank container availability at the demand execution time. In addition, the demand receipt is revealed gradually over time. Erera et al. (2005) emphasized the "quotation-booking" process in tank container management, but assumed all demands are known and deterministic in the planning horizon.

Third, there is a lack of decision support methods for developing quotations to meet individual customer demands. Support is required in determining precisely how to service individual demands, calculating expected costs and subsequently maximising profits through the quotation process. This problem becomes even more complex with the option to lease containers, which can take the form of planned leasing or spot/emergent-leasing, in more real-time, with their different costs.

Forth, process uncertainties need to be included. For example, tank containers are transported by third parties, so tank container operators face significant uncertainties from FFs and shipping companies. This is because, different freight forwarders provide different level of services per costs and low-service-level freight forwarders are less reliable and may not be able to finish tank container operators' tasks effectively. Also, as practitioners from the TC industry pointed out, it is difficult to finish cleaning on time between different commodities, so deterministic, standardized cleaning times are not realistic.

Fifth, ETCR is more expensive as TC operators have no ships and there are the third-party sources of uncertainty mentioned above. The planned and forecast execution of booked customer demands in the future may influence the volume of ETCR at the present time, but something unforeseen in the future may make the current ETCR ineffective.

2.6.2 Research gaps at strategic/tactical level

First, since TCOs normally operate a global business, it is essential to design the TC depot network with the balance of their global market distribution and the easy access to intermodal supply chain. Namely, the TC depot network structure should match the global market pattern and bridge the external logistics networks to provide efficient and effective support to TC flows. However, the industrial specialities made TC container flow planning is never the same as DCs. Especially, it is very expensive for TCOs repositioning self-owned TCs through the sea, long-term decisions such where and how many depots should be placed in a region are more critical to TCOs, as the overall TC depot network used as a whole to serve its customers but quite isolated internally and regionally when it comes to cooperation. Consequently, it is more difficult for TCOs matching the market characteristics and requirements with a long time static network design. The limitations embedded in TC network reduces the flexibility in coping with dynamics, and any changes in the market (e.g. trade patterns or change of shipping line routes) may cause greatly distortion of the TC flows and the expected TC profitability and utilization can be significantly influenced as well. In addition, issues such as the high reliance on special cleaning facilities and customer over-holding TCs can overburden the problem further. In turn, the industrial speciality made the existing studies and practices are hard to be applied to TCOs' use. The need of investigating and developing the TC based planning for the underlying issues are important.

Two, there is lack of studies that can effectively address TC customer holding issue. The great reliability and high standards on safety made TC popularly used as a temporary storage equipment, but it left delays TC return journey and undermined uncertainties in managing overall TC flow. Due to the similarities between TC customer-holding and DC D&D, pricing mechanism shows the ability to address TC overholding issues (e.g. Fazi and Roodbergen, 2018). However, differences between them can limit the direct application of studies about D&D into TC overholding. Those differences include (1) longer duration is more likely for TC overholding; (2) no clear boundary from port terminal to hinterland transport throughout the whole period; (3) TC overholding will be linked with uncertain TC cleaning. Therefore, in a long run, TCOs need make decisions on TC overholding price and free days policies to maintain good TC information visibility and efficient TC flow but without compromising TC hire revenue.

Three, there is no such research that have target TC from asset management perspective and carried an integrating and panoramic analysis regarding it. As we appreciated, the ultimate objective of asset management is achieving the optimal asset utilisation and profitability. All activates throughout its lifecycle from every aspect need to be dynamically and interrelatedly analysed. Hence, researches from single viewpoint without interrelations with other dimensions (e.g. the interrelation between operational and tactical level decisions) may cause the limitations of their realistic application.

2.6.3 Research objectives

Before the proposing of the research objectives, above discussed research gaps are firstly classified (table 2.8) with respect to different issues, so it helps to build up the research objectives respectively.

Planning level	Operational level		Strategic/tactical level		
Topics	Job fulfilment	ETCR	Container flow network design	Fleet sizing	Pricing mechanism to enhance container return
Research gaps	Lack of model designed to capture the delays, complex and uncertainties embedded in	The consideration of FF reliability	uncertain container return with respect to cleaning and	the joint optimisation with pricing strategies	TC customer overholding

	TC "quotation-booking"		customer overholding		
	Difference between pre-leasing and spot-leasing	Only intra-regional ETCR is allowed	Explicit leasing and rejecting decisions	uncertainties caused by container cleaning and overholding	
	Uncertain container cleaning				

Table 2.8 Highlights of research gaps

Regarding the identified research gaps, we wish to break down the TC asset management problem to different planning levels, and re-integrated them through simulating, evaluating and optimising the associated subproblems with consideration of the key industrial features, dynamic interrelationship, and uncertainties. Specifically, four explicit research objectives can be identified.

1. To build a model that can simulate, evaluate and optimise the TC "*quotation-booking*" process under various uncertainties, as well as giving decision support to job-fulfilment, ETCR arrangements and selection of freight forwarders;
2. To form the systematic way of setting up inventory control policies that can help TC operators cope with uncertainties and manage more efficient TC flow;
3. To design TC flow network that meets both customer delivery and holding demand with optimised TC profitability at strategic viewpoint;
4. To jointly optimise TC container fleet size and TC over-holding pricing strategy which can control and lead the overall TC network flow with increased efficiency and profitability.

By achieving above objectives, significant contributions can be made both academically and practically. From the academic perspective, this research can help to raise more academic attention to this particular field. It has comprehensively explored the existing researches, summarised the main achievements and identified several research gaps within this fields. Moreover, it pumps new blood to the knowledge body of TC area, and some of the issues (e.g. freight forwarders, TC over-holding, container cleaning etc.) that addressed by this research can also provide reference to the operations of other type of containers. As a result, the realistic applicability of some existing studies can be improved as well. At last, throughout the overall research process of this research, multiple future research opportunities can be inspired within this field or beyond. From the practical viewpoint, the potential research outcomes can help practitioners with better decision-making when they are facing the complexity of TC operational process and various uncertainties. It provides practitioners the "*top-down*" (from strategic level to operational level) strategies to manage their assets for better utilisation and profitability. By addressing some ignored issues (e.g. TC over-holding and selection of freight forwarders), it can raise the awareness of the industry and provide the tools for practitioners to re-evaluate their performance and take actions. Moreover, it can make significant contribution to the suitability of this industry through the reduction of ETCR movements (environmentally & economically), effective inventory control (environmentally and socially), and improved TC over-holding (economically & environmentally) etc.

Followed, the next Chapter will discuss in detail of the methodologies that will be used by this thesis regarding our identified research objectives.

3. Methodology

As Novikov (2013) defined in his book, research methodology refers to "*the process that is the specific used for identifying, collecting, and analysing information of a topic, and also includes various techniques for evaluating a study's overall validity and reliability*". To achieve the research objectives that we proposed in previous section, strategies for the research methodology of this thesis is built upon three pillars (illustrated by figure 3.1).

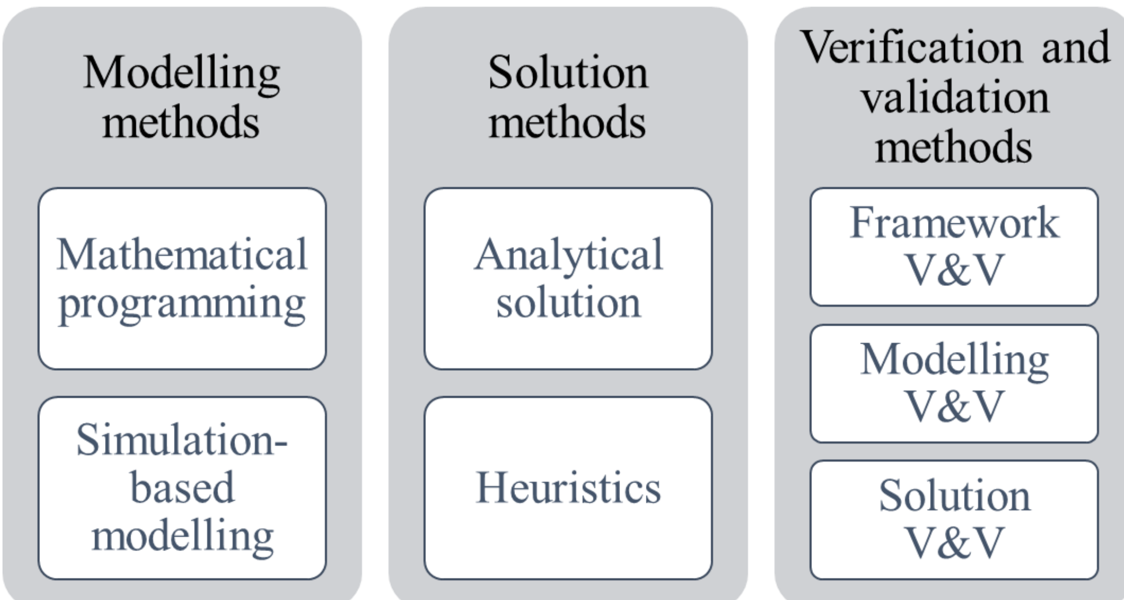

Figure 3.1 Three pillars of methodologies

According to how the research problems are described, the first pillar of the research methodology is about finding the appropriate process of formulating the research questions. Particularly, this includes the processes of transforming real-time operations, rules, networks and key events etc. into an integrated system, and meanwhile, various techniques are involved for simplifying, generalising and constraining the underlying problems, to ensure the research is properly framed with effective boundaries, so the research questions are correctly addressed, and the research objectives are solvable (Creswell, 2014). Followed the formulation of the research problems, the second pillar of the research methodology is about using the effective and efficient processes and techniques to solve the problems (problem solutions). This pillar normally details how information is collected, processed and delivered, so that the targeted research objectives can be achieved by obtaining specific results. In addition, methodology for solutions will also determine what research resources (i.e. time, tools, external support etc.) are going to be required and how they will be utilised. At last, the final pillar of the research methodology is a series of methods that are related to the verification and validation of the development process of this research and its corresponding results (ibid). Specifically, the verification and validation include processes of checking, confirming, making sure, and being certain of the reliability and validity of the research results as well as how the associated research problems are proposed and formulated. In another word, it is the core of the rigor of the underlying research. Accordingly, three main sub-sections in the following are going to be presented regarding the three pillars respectively.

3.1 Modelling methods

As Bouyssou et al. (2006) summarised, the methods used for problem formulation includes four approaches: The Normative Approach, the Descriptive Approach, the Prescriptive Approach, and the Constructive Approach. Differences of those four approaches lie in the characteristics of every approach and the process of obtaining the model. According to the questions and purposes of this research, the constructive approach is the appropriate one that can be used for modelling the underlying problems. Specifically, the process of obtaining the model for constructive approach considers no preferences pre-exist but lets the to-be-researched object construct its system of values while the model is being constructed, recognise that one construction cannot be isolated from the other (ibid). Also, the final model is expected to be validated through a consensus reached between the people involved in the system and the researchers. In this research, the problems come out from the system of TC asset management itself and the system forms its own construction, the way of formulating the research problems will not alter the TC operation itself but wish to achieve better decision-making and obtain insights from modelling and simulating the system itself. Therefore, the constructive approach is adopted by this research. In addition, since we wish to look at numerical relationships, dynamic correlations and decision-makings among different factors through the system simulation and modelling, quantitative modelling techniques will be the major components of the constructive approach.

According to the existing literatures, the quantitative methods and techniques that used for formulating problems in maritime container operation management include two major categories (Song and Dong, 2015). The first category of the modelling techniques adopted the network flow models and often applies mathematical programming to produce a set of arc-based matrices. In particular, the element in each matrix is a numerical value representing the quantity of maritime containers to be moved by an arc for various purposes (i.e. job fulfilling, ECR, leasing etc.). For example, Shen and Khoong (1995) construct a network model to optimise the flow of empty containers over a multiperiod planning horizon. Choong et al. (2002) built a time-space network model which contains four decision variables over various arcs that form the linkages between customer location nodes and container supply pool nodes. Song and Carter (2009) applied a linear programming to evaluate ECR strategies with network flow models. In the model, regions are modelled similar to the nodes in previously discussed models, and the region nodes are linked by shipping route which is also similar to the arcs as we mentioned before. Erera et al. (2009) introduced the arc-based network model for an adjusted robust optimisation problem so decisions for container values over each arc include both fixed variables and dynamic recovery action variables in addressing uncertainty. Brouer et al. (2010) developed a path-flow formulation based on its arc-flow formulation for a cargo allocation problem with empty repositioning. Long et al. (2012) incorporated a two-stage arc-flow based model to decomposition known and unknown information, and then running the model in a rolling-horizon manner with multi-scenario mixed-integer programming to make all the decisions for the whole planning horizon. Di Francesco et al. (2013) construct a similar network flow model with uncertainties, but they make decisions for whole planning horizon with known information and only the here-and-now decisions will be executed. When the model rolls forward, new information will be updated, new series of decisions for the rest of the horizon will be made, and again, only the decisions made at that period will be executed.

As all above papers demonstrated, network flow models have large diversity with different mathematical programming techniques (e.g. linear programming, stochastic programming, or multi-scenario mixed-integer programming etc.) or different application methods (e.g. two-stage network model or rolling-horizon network model etc.). Nevertheless, the core of the arc-based network flow model is represented alike (i.e. time expanded nodes connected by arc, and the corresponding optimisation is done for the values carried by each arc), so the advantages of taking this model formulation methodology can be summarised as:

1. As Song and Dong (2015) described, to formulate research problems with arc-based network flow model is simple and easy to understand. Especially, different realistic container flows (i.e. ECR flow, leased container flow etc.) can be developed and distinguished from laden container flows over the arc structure, in turn, various operation activities associated with container flows can be included and presented in the way as how they existed in real-time operation.

2. With the help of time expanded planning horizon, the model has the flexibility of handling demands and planning decisions across a long period of time or modelling more details and more complicated system configurations with a shorter time periods. Once the model is properly constructed, how container flow is arranged (with predefined objectives) to satisfy customer demands over the given planning horizon can be presented in a panoramic view.

3. Since various geographic locations involved in maritime operation are considered by arc-based network model and linked by the virtual arcs, it opens up the opportunity that the realistic shipping service routes or cargo movement paths can be associated with and identified on the network structure. By doing so, more specific planning can be considered such as the better use of service routes for certain customer demands or transhipment designing.

However, due to the complicated structure of the model and the associated large sets of constraints, drawbacks of using arc-based network flow model are also significant.

1. Arc-based network flow model requires finding all the optimal values for different container flows on arcs across the whole planning horizon, as a result, large computation is likely to happen, and it will be very difficult to be solved. It is extensively discussed in different studies (e.g. Epstein et al, 2012; Long et al., 2015; Song and Dong, 2015), and especially, when uncertainties or large number of decision variables are involved, arc-based network flow models will not be suitable for finding the solution space.

2. Arc-based network flow model is less suitable for short-term operational planning. The reasons are two-fold. First, researches about short-term operation focus more on detailed plans of meeting external opportunities and coping with dynamics. Issues such as processes, various events in a short period of time or dynamic decision-makings are hard to be modelled as network flow model is rather static. Second, when network flow model is used for research questions, it is normal to simplify or neglect some details or less relevant elements. In this case, network flow model is hard to be directly applied into real-time practice. Because the less considered elements could result in great discrepancies between the model results and reality, yet the network model only outputs the overall optimality at the same time with given settings, so when one plan cannot be executed as expected, all the plans afterwards are distorted and hard to be implemented as well. Such problem can be further escalated with the consideration of uncertainties.

Alternatively, the second group of methodology used for problem formulation aims to develop effective state-feedback control policies with respect to underlying research questions, and normally, those policies are associated with inventory control mechanisms, dynamic programming and simulation-based optimisation techniques. Generally speaking, the way of implementing this type of methodology consists of a number of decision-making rules associated with system dynamic states such as inventory levels of containers. For example, Lam et al. (2007) used a simulation-based approximate policy iteration algorithm to obtain an optimal average cost for ECR over an infinite planning horizon. Dong and Song (2009) used a control policy to find the optimal container fleet size and ECR deployment with stochastic demands. Yun et al. (2011) built a (s, S) inventory policy for an inland transportation system in dealing with uncertain demand. Dang et al. (2013) took both ECR and leasing options into account with the optimisation of a double threshold policy in an inland-depot system with uncertain order-arrival time. Dynamic inventory replenishment processes are simulated by the proposed model. These papers presented how decision-making rules are associated with system dynamic states, such as inventory levels of empty containers, and how decisions can be implemented in the same time period once they are made.

As above papers illustrated, no matter what state-feedback control policies are applied, this method is always about planning decisions dynamically regarding certain rules with respect to specific state-feedbacks. In particular, the model normally runs forward epoch-wise, and at each epoch, a series of plans will be made according to the new updated information and under what rules the information will be processed. Then, running the model till the end of planning horizon and the objective of such model is to find the optimal rules that can lead to the best overall performance. According to how such model is formulated and the characteristics of this method, several merits below can be concluded.

1. Since the methodology of using state-feedback control policies is normally associated with simulation-based optimisation techniques, it can be easier applied to real-time practice. When simulation model is constructed, operation processes or at least, the key operational steps are emulated by the system. Therefore, it makes more sense to practitioners that when and how decisions are made with the help of the model. Also, the simulation-based model provide better platform for expanding operational details. Because, simulation model contains process chain, and when more considerations are added to the simulation model, it could only incur several more processes or state transitions. But for network flow model, it could mean a huge number of new adding nodes and arcs. Therefore, the computation difficulties (for simulation model) will be smaller when comprehensive operational planning needs to be achieved.

2. Rather than finding precise optimal values required by arc-based network flow models, the state-feedback control policy-based models are looking at obtaining the rules (policies) that can lead to the overall optimal (or -near optimal) results. In this sense, the system will try to maintain and recover to a certain state despite the external environment changes (e.g. a certain level of inventory). Normally, when the state of the system jumped out of the controlled-range, it takes time to get it recovered, but meanwhile, the external demands are being satisfied simultaneously. Therefore, the design of the state-feedback control policies will always consider a certain degree of capacity that allows to buffer uncertainties while the system recovers to the expected state. Compare to network flow-based models, the state-feedback controlled one can perform better in accommodating uncertainties.

However, due to the features of the state-feedback control policy-based models and its potential solutions, several drawbacks may limit its use under certain circumstances.

1. The state-feedback control policy-based models are focusing on modelling the details of individual decision-making epoch and linking them with certain process, therefore, what the state is going to be in later epochs cannot be presented until the process runs to that point. Comparatively, the arc-based network flow model presents a static and panoramic view of all the operational activities within the planning horizon, so it is better for upper level planning that decision makers can appreciate the influence of the upper level planning over the whole picture better.

2. Compare to network flow models, the state-feedback control policy-based models are less likely to achieve the best performance. As we mentioned before, the state-feedback control policy-based models aim at reaching an average optimality, while the arc-based network model tries to fill up the arc matrices with optimal values. Therefore, the results that can be obtained from arc-based network model will be the upper bound of the simulated one, however, it is questionable that whether the upper bound results can be reached by the simulated one.

3. The state-feedback policy control-based model is efficient for carrying scenario analysis, finding various patterns of research problems, or evaluating sensitivities of different parameters (Severance, 2001). But if the research aims to obtain analytical solutions to the underlying problems or get mathematical induction for some interrelated factors, it is less effective compare to mathematical based models (e.g. the network flow model). This is because, for the state-feedback policy control-based model, it focuses on the dynamics of individual state of the model. If we wish to investigate how one factor influences the overall performance of the model, it requires the model to run many times, then a certain relationship/behaviour could emerge regarding the simulating results. But if the relationship/behaviour is required to be quantified by mathematical function(s), it will be more challenging to get a precise one. For arc-based network flow models, they are mathematical programming related and are rather static, which in turn, provide better foundation for developing further mathematical inductions or finding analytical solutions.

Considering the underlying research objectives, the first two objectives can be jointly addressed by an inventory control-based simulation model. This is because the "quotation-booking" process is dynamic and complicated. Different planning tasks are involved by this process even at the same period of time (e.g. develop quotation, plan job fulfilment or ETCR etc.), plus, they are very likely to be adjusted in next or further period due to the unpredictable environment. Hence, rather than setting up a static panoramic model, focus on the dynamic changes of the process is more appropriate and effective. In the meantime, incorporating inventory control as the backbone of the model enables flexibility for unpredictable uncertainties, and also, can provide a simple mechanism for practitioners to control TC flow without managing the flow itself.

For the rest of the research objectives, they are more concentrating on designing the upper level policies so that the specific customer behaviour (TC over-holding) can be manipulated and evaluated, and also, the overall TC flow can be improved. Therefore, an arc-based network flow model is ideal for addressing the other two objectives together. In this way, it is more straightforward to see how the influences of the underlying polices would be placed on the overall operation as whole, and meanwhile, the mathematical programming-based model is easier for us to seek the mathematical inductions for the relationship between customer over-holding policies and the corresponding over-holding days. Then the analytical solutions can be obtained for making more precise long-term decision-making.

In addition, regardless the simulation-based or mathematical programming-based models, decompose model into several stages deliberately has its significant meanings. Some papers used multi-stage models for decomposing different planning levels (e.g. Dong and Song, 2012; Dong et al., 2015). This is because, some models address problems with multi-planning levels and sometimes, they final solutions can only be obtained if the upper level planning is decided first. Hence, split the model into different stages and linked them with proper interfaces enables the feasibility of the model to reach an overall optimality, as well as presents a clear structure that matches the addressed problems themselves. Also, some models contain several stages are due to the different information visibility conditions in different stages (e.g. Cheung and Chen, 1998). By doing so, plans for stages that contain the perfect information can be made first, and the results will be incorporated as the inputs for stages that are happened afterwards. In our research context, both of the two proposed models need to be decomposed into two stages. Because, they both require determining the upper level decisions first (i.e. inventory policies for the first one and customer over-holding policies for the later one), and then the rest of the model can be finalised accordingly. Therefore, a two-stage inventory control-based simulation model and a two-stage time-space network flow model will be built respectively.

3.2 Solution methods

In operational research spectrum, methods for problem solution is a systematic process to solve formulated and constructed models and try to obtain the optimal solutions for them (White, 1985). These methods sometimes could be optimal solutions to the underlying problems or evaluating techniques for exploring the performance of candidates (ibid). In some occasions, researchers or analysts are required to develop new techniques for addressing specific problems. Followed by the chosen research formulation methods, the methods that can be applied for solving each formulation will be discussed and clarified respectively.

(a) Solution for the simulation-based model

First, in addressing simulation-based models, different methods are applied in operational research-based papers. For example, Dang et al. (2012) and Dang et al. (2013) proposed different heuristic rules for arranging ECR flow and used genetic-based optimisation procedure to find the optimal inventory control policies. SONG and Zhang (2010) applied a dynamic programming approach for inventory-based model with a two-state Markov demand process. Dong and Song (2009) proposed a simulation-based optimisation tool to decide container fleet sizing and ECR policy. Due to the large scale of the problem (several service routes with more than two ports and multiple deployed vessels), the solution is built upon rule-based and solved by Genetic Algorithms (GA) and Evolution Strategy combined with an adjustment mechanism. In order to find the optimal inventory control policy for multi-port operation, Li et al. (2007) built heuristic methods based on the average cost of using different inventory control policies. With the help of numerical experiments, the effectiveness of the solution is evaluated and verified. Yun et al. (2011) designed an optimisation procedure for deciding the optimal empty container inventory control policy and the results are obtained by commercial software.

As those researches demonstrated, the formulated problems are majorly addressed by specifically designed rules, and equipped with heuristic or meta-heuristic techniques. This is because, simulation-based models are normally associated with complicated processes, sufficient details and various uncertainties, therefore, they are hard to be solved analytically and very time-consuming. Take the potential context of our research into account, there are three aspects will significantly increase the complexity of the formulated model, and in turn, computational intractability is very likely to happen. One, the complex "quotation-booking" process is associated with various constraints, many state changes and multiple decision-makings. Two, TCs are globally operated which are normally associated with large network structure including different regions, depots, and customer locations as well. Three, different uncertainties need to be addressed throughout the whole study. For example, uncertain container cleaning, uncertain customer demands, and uncertain freight forwarder reliability etc. Therefore, to obtain the results in an effective and efficient manner, Genetic Algorithm is chosen as the solution for the first model of this research.

As various researches illustrated (e.g. Sivanandam and Deepa, 2008; Goldberg, 1989), GA has the advantages in addressing problems with large parameters, stochasticity and un-smoothed objective functions. Unlike gradient-like methods, genetic algorithm requires no mathematical model for the objective function and more likely to obtain a global optimum. Therefore, it is more efficient for realistic problems especially those have discrete variables and implicit form of constraints. The basic steps for completing a GA-based solution is depict by figure 3.2.

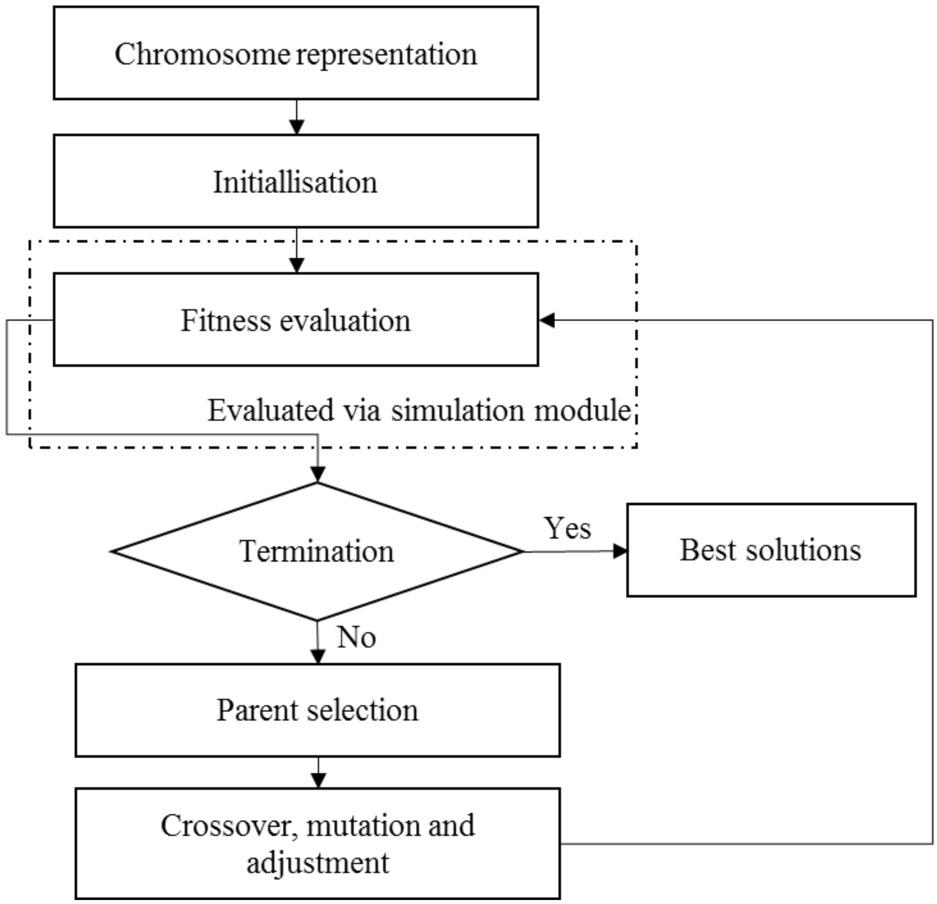

Figure 3.2 Flow chart of GA solution

Source from: Dang et al. (2012)

As the first step, chromosome representation will recode the potential results as a chromosome fashion (normally a binary string) and ensure them satisfying all the known constraints as well. Followed, the solution will kick off with generating a series of initial populations randomly or heuristically. Particularly, random generation gives the initial population great diversity, while heuristics generation gives better quality but may lead to a local optimal solution due to the limited diversity among the initial population. Meanwhile, it is also important to check all the generated chromosomes satisfy the constraints of the problem before moving to next step. If any initial population doesn't meet the constraints, the genes of that chromosome need to be repaired to be fit. Followed, the fitness evaluation step is about triggering the simulation process with those population and evaluate their results with fitness functions. Depending on the nature of the problem (i.e. maximisation or minimisation), the fitness function will be defined and fitness value for each population will be calculated. With the help of different selecting strategies, the parent selection step will use the fitness value of every individual chromosome (F_i) to randomly pick two individuals for producing the next generation population. Here we use the roulette wheel selection sampling strategy (Goldberg, 1989) as an example for parent selection strategy. In particular, each of two parents is selected from a binary tournament, which randomly picks two individuals from the entire population and retains the one with the best fitness value. The details are as follow:

Step 1: Calculate the sum of all fitness values of the population (*TF*), i.e. $TF = \sum_{i=1}^{P} F_i$, where *P* is the population size, and i is the index of chromosome.

Step 2: Calculate the selection probability (SP_i) of each chromosome, i.e. $SP_i = F_i / TF, i = 1, 2, ..., P$.

Step 3: Calculate the cumulative probability (CSP_i) of each chromosome, i.e. $CSP_i = \sum_{j=1}^{i} SP_j, i = 1, 2, ..., P$.

Step 4: Generate a random number r in the range $r \in (0,1]$. If $CSP_{i-1} < r \leq CSP_i$, Chromosome *i* is selected.

Followed, from the selected parent chromosomes, the next generation offspring can be obtained by conducting the crossover operation. Specifically, the selected parent chromosomes need to swap their genes for producing the new generation. However, in order to maintain a certain degree of diversity, the crossover operation is normally deployed alongside the mutation operation simultaneously with the given probabilities. That is to say, part of the genes for the new chromosome are coming from swapping and recombining their parent genes and part of the genes are coming from mutating existing genes to new ones. After the generation of the new populations, their corresponding fitness value will be calculated again for determining the acceptance of the offspring. In the end, the overall process needs to be terminated when certain conditions are met, for example, after a certain number of generations, or after a certain period of time, or after a certain number of generation the best fitness value makes no significant changes etc.

However, since the GA solution is a non-deterministic method, the results it obtained may vary largely each time it is ran on the same instance. It has also been pointed out by Beg and Islam (2016) that, the quality of solutions obtained by GA is highly relied on the initial populations, the way how the genetic operations are implemented (e.g. crossover strategies or selection strategies) and the probabilities of crossover and mutation. Therefore, GA can provide an optimal solution, but it can never guarantee optimality. To avoid or mitigate the limitations of using GA, it is recommended that the efficiency and effectiveness of GA can be enhanced by conducting some pilot testing for better configuration and developing some adaptive techniques to ensure the GA is more suitable for the underlying research problems.

(b) Solution for the arc-based network flow model

Next, in addressing the second model, the solution methods should belong to the mathematical programming-based researches with stochastic considerations. For example, Cheung and Chen (1998) formulated the dynamic empty container allocation problem with a two-stage stochastic network and solved it with a stochastic quasi-gradient method and a stochastic hybrid approximation procedure. Li and Han (2009) formulated a mixed integer programming model for ECR problem under demand and supply uncertainties, and they used chance constrained programming technique to cope with random parameters and solved the model with Branch and Bound method. Also, scenario-based techniques are commonly applied to address uncertain maritime network problems as it can effectively capture a high level of details and allow the application of deterministic optimisation techniques. Di Francesco et al. (2009) formulated an ECR problem with uncertainties by multi-scenario model and solved with linear optimisation techniques. In dealing with problem with a large number of scenarios, Topaloglu and Powell (2006) applied Approximate Dynamic Programming (ADP) for multi-commodity problem in a dynamic resource allocation research. Simao et al. (2009) used ADP to solve a dynamic fleet management problem with large-scale case. However, for most of the multi-scenario methods, one of the main challenges is the pre-requisition of a good cost-to-go function to represent the ultimate total cost (Long et al., 2012). Therefore, in order to avoid the needs of the approximation of the value function, Sample Average Approximation (SAA) method is normally applied to solve stochastic problems with multiple scenarios (e.g. Long et al., 2012; Long et al., 2015). This method is normally associated with a decomposition method, so that the main decisions can be made without the considering the influence of individual sample and the subproblems will deal with the large scale of scenarios.

Considering the research context of our study, the SAA method is selected to solve the underlying model due to three reasons. First, considering the large scale of the overall network (e.g. customer sites, TC depots, regions and different arcs), it is hard to address it with uncertain elements directly with gradient-based techniques. Two, without determining the upper level decisions, the lower network cannot be structured, so the approximation of the overall value function cannot be presented. Third, by decomposing the model to two-stages, the subproblem of the model can be covert to a large-scale SAA problem and it can be solved efficiently by commercial software. Regarding the research carried by Long et al. (2012), the proper form and steps of carrying SAA with decomposition are as follow.

First, according to the nature of the research problem (e.g. different planning level decision-making), it needs to be decomposed into different stages. Then identify the key decision variables for each stage and construct the mathematical model respectively. Next, generate a series of samples for the lower level problem (samples could be independent or not depending on the nature of the study) within the given probability distribution of the random parameters. Finally, use deterministic optimisation techniques to obtain the optimal solutions to the whole model in regard to all the realised samples.

Nevertheless, even though SAA method shows the strength of dealing with large-scale stochastic problems, the efficiency and effectiveness of this method will be constrained by the sampling method and the hardness of the problems (e.g. NP-hard). Different studies have developed further mechanisms based on SAA to increase the efficiency or computation ability of their solution (e.g. Long et al., 2012; Long et al., 2015; Dong et al., 2015). Therefore, in our research, SAA will only provide the fundamental solution for the research problem, but the actual implementation will be more tailored regarding the features and requirements of the problem itself.

(c) *Progressive Hedging Algorithm (PHA)*

Followed by SAA mechanism, PHA algorithm is one type of SAA derivatives which is developed to address more difficult problems. This is firstly proposed by Rockafellar and Wets (1991). The idea of this algorithm is to add the only constraints that tie together the different scenarios to the objective function through Lagrangian multipliers.

Different from SAA problem, PHA solution uses Lagrangian relaxation techniques to decompose master problem into a number of scenario-based sub-problems with given samples of random parameters. It incorporates penalties to relax constraints that require solutions to be equal across all samples. Therefore, instead of finding optimality to all samples simultaneously, PHA solution can solve each scenario-based sub-problems independently. Then, evaluating (with an assigned small positive value p) the sum of difference between each scenario-based solution and its average solution, incrementing penalties positively proportional to the absolute value of the different between scenario-based solution and its average solution, each scenario-based solution will be forced to be as close as possible. As a result, it helps to find the global optimality. Generally, PHA algorithm includes the following processes:

1. Initialization and set the penalty values as zeros for all relaxed constraints. Define value for p, and set iteration number as zero;
2. Solve each scenario-based problems and obtain the corresponding optimal value;
3. Compute the average solution value as the reference point;
4. Evaluating the difference of each scenario-based solution to its reference point, and check the sum of those differences against the predefined p (terminate the process if the sum of those differences is smaller than p).
5. Increment Lagrangian multipliers;
6. Increment iteration number.

3.3 Verification and validation of computer simulation model

Throughout the overall research journey of this study, verification and validation (V&V) activities are carried out. They are crucial to safeguard the credibility of the proposed simulation models, and make sure they 1) are implemented properly at technical level (e.g. with codes, equations and calculations etc.); and meanwhile, 2) reasonably represent the systems with respect to the real systems' characteristics. As quoted by Sargent (2011), for computerised model, verification refers to "*ensuring that the computer programme of the computerised model and its implementation are correct*", while model validation refers to "*substantiation that a computerised model within its domain of applicability processes a satisfactory range of accuracy consistent with the intended application of the model*" (Schlesinger et al., 1979). Regarding the nature of a simulation model, it is rather an abstract of the system it represents. Therefore, some unnecessary details of the represented system need to be eliminated and some assumptions are inevitability required. To judge the goodness of the model with respect to the system, whether the model has implemented the assumptions correctly and whether it has answered the system's purpose(s) need to be ascertained. In particular, verification process for simulation-based models are similar to the debugging process. It aims at ensuring the whole model behaves as what it is intended to be. Comparatively, validation is the task of demonstrating the model is a proper representation of the actual system. Which means, it needs to produce system behaviour with enough fidelity to satisfy analysis objectives. Hence, neither can model verification imply model validation, nor can validation imply verification. To present a clear implementation of V&V for models of this PhD thesis, study carried by Sargent (2011) is thereby applied as the guidelines and the details are as below (figure 3.3):

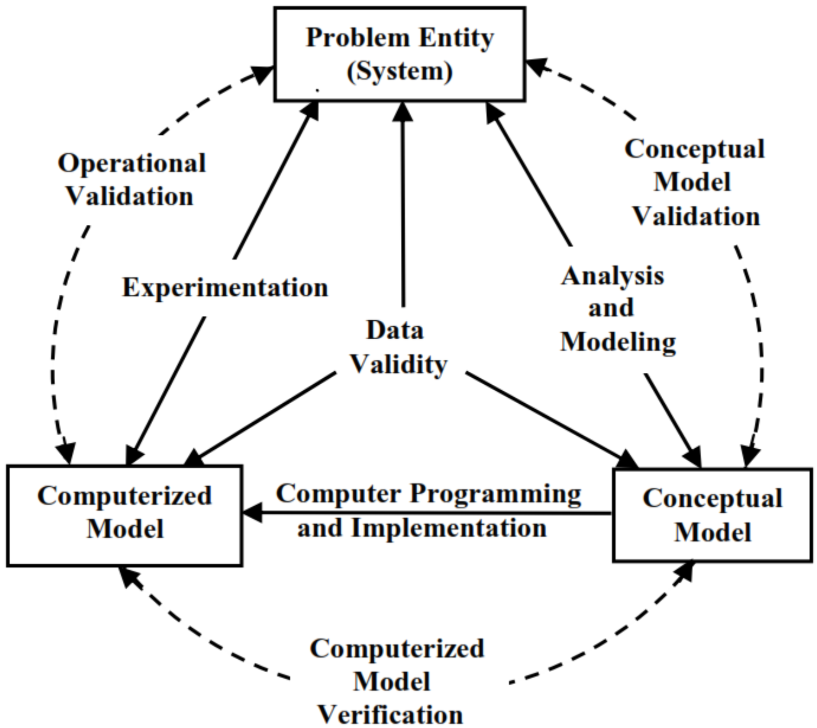

Figure. 3.3 verification and validation for modelling process

Source from: Sargent (2011)

From the identified research problems to the formulation of the conceptual model, conceptual model validation is required. It is used for determining that the theories and assumptions underlying the conceptual model are effectively made and the model representation of the problem entity (the system) is "reasonable" for its intended purpose of the model. As suggested by Sargent (2011) and Kleijnen (1995), several techniques can be used for completing the conceptual model validation. In order to ensure assumptions and ground theories used by the research are appropriate, mathematical analysis and statistic methods are applied in processing the initial data. For example, we can use statistic methods to find the patterns and probabilities of the uncertain parameters addressed by our model, and then compare it to industrial reports and ask for practitioners' advices. Assumptions such as linearity of price and demand and independence of certain variables can be validated through mathematical analysis. Let an "expert" from the underlying industry to examine the conceptualised model with respect to the system. Industry report can be used for validating the existence of difference between planned-leasing and emergent-leasing. Evidence can be found on industrial news for different reliability levels for freight forwarders.

Next, the conceptual model needs to be converted to a computerised one, and it requires a series of computerised model verifications. First, it is vital to ensure the model is correctly programmed. It requires the verification of intermediate simulation output. For example, when finish some sub-functions of the programming, we can manually calculate the results to check whether it matches the results from the function output. Also, since most of the commercial software provides 'debuggers', it can be used for verifying the intermediate output during the programming process (Kleijinen, 1995). Also, as asserted by Davis (1992), the whole computer code will be designed modularly, so the intermediate outputs of the model can be verified module by module. It also provides the convenience for testing pseudo random number generator separately, so that the randomness component of the model is more trustworthy and reliable as its intended use.

Second, the final results of the model need to be verified as well. To completing this step, we can use simplified version of the simulation programme with a known analytical solution to verify it. It can be simplified by inputting less data, using deterministic parameters instead of stochastic ones and neglecting some minor functions. In addition, since most of the commercial software provide the animation function, therefore, the verification process can also be assisted by dynamic displays of simulating results and any programming errors or conceptual errors are easier to be detected. By executing above steps, the computerised model can be assured to be properly converted from the conceptual model and programmed as its intended purposes.

Finally, after finishing the computerised model, the operational validation is necessitated for ensuring the behaviour of the simulation model's output matches the model's intended purpose over the domain of the model's intended applicability. This is important as the research will eventually be applied in real-time operation, and this step will help to decrease potential deficiencies that undermined during the development of the model with respect to assumptions or the use of invalid data. According to the validation techniques discussed by Sargent (2011), the following activities are later implemented into the underlying research.

a) Event Validity

This method refers to the match of the “events” occurrences of the simulation model and of the realistic system. A detailed flow chart of the real system event needs to be created and better accredited by professionals (if possible) for this research, and then a walkthrough comparison need to be done with the events in the model, so the event validity can be confirmed.

b) Extreme Condition Test

This method implies that, in order to assure the validity of the model behaviour, the overall model structure and outputs should be plausible for any types of extreme and unlikely combination of levels of factors in the system. For example, if the plan-leasing jobs is extremely expensive, the plans for job fulfilments will only be using self-owned containers or reject jobs.

c) Historical Data Validation

Also, since historical data is available to us, it can be break-down into two parts. Then part of the data can be used for model construction purpose, while another part of the data can be used for validation purpose, so that we can compare the behaviour of the output data and the historically archived data to make sure the model behaves as how the real system does.

d) Internal Validity

This method is used for addressing problems caused by large amount of variability from stochastic parameters, and the model’s results might be questionable and dependent on the realisation of the stochastic parameters. Hence, it is important to carry several replicants of the stochastic model, and use statistical analysis techniques to mitigate the uniqueness of individual samples. Also, to fix the random number generator seed, so the random stream can be replicated and the influence of randomness will not be passed onto the analysis of other deterministic parameters.

e) Sensitivity Analysis

By changing the values of input data or internal parameters of the model, the associated effects upon the model behaviour can be evaluated and benchmarked. Therefore, it can be used for validating the appropriateness of the model behaviour. Because, when we design the sensitivity analysis, the way how the parameter varies, the output behaviour (or we can say, the changes of the output) should in line with the behaviour in real system. If any counter-intuitive behaviour occurs, it could be either a mistake of the model itself, or something valuable hidden in real system that is not accounted when conceptualising the model.

Apart from all above verification and validation methods used for different modelling processes, data validity issue is also important which could cause the failure of the whole model (Sargent, 2011). Ideally, from the construction of the conceptual model to the finish of the computerised model, it is required to have appropriate, accurate, and sufficient data to support the validity of the model (ibid). However, since it is the secondary data that used by this research, there are very little can be done to ensure the data is correct. Some internal procedures can be conducted to enhance the quality of the data used by this research such as internal consistency checks of the data or screening the data for outliers and check if the correctness of the outliers.

Next, the following chapters will sequentially formulate models and devise solutions to address our identified research objectives with appropriate methodologies.

4. TC tactical/operational planning: inventory policy optimisation and quotation-booking planning

Due to the uncertain and complex TC quotation-booking planning, TCOs face a set of unique challenges not faced by general shipping container operators, especially from the process uncertainties arising from TC cleaning and the use of FFs. Yet, it is essential to conduct effective TC quotation-booking planning and evaluation for TCOs due to their great influence over the performance of TC asset management. In short, operational planning activities surrounding TC asset management is integrated by TC quotation-booking process. TCOs need to find an optimal combination of both internal and external resources in seizing market opportunities and mitigating uncertainties. For example, TCOs need to decide how each individual customer demand is fulfilled by effective intermodal connections and the right type of TCs with reasonable costs through the quotation-booking process. Hence, TCs' profitability level is greatly influenced by how TC quotation-booking process is deployed. In a long run, TC quotation-booking process is the core business channel that TCOs link with their market and contribute to capital increase. For example, how flexible the quotation-booking process can be provided to customers (e.g. different intermodal connections, different service levels etc.) can differentiate TCOs from one to another and TCOs with more profitable quotation-booking performance indicates stronger financial capability. Thus, maintaining good performance of quotation-booking process has the strategic meaning to enhance TCOs' market position. In this chapter, the major challenges surrounding quotation-booking process is re-addressed after the literature review chapter. It will also point out some of the issues that are not mentioned when reviewing existing studies. Followed, a detailed problem description is given to picture the whole process and summarise the to-be-researched issues. Then, a simulation-based two-stage optimization model is developed to address these challenges. The solution procedure is based on the simulation model combined with heuristic algorithms including an adjusted Genetic Algorithm, mathematical programming, and heuristic rules. Numerical examples based on a real case study are provided to demonstrate the effectiveness of the model.

4.1 The main challenges with respect to "quotation-booking"

In the literature review chapter, the main challenges that coming from TC quotation-booking process are extensively discussed, especially the challenges caused by industrial characteristics of TC. For example, uncertainties associated with time delay in between demand receipt and execution; reliance on external resources for quotation development; constrained ETCR planning and stochastic equipment cleaning etc. In addition, when TCOs build quotations for customers' demands, the time delay in between demand receipt and demand execution allowed TCOs the chance for planned leasing activities. Different from spot leasing (or emergent leasing), planned leasing is defined as leasing that the TCO requests from lessors at least one day before the actual required time, whereas emergent leasing is requested on the same day as the actual use of the TC. In practice, planned leasing (pre-booked leasing) is cheaper than emergent leasing. This concept is analogous to the 'advanced purchase discount model', which is widely applied in the airline industry or other asset leasing activities (Gale and Holmes, 1992; Dana, 1998). From a supply chain coordination perspective, planned leasing contributes to information sharing under an uncertain environment (Tang and Girotra, 2017). TC lessors provide incentives to encourage their customers to do so. Taking the planned leasing and emergent leasing into consideration in the quotation-booking process enables TCOs to make strategic choices between these two options. In particular, when TCOs expect there will not be enough inventory to execute the demands received, they can arrange planned leasing to avoid higher emergent leasing costs. Furthermore, a cheaper leasing option could provide the opportunity for TCOs to plan to serve some demands with leasing containers to maintain more balanced container flows overall.

In addressing above issues, this research will formulate the overall problem and design the corresponding solutions from two stages. At the first stage, it will help TCOs adopt appropriate inventory control policies to maintain effective empty container repositioning and to cope with mid-term uncertainties. At the second stage, it will give decision-making support to deal with everyday customer demands with the emulated quotation-booking process, particularly decisions about how to satisfy customer demands and how to manage the container fleet on a daily basis in the presence of uncertainties. Reasons to set up the two-stage structure are two-fold which are mainly caused by the research objectives and the nature of the problems. First, as discussed in the methodology chapter, complexity and the uncertain features of TC operation can easily lead to computational intractability. Hence, inventory control-based simulation model is more feasible for the underlying context. This also matches our first two researches objectives (set up inventory policy + improved operational decision-making within quotation-booking process) that will jointly addressed by this chapter. However, an inventory control policy is normally an average optimal setting based on a long-term horizon (Song and Dong, 2015) while everyday operational decision-makings (e.g. job fulfilment and ETCR) focus on the best choices up-to-now, thus the use of different length of information requires these two objectives to be decoupled by different stages. Second, these two objectives should be achieved sequentially. Inventory control policy is the rule that aims at improving TC flow effectiveness and needs to be set up firstly so that decisions related to TC flow (i.e. ETCR or job fulfilment types) can be made accordingly. Without the inventory control policy, the simulation model is hard to be executed due to lack of controlling rules and responses.

4.2 Problem Description

TCOs have no ownership of maritime transportation services, instead serving customer demands through contracts with third-party transport providers. In the daily operation, customer demands are received including job start date, origin and destination. TCOs need to plan on these, developing corresponding quotations. TCOs exploit known information about costs and profits to decide how much they need to charge customers and how the demands should be served using three types of jobs; self-container jobs using TCOs' self-owned containers, planned leasing jobs and emergent leasing jobs.

As depict by Figure 4.1, TCOs' operation has the following features. Demands from customers are not executed on their receiving date. Instead, they have a demand execution date set by the planning process, and the gap between the two dates varies from one demand to another. Once an execution date is set it is fixed, i.e. plans made each day have no influence over previously made plans as these have been returned already to the customer. The only change allowed to a planned job is if there is not enough inventory when the execution date arrives for a self-container job, which is then replaced by an emergent-leasing job. If at the planning stage it is forecast that there will not be enough self-containers on the execution date, then planned-leasing containers are scheduled for use, or the job can be rejected on profitability grounds. To simplify the narrative and formulation, it is assumed that quotation request, quotation return or rejection, and booking confirmation occur on the same day. For all the demands received on a given day, the latest of their execution dates forms the limit of the planning horizon on that day, so the planning horizon is dynamic and varying between days. Once move to the next day, a new set of customer demands will arrive, and then, they will determine the new planning horizon and repeat the same steps from the last day without interfering previous plans.

Considering the quotation-booking process, it is challenging to make effective decisions for the following three reasons in particular:

(1) Uncertain events occur along the supply chain, especially during the container return leg. However, once a quotation is returned to the customer it cannot be changed, so if there are not enough self-containers available for self-container jobs on a given execution day, TCOs will have to emergent-lease TCs. This increases the cost greatly.

(2) Leasing is in practice essential to provide flexibility without having excess capacity of self-containers and excessive just-in-case ETCR. However, pre-booked planned-leasing is much cheaper than emergent leasing. Therefore, TCOs need to consider not only how to avoid emergent leasing but also whether to use planned-leasing to achieve lower leasing and ETCR costs.

(3) In their niche market, TCOs have the bargaining power to reject some customer demands without losing future business. A job might be advantageously rejected if it would have knock-on effects or interactions with other jobs causing higher costs and lower profits. However, the time gap between returning a quotation and actual execution makes it difficult for TCOs to evaluate whether or not to reject.

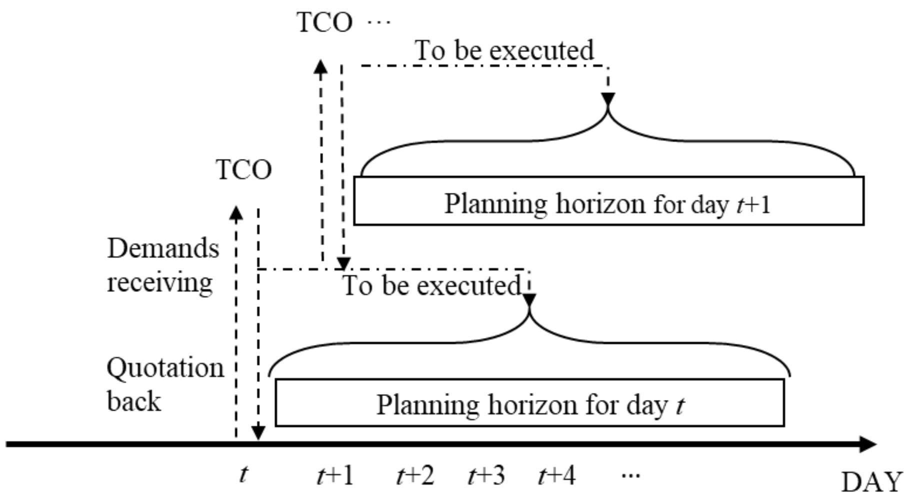

Figure 4.1 the Quotation-Booking Process

TCOs need effective strategies for the complex decision-making involved in dealing with these challenges. Unlike the dry container industry, TCOs need FFs to book external transport services for their TCs. Since maritime transport companies have limited capacity on specified routes, they will prioritize bookings for FFs with whom they have closer relationships. FFs with low priority will be less able to guarantee booking requests, so some of their TCOs' container transportation may not be completed as planned. The model developed here translates this into higher costs for FFs to maintain close relationships with transport companies, and these costs are passed on to TCOs, i.e. the higher the cost of an FF the higher its booking success rate. FFs providing 100% successful booking rates are defined as 'best FFs'. When TCOs choose FFs that are cheaper than best FFs, they will have the possibility of unsuccessful bookings. Regarding industrial practice and the communication with practitioners from TCOs. The successful booking rate is modelled as a discrete random variable that takes the value 50% or 100%, and the probability of a 100% successful rate is given by the cost of the chosen FF divided by that of the best FF. For example, if the cost of the best FF is £100, while the cost of the chosen FF is £60, the successful booking rate has a 60% chance of being 100% and 40% chance of being 50%. In the model, the choice of FF is made only for ETCR because only best FFs are used when meeting customer demands to avoid unsuccessful bookings for confirmed jobs. For ETCR, TCOs may choose appropriate inventory control policies with less than 100% successful booking rates to reduce costs. The safety stocks of TCs at each depot provide a buffer to guard against uncertainties caused by cheaper FFs (and other uncertainties explained later). According to the TC industry, inter-regional ETCR is far more expensive and seldom adopted, so the model categorizes depots into different regions geographically and only intra-regional ETCR is allowed.

In observed practise, TCOs can estimate accurately the container outflows from every depot to their destinations two weeks ahead. Hence, the data from the two-week customer-demand forecast is considered here in the decision-making. Figure 4.2 summarizes the key aspects of TC assets management.

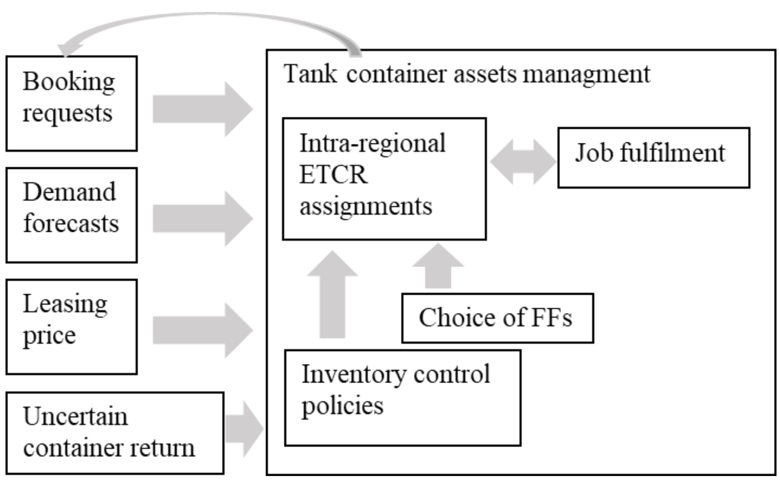

Figure 4.2 Tank container assets management overview

As Figure 4.2 illustrates, the whole tasks of TC asset management at the operational and tactical level include making daily decisions for job fulfilments based on designed inventory control polices and choices of FFs. Moreover, information of known customer demands, planned customer bookings, TC leasing terms and prices, and on-the-way container flows will be further exploit to help job fulfilment decision-makings as well.

TCOs' operations can be different in many aspects. The following simplifying assumptions are made here to make the problem tractable:

1. Only the 20-foot equivalent unit (TEU) TC is used.
2. TC lessors have infinite fleets and leasing demands are met immediately.

3. Once a container-cleaning process has started, the cleaning time for that container becomes known.

4. FF cost is positively correlated with the shipping-slot booking success rate.

5. Selected FF will not vary from depot/region to depot/region, so only one FF will be used for global ETCR planning each day.

6. ETCR is only intra-regional, on routes available between any two depots.

7. Unloaded containers must be cleaned before reuse, with random duration in range 3 to 7 days.

8. Execution dates of customers' demands are later than their received dates.

9. Emergent leasing is more expensive than planned leasing, and leased containers are returned to lessees immediately after jobs.

10. The customer demand pattern remains similar for any two consecutive years. TCOs can forecast customer demands accurately two weeks ahead.

11. Self-owned TCs are always used first to meet customer demands during the demand-planning phase.

The justifications for above assumptions are as follow. Assumption 1 refers to the most common type of containers. In practice, 40-foot TCs are also used often but they can be treated as two TEUs (e.g. Dong and Song, 2009; Li et al., 2007; Choong et al., 2002). As for assumption 2, TC lessors focus on providing equipment leasing business and it is essential for them to keep TC availability at all time (e.g. Perez-Rodriguez and Holguin-Veras, 2014; Dang et al, 2013). In addition, as figures from ITCO (2017) indicated, the large TC fleet size owned by TC lessors shows the ability to maintain their TC availability. As for assumption 3, it is reasonable to assume the cleaning time certain if this cleaning job is fully ready. This is because reasons that caused uncertain cleaning duration are the different cleaning requirements of different liquified cargoes and the availability of dedicated cleaning facility. But when the cleaning process is started, those uncertainties are determined, and the cleaning duration can be confirmed. Assumption 4 is made to match the industrial practice which indicates higher cost FF will guarantee better service level, and equivalently, it refers to better slot booking reliability. Due to the complex and dynamic nature of the underlying model, assumption 5 is made to simplify the model computation. As for assumption 6, due to the high cost of ETCR activities, it is common in this industry that TCOs only carry short-distance ETCR. Assumption 7 is a common industrial practice that the average cleaning duration is assumed to be 3-7 days prior to the beginning of cleaning. As for assumption 8, TCOs need to go through the quotation-booking process to fulfil customers' demands (Erera et al., 2005), the time gap is widely existed in this industry between demand receipt and demand execution. Section 4.1 has extensively discussed the possibility of incorporating planned leasing, which in turn, formed the theoretical foundation of assumption 9. For assumption 10, according to ICIS Global Petrochemical trade index (2017), despite the total trade volume is on a stable increase, but the changes for any two adjacent years are very small and keeps similar ups and downs pattern monthly. The final assumption indicates that it makes business sense for TCOs use self-owned TCs first due to high cost of using leased TCs.

4.2.1 Notations

To formulate the system, the following notation sets are introduced:

Indices

i, j	Indices of TC depots.
s, t	Indices of date.
r	Index of regions.
d	Index of customer demands.
y	Index of predicted customer demands that is used in Stage 2 model.

Sets

T	Set of time periods for Stage 1 model; each element in T represents a day.
R	Set of regions.
P	Set of depots.
D_s	Set of customer demands received on day s. A customer demand is a tuple d, which contains the information of journey origin, destination, job received date, job start date, and number of containers. It is denoted as $(O_d, D_d, S_d, T_d, M_d)$, where $O_d, D_d \in P, O_d \neq D_d, S_d = s < T_d, M_d = 1$. Note that in TC operations, one demand is usually one unit. It is therefore assumed M_d = 1. However, the model can be modified easily to handle the case M_d >1.
D	Set of customer demands received on the days in T, which will be used in Stage 1 model.

Y_t	Set of customer demands for the next two weeks forecasted on day t. Each predicted demand y is denoted as $(O_y, D_y, S_y, T_y, M_y)$ and it represents a demand from depot O_y to D_y to be received on date S_y, where $O_y, D_y \in P, O_y \neq D_y; S_y \in [t+1,\ t+14]; M_y = 1$. Consistent with the above tuple, T_y represents the execution date of the forecasted demand, but its actual value cannot be forecasted and it is unknown at time t.

Input parameters

N	TC fleet size.
C_i^h	Inventory holding cost per TEU per day at depot i, where $i \in P$.
C_{ij}^p	Penalty cost for unmet demands per TEU from depot i to depot j, where $i, j \in P, i \neq j$.
C_i^o	Lifting-on cost per TEU at depot i, where $i \in P$.
C_i^f	Lifting-off cost per TEU at depot i, where $i \in P$.
C_b^t	Cost per TEU for choosing the best FF to move empty TCs on day t.
C_{ij}	Transportation cost per TEU (for both laden and empty) from depot i to depot j where $i, j \in P, i \neq j$.
C_i^c	TC cleaning cost per TEU at depot i, where $i \in P$.
C_i^l	Planned (pre-booked) leasing cost per TEU per day at depot i, where $i \in P$.
C_i^{le}	Emergent leasing cost per TEU per day at depot i, where $i \in P$.
E_d	Revenue of demand d.
a_{ij}	Transportation time in days from depot i to j, where $i, j \in P, i \neq j$.

Inventory state and intermediate variables

$S_i(t)$	Inventory level of depot i at the beginning of day t, where $i \in P$.
$S_i^m(\mathrm{t})$	Adjusted inventory level of depot i on day t after confirmed container flow is completed, where $i \in P$.

Derived variables

b_i	Cleaning time in days at depot i, where $i \in P$. It is a random variable.
β^{t}	Shipping slot booking success rate on day t. A discrete random variable that takes two values: β^{t} = 100% with probability f_t/C_b^t; β^{t} = 50% with probability $(1 - f_t/C_b^t)$.
M_i^t	Length of each dynamic planning horizon, which equals the number of days from day t to the latest execution date in the demands received on day t at depot i where $i \in P$.

Decision variables

W_d	Equals 1 if demand d is rejected, otherwise equals zero. $d \in D$ in Stage 1 and $d \in D_s$ in Stage 2

X_d^p	Equals 1 if demand d is planned to be delivered by self-container, otherwise equals zero. $d \in D$ in Stage 1 and $d \in D_s$ in Stage 2.
X_d^a	Equals 1 if demand d is actually delivered by self-container on day T_d, otherwise equals zero. $d \in D$ in Stage 1 and $d \in D_s$ in Stage 2.
g_{ij}^t	Amount of ETCR containers from depot i to depot j on day t, where $i, j \in P, i \neq j$, $t \in T$, $d \in D$ in Stage 1 and $d \in D_s$ in Stage 2
Z_d^p	Equals 1 if demand d is planned to be delivered by leased container, otherwise equals zero. $d \in D$ in Stage 1 and $d \in D_s$ in Stage 2.
Z_d^e	Equals 1 if demand d is actually delivered by emergent-leasing container on day T_d, otherwise equals zero. $d \in D$ in Stage 1 and $d \in D_s$ in Stage 2.
f_t	FF cost per TEU at day t ($t \in T$) subject to $f_t \in [2/5C_b^t, C_b^t]$. It determines the reliability of FF to complete the ETCR activity.
$[\mathrm{L}_i, \mathrm{U}_i]$	Upper and lower bounds of container inventory control policy at depot i, used for determining whether depot i is a surplus or deficit depot, where $i \in P$.

4.2.2 Outline of the formulation approach

A two-stage simulation-based optimization approach is proposed to achieve two goals. The first goal is an optimized inventory control policy that leads to more effective ETCR at the tactical level by assuming all demands are accepted. The second is a decision-making support tool at the operational level for determining how new customer demands will be served every day to maximize profit by integrating with container operations planning. Figure 4.3 below illustrates the structure of the underlying approach.

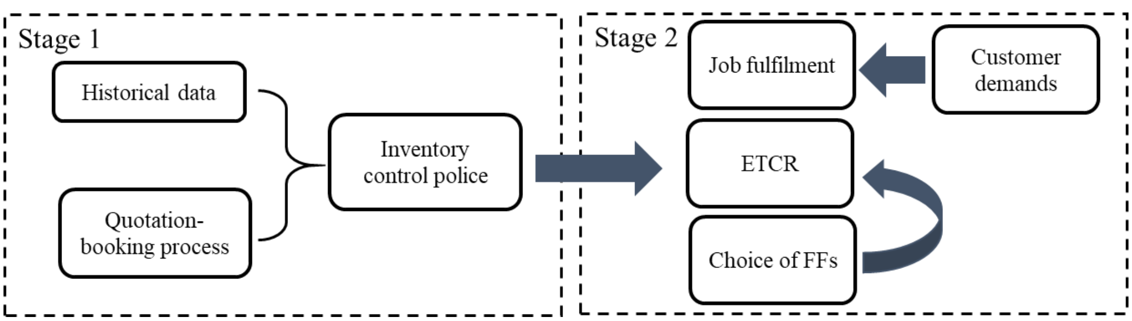

Figure 4.3 the basic idea of the two-stage formulation

The different goals and their different preliminary settings require separate optimization processes. They are different in their planning levels. The inventory control policies are normally obtained through analysis of long-term statistics, which in turn, enables their adaptation to the associated environment. According to Braekers et al. (2011), inventory-control based optimization is tactical planning as it aims at ensuring the efficiency and rationale of existing resources over a medium horizon. Practically, once the inventory control policies are established, they will direct a series of operations, i.e. transportation, replenishment planning and production etc. Therefore, they are often maintained for a certain period of time to ensure the continuity of operations. In contrast, the second goal is at the operational level dealing with day-to-day operations. Customer demands are received on a daily basis, and associated decisions are made using current information. Therefore, only 'best-decisions-for-now' can be made when new demands are received, while demands received later can be planned using any subsequently available information, e.g. previously uncertain information may become certain.

Another critical reason why the two processes should be decoupled is that the two goals have different focuses. The inventory-control optimization seeks a long-term solution to TC management facing imbalanced trade flows and uncertain cleaning times by maximizing profit for the entire planning horizon. Whereas, the decision-making support tool is maximizing profit in serving customer orders (job quotation, planning and execution) on a daily basis within a dynamic planning horizon. The outputs of Stage 1 are used as inputs to Stage 2. On the other hand, the evaluation and optimization of the inventory-control policies rely on the simulation of simplified daily operations over the entire planning horizon.

The inventory-control based optimization is Stage 1 of the proposed simulation model. Specifically, a double-threshold inventory control policy is optimized through simulation of the entire planning horizon. To reflect industrial practice of daily operations, a special rolling-horizon approach is introduced that is different from the traditional rolling-horizon. As defined by Di Francesco et al. (2013), a 'rolling-horizon' refers to how a time-extended optimization model plans all the decisions for all periods of the planning horizon, but it will only implement the decisions for the first period and the model will be run again to plan and implement new decisions in the next period, when new information becomes available. Therefore, as the model runs forward, the total length of the planning horizon decreases by one period each period, so that the planning horizon at period t is (t, |T|). In contrast, the length of the rolling planning horizon in our model is determined dynamically.

Planning happens every day that new demands are received, and the planning horizon is defined by the latest execution date (M_i^t) of the newly received demands. At every decision-making point, plans are made for the horizon (t, t+M_i^t). After this point TCOs can only adjust 'how' these scheduled demands will be served (self-owned containers or emergent-leased containers). They cannot alter execution times or reject jobs later on. This dynamic rolling-horizon is tailored to reflect the TC quotation-booking practice and, as it has not been seen in the literature, we believe it is novel.

Since historical data is used for the simulation at Stage 1, all the customer demands are accepted using either self-owned containers or planned-leasing containers. After all the known container flows are completed on this day, ETCR performed by following the inventory control policies. According to the initial inventory level of empty containers, every depot is classified as being either in surplus, in deficit or 'normal'. The deficit depots call for ETCR from surplus depots in their own region until either all the deficit depots are filled up to their lower bound threshold or all the surplus depots have repositioned out their TCs down to their upper bound. In Stage 1, it is assumed ETCR is 100% reliable as the 'best FF' is selected. By applying an Adapted Genetic Algorithm (AGA), a series of near optimal threshold-pairs can be generated through simulation using the historical data. With the completion of the Stage 1 simulation, the optimized inventory control policies are obtained.

In Stage 2, the optimized inventory control policies are implemented for ETCR. Whenever new demands arrive, all the demands received in the same period will be planned together. Similar to Stage 1, the demands are planned with the new dynamic rolling-horizon. However, Stage 2 seeks the most profitable way to serve the newly received customer demands, with demand rejection considered within the context of a two-week demand prediction. Experience has given industrial practitioners confidence in two-week time predictions, therefore they are used here when making decisions on customer demands. TCOs also need to decide which FFs are hired for ETCR on a given day, which incurs an additional process uncertainty in the reliability of ETCR. A more 'standard' GA is applied to select FFs on a daily basis within a dynamic planning horizon along the overall planning horizon.

4.3 Model formulation

4.3.1 Model at Stage 1: The Threshold Policy Optimization

Events in Stage 1

Stage 1 aims to find the optimal inventory control policies for all depots based on historical data. One year's daily operational data is used. It consists of the following four events and its mathematical model is formulated below.

1. *Inflows*. Inventory at each depot is updated with inflows of self-owned TCs from finished jobs and ETCR. Leased TCs are not counted because they are returned directly to the lessors. Since containers need to be cleaned after jobs only ETCR containers go directly into inventory.
2. *Outflows*. Container outflow occurs for demands planned already for execution on that day. Although the 'to-be-executed' self-container and leased container jobs are planned, uncertainties may cause container unavailability. Once actual inventory cannot cover self-container jobs, emergent leasing is required.
3. *ETCR*. The remaining inventory in every depot is gauged with the specified inventory control policies, and ETCR determined accordingly. The real inventory levels in every depot must be modified by including the expected overall future container inflows and outflows within the planning horizon before comparison with associated threshold values. This avoids lead-time-caused repetitive ETCR and yields better inventory availability for upcoming demands.
4. *New Demands*. The dynamic rolling horizon for executing new demands is from the next day to the latest execution date of the new demands. Following a chronological sequence within the rolling horizon, the model simulates the expected container inflows and outflows on every demand execution date. Inventory on the demand execution dates is checked to see if there is enough to satisfy the 'to-be-executed' demands. If yes then demands are served by self-containers, otherwise planned leasing is required.

Mathematical model of Stage 1

Event 1: Inbound flow to receive self-owned containers on day *t*

At the beginning of day t, the inventory level for depot i is updated by adding the ETCR containers that have arrived and those that have returned from cleaning. Once the container cleaning process is started, the cleaning time becomes known. Let τ_d represent the cleaning time for job d, which is a realized sample of random variable b_i, then:

$$S_i(t)' = S_i(t) + \sum_{j \in P} g_{ji}^{t-a_{ji}} + \sum_{d \in D} \sum_{D_d = i} \sum_{O_d = j, j \in P} \sum_{T_d = \mathrm{t} - \tau_d - a_{ji}} X_d^{\mathrm{a}}; \tag{4.1}$$

Equation (4.1) indicates the expected inventory level for depot i after adding in TCs returning from ETCR or cleaning.

Event 2: Outbound flow to execute jobs on day *t*

The inventory level is updated with the planned container outflows for day t. Due to uncertain cleaning times, the actual inventory level may not satisfy all planned outflows. Therefore, emergent leasing may be required, so the most cost-effective way to assign the jobs among self-containers and emergent-leased containers must be determined. Let:

$$S_i(t)'' = \mathrm{Max}\ \{0, S_i(t)' - \sum_{d \in D} \sum_{O_d = i} \sum_{T_d = \mathrm{t}} X_d^{\mathrm{p}}\}; \tag{4.2}$$

$$\text{If } S_i(t)'' > 0, \text{ then } X_d^a = X_d^p,\ Z_d^e = 0; \tag{4.3}$$

If $S_i(t)'' = 0$, then the assignment of jobs among self-containers and emergent-leasing containers is determined by solving the following mathematical programming problem:

$$Min \sum_{d \in D} \sum_{O_d = i} \sum_{D_d = j, j \in P,} \sum_{T_d = t} Z_d^e * C_i^{le} * a_{ij} \tag{4.4}$$

Subject to:

$$\sum_{d \in D} \sum_{O_d = i} \sum_{T_d = \mathrm{t}} \mathrm{X}_d^{\mathrm{a}} \leq S_i(t)',$$

$$X_d^{a} + Z_d^{e} = X_d^{p}; \text{ for } d \in D \text{ with } T_d = t. \quad (4.5)$$

Equation (4.2) gives the potential inventory level for depot i after the job associated TC outbound flow. Equation (4.3) determines whether or not the current inventory is still able to cover the planned self-container jobs. Equation (4.4) determines how to assign self-container jobs and emergent-leasing jobs when the current inventory is unable to cover the planned self-container jobs.

Event 3: ETCR

ETCR is driven by inventory control policies every day, but intrinsic problems may emerge. Before in-transit ETCR containers arrive at a deficit depot, the 'to-be-replenished' depots will still be in deficit and will keep asking for ETCR from surplus depots. If no intervention is made, repetitive ETCR assignments will occur. Also, since part of the future container flow information is already known, it makes no sense to reposition TCs out of a depot that is surplus today but will soon be a non-surplus depot because of planned jobs. Likewise, there is less need of ETCR for a deficit depot if TCs will be available soon from finished jobs or previously arranged ETCR. Consequently, the need for inventory adjustment arises. First, the horizon length of adjusted inventory needs to be decided, i.e. how far into the future does information on planned operations need to be taken into account? Since the main target of the adjusted inventory process is to enable effective ETCR, while the target of ETCR is to ensure better container availability to meet the received demands, the latest execution day of the received demands will be used to define the adjusted inventory horizon length. Then, the imminent inventory adjustments described above need to be calculated. Within the determined horizon, the future container arrivals and confirmed container outflow are the main adjustments. The future container arrivals come from finished jobs and previous ETCR. For any depot i, the future container arrival of previous ETCR planning is the sum of all ETCR from other depots to depot i that departed before the decision-making day and will arrive at depot i within the horizon. Another adjusted component is the containers returned from finished jobs. Since self-owned containers need to be cleaned before their next job, they face two scenarios. One, cleaning has already started and the container will return to the depot within the planning horizon. Two, cleaning has not started, but it is expected to be finished and the container returned to the depot within the planning horizon period. For the first scenario, the return day is certain. For the second, since cleaning has not started, the cleaning duration is a random number that needs to be estimated (Figure 4.4). To simplify the computation, the mean value of the cleaning duration is used. Finally, since no customer demands will be rejected at Stage 1, the overall container outflows are estimated by the demands that arrived on or before the decision-making day, while their execution dates are within the planning horizon.

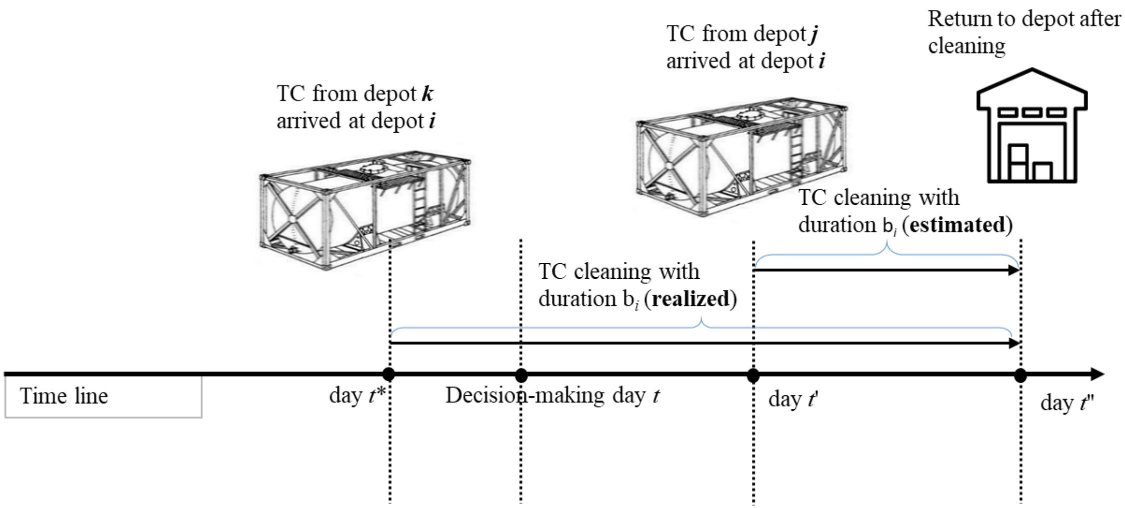

Figure 4.4 Two scenarios of container return after cleaning

Following the above discussion, let:

$\Omega_{ji,0}^{t}$ ={ $s \in T | t+1-a_{ji} \leq s \leq min\,\{\mathrm{t}+M_i^t - a_{ji}, t-1\}\}$ represent the time periods before time *t* and the deployed ETCR containers from depot *j* to depot *i* will be available in time period *t* + 1 to *t* + M_i^t;

$\Omega_{i,1}^{t} = \{d \in D | D_d = i, O_d = j, j \in P, T_d + a_{ji} \leq t, t < T_d + a_{ji} + \tau_\mathrm{d} \leq t + M_i^t\}$ represent the containers that have finished jobs and started cleaning, and will be available in time period *t* + 1 to *t* + M_i^t;

$\Omega_{i,2}^{t} = \{d \in D | D_d = i, O_d = j, j \in P, S_d < t, T_d + a_{ji} > t, T_d + a_{ji} + \bar{\mathrm{b}}_i \leq t + M_i^t$ represents the containers that are still fulfilling jobs but expected to be available in the time period *t*+1 to *t*+M_i^t. $\bar{\mathrm{b}}_i$ represents the expected TC cleaning time;

$\Omega_{i,3}^t = \{d \in D | D_d = i, O_d = j, j \in P, S_d < t, T_d > t, T_d + a_{ji} + \bar{\mathrm{b}}_i \leq t + M_i^t$ represents the containers that are planned to use self-containers but not yet shipped out, and are expected to be available in the time period t + 1 to $t + M_i^t$, then the adjusted inventory level is:

$$S_i^m(t) = S_i(t)'' + \sum_{j\in P}\sum_{s\in\Omega_{ji,0}^t} g_{ji}^s + \sum_{d\in\Omega_{i,1}^t} \mathrm{X}_d^{\mathrm{a}} + \sum_{d\in\Omega_{i,2}^t} \mathrm{X}_d^{\mathrm{a}} + \sum_{d\in\Omega_{i,3}^t} \mathrm{X}_d^{\mathrm{p}} - \sum_{d\in D}\sum_{O_d=i, S_d\leq t}\sum_{T_d=\mathrm{t}+1}^{T_d=\mathrm{t}+M_i^t} M_d. \tag{4.6}$$

On the right-hand-side of Equation (4.6), the second to fifth terms are the container inflows specified above. The last term is the overall self-owned container outflows received on and before time t, and to-be-executed from t + 1 to $t + M_i^t$.

After the inventory levels are adjusted for all depots, ETCR assignments need to be determined. As inter-regional repositioning is not used, all ETCR is within the same region as follows. Let $P^s{}_{r,t}$ denote the set of surplus depots in the selected region r at time t, namely, $P^s{}_{r,t}$:= { $i \in P_r$ | $S_i^m(t)$-$\mathrm{U}_i > 0$}, where P_r is the set of depots in region r. Similarly, let $P^d{}_{r,t}$ denote the set of deficit depots in the same region r at time t, i.e. $P^d{}_{r,t}$:= { $i \in P_r$ |$\mathrm{L}_i - S_i^m(t) > 0$}. The ETCR assignments $\{Y_{ij}^t\}$ are determined by solving the following mathematical programming problem:

$$\text{Min} \sum_{i\in P_{r,t}^s}\sum_{j\in P_{r,t}^d} g_{ij}^t * C_{ij}; \tag{4.7}$$

s.t.

$$\sum_{i\in P_{r,t}^s}\sum_{j\in P_{r,t}^d} g_{ij}^t = Min\left[\sum_{i\in P_{r,t}^s} (S_i^m(\mathrm{t}) - \mathrm{U}_i), \sum_{j\in P_{r,t}^d}(\mathrm{L}_j - S_j^m(\mathrm{t}))\right]. \tag{4.8}$$

After this event, the inventory levels at surplus depots are updated, which determines the inventory levels at the beginning of the next period:

$$S_i(t)''' = S_i(t+1) = S_i(t)'' - \sum_{j\in P_{r,t}^d} g_{ij}^t; \text{ for } i \in P_{r,t}^s. \tag{4.9}$$

Event 4: Planning execution of new demands received on day *t*

This event plans the most profitable way to fulfil the new demands arriving on day *t*. Although execution of these jobs will be in the future, how this will be done must be decided on the receiving day. At the current stage, there are self-container jobs and planned-leasing jobs. When a job's execution date arrives, it will be executed as planned unless there are not enough self-containers, in which case an emergent-leasing job will arise. When time moves to the next day (*t*+1), the process is repeated and the new decisions are built on top of all the old plans without affecting them (Figure 4.5), i.e. plans once made are set firm and cannot be modified in the light of new demands or other data on subsequent days.

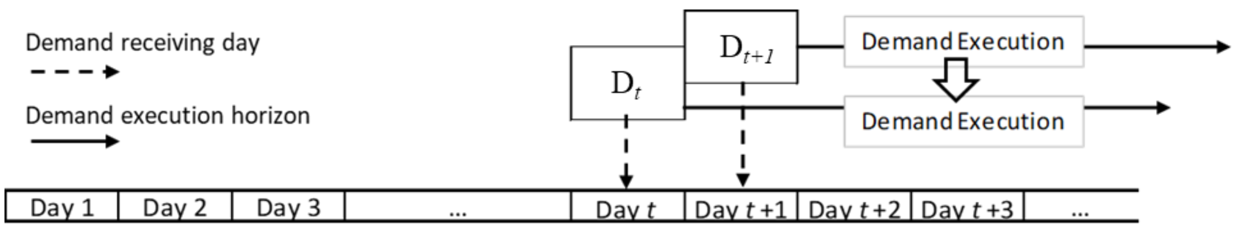

Figure 4.5 Overview of new demands receiving and planning

For a series of new demands, the rules for their planning are as follows. First, the latest execution date among these demands defines the current length of the planning horizon. Then, demands from the earliest execution date until the latest execution date will be planned. Second, within the planning horizon, if depot *i* has demands to be executed on day *t* + *q*, the inventory level of depot *i* is first updated with all the known information. This process is similar to the inventory adjustment in the previous event. $\Omega^t_{ji,0}$ is used to represent the time that ETCR activities have been arranged and those containers from depot *j* to depot *i* are expected to be available in time period *t* + 1 to *t* + *q*; $\Omega^t_{i,1}$, $\Omega^t_{i,2}$, $\Omega^t_{i,3}$ represent the sets of jobs with respect to different status. $\Omega^t_{i,1}$ comprises containers that have finished jobs and started cleaning, and will be available in time period *t* + 1 to *t* + *q*; $\Omega^t_{i,2}$ comprises containers that are still fulfilling their jobs and are expected to be available in the time periods from *t* + 1 to *t* + *q*; $\Omega^t_{i,3}$ represents the demands that have been planned to use self-containers but have not been shipped out yet, but are expected to be available in the time period from t + 1 to t + q. Their mathematical definitions are:

$$\Omega_{ji,0}^{t} = \{ s \in T | t + 1 - a_{ji} \le s \le \min(t + q - a_{ji}, t - 1)\}; \quad (4.10)$$
$$\Omega_{i,1}^{t} = \{d \in D | D_d = i, O_d = j, j \in P, T_d + a_{ji} \le t, t < T_d + a_{ji} + \tau_d \le t + q\}; \quad (4.11)$$
$$\Omega_{i,2}^{t} = \{d \in D | D_d = i, O_d = j, j \in P, S_d < t, T_d + a_{ji} > t, T_d + a_{ji} + \bar{b}_i \le t + q\}; \quad (4.12)$$
$$\Omega_{i,3}^{t} = \{d \in D | D_d = i, O_d = j, j \in P, S_d < t, T_d > t, T_d + a_{ji} + \bar{b}_i \le t + q\}. \quad (4.13)$$

If the updated self-containers are enough to cover all the 'to-be-executed' demands at that depot, those demands are planned as self-container jobs. If not, planned-leasing containers are needed. Mathematically, the assignments are described as follows:

$$S_i(t+q)' = S_i(t)''' + \sum_{j \in P} \sum_{s \in \Omega_{ji,0}^{t}} g_{ji}^{s} + \sum_{d \in \Omega_{i,1}^{t}} X_d^{a} + \sum_{d \in \Omega_{i,2}^{t}} X_d^{a} + \sum_{d \in \Omega_{i,3}^{t}} X_d^{p} - \sum_{d \in D} \sum_{O_d = i} \sum_{S_d \le t} \sum_{T_d = t+1}^{T_d = t+q} X_d^{p}. \quad (4.14)$$

On the right-hand side of Equation (4.14), the second term represents the accumulated ETCR jobs that have been scheduled and will arrive between time t + 1 to t + q. From the third to the fifth term are the accumulative container inflows related to self-container jobs between time t + 1 to t + q. The last term is all the scheduled container outflows between time t + 1 to t + q.

If $S_i(t+q)' \ge \sum_{d \in D} \sum_{O_d = i} \sum_{S_d = t} \sum_{T_d = t+q} M_d$, then $X_d^{p} = 1$ for any $d \in \{d \in D | O_d = i, S_d = t, T_d = t + q\}$; (4.15)

If $S_i(t+q)' < \sum_{d \in D} \sum_{O_d = i} \sum_{S_d = t} \sum_{T_d = t+q} M_d$, then the self-container jobs and planned-leasing jobs are determined by solving the following mathematical programming problem:

$$\text{Min} \sum_{d \in D} \sum_{O_d = i} \sum_{D_d = j, j \in P} \sum_{S_d = t} \sum_{T_d = t+q} Z_d^{p} * C_i^{l} * a_{ij}; \quad (4.16)$$

s.t.

$$\sum_{d \in D} \sum_{O_d = i} \sum_{D_d = j, j \in P} \sum_{S_d = t} \sum_{T_d = t+q} X_d^{p} \le S_i(t+q)'; \quad (4.17)$$

$$X_d^p + Z_d^p = M_d \text{ and } \{d \in D | O_d = i, S_d = t, T_d = t + q\}; \quad (4.18)$$

Equations (4.15) and (4.16) define the two scenarios of demand assignments by comparing the inventory level and customer demands. Specifically, if there are not enough self-containers, planned-leasing containers are used. Equation (4.16) assigns the different types of jobs. Equation (4.17) and (4.18) define the constraints for the optimization equation.

Inventory control policy optimization

The objective of this model at Stage 1 is to find the optimal inventory control policy that leads to the most profitable TC operations, with profit defined as total revenue minus total cost. Here, the cost components include container-holding cost, laden and empty container moving cost, leasing cost, container-handling cost and container-cleaning cost. The optimal threshold values $\{[L_i, U_i] \mid i \in P\}$ are found by maximizing the following expected profit:

$$\text{Max } EXP\ \{\sum_{d\in D} M_d * E_d - \sum_{t\in T}\sum_{i\in P} S_i(t) * C_i^h - \sum_{d\in D}\sum_{O_d=i,i\in P}\sum_{D_d=j,j\in P} M_d * (C_{ij} + C_i^o + C_j^f) - \sum_{t\in T}\sum_i\sum_j g_{ij}^t * (C_{ij} + C_i^o + C_j^f) - \sum_{d\in D}\sum_{D_d=j,j\in P} X_d^a * C_j^c - \sum_{d\in D}\sum_{O_d=i,i\in P}\sum_{D_d=j,j\in P} Z_d^p * C_i^l * a_{ij} - \sum_{d\in D}\sum_{O_d=i,i\in P}\sum_{D_d=j,j\in P} Z_d^a * C_i^{le} * a_{ij})\}. \quad (4.19)$$

4.3.2 Model at Stage 2: customer demands fulfilment

Stage 2 assists decision-making in terms of how the new customer demands will be served every day to make better profits, whilst facing the additional uncertainties caused by FFs' abilities to fulfil ETCR. The focus is on operational decisions, and the ETCR inventory-control policies from Stage 1 are inputs.

Events in Stage 2

There are four events with Events 1 and 2 being similar to those in Stage 1, whereas Events 3 and 4 are more complicated due to choosing FFs, job rejections and future demand forecasting.

Event 3 plans ETCR. Since this happens before demand planning (Event 4), all received customer demands and future demand prediction are considered in adjusting the inventory levels. Event 3 plans the ETCR deployment but not the amount, which will be influenced by the choice of FF in Event 4 (see Equation (4.28)).

Event 4 makes decisions on satisfying demands in terms of choice of FFs, self-container jobs, planned-leasing jobs and demand rejections. FFs are chosen by an iterative procedure, with the other decisions being made following this selection, within each iteration. Figure 4.6 illustrates this iterative procedure and its mathematical formulation is given below.

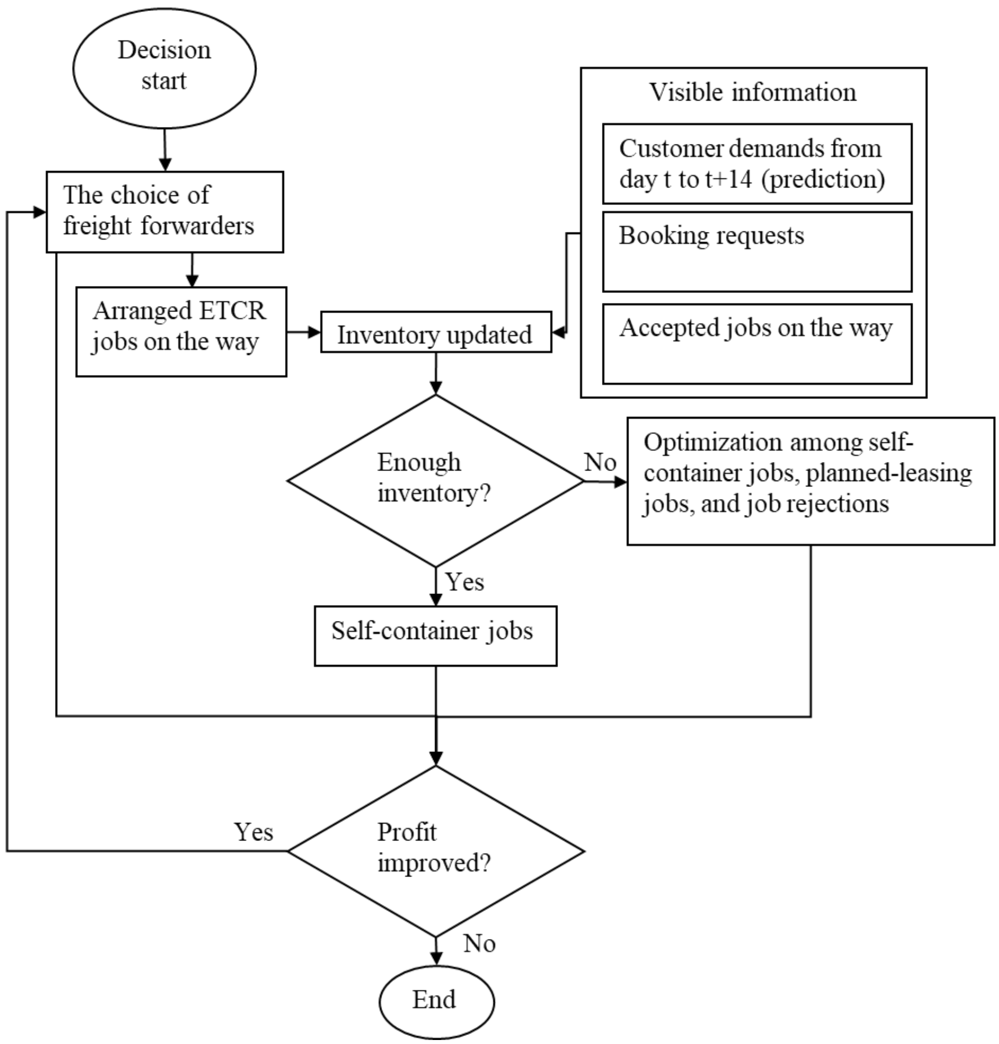

Figure 4.6 Decisions on new demands and choice of FFs

Mathematical model of Stage 2

With the determined inventory policies (threshold values for each depot), decisions in Stage 2 are made as follow.

Event 1: Inbound flow to receive self-owned containers on day *t*.

This event is the same as Event 1 in Stage 1 except the amount of ETCR is influenced by the choice of FFs. Also, since the FFs for the inflow ETCR are decided already, the associated booking success rate is known. Likewise, the cleaning duration for newly available containers is known. Let τ_d denote the known cleaning duration sampled from random variable b_i, and β_s $(s < t)$ be the known booking success rate on day *s*. The inventory level on day *t* is updated after Event 1 using Equation (4.20):

$$S_i(t)' = S_i(t) + \sum_{j \in P} g_{ji}^{t-a_{ji}} * \beta_{t-a_{ji}} + \sum_{s=0}^{s=t-1} \sum_{d \in D_s} \sum_{D_d=i} \sum_{O_d=j, j \in P} \sum_{T_d=t-\tau_d-a_{ji}} X_d^a; \tag{4.20}$$

Event 2: outbound flow to execute jobs on day *t*.

$$S_i(t)'' = max\ \{0, S_i(t)' - \sum_{s=0}^{s=t} \sum_{d \in D_s} \sum_{O_d=i} \sum_{D_d=j, j \in P} \sum_{T_d=t} X_d^p\}; \tag{4.21}$$

If $S_i(t)'' > 0$, then $X_d^a = X_d^p$, $Z_d^e = 0$, where $d \in D_s$; (4.22)

If $S_i(t)'' = 0$, then the assignments of the actual self-container jobs and emergent-leasing jobs are determined by solving the following sub-optimization problem:

$$\text{Min } \sum_{s=0}^{s=t-1} \sum_{d \in D_s} \sum_{O_d=i} \sum_{D_d=j, j \in P,} \sum_{T_d=t} Z_d^e * C_i^{le} * a_{ij}; \tag{4.23}$$

s.t.

$$\sum_{s=0}^{s=t-1} \sum_{d \in D_s} \sum_{O_d=i} \sum_{T_d=t} X_d^a \leq S_i(t)',$$

$$X_d^a + Z_d^e = X_d^p; \text{ for } d \in D_s,\ s<t, \text{ and } T_d = t \tag{4.24}$$

Equations (4.21)-(4.24) jointly determine the laden TC outflows at depot *i* on day *t*.

Event 3: ETCR deployments.

ETCR is guided by the optimized inventory control policies obtained from Stage 1, while the actual process is the same as Event 3 in Stage 1.

$\Omega_{ji,0}^{t}$ ={ $s \in T | t+1-a_{ji} \leq s \leq \min(t+M_i^t - a_{ji}, t-1)$} is used to represent the time periods before time *t* and the deployed ETCR containers from depot *j* to depot *i* will be available in time period *t* + 1 *to t* +M_i^t;

$\Omega_{i,1}^{t} = \{d \in D_s | D_d = i, O_d = j, j \in P, T_d + a_{\mathrm{ji}} \leq t, t < T_d + a_{ji} + \tau_{\mathrm{d}} \leq t + M_i^t\}$ represents the containers that have finished jobs and started cleaning, and will be available in time period *t* + 1 to *t* + M_i^t;

$\Omega_{i,2}^{t} = \{d \in D_s | D_d = i, O_d = j, j \in P, s < t, T_d + a_{ji} > t, T_d + a_{ji} + \bar{\mathrm{b}}_i \leq t + M_i^t\}$ represents the containers that are still fulfilling jobs but expected to be available in time period *t* + 1 to *t* + M_i^t;

$\Omega_{i,3}^{t} = \{d \in D_s | D_d = i, O_d = j, j \in P, s < t, T_d > t, T_d + a_{ji} + \bar{\mathrm{b}}_i \leq t + M_i^t\}$ represents the containers that are planned for use in self-container jobs but have not shipped out yet and are expected to be available in time period *t* + 1 to *t* + M_i^t. Equation (4.25) gives the adjusted inventory level.

$$S_i^m(t) = S_i(t)'' + \sum_{j \in P} \sum_{s \in \Omega_{ji,0}^t} g_{ji}^s * \beta_s + \sum_{d \in \Omega_{i,1}^t} \mathrm{X}_d^{\mathrm{a}} + \sum_{d \in \Omega_{i,2}^t} \mathrm{X}_d^{\mathrm{a}} + \sum_{d \in \Omega_{i,3}^t} \mathrm{X}_d^{\mathrm{p}} - \sum_{s=0}^{s=t-1} \sum_{d \in D_s, O_d = i} \sum_{T_d=\mathrm{t}+1}^{T_d=\mathrm{t}+M_i^t} M_d - \sum_{y \in Y_t} \sum_{O_y = i} \sum_{S_y=\mathrm{t}+1}^{S_y=\mathrm{t}+14} M_y \quad (4.25)$$

Equation (4.25) is the adjusted inventory process, and it is similar to Stage 1 except the booking successful rate, rejected jobs and predicted demands are included. β_s is the realized value for the successful booking rate of ETCR on day *s*. The last term is the total predicted container outflow for the following 14 days, i.e. the two-week forecast used in industry.

After every inventory level is adjusted, ETCR assignments are determined. If $P_{r,t}^s$ is taken as a set of surplus depots in region *r* at time *t*, any depot *i* of $P_{r,t}^s$ needs to be $\{i \in P_{r,t}^s | S_i^m$(t)-$\mathrm{U}_i > 0\}$. Likewise, if $P_{r,t}^d$ is the set of deficit depots in the same region, any depot *i* of $P_{r,t}^d$

should be $\{i \in P_{r,t}^{d} | \mathrm{L}_i - S_i^m(\mathrm{t})>0\}$. Equation (26) determines the ETCR assignments at time t.

$$\mathrm{Min} \sum_{i\in P_{r,t}^{s}} \sum_{j\in P_{r,t}^{d}} g_{ij}^{t} * C_{ij}; \tag{4.26}$$

s.t.

$$\sum_{i\in P_{r,t}^{s}} \sum_{j\in P_{r,t}^{d}} g_{ij}^{t} = Min\,\{\sum_{i\in P_{r,t}^{s}} (S_i^m(\mathrm{t}) - \mathrm{U}_i), \sum_{j\in P_{r,t}^{d}} \left(\mathrm{L}_j - S_j^m(\mathrm{t})\right)\}. \tag{4.27}$$

Event 4: Decisions towards new demands.

Since the consideration of FFs has been introduced at Stage 2, the determined ETCR amount from Event 3 may not be the actual repositioned amount due to the unreliability of the selected FF. To achieve greater profits, the choice of FFs will be optimized together with the decisions on meeting customer demands. However, without knowing the choice of FFs, this event cannot proceed. Hence, an FF is randomly selected with a cost of $f_t \in [\frac{2\mathrm{C}_b^t}{5}, \mathrm{C}_b^t]$. Based on the chosen FF, the associated booking success rate β_t can be realized, and the inventory level can be further updated to:

$$S_i(t)''' = S_i(t)'' - \sum_{j\in P_{r,t}^{d}} g_{ij}^{t} * \beta_t \tag{4.28}$$

Then, taking the newly received demands D_t with execution date of $t + q$ as an example for the job assignments process, and using $\Omega_{ji,0}^{t}$ to represent the time periods before time t and the deployed ETCR containers from depot j to depot i will be available in the time periods from $t + 1$ *to* $t + q$, then $\Omega_{ji,0}^{t} = \{ s \in (0,t) | t+1-a_{ji} \le s \le \min(t+q-a_{ji}, t-1) \}$; $\Omega_{i,1}^{t} = \{d \in D_s | D_d = i, O_d = j, j \in P, 0 \le s < t, T_d + a_{ji} \le t, t < T_d + a_{ji} + \tau_d \le t+q\}$ represents the containers that have finished jobs and started the cleaning process, and will be available in time period $t + 1$ to $t + q$; $\Omega_{i,2}^{t} = \{d \in D_s | D_d = i, O_d = j, j \in P, 0 \le s < t, T_d + a_{ji} > t, T_d + a_{ji} + \bar{\mathrm{b}}_i \le t+q\}$ represents the containers that are still fulfilling jobs but are expected to be available in time period $t + 1$ to $t + q$; $\Omega_{i,3}^{t} = \{d \in D_s | D_d =$

$i, O_d = j, j \in P, 0 \leq s < t, T_d > t, T_d + a_{ji} + \bar{\mathrm{b}}_i \leq t + q\}$ represents the containers that are planned for use in self-container jobs but have not shipped out yet, and are expected to be available in time period $t + 1$ to $t + q$:

$$S_i(\mathrm{t+q})' = S_i(t)''' + \sum_j \sum_{s \in \Omega_{ji,0}^t} g_{ji}^s * \beta_s + \sum_{d \in \Omega_{i,1}^t} \mathrm{X}_d^{\mathrm{a}} + \sum_{d \in \Omega_{i,2}^t} \mathrm{X}_d^{\mathrm{a}} + \sum_{d \in \Omega_{i,3}^t} \mathrm{X}_d^P - \sum_{s=0}^{s=t} \sum_{d \in D_s} \sum_{O_d = i} \sum_{T_d = \mathrm{t+1}}^{T_d = \mathrm{t+q}} \mathrm{X}_d^P; \quad (4.29)$$

Equation (4.29) is used to calculate the expected inventory level for depot i on day $t + q$ after the planned container inflows and outflows are finished. The second term is used to obtain the amount of ETCR arrivals in time period $t + 1$ *to* $t + q$, and parameter β_s is the known value of the booking success rate for every ETCR arrangement on its associated day.

If $S_i(\mathrm{t+q})' \geq \sum_{d \in D_s, s=t} \sum_{O_d = i} \sum_{T_d = \mathrm{t+q}} M_d$, $\forall\ \mathrm{X}_d^{\mathrm{p}} = 1$, $\mathrm{Z}_d^{\mathrm{p}} = \mathrm{W}_d = 0$, for $\forall d \in \{d \in D_s | O_d = i, s = t, T_d = \mathrm{t+q}\}$. (4.30)

If $S_i(\mathrm{t+q})' < \sum_{d \in D_s, s=t} \sum_{O_d = i} \sum_{T_d = \mathrm{t+q}} M_d$, the assignment of self-container jobs, planned-leasing jobs and job rejections are determined by solving the following mathematical programming problem:

$$\mathrm{Min} \sum_{d \in D_s, s=t} \sum_{O_d = i} \sum_{D_d = j, j \in P} \sum_{T_d = \mathrm{t+q}} (\mathrm{X}_d^{\mathrm{p}} + \mathrm{Z}_d^{\mathrm{p}}) * \mathrm{C_{ij}} + \sum_{d \in D_s, s=t} \sum_{O_d = i} \sum_{D_d = j, j \in P} \sum_{T_d = \mathrm{t+q}} \mathrm{Z}_d^{\mathrm{p}} * \mathrm{C}_i^{\mathrm{l}} * a_{\mathrm{ij}} + \sum_{d \in D_s, s=t} \sum_{O_d = i} \sum_{D_d = j, j \in P} \sum_{T_d = \mathrm{t+q}} \mathrm{W}_d * \mathrm{C}_{ij}^{p}; \quad (4.31)$$

s.t.

$\mathrm{X}_d^{\mathrm{p}} + \mathrm{Z}_d^{\mathrm{p}} + \mathrm{W}_d = 1$ for $\forall d \in \{d \in D_s | O_d = i, s = t, T_d = t + q\}$; (4.32)

$\sum_{d \in D_s, s=t} \sum_{O_d = i} \sum_{T_d = \mathrm{t+q}} \mathrm{X}_d^{\mathrm{p}} = S_i(t+q)'$; (4.33)

$S_i(t+q)'' = S_i(t+q)' - \sum_{d \in D_s, s=t} \sum_{O_d = i} \sum_{T_d = t+q} \mathrm{X}_d^{\mathrm{p}}$. (4.34)

Equations (4.30) and (4.31) are the rules for assigning self-container jobs, planned-leasing jobs and rejections, and if there are not enough self-containers, the specific assignments are obtained by solving Equation (4.31). Equations (4.32)-(4.34) are the constraints for planning container outflows, if there are self-container jobs, planned-leasing jobs or rejections. The above steps, Equations (4.28)-(4.34), are repeated to finish the job assignments for all the demands received on day t.

According to the event description at the beginning of this stage, the optimized choice of FFs can be searched for within the range of f_t by running the loop from Equations (4.28)-(4.34) to maximize profit in Equation (4.35). β_t is the realized booking success rate for each loop:

$$\max_{f_t} \quad EXP \quad \{\sum_{d\in D_t}\sum_{T_d=\mathrm{t+1}}^{T_d=t+M_i^t}(M_d - W_d) * E_d - \sum_{d\in D_t}\sum_{i\in P}\sum_{T_d=\mathrm{t+1}}^{T_d=t+M_i^t} S_i^{T_d} * C_i^h - \sum_{d\in D_t}\sum_{O_d=i,i\in P}\sum_{D_d=j,j\in P}\sum_{T_d=\mathrm{t+1}}^{T_d=t+M_i^t}(M_d - W_d) * (C_{ij} + C_i^o + C_j^f + \mathrm{C}_b^t) - \sum_{i\in P}\sum_{j\in P} g_{ij}^t * \beta_t * (\mathrm{C_{ij}} + C_i^o + C_j^f + f_t) - \sum_{d\in D_t}\sum_{D_d=j,j\in P}\sum_{T_d=\mathrm{t+1}}^{T_d=t+M_i^t} X_d^a * C_j^c - \sum_{d\in D_t}\sum_{O_d=i,i\in P}\sum_{T_d=\mathrm{t+1}}^{T_d=t+M_i^t} Z_d^p * C_i^l * a_{ij} - \sum_{d\in D_t}\sum_{O_d=i,i\in P}\sum_{D_d=j,j\in P}\sum_{T_d=\mathrm{t+1}}^{T_d=t+M_i^t} \mathrm{W}_d * C_{ij}^p\}. \tag{4.35}$$

4.4 Solution methods

4.4.1 The needs

The Stage 1 and Stage 2 models are difficult to solve analytically. First, they involve random variables and a large number of operational decisions (taking integer values). Second, to reflect the practices of real TCOs, these operational decisions need to be determined on an event-driven basis, which is difficult to formulate in a single mathematical programming model. Hence, the solution method proposed is a simulation-based heuristic, which allows the handling of workflow and constraints as well as the searching of the solution space and the execution of associated evaluations. However, some of its required input data comes from local mathematical programming optimizations, e.g.

the everyday ETCR assignments are determined by linear programming. Therefore, hybrid elements are introduced to make the heuristic method a mixed optimization solution. For example, during Events 2, 3 and 4 in both simulation stages, linear programming is used jointly with certain rules to optimize ETCR amounts and job assignments. This allows:

i) an increase in computational tractability by using a heuristic method;

ii) an increase in effectiveness and efficiency by using a mathematical optimization method to find the local optimum.

Similarly, a math-heuristic is another hybridized optimization algorithm that uses interoperation of heuristics and mathematical programming. For example, Rath and Gutjahr (2014) propose a math-heuristic to optimize warehouse location routing. They use a mixed-integer linear programming formulation as the backbone and a constraint pool heuristic to reduce the expensive computational part for dealing with large problem spaces. Chen and Lau (2011) use a math-heuristic for resource scheduling in maritime logistics. They decompose their problem into two sub-problems, using heuristics for their machine-scheduling sub-problem, while using linear integer programming for their equipment allocation sub-problem. Comparing math-heuristics to the solution method applied in this paper, no matter how the mathematical and heuristic parts are structured, they are not built upon event-driven simulation. They are just an extension to either heuristic or mathematical programming methods to combine both of their advantages. In this paper, a math-heuristic can hardly be applied. This is because without the simulation process, it is hard to formulate the dynamic traits of the changing planning horizon and variable container cleaning times causing different container returns, and it is hard to handle some subtle issues such as the 2-week demand forecast and different groups of job-finished containers etc. Instead, a novel mixed optimization method is designed here to address the problem formulated in Section 3.

The simulation-based optimization method developed here consists of a GA search module and a simulation-based decision-making module. The latter uses a discrete event model of the operational level process of TC management and flows. This allows tracing of the TC holding cost, laden and empty container transportation costs, planned and emergent leasing costs, FF cost (Stage 2), container lifting-on/off cost, container cleaning cost and job rejection penalty of each order at each region and depot. It outputs the profit of a given solution, whereas the GA searches for better solutions.

4.4.2 Simulation module

The structure of the simulator is described in Appendix 1 and Appendix 2. In Stage 1 and Stage 2, it simulates the same daily process of each depot simultaneously (receive containers returned from cleaning and repositioning; arrange outflow containers to execute customer demands, determine ETCR and leasing; cope with new customer demands and planning etc.). It takes a set of input data including customer demands, inventory thresholds and initial net stock, and the shipping network with distances between regions and depots. It interacts with the decision-making module to receive its outputs for use in executing the four events. It records and allows tracing of the storage, loading, transhipment and unloading processes of each job and the inventory level of each depot. It outputs an operational level performance measure; the total profits.

In Stage 1, the decision-making module is limited to the assignment of self-container jobs and planned-leasing jobs and linear optimization of the order in which to take the jobs. In Stage 2, decisions are made with consideration of the 2-week demand forecast, and job rejections and choice of FFs are considered jointly. The job assignments are again made by linear optimization, and the output performance measure is used to determine the best choice of FFs. ETCR is the same for both stages. It first determines a depot's status as deficit or surplus, by comparing the current inventory, 'on the way' containers and deterministic future demands against the thresholds. Then, the ETCR activities (the quantities, origins and destinations of reposition containers) are deployed by solving a classic assignment problem. This decision-making process is performed dynamically in an event-driven module based on the input threshold values, customer demands and dynamic information obtained from the simulator.

To evaluate the performance of the system, in Stage 1 the relevant costs including handling costs, transport costs, leasing costs and inventory costs are calculated. The Stage 1 simulation terminates when the defined total simulation days are reached, in this case 180 days. In Stage 2, the FF costs and job rejection penalties are also calculated. Whenever ETCR is required on a given day, the FF optimization is run, and the overall simulation terminates when the defined total simulation days are reached, as for Stage 1.

4.4.3 The Heuristic Search Method (HSM)

To emulate observed industrial practice a heuristic is introduced to determine the threshold values in the inventory control policy. This utilizes the statistics of customer demands and inventory dynamics across the whole planning horizon. First, all the depots are grouped into surplus and deficit depots according to their overall TC net flow (e.g. a net import depot is a surplus depot). Next, the following key statistical indicators are estimated:

i. Average jobs per day in depot *i* (μ_i);
ii. Standard deviation of demands in depot *i* (σ_i);
iii. Least Inventory Level (LIL_i) for every depot *i* based on given container flow information;
iv. Largest Backlog Order (LBO_i) for depot *i*;
v. Largest Consecutive Container Net Outflow ($LCCNO_i$) for depot *i*.

Specifically, μ_i, σ_i, LBO_i and LIL_i can be obtained simply from demand information, while $LCCNO_i$ is determined as follows. Each depot's container net flow is monitored daily and, when its first net outflow occurs, the amount is recorded as the first Continuous Container Net Outflow ($CCNO_i$); this is a negative number. $CCNO_i$ is updated according to the net flow in the following days. Once $CCNO_i$ is updated as a positive number, it is returned to zero and this round of $CCNO_i$ updating is finished. The next round of $CCNO_i$ updating starts with the next net outflow. This is repeated until the end of the planning horizon, and for each depot. During the first iteration $LCCNO_i$ is set as the largest negative $CCNO_i$. At each further iteration, if there is a larger negative $CCNO_i$ then $LCCNO_i$ is updated, so it is the largest across all iterations. Appendix 3 summarises this process.

$LCCNO_i$ is the inventory a depot requires to meet all its customer demands. If it has less, leasing is required. If it has more, these can be fed to other depots. Therefore, the $LCCNO_i$ values are used as the upper threshold values for surplus depots, encouraging them to transfer TCs. The lower threshold values for surplus depots are decided from LIL_i, LBO_i and $\mu_i + \sigma_i$. If $LIL_i > 0$, the lower threshold value for the depot is set as 1, which means, with the safeguard of the upper threshold, it needs no external help to meet its demand. If $LIL_i = 0$ and $LBO_i > 0$, then even though this is a surplus depot, it still has a stock-out risk on a given day. Thus, minimum (LBO_i, $\mu_i + \sigma_i$) determines whether this depot should call for help based on the inventory level falling below the level required to meet its average demand.

For deficit depots, apart from the statistical indicators used above, Most Inventory Level (MIL_i) and 'Largest that can be Repositioned Amount' (LRA) in this region are also needed. MIL_i is the highest inventory level that this depot has ever reached. LRA is the total number of containers available for repositioning in the region. Maximum (MIL_i, $\mu_i + \sigma_i$) determines the lower bound for the deficit depot, helping it to call for more ETCR to increase the number of self-container jobs. The upper bound for deficit depots is set as minimum ($LCCNO_i$, LRA). This is because ETCR can only be intra-regional for the TC industry, therefore, $LCCNO_i$ is the amount that allows the deficit depots to meet all demands with self-owned containers, but it cannot exceed LRA. Appendix 4 summarises the heuristic for threshold values.

4.4.4 The Adapted Genetic Algorithm (AGA)

Alternatively, the threshold value in Stage 1 can be obtained and optimized using an AGA; one of the most commonly used meta-heuristic optimization approaches in container operations research (e.g. Dong and Song, 2009; Dang et al., 2013). The AGA used here is built upon a modification of the 'standard' or default Genetic Algorithm (GA) implemented in Matlab® using scattered crossover and Gaussian mutation (MathWorks, 2018). It is illustrated in Appendix 5.

As the first operation, the standard GA is performed with respect to the underlying problem. For the genetic representation (chromosome), the candidate solution consists of the double threshold values for each depot, coded as a vector of non-negative integers denoted as $\{[L_i, U_i] \mid i \in P\}$, where L_i and U_i are the lower and upper bounds of the inventory thresholds for depot i. A valid chromosome should satisfy the constraint $0 \le L_i \le U_i < N$. The initial population of solutions is generated randomly. Since the optimization is to maximize profit, the higher the objective function value (profit), the higher the solution fitness value should be. To achieve this, $E(q)$ is used to represent the total profits under the solution represented by chromosome q, then the fitness value of chromosome q is defined as $F_q = E(q) - \min\{E(q) : 1 \le q \le N_p\}$, where N_p is the population size. For the parent selection process, roulette wheel sampling is used; each of two parents is selected from a binary tournament, which randomly picks two individuals from the entire population and retains the fittest. The two selected parents generate a child using scattered crossover. Fourth, probabilities are selected for crossover and mutation, and also, since pairs of elements in Stage 1 are formed by the lower and upper inventory bounds of a specific depot, these must be copied together to the offspring as a pair during crossover. Finally, all the parent and offspring chromosomes are sorted into descending fitness order and only the chromosomes with sequence numbers less than or equal to N_p are carried into the next generation.

After the setting of the standard GA, the next operation will run the simulation module iteratively to find an improved variable range for the target variables. Because, as a pilot study indicated, the variable range bordered by the current constraints (i.e. $0 \le L_i \le U_i < N$) is too broad to find a good result within an acceptable computation time, especially when the problem scale is large. Therefore, the range needs to be more precise (narrower) to help the GA to evolve fitter solutions within a shorter time. Specifically, this operation involves three major steps to reduce the variable constraints range and to fit the standard GA. First, the initial variable range is used to run the GA for a fixed number of generations to generate the first series of ‘optimized’ results. A value of 70 is used as the initial upper bound for the variable range because beyond this value the rate of convergence to optimality slowed down greatly in pilot experiments. Second, the upper threshold values (i.e. U_i) are gradually reduced concurrently, e.g. 65 to 61, and the simulation module is re-run to see if performance is affected. If it is not, it means the current value is too large and the range should be reduced further. This process is repeated until the evaluation results change, then values from the last run that made no changes to overall evaluation are used as the new variable range, and the GA optimization solver is run again to obtain the new series of 'optimized' results. In the final step, the GA parameters such as crossover and mutation probabilities, population size, stall generation limit (stop limit for no improvement) and selection methods are re-evaluated to determine the final results.

The above AGA is needed only for the Stage 1 threshold-value optimization problem, as the standard GA in Matlab® is effective and efficient enough for the Stage 2 FF optimization. In Stage 1 the population size is 50, and the GA terminates after 100 generations or when the improvement in best fitness < 0.001 for 10 consecutive generations. Stage 2 uses a population size of 20 and terminates after 20 generations or when the improvement in best fitness < 0.001 for 5 consecutive generations. Crossover rate is 0.8 and mutation rate is 0.2 for both stages.

4.4.5 Verification and Validation (V&V) for model formulation and results

Up to this point, problems addressed by this chapter is formulated and solved with different techniques. Guided by the V&V methods introduced in section 3.3, this section will briefly introduce how the V&V process of the computerised model in this chapter is implemented.

Prior to the V&V activities about the conceptual model and computerised model, data validation is firstly carried out. This is because the historical data from real system is the key for carrying out model validation and verification later on, it is essential to ensure the data obtained is reliable. Yet, since I have no direct access to the data's owner (the case company), there are two ways carried to check the data validity. One, all the data is manually screened. This step is carried to filter out some abnormal records that are either obvious errors (e.g. travel days from Shanghai to Long beach are only 3 days) or are abnormal comparing to other data within the same type (e.g. travel cost for the same journey is largely outside of the normal range). For error data, all the related records are deleted while the abnormal ones are validated with the help of literatures, company reports or industrial reports. If there's abnormal data cannot be validated effectively, they are excluded from the model simulation and solution process. The second way for data validation is that patterns and behaviour of data are validated thoroughly. This refers to data records with similar setting should follow similar pattern, for example, records for demands between the same cities are considered similar patterns from one cycle to another. If abnormal pattern spotted, same process is carried as how abnormal data is treated.

I. Conceptual model validation

The conceptual model is constructed from the underlying system and needs to be validated. To ensure the two-stage conceptualised model has effectively represented the intended system, this is firstly validated through several meetings with industrial practitioners. Alongside a series of supported information, a workflow chart is constructed to describe the details of this conceptual model (see Appendix 1 and 2), and it is agreed by practitioners from this industry. Especially, how the main events are going to be simulated and what assumptions will be included are validated by industrial professionals. Meanwhile, in order to further justify the rationale for assumptions proposed during model conceptualisation process, different papers and ground theories are searched and cited (e.g. Stolt-Nielsen (2017) has reported the TC leasing issue; Dong and Song (2009) to support the assumption about 40-foot TEUs; Erera et al. (2005) to support the assumption about TC cleaning). At last, to validate the model conceptualisation, traces are used to determine if the logic for each sub-model and overall model is correct. This is done by going through the equations of the conceptual model with comparing to the intended purpose of the real system. Measurements from real system (e.g. data from case company) are used to exam whether the conceptual model is valid. For example, inventory data on each day can be used to check whether the proposed inventory management process from the conceptual model is reasonable; or historical customer demands and job information can be used to check whether the proposed job handling mechanism in conceptual model is valid.

II. Computerised model verification

Regarding the validated conceptual model, the constructed computerised model (simulation model) is verified with different techniques. First, the whole simulation model is designed with different modules. Each module represents different events with different functionalities. In this way, each module can be verified independently with appropriate data input and output. For example, a simple scenario is used to check whether the ETCR activity is deployed as it is intended to be and it is appropriately linked to its correlated module(s). Two, auxiliary variables and counters are introduced to help observing the dynamics and behavior of the computerised model. For example, job counter is used to show the up-to-now new added jobs which can be used to check the status of customer demand fulfilment; repositioning job counter can be used to obtain the very recent sum of reposition jobs and verify the correctness of ETCR related costs. Third, the "debugger" function provided by the programming software is used to verify the computerised model. One the one hand, it can be used to check whether there's any coding language related mistakes or ineffectiveness (e.g. inappropriate use of condition language or operation symbols), on the other hand, it allows us to verify the results in the middle of some processes with the help of manual calculation techniques. For example, we can manually calculate container inflow and outflow amount everyday for a particular depot to verify the result from the computerised model. Fourth, with the use of historical data as inputs, the overall simulation model is verified by comparing its overall output to historical records. Especially, by disabling the ETCR function of the simulation model, it should get the same results as the historical records in terms of demand vs. job fulfilment, revenue and inventory level etc.

III. Computerised model validation

Once the constructed computerised model is verified, it needs to be further validated with respect to the underlying system. The major activities used to validate the computerised model come from two aspects. First, the model behavior is explored. For this validation activity, experts (industrial practitioners) are involved again to give both quantitative and qualitative validation for the computerised model. For example, they will check whether the current optimised result is feasible and they will also explore how the model will respond when different scenarios are incorporated with respect to their own expertise. Two, comparison of output behaviors is conducted to validate the computerised model. The day-to-day inventory level for each depot is plot and presented with respect to the change of container cleaning time distribution. Under different circumstances, the current computerised model should be able to both handle customer demands and mitigate unbalanced container flow pattern.

In conclusion, above implementation has completed the V&V framework elaborated in Section 3.3. Although there are more techniques introduced in that section, some of them are hard to be implemented by this research. Because reasons include limited time for this research, limited computational ability and no observable real system etc. However, it opens up the opportunities to carry further V&V activities in the author's future research life.

4.5 Numerical examples

Computational tests of the model have been conducted with 'real' operational data from a major, global TCO. These tests have three purposes:

i. to investigate the feasibility of the model in solving realistically sized problems with basic PCs;
ii. to benchmark against general practices to understand the economic significance of the proposed tool in achieving better decision-making. (Stage 1 compares the performance of the optimization system with the practices in managing TC inventory, Stage 2 compares it with the practices choosing FFs and using different customer demand predictions);
iii. to quantify the influences of different factors on operational profits to generate managerial insights.

4.5.1 Initialisation of the experiments

Due to the different objectives of the two stages, two different simulation environments were created. For both stages, the simulation horizon (i.e. overall planning horizon) is 180 days discretized in days. In delineating the global operation, nine depots are picked across three regions as shown in Figure 4.7.

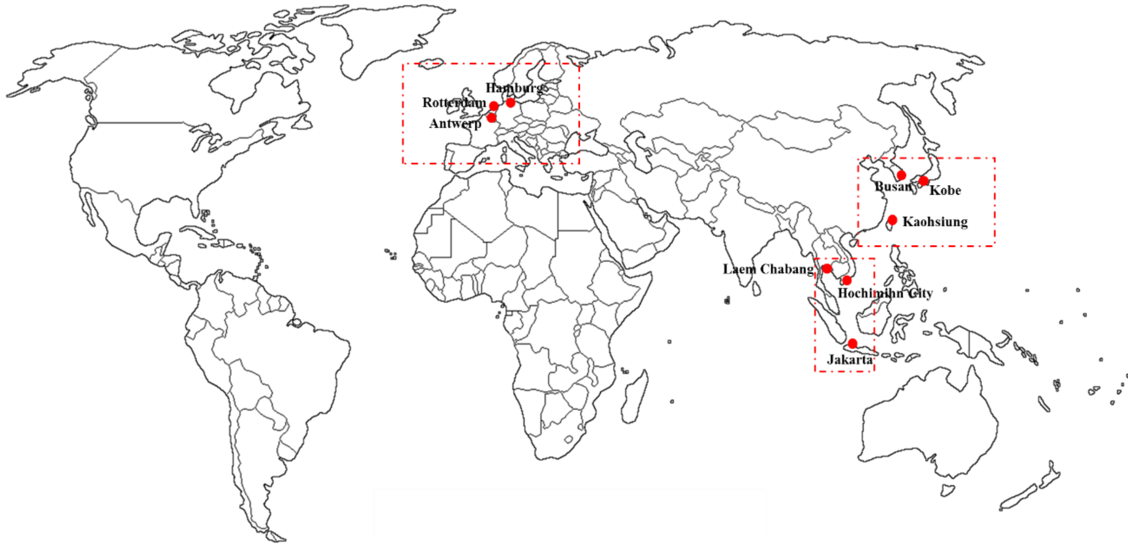

Figure 4.7 the depots and their related regions

Among the nine depots, the travel distances between any two are known and measured as shipping days. Transportation between any two depots is available but due to cost considerations, ETCR is only intra-regional.

During the 180 days in Stage 1, 1,003 customer demands occur. Every single demand represents one booking request and only one container is needed per booking. Demands are specified with origins, destinations, receiving date, execution date and expected revenues. The unit costs of inventory, lift-on/lift-off, container cleaning and job rejection penalty are listed in Table 1. The transportation cost per self-owned TC between two ports is assumed to be the transit time in days multiplied by a constant of £10. If the job is fulfilled with pre-planned leasing containers, the pre-planned leasing cost is £100 per day. For emergent leasing containers, the cost is £130 per day. The revenue per container ranges from £287 to £6,769. These values are generalized from the case TCO's data.

The initial inventory levels at the depots are uniformly distributed. The initial fleet size is designed to match the overall demands. Taking the average demand per day, the demand standard deviation and the average duration time for one job into consideration, the fleet size is rounded to 135 units in total.

Container cleaning duration is modelled as a random variable with a uniform distribution in the range 3 to 7 days. Again, this is a generalization of industrial data. Later, the truncated Normal distribution is used to evaluate the influence of different variances.

The model is implemented using Matlab® 2015 and a PC with a four-core 3.30 GHz processor and an 8 GB RAM.

Table 4.1 Cost parameters per TC

Inventory holding cost	Lift on & off	Job-Rejection Penalty	Cleaning	Self-container transportation	Planned leasing	Emergent leasing
£3/day	£20	£200	£20	£10/day	£100/day	£130/day

4.5.2 Computation results in Stage 1

Experimental results in Table 4.2 compare ETCR with AGA and No ETCR. Also, it is compared with two other ETCR approaches seen in TCOs. First, ETCR is guided by a 'Regional Average Inventory Level' (RAIL) for each region. RAIL is obtained by averaging the up-to-date inventory level of all depots in the region. Depots with inventories lower than RAIL are fed by depots with inventories above RAIL. Figure 4.8 illustrates the process. Second, the threshold values of ETCR are determined heuristically by HSM.

Table 4.2 Comparison of results for No ETCR, ETCR with AGA, RAIL, and HSM

Indicators	ETCR with AGA	No ETCR	% change from ETCR with AGA	ETCR with RAIL	% change from ETCR with AGA	ETCR with HSM	% change from ETCR with AGA
Self-container jobs	730	685	-6.2%	784	+7.4%	708	-3.0%
Planned-leasing jobs	230	242	+5.2%	157	-31.7%	228	-0.9%

Emergent-leasing jobs	43	76	+76.7%	62	+44.2%	67	+55.8%
Number of ETCR	76	n/a	n/a	458	+502.6%	21	-72.4%
Total costs	£320,469	£401,130	+25.2%	£387,239	+20.8%	£373,009	+16.4%
Total profits	£1,105,154	£1,024,493	-7.3%	£1,038,384	-6.0%	£1,052,614	-4.8%
Total inventory costs	£37,869	£40,860	+7.9%	£35,469	-6.3%	£39,609	+4.6%
Cost of self-container jobs	£84,890	£77,070	-9.2%	£89,900	+5.9%	£79,810	-6.0%
Cost of planned-leasing jobs	£121,900	£165,200	+35.5%	£87,400	-28.3%	£148,800	+22.1%
Cost of emergent leasing jobs	£38,870	£84,240	+116.7%	£109,590	+181.9%	£69,940	+79.9%
Utilization	67.1%	47.3%	-29.5%	75.6%	+12.7%	61.7%	-8.0%
Utilization for jobs	62.9%	47.3%	-24.8%	58.4%	-7.2%	59.2%	-5.9%

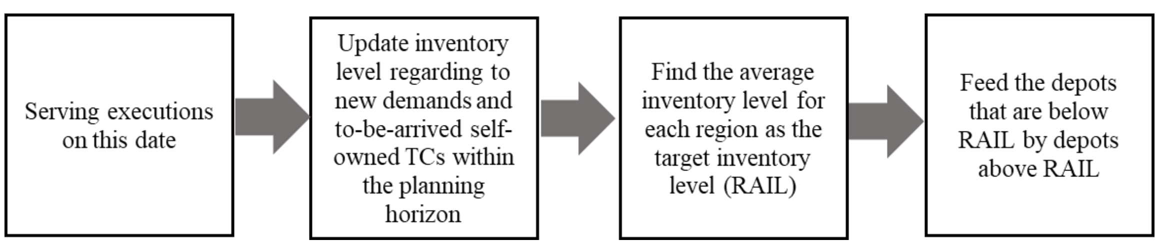

Figure 4.8 the process for RAIL-based ETCR

Compared to ETCR with AGA, the profit with No ETCR is 7.3% lower, ETCR with RAIL is 6% lower and ETCR with HSM is nearly 5% lower. The improvement with ETCR with AGA is mainly due to reductions in planned-leasing and emergent leasing costs. Specifically, No ETCR yields 35.5% higher planned-leasing cost and 116.7% higher emergent leasing cost, ETCR with RAIL yields 181.9% higher emergent leasing cost (reduction of planned-leasing cost for ETCR with RAIL is not enough to compensate for higher emergent leasing cost), and ETCR with HSM yields 22.1% higher planned-leasing cost and 79.9% higher emergent leasing cost. Strikingly, ETCR with RAIL results in approximately 6 times more ETRC movements than ETCR with AGA.

To understand what is happening, first note that No ETCR yields 5.2% more planned-leasing jobs than ETCR with AGA, but the increase in the planned-leasing cost is nearly 7 times more at 35.5%. To understand this, consider an example with two depots starting with inventory levels of 2 and 8 self-owned containers respectively. Suppose each depot has 10 demands, 4 of which are long duration and 6 short duration. Without ETCR, the first depot would have to service 2 long duration demands with planned-leasing containers. If instead the inventory had been rebalanced by ETCR, say to inventory levels of 4 and 6, then there would be no need to service long duration jobs with planned-lease containers. Therefore, although the overall number of planned-leasing jobs would remain the same at 10, the cost would fall significantly. This means ETCR is not so much reducing the number of planned-leasing jobs as focusing them on to shorter duration demands by having more balanced inventories across the depots.

The more balanced inventories are also spreading out the ability of inventory to provide a buffer to protect against stochasticity and subsequent emergent leasing, with ETCR with AGA reducing the number of emergent leasing jobs by 43% (No ETCR is 76.7% higher), and their cost by 54% (No ETCR is 116.7% higher). If inventory is not balanced then low-inventory depots will arise and these are more likely to need emergent leasing.

The very high volume of ETCR movements for ETCR with RAIL (approximately 6 times ETCR with AGA) means more inventory balancing is occurring, resulting in more self-container jobs, and therefore less planned-leasing, because the self-containers are more often in the right place for outflows. However, compared to ETCR with AGA this does not translate into higher profits. This is predominantly because ETCR with RAIL yields a big increase in the number (44.2%) and cost (181.9%) of emergent jobs in addition to the greatly increased amount of ETCR, which is not offset by a sufficient reduction in planned leasing. The increase in emergent-leasing costs is more than four times the increase in number of emergent-leasing jobs. This means that ETCR with RAIL not only yields more emergent leasing, but this tends to be for more expensive longer duration jobs, i.e. a double or amplified shortcoming. Two more metrics were introduced to further analyse this phenomenon. ‘Utilization’ is the average total time TCs spend on job related activity or ETCR during the whole planning horizon (180 days), with job activity including laden delivery, holding by receiver, cleaning and return to inventory. ‘Utilization-for-jobs’ is just the average time TCs spend on job related activity excluding ETCR. In Table 2, these show that while ETCR with RAIL is keeping TCs very busy, much of this activity is taken up with ETCR with the result that the Utilization-for-jobs is less than for ETCR with AGA, which in turn is better than ETCR with HSM.

What we are seeing is that ETCR with RAIL results in hugely excessive TC repositioning. It does yield higher profits than No ETCR, but these are still 6% less than ETCR with AGA yields with a sixth of the amount of repositioning. This is a very important result as ETCR with RAIL is a natural way for industry to work, demonstrating the practical value of the new ETCR with AGA. ETCR with RAIL is too focused on immediate rebalancing of inventories rather than planning using a longer-term perspective of net flows and inventory levels. For example, excessive ETCR can be caused when a long-term deficit depot temporarily has sufficient inventory, or a long-term surplus depot is temporarily deficient. ETCR with AGA looks further ahead, making more considered decisions, rather than rushing to reposition based on current inventory levels.

ETCR with HSM yields far fewer ETCR movements than ETCR with AGA (-72.2%) but far more emergent leasing (+55.8%) with an even bigger increase in emergent leasing costs (+79.9%). Quite simply, ETCR with HSM is simply not doing enough repositioning and this is resulting in a big increase in emergent leasing to cover for local shortages. Clearly, ETCR with AGA is yielding better results by achieving a better balance between over and under repositioning, compared with ETCR with RAIL and ETCR with HSM.

The cleaning duration is stochastic. In order to evaluate the ETCR policy’s robustness and sensitivity to the spread of the cleaning times within the range [3,7], the time is modelled using a Normal distribution with mean 5 days and truncated beyond the [3,7] range. Then, three experiments were run with the variance set to 0.5, 1 and 2 respectively, with the results in Table 4.3 (it is the average of ten times experiments with respect to different random cleaning setting).

Table 4.3 Comparison of results under normal distribution with different standard deviations

Indicators	**AGA with normal cleaning $b_i \sim N(5, 0.5)$**	**AGA with normal cleaning $b_i \sim N(5, 1)$**	**Difference from $b_i \sim N(5, 0.5)$**	**AGA with normal cleaning $b_i \sim N(5, 2)$**	**Difference from $b_i \sim N(5, 0.5)$**
Self-container jobs	732	734	+0.3%	727	-0.7%
Planned-leasing jobs	227	227	+0.0%	230	+1.3%
Emergent-leasing jobs	44	42	-4.6%	46	+4.6%
No. of ETCR movements	78	75	-3.9%	73	-6.4%
Total costs	£309,439	£311,549	+0.7%	£316,434	+2.3%
Total profits	£1,116,184	£1,114,704	-0.1%	£1,109,189	-0.6%
Inventory costs	£37,389	£37,569	+0.5%	£37,704	+0.8%
Cost of self-container jobs	£85,770	£85,660	-0.1%	£85,200	-0.7%
Cost of planned-leasing jobs	£122,200	£120,000	-1.8%	£121,900	-0.3%
Cost of emergent leasing jobs	£27,040	£31,330	+15.9%	£34,840	+28.9%

Table 4.3 shows that the key effect of increased variability in cleaning times is a shift in costs to emergent leasing. This is understandable as emergent leasing is used to cope with unavailability of self-owned TCs. The practical implication is that TCOs should increase the reliability and certainty of the container cleaning process, not just the mean duration, to reduce emergent leasing costs and increase profits.

To further justify the effects of changes in the random cleaning time settings, Table 4.4 below listed the range of the ten experiment results for the key indicators (total profits and total costs) regarding each random cleaning setting.

Indicators		**Statistics for ten times experiments**				
		AGA with normal cleaning $b_i \sim N(5, 0.5)$	**AGA with normal cleaning $b_i \sim N(5, 1)$**	**Difference from $b_i \sim N(5, 0.5)$**	**AGA with normal cleaning $b_i \sim N(5, 2)$**	**Difference from $b_i \sim N(5, 0.5)$**
	Upper	£309,846	£312,347	+0.9%	£318,778	+3.3%

Total costs	Lower	£309,113	£311,131	+0.6%	£314,154	+1.7%
	Ave.	£309,439	£311,549	+0.7%	£316,434	+2.3%
	Std./ Ave. (%)	0.27%	0.38%	/	1.2%	/
Total profits	Upper	£1,117,069	£1,115,312	-0.25%	£1,110,736	-0.4%
	Lower	£1,115,767	£1,113,864	-0.08%	£1,107,996	-0.7%
	Ave.	£1,116,184	£1,114,704	-0.13%	£1,109,189	-0.6%
	Std./ Ave. (%)	0.6%	0.7%	/	1.3%	

Table 4.4 the highlights of the ten experiments for TC cleaning sensitivity analysis

Table 4.4 illustrates the largest and lowest result out of ten times experiments regarding two varied TC cleaning random distribution. As the result demonstrates, when variance of TC cleaning distribution tends to be heavier, the total costs all tend to be larger (increase from 0.6% to 0.9% when standard deviation increase to 1 and increase from 1.7% to 3.3% when standard deviation increase to 2) and total profits are thereby shrunk (within the range of -0.25% to -0.08% and -0.7% to -0.4% for the two settings) with the given samples.

4.5.3 Computation results in Stage 2

In this stage, the model is advanced to apply the joint decision-making process associated with ETCR, job fulfilments and choice of FFs on a day-to-day basis. In addition to the cost components in Stage 1, the FF cost and the cost of job rejection are introduced. To reduce the computation complexity, the cost of the best FF is fixed at £40 per job across all regions. In reality, the cost of an FF may be different from region to region or even from route to route. However, the simplified value used here is sufficient to demonstrate the effectiveness of the model. During real-time decision-making, TCOs do not need to simulate such a long period as in the tests here, so their computation time will be less, allowing them to increase data complexity.

This stage introduces a penalty cost for rejecting demands to achieve greater profits. It is first set as £200 per job and varied later to test the model's sensitivity to it. The two-week look-ahead approach observed in industry is used, so in ETCR calculations the adjusted inventory level will allow for predicted customer demands. The demands' mean and standard deviations from Stage 1 are used to generate new demands. Decisions are then made on job fulfilment for demands received daily and the FF for ETCR based on the threshold values obtained from Stage 1. The simulation length is again 180 days, and performance is evaluated with indicators at the end of the planning horizon. Since the influence of different FFs over ETCR is subject to the stochasticity in the model, the simulation is run 10 times and the results averaged for each scenario.

To articulate the significance of optimizing the FF choice with the proposed model, the best, lowest-cost, and random FFs (uniform probability) are also applied for comparison. Using best FFs represents TCOs who wish to guarantee smooth execution of their plans, i.e. to compete on service quality, although this is expensive. Using lowest-cost FFs represents TCOs competing on price by offering low-cost services, but to the detriment of service quality/reliability. Random FF represents TCOs with limited access to the FF market and limited market power in making choices; they have to take whatever they can get due to capacity constraints in the industry.

Table 4.6 shows best FF yields better profits and job fulfilment than random FF and lowest-cost FF, but optimal FF yields the best profit. This is achieved by big reductions in FF cost (best FF is 114.9% higher) and the cost of emergent leasing jobs (best FF is 19.9% higher). Underlying the improvement is a substantial reduction in ETCR movements (best FF is 11.4% higher). From a strategic management perspective, this has advantages beyond just an increase in profit. It also means that the TCO is not beholden to just the best FF as another better FF can be identified due to its lower costs. Even if the profit differences are small, having a feasible alternative opens up competition that could drive costs lower, and having options in service providers is always strategically important.

In order to evaluate the continued robustness of the model at this stage, a simulation was run with no ETCR and no job rejection, yielding a total profit of £1,042,336. This is clearly less than that achieved across Table 4.5, demonstrating the continued effectiveness of ETCR.

Table 4.5 Results for Optimized and Non-Optimized FF choices

	Indicators	Optimal FF	Best FF	% Diff. to optimal FF	Random FF	% Diff. to optimal FF	Lowest cost FF	% Diff. to optimal FF
	Self-container jobs	746	750	+0.5%	717	-3.9%	708	-5.1%
	Planned-leasing jobs	230	231	+0.4%	241	+4.8%	258	+12.2%
	Emergent leasing jobs	46	43	-6.5%	59	+28.3%	49	+6.5%
	Rejected jobs	53	51	-3.8%	58	+9.4%	60	+13.2%
	No. of ETCR	79	88	+11.4%	51	-34.5%	34	-57.0%
	Total revenue	£1,387,056	£1,391,380	+0.3%	£1,381,441	-0.4%	£1,376,596	-0.8%
costs	Inventory	£38,184	£38,151	-0.1%	£39,129	+2.5%	£39,717	+4.0%
	FF	£1,638	£3,520	+114.9%	£1,427	-12.9%	£544	-66.8%
	Penalty	£10,600	£10,200	-3.8%	£11,600	+9.4%	£12,000	+13.2%
	Self-container jobs	£94,300	£94,220	-0.1%	£92,760	-1.6%	£91,350	-3.1%
	Planned-leasing jobs	£51,600	£52,200	+1.2%	£55,400	+7.4%	£52,300	+1.4%
	Emergent leasing jobs	£46,800	£56,100	+19.9%	£57,880	+23.7%	£59,400	+26.9%
	Total (not sum of above)	£280,852	£292,511	+4.2%	£293,871	+4.6%	£290,655	+3.5%
	Total profits	£1,106,203	£1,098,869	-0.7%	£1,087,570	-1.7%	£1,085,941	-1.8%

The optimized and lowest cost FFs are a source of stochasticity due to their random reliability value. To see their effect, Figure 4.9 presents the profits from 10 repeated experiments with the same randomly generated stream of container cleaning times, but different random values for FF reliability. As the reliability of the best FF is constant at

100%, its profits are constant. The optimized FF gives higher profitability than the best FF in 7 experiments. The lowest cost FF yields the highest profit in 2 experiments when by random chance it produces high reliability, but it clearly gives the lowest profits on 5 occasions. The random FF yields a dynamic profit-making ability, but with lower average profits close to that of the lowest cost FF.

The reliability of the optimized FFs during each experiment ranged from 50% to 80%, showing that this optimization is truly using the FF range and not just going for high reliability FFs.

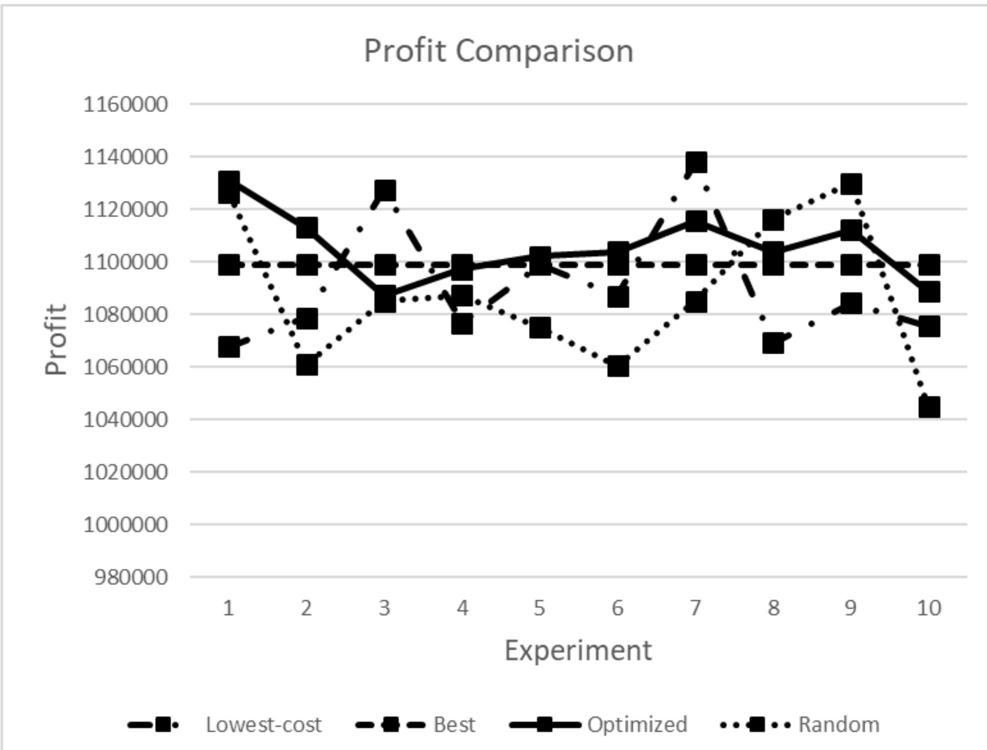

Figure 4.9 Profit by experiment for different FF criteria

Table 4.6 shows that optimizing the FF reduces leasing costs. If the penalty cost of rejecting a job were increased one would expect to see more leasing to accommodate a reduction in rejections. Table 4.6 presents the results when the penalty cost for rejecting jobs is varied. This shows that as the penalty cost, planned leasing cost or emergent leasing cost increase so FF optimization yields greater improvements in profit. This is due to large decreases in costs rather than increases in revenue that remain slightly lower in the experiments conducted.

Table 4.6 Effect of Key Cost Coefficients on Change in Profit for Optimized FF compared to Best FF

Penalty Cost	Planned leasing	Emergent leasing	Profit	Revenue	Cost
£100	£100	£130	-2.1%	-1.2%	+2.1%
£100	£120	£130	-0.7%	-0.3%	+0.9%
£100	£120	£150	+0.4%	-0.6%	-1.2%
£500	£100	£130	+1.1%	-0.5%	-5.3%
£500	£120	£130	+1.8%	-0.5%	-7.2%
£500	£120	£150	+2.9%	-0.3%	-8.4%
£1000	£100	£130	+2.4%	-0.2%	-8.1%
£1000	£120	£130	+3.1%	-0.3%	-8.9%
£1000	£120	£150	+4.4%	-0.4%	-9.6%

Moreover, to enhance the confidence of the conclusion drawn from Table 4.6, Table 4.7 has contained the range of results (both largest and smallest change in percentage for every indicator) from ten experiments for every one cost coefficient change in profit. It can be seen that every ten experiments for each cost coefficient change illustrate the same tendency as stated above and this thereby enhances the quality of findings obtained from above sensitivity analysis (Table 4.6).

Table 4.7 highlights of the ten experiments of change in profit for optimized FF compared to Best FF

Penalty Cost	Planned leasing	Emergent leasing	Profit		Revenue		Cost	
			min	max	min	max	min	max
£100	£100	£130	-2.8%	-1.7%	-1.8%	-0.7%	+1.9%	+2.6%
£100	£120	£130	-1.6%	-0.4%	-0.9%	-0.1%	+0.4%	+1.3%
£100	£120	£150	+0.1%	+0.7%	-1.6%	-0.3%	-1.8%	-0.9%
£500	£100	£130	+0.4%	+2.1%	-1.5%	-0.3%	-7.5%	-3.8%
£500	£120	£130	+0.9%	+2.4%	-0.9%	-0.3%	-8.1%	-6.9%
£500	£120	£150	+2.1%	+3.4%	-0.8%	-0.1%	-9.5%	-7.8%
£1000	£100	£130	+1.8%	+3.2%	-0.9%	-0.1%	-9.4%	-7.6%
£1000	£120	£130	+2.5%	+3.8%	-1.1%	0%	-9.8%	-8.4%
£1000	£120	£150	+3.7%	+4.9%	-0.8%	-0.2%	-9.9%	-8.7%

In line with industrial practice, a 2-week forecast was used in optimizing ETCR and inventory planning in Stage 2. To understand the effectiveness of incorporating the 2-week forecast into the optimization (2-week forecast + ETCR with AGA), it is compared with not using the forecast in Table 4.8. This shows that including the forecast yields a substantial decrease in leasing, penalty and ETCR costs with a corresponding increase in profits. The increased visibility given by the forecast is allowing the plans to achieve more with self-containers instead of resorting to leasing and excessive container repositioning.

To see if including the forecast changes the superiority of ETCR with AGA, Table 4.9 presents the change in performance seen when using ETCR with AGA compared to ETCR with HSM and ETCR with RAIL, with all three now using the 2-week forecast. This shows that ETCR with AGA is still the most profitable, increasing profit by 6.7% and 7.3% respectively, as it makes better use of self-containers resulting in lower leasing and ETCR costs.

Table 4.8 Change in ETCR with AGA performance after including 2-week forecast

Indicator	Change in performance with 2-week forecast
Revenue	+3.4%
Profit	+4.7%
Total Cost	-9.6%
Cost of self-container jobs	+2.1%
Cost of planned-leasing jobs	-6.4%
Cost of emergent-leasing jobs	-8.2%
Penalty cost	-9.2%
ETCR cost	-12.3%

Table 4.9 Change in performance when using ETCR with AGA compared to other optimization methods after including 2-week forecast

Indicator	ETCR with HSM & 2-week forecast	ETCR with RAIL & 2-week forecast
Revenue	+3.7%	+2.8%
Profit	+6.7%	+7.3%
Total Cost	-18.7%	-22.4%
Cost of self-container jobs	+9.4%	+3.5%
Cost of planned-leasing jobs	-15.7%	-34.7%
Cost of emergent-leasing jobs	-17.1%	-87.1%
Penalty cost	-14.1%	-19.1%
ETCR cost	-4.4%	-476.7%

Having seen the benefits of incorporating a 2-week forecast into the optimization, sensitivity to the length of the forecast period was investigated. Table 4.10 compares the results for 1, 2, 3 and 4-week forecasts with optimized FF. The 3-week forecast yields the highest profit through increasing the number of self-container jobs, resulting in decreased leasing jobs, and particularly the cost of these as it is longer more expensive jobs that are being switched to self-containers. The 1-week and 4-week forecasting periods result in increased ETCR. In the case of 1-week this is because it is too short to take into account future demands for the surplus depots, i.e. it is approaching no ETCR, so TCs are shipped to deficit depots too readily. In the case of 4-week forecasting, although more of the future demand forecast is considered, the forecast demand only tells where the origin is, but not the destination. Therefore, when the inventory is planned for the future, some of the future arrivals are not clear. However, if containers are reserved or repositioned for the whole 4-week forecast, too many TCs may be kept or moved, as the cleaned arrival TCs replenish the inventory as well.

Considering the current average job and cleaning durations, most containers will be ready for their next job within three weeks. Combining this with the above result the inference is that it is not beneficial to forecast beyond the typical job plus cleaning time. As the average job plus cleaning duration may be subject to change, due to changes in demand patterns, transport facilities or cleaning processes etc., it follows that TCOs should monitor this and adjust the forecast period accordingly.

Table 4.10 Sensitivity analysis to forecast period with optimized FF

Indicators		**Forecast Period**			
		1-Week	**2-Week**	**3-Week**	**4-Week**
Self-container jobs		724	746	763	733
Planned-leasing jobs		244	230	221	241
Emergent leasing jobs		49	46	43	46
Rejected jobs		58	53	48	55
No. of ETCR		92	79	71	88
Total revenue		£1,384,251	£1,387,056	£1,391,093	£1,385,596
Costs	Inventory costs	£35,772	£38,184	£36,594	£43,683
	FF cost	£1,940	£1,638	£1,149	£1,868
	Penalty costs	£11,600	£10,600	£9,600	£11,000
	Cost for self-container jobs	£91,630	£94,300	£98,820	£92,350

	Cost for planned-leasing jobs	£54,200	£51,600	£49,200	£53,300
	Cost for emergent leasing jobs	£48,100	£46,800	£38,740	£45,240
	Total (not sum of above)	£297,537	£280,852	£271,093	£294,651
Total profits		£1,086,714	£1,106,204	£1,120,000	£1,090,945

In addition, on top of the different average effects demonstrated in Table 4.10 with the application of different forecast period, result for each sample experiment is further examined and listed below in Table 4.11. They have provided further evidence to the finds obtained regarding Table 4.11.

Table 4.11 solution quality evaluation for sensitivity analysis to forecast period with optimised FF

Indic-ators	**Forecast Period**											
	1-Week			**2-Week**			**3-Week**			**4-Week**		
	min	max	s/m*	min	max	s/m*	min	max	s/m*	min	max	s/m*
Total Costs	£293,448	£299,841	0.8%	£275,321	£284,432	2.0%	£268,147	£276,412	2.3%	£291,065	£297,813	1.2%
Total profits	£1,079,832	£1,089,728	1.0%	£1,105,663	£1,108,312	0.4%	£1,114,331	£1,145,731	2.3%	£1,080,745	£1,100,257	0.7%

*s/m means Std./mean in %

4.6 Summary of this chapter

To improve Tank Container (TC) operations management, this chapter has proposed a two-stage model that enables optimization of a double-threshold inventory control policy for tank Container Operators (TCOs) to gain better operational profits, as well as demand fulfilment, during the quotation-booking process comparing to general practices. On top of the optimized inventory policy, the model simulates and optimizes the choice of FFs under a more realistic operational environment including job rejections under a two-week demand forecast, on a rolling planning basis. The effectiveness of the two-stage model in optimization has been demonstrated through a series of numerical tests. Sensitivity analysis has articulated the managerial insights associated with the model with respect to different uncertainty levels, different FF costs and different demand forecast lengths.

Through numerical experiments understanding of the economics behind the decisions in this important industrial operation has been gained. Common practices including inventory control policy, choice of FFs and customer demand prediction have been emulated and their performance compared with that of the new optimization model presented here. Key findings from the experiments include four aspects. First, the optimised inventory control policy demonstrates the ability for more precise resource allocation and better exploitation of market opportunities; Two, it is essential for TCOs to optimise the choice of FFs in leading better asset profitability; Three, a more reliable TC cleaning can result more certain cleaning duration, and better TC flow efficiency can be yield; Four, TCOs need to adapt their demand forecast ability to their demand pattern and use the forecast information and develop such capability accordingly.

The current model is tailored to fit in the “quotation-booking” process with comprehensive consideration of daily operations, however, some issues at a higher level that have influence or should be influenced in a long-term are hard to be addressed by the current model and solutions. The reasons for this are threefold. First, as we discussed in literature review section, TCOs have global-based network to be operated on, an operational-oriented model is hard to find the optimality for large scale problems within a long-term planning horizon. Even though, the designed and optimised inventory control policies belong to long-term decisions, inventory control mechanism just used as inputs for better daily operation and decision-making, and the core process is still down to the performance with respect to “quotation-booking” rather than the performance regarding to different inventory-control policies. Second, different from the operational-oriented model, the decisions are made at a short-term basis, therefore, all the optimised decision-makings can only guarantee the best choices up to that time point. Even though the model is running for a long time with a deterministic setting, the way how information is processes still follows the operational way. Hence, the overall result is hard to be optimal holistically, but for long-term decisions, it is more important the model is optimal or near-optimal for the whole planning horizon. Third, uncertainties with the current model is dealt with heuristic techniques (e.g. different realisation way for container cleaning duration), they prove to be effective for short-term performance because of the safeguard from the inventory control policies and the influence from discrepancies are relatively small in a short time. But as the numerical test illustrated, effectiveness of the model is significantly influenced when the variability level of uncertain parameters changed. Therefore, if all the uncertainties throughout a long-term horizon are taken into account in a static manner, the current way of coping with uncertainties may let the system lose its robustness.

Considering the rest of the research objectives, a new model formulation and the associated solution need to be developed, so that the TC customer overholding issue within a global network can be controlled and optimised with proper pricing strategy while the uncertain container cleaning is considered.

5. TC strategic/tactical planning: fleet sizing, overholding pricing and network optimisation

5.1 Significance of TC overholding

Following the previous chapter, solutions are built to provide better customer job fulfilment with increased overall profits and asset utilisation. However, as the objective of asset management requested (see the definition of asset management in section 2.3), the profitability and utilisation for TCs should be jointly investigated throughout their overall journey. Specifically, the full journey for TCs fulfilling customer demands includes both outward and inward journeys. For the outward journey, empty TCs will be loaded, departed, delivered and receipt as the quoted itinerary required. Then, from the time point that customer received TCs until them returned back to TCOs' appointed depots, TC inward journey is completed. In Chapter 4, the built-up model and designed solutions focus on optimising the performance of TC "quotation-booking" process, which particularly, have less considered issues and challenges associated with TC inward journey. As a major part of TCs' demand fulfilling lifecycle, improving TC return effectiveness and reducing TC return uncertainties can surely contribute to the overall performance of TC asset management. Therefore, it draws our attention to investigate further about operations within TC inward journey, and hopefully, it can seize more chances to make further improvement of TC asset management.

The TC inward journey is majorly comprised by customer holding period. Specifically, it refers to the time when TCs arrived at customer designated port terminal until they return back to TCOs' depot or pre-agreed locations. As mentioned in section 1.1, TCs are characterised as reliable and safety storage equipment, especially for hazard products such as chemical or petroleum commodities. Consequently, it is prevalent that TCs are overheld by their customers as storage equipment to meet production purpose. The motivations for such behaviour are two-fold. In this industry, to build dedicated storage facilities for liquified products are very costly, and as a result, paying the TC over-holding charge as alternative is regarded as a more flexible and economic way. Also, the petrochemical industry is highly volatile and unpredictable, even though the overall trend is on rise for the past decades (fig. 5.1), but the fluctuation within every 3-5 years made it hard to optimise the investment over long-term capacities. Hence, it is easier and cheaper to use TCs to cope with production dynamics.

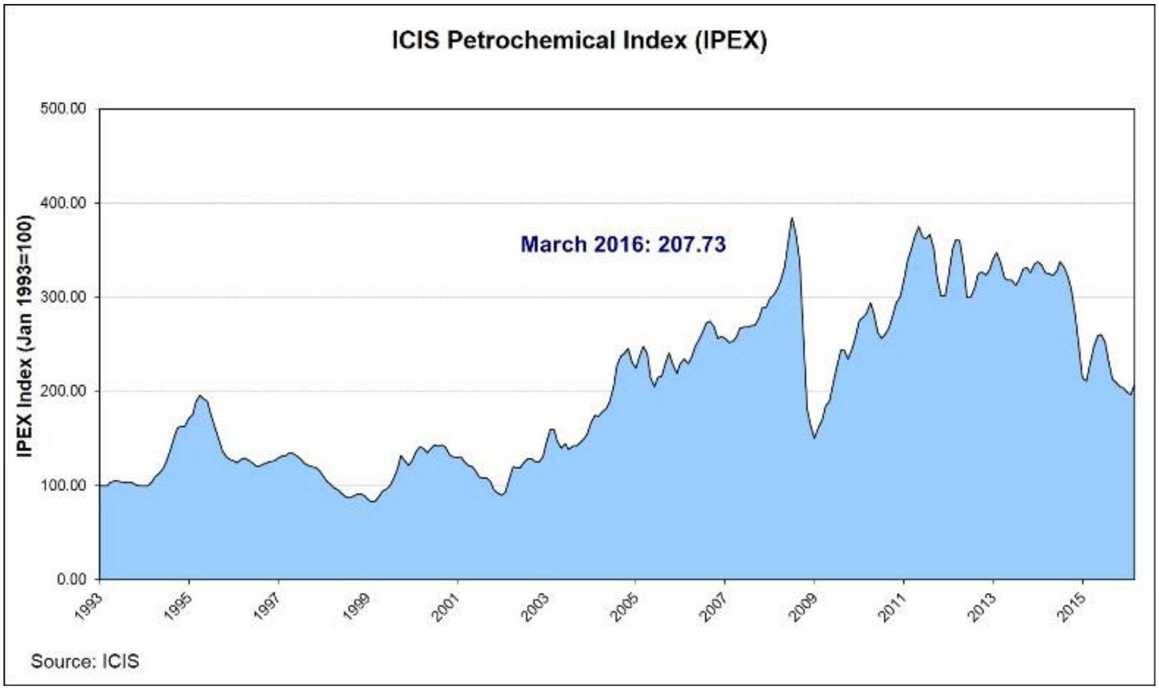

Figure 5.1 the petrochemical index from 1993-2016

Source from: ICIS 2016

Due to such behaviour, 'blind-spot' is created when customer keep holding TCs because TC operators (TCOs) have little information of when those TCs will return to their inventory. Even though TC overholding charge is introduced, the current policy only generates TCOs another profit resource but makes little difference to the behaviour itself. Therefore, the TC flow is less efficient and hard to be controlled. Nevertheless, since TC overholding produce large amount of income for TCOs, and customers find the value of overholding TCs, a so-called "*win-win*" situation is created. As a result, risks and negative impacts associated with TC overholding are disregarded by the whole industry, but from the asset management perspective, they are worth to be pointed out.

i. Making profits from TC overholding is not a sustainable business mode as this revenue is generated by customers' dependence on TCs' for storage needs. This goes far off the core business of TCOs and when such dependence is reduced in the future (e.g. cheaper storage facilities), TCOs will incur a great profit loss and the current ignorance makes them lack of effective resilient strategies.

ii. although TC over-holding generates significant profits for TCOs, it creates sophistications for overall operational planning. When over-holding occurs, an information "blind spot" is created in between customers and TCOs. Therefore, it is difficult to estimate when the return of those TCs and the overall TC flow planning becomes ineffective (Song and Carter, 2009). It is thereby questionable to determine whether the pros brought by TC over-holding outweigh its cons.

iii. the "win-win" situation increased the ignorance of the TC over-holding problem from both TCO's side and customer's side. Hence, there are few associated practices developed to address such issue. Specifically, there are lack of support for integrated planning of job fulfilments (e.g. leasing or rejects) and ETCR when over-holding increases the uncertainty of TC return.

iv. the uncertain operational environment will worsen the ineffectiveness that TC over-holding brought to the operations planning. Notably, TCs requires thorough cleaning after each job journey, yet the cleaning process varies due to different moved products and the associated cleaning requirements (Erera et al., 2005), so the cleaning duration is hard to be determined. Take the TC over-holding and uncertain container cleaning jointly into account, it increases the difficulties of tracking TCs real-time status and scheduling the TC flows.

Considering the above points, this chapter will look into mechanisms that can address TC overholding issue in a long term with the consideration of uncertain container cleaning. Most importantly, it aims at mitigating the TC overholding influences and designing the optimised policies to achieve better TC profitability at the tactic level under the influences of industrial uncertainties. By doing so, research gaps at strategic/tactical level illustrated in section 2.6.3 can be filled up and the corresponding research objectives (objective 3&4 in section 2.6.3) can be achieved as well. Next, the research problem will be described in detail, and the modelling and solution techniques are selected and designed accordingly.

5.2 Problem formulation

5.2.1 The description of TC operation

Regarding the feature of "quotation-booking" process, TCOs need to clarify different time window constraints or different length of free days for developing quotations as per different customer demands. The time window constraint refers to the horizon that TCOs need to complete the delivery task within the given earliest job start time and latest job finish time. And the free days are the buffer time that allows customers to return the empty container back to TCOs' premises without extra costs. To simplify the narrative of TC operation, it can be broken down to four stages: 1) customers place itinerary inquiries; 2) TCOs develop the corresponding quotations based on their internal and external resources; 3) Customers book quotations; 4) empty TCs are assigned to the load and moved from their depot to the customers. As part of the quotation, it is very challenging to develop effective TC free days and TC hire cost. This is because, 1) TCOs need to make trade-offs in deciding TC free days and TC hire cost as they on one hand influence the profitability of TC hire business, while on the other hand influence the overall TC flow effectiveness and visibility; 2) the correlation between TC free days and TC hire costs make such decisions more complicated. Namely, decisions over TC free days and TC hire costs are not independent and subtle changes in one would make difference on another. For example, it is hard to tell whether longer free days with lower TC hire costs or shorter free days with higher TC hire costs could lead to shorter TC over-holding days; 3) the effectiveness of the underlying decisions are built upon the overall operational performance, which means, they aim at bringing better job fulfilments and job profitability. Therefore, the underlying decisions need to be optimised comprehensively in considering other TC operational decisions.

As the common practice, TCOs design the TC free days and hire costs first in a long run. This can give TCOs a panoramic view of the average customer holding time for helping plan day-to-day TC flows, and meanwhile, it stabilises the market with less fluctuated price terms. When the price policies are made, customer behavior (here refers to the TC customer holding time) is emerged subsequently. Therefore, under the guide of their relationship picture, TCOs make their daily operational plans within their TC flow networks. Moreover, in a long run, TCOs should decide the total TC fleet size as well. It is a strategic decision that balances the investment cost and daily TC flow efficiency. As rich literatures demonstrated, TC fleet sizing is highly related to operational issues such as empty container movements and job fulfilment performance (i.e. Cheung and Powell, 1996; Crainic, 2000), it should be jointly optimised at the tactical/strategic level to yield better profits and TC utilisation at operational level.

At the operational level, within the TC flow network, there are three significant network nodes. First, the place where TCOs keep empty TCs or prepare the departing laden TCs is a TC depot. A group of TC depots that are geographically close to each form a TC depot region. Second, the place that customers required to receive the laden TCs are called customer sites. Normally, for the convenience of customers, a group of customer sites are served by a nearby depot, in that way, all the emptied and cleaned TCs can be returned to it. Third, in between a customer site and its corresponding depot, a place equipped with TC cleaning facilities is called the TC cleaning depot. In this site, all the returned TCs are thoroughly cleaned with different processes according to the commodities they just delivered.

Within such network, the daily operation plans are made dynamically. Specifically, they need to decide the types of job fulfilments and the flow of empty containers to cope with trade unbalance. There are three types of job fulfilments, which include delivering jobs with self-owned containers (such job defined as self-container jobs), delivering jobs with leased containers (such job defined as leased jobs), or rejecting some demands (defined as rejects). As long as the daily operational plans are clarified, TC containers will be flown per their life cycles according to the nature of their missions. For TCs serving self-container jobs, they always go through departing from depot to defined customer sites. When customers finished the hire of the TCs, they should be returned to the nearest (or TCOs pointed) cleaning depot for TC cleaning and then flow back the depot that customer sites attached to. For TCs serving leased jobs, their life cycle is always starting from depot and finishing at customer sites. When customers finish the hire of those TCs, they will be returned directly to lessors, and the length of customer holding time for leased TCs do not influence TCOs' own TC flows. For empty TC movements, they are only moved in between depots. Theoretically, empty TCs can be moved from any depot to another, however, since TCOs need to use external resources for completing maritime transport, so empty TC movements are normally limited intra-regionally to control the ETCR costs. Figure 5.3 in section 5.2.3 shows the different moving routes graphically.

5.2.2. the outline of the research approach

With respect to above description, we propose a two-stage time-space network model to portray the TC operation and address the underlying research questions. Specifically, the first stage of the model will formulate the strategic/tactical level decisions (customer holding policy and TC fleet size). At the second stage, the model will build a time-space network based on historical data to represent the overall TC flows driven by fulfilling customer demands, ETCR and TC return from jobs in a defined planning horizon. Meanwhile, decisions from the first stage will be included in the second stage, which influence the overall structure of time-space network. By doing so, this model is able to optimise the first stage decisions that lead to optimal TC flow performance in the second stage. Figure 5.2 below depicts the outline of this approach.

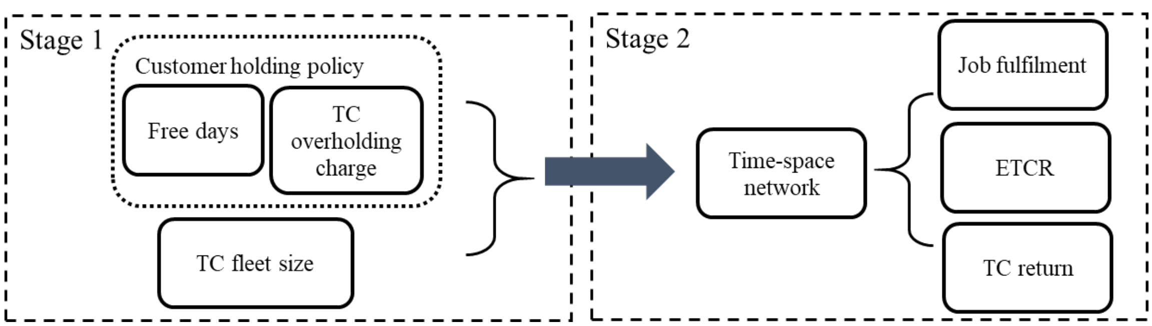

Figure 5.2 the overview of the two-stage time-space network model formulation

Reason of why constructing a time-space network is stated in Section 4.6 and why it is decoupled by two stages is because decisions for TC customer holding policy and fleet size are long-term scheduling activities which influence the overall structure of the time-space network, while decisions related to components of the time-space network can only be made with the acknowledgement of the first stage decision variables. Followed by this research method, the model formulation is developed in the next section.

5.2.3 the model formulation

To match the industrial practice, the model will determine the customer overholding policy (free days & over-holding charge) for every depot and the total TC fleet size at stage 1 first (tactical level). Once those parameters are determined, customer holding time for each depot area is defined and the initial TC fleet size investment is known. Followed, the rest of the operational decisions can be optimised at next stage accordingly. Specifically, the optimisation process at second stage involves decisions about job fulfilments and ETCR arrangements with the consideration of uncertain container cleaning and defined customer holding time.

Next, to support the second stage optimisation process, a time-space network model is created. It presents the physical TC flows through a series of artificial arcs and with their linkages to physical nodes in a time expanded fashion. In particular, when the TC customer holding time and TC cleaning time is certain, arcs of the network can be created, and the rest of the operational decisions are made by optimising the values over each arc.

At last, prior to the model formulation, assumptions need to be pointed out as below:

1. Only the 20-foot equivalent unit (TEU) TC is considered.

2. TC lessors have infinite container fleet and leasing demands can be met immediately.

3. Once free days and TC over-holding charge is decided for one depot, the average total TC customer holding time for all the customer sites surrounding that depot is defined.

4. Customer sites linked to the same depot have the same customer holding time and it equals to the average customer holding time.

5. Customers will always take advantage of TC free days.

6. All the customers have the same longest customer holding time (λ) regardless of their location, TC free days and customer over-holding charges.

7. TC return time consists of customer holding period and TC cleaning duration. Travel time for container return is assumed as zero.

8. ETCR is only intra-regional on routes available between any two depots.

9. All unloaded containers must be cleaned prior to reuse with random duration days.

The validity of above assumptions is explained below. Assumption 1 is common in the literature on maritime container operation researches, e.g. Li et al. (2004, 2007); Dong and Song (2009) etc. This is because, 1) in TC market, 20ft TC is main type which takes approximately 95% of world fleet size (Tuscor Lloyds, 2018), and it also takes about 90% of the world TC fleet size (ITCO, 2017); 2) other sizes such as 40ft TC can be converted to 2 TC units. Assumption 2 is used to indicate the better TC availability provided by TC lessors (details see Section 4.2), and it can also simplify the model to reduce the possibility of computational intractability. Assumption 3 and 4 are used to simplify our model. As we discussed in Section 5.2.1, price and TC free days are the two main factors determining the length of customer over-holding days. Therefore, similar to any price and demand relationship model, once these two factors are decided for an area, the average customer holding time is known. Since the aim of our research is looking at long-term policy, the variation coming from individual customer holding time is neglected. By doing this, we are provided the tool to discover the dynamic relationship between customer holding policy and TC operational performances. Also, it provides the opportunity to consider more complex context (e.g. customer overholding time is different at customer site level) with the same mechanism in future research. Assumption 5 and 6 are reasonable because that first TC customers would always like to take fully use of the container free hire days; two since TCs need to be cleaned before next use, it is not possible that customers will hold the container forever if their production job is finished. Assumption 7 is another common assumption in literature (e.g. Choong et al., 2002; Dong and Song, 2009). It indicates the sea leg journey of TCs occupies most of the distances that TCs travel to fulfil their customer demands. Thus, the distance from depot to its surrounding customer sites is comparatively short and not considered. Assumption 8 and 9 are in line with industrial practices that TCO has no ownership of vessels, therefore it is not economically efficient to deploy crossregional ETCR(s). Meanwhile, due to the special features of commodities that TC carries, cleaning is a must-do process, but the duration is hard to be predicted.

The model

Index, sets and parameters for the time-space network structure

T	total planning horizon
R	the set of regions, r is an index for a region where $r \in R$
P	the set of depots, $p, q \in P$
P_r	the set of depots in region $r, P_r \subset P, r \in R$
M_p	the set of customer sites surrounding depot p, $m_p \in M_p$, $p \in P$
t_{ij}	the container travel time from any physical location i to another physical location j, $i, j \in P \cup M_p$
t_p^f	the customer free time at depot $p \in P$
t_p^h	the average customer over-holding time surrounding depot p area

Firstly, a time-space network is constructed as the research context (Figure 5.3).

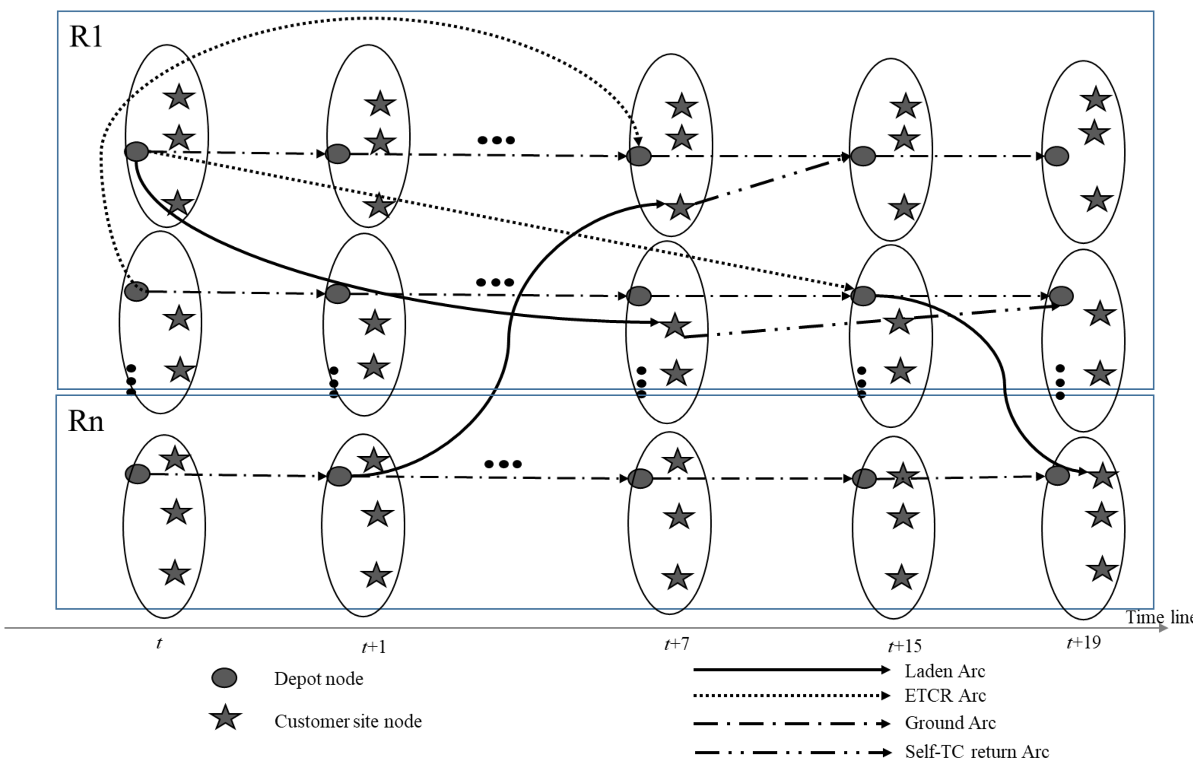

Figure 5.3 Time-space network flow structure

Let $G=(N,A)$ be a graph with depot node set, customer node set and various arcs respectively. Specifically, $N=N_{r|r\in R}\cup N_{p|p\in P}$ indicates that the node sets include both depot nodes (N_r) and customer nodes (N_p).

N_r: The depot node set refers to depots in the same region $r\in R$ with discretised time: $N_r=\{p^t \mid p\in P_r, t\in T\}$;

N_p: The customer node refers to customer sites served by the same depot $p\in P$ with discretised time: $N_p=\{\, m_p^t \mid m_p\in M_p, t\in T\,\}$.

For arc set, it is comprised by four types: $A=A_G\cup A_V\cup A_C\cup A_E$.

A_G : It represents the inventory arc which links node p^t and p^{t+1} : $A_G=\{(p^t,p^{t+1}) \mid p^t,p^{t+1}\in N_r, t\in T\}$;

A_V: It is used for representing the laden container moving arc from depot node p^t to customer node $m_q^{t+t_{p,m_q}}$ and it is $A_V=\{(p^t,m_q^{t+t_{p,m_q}}) \mid p^t\in N_r, m_q^{t+t_{p,m_q}}\in N_p, t\in T\}$;

A_C: It is used for the arc representing self-owned TC return, it connects nodes m_p^t & $p^{t+t_p^f+t_p^h+\mu}$ ($\mu>0$). Arc A_C can be written as $A_C=\{(m_p^t,p^{t+t_p^f+t_p^h+\mu}) \mid m_p^t\in N_p, p\in P, \mu>0\}$. Here μ is used to represent a realised TC cleaning time and $\mu\in[3,7]$ according to industrial practice;

A_E: It is used for ETCR arcs. Since only intra-regional ETCR is considered, this arc links the depot nodes in the same region. If we use function $Rg(p)$ to locate the belonging region of depot ($p\in P$), then $A_E=\{p^t,q^{t+t_{p,q}} \mid p^t,q^{t+t_{p,q}}\in N_r, Rg(p)=Rg(q)\}$.

Next indices and sets regarding customer demands are introduced.

Index, sets and parameters regarding customer demands

Ω	the entire populations of TC cleaning durations
ω	a sample of random variable for TC cleaning duration for a particular job

K	a set of commodity $k \in K$ is a tuple $(O_k, D_k, d_k, r_k, t_k, \tau_k)$, O_k is the origin node, D_k is the destination node. If we use $\mathbb{R}(k)$ to get the physical location of O_k and $\mathbb{Q}(k)$ to get the physical location of D_k, then $O_k = \mathbb{R}(k)^{t_k}$, D_k = $\mathbb{Q}(k)^{t_k + t_{\mathbb{R}(k),\mathbb{Q}(k)}}$. d_k is the amount of containers, r_k is the revenue per container, t_k is the job starting date, τ_k is the cleaning time for this job. Meanwhile, τ_k is a stochastic input in a certain range and $\tau_k(\omega)$ is a sample of τ_k
C_{ij}	the unit travel cost per TC per travel day for arc (i, j) from node i to j, $(i, j) \in A_V \cup A_E$
C	the unit cost per TC leasing per day
C_p	the penalty costs per job rejected
C_n	the unit cost per TC cleaned
C_h	the inventory costs per TC per day
C_c	the unit capital cost per TC per period
t_{LH}	the longest customer holding time for all depots

Intermediate and state variables

$F_{i,j}^k$	After serving commodity k, the amount of self-owned TC returning from customer site node i to depot node j. Where $i = D_k = \mathbb{Q}(k)^{t_k + t_{\mathbb{R}(k),\mathbb{Q}(k)}}$, $j = Dp(\mathbb{Q}(k))^{t_k + t_{\mathbb{R}(k),\mathbb{Q}(k)} + t_p^f + t_p^h + \tau_k}$ and arc $(i, j) \in A_C$. Node j is a stochastic variable and $j(\omega)$ is a realised node with given sample ω, where $j = Dp(\mathbb{Q}(k))^{t_k + t_{\mathbb{R}(k),\mathbb{Q}(k)} + t_p^f + t_p^h + \tau_k(\omega)}$.
$S(p^t)$	the inventory amount on arc $(p^{t-1}, p^t) \in A_G$

Decision variables:

$X_{i,j}^k$	self-owned containers for commodity k on arc (i, j), $(i, j) \in A_V$, $k \in K$. It is a binary variable takes value 1 or 0.
$Y_{i,j}$	the amount of ETCR on arc (i, j), $(i, j) \in A_E$.
$Z_{i,j}^k$	leased containers for commodity k on arc (i, j), $(i, j) \in A_V$, $k \in K$. It is a binary variable takes value 1 or 0.

$W_{i,j}^{k}$	rejected jobs for commodity k on arc (i,j), $(i,j)\in A_V, k\in K$. It is a binary variable takes value 1 or 0.
t_p^f	the free days at depot p
C_p^h	the container over-holding charge per TC per over-holding day at depot p
B	the container fleet size
C	**C**= { $C_1^h,\ldots,C_p^h,\ldots C_{\lvert P\rvert}^h$ }, a vector consisting of all container over-holding charge rates and free days at all depots
$\boldsymbol{T_f}$	$\boldsymbol{T_f}$ = { $t_1^f,\ldots,t_p^f,\ldots t_{\lvert P\rvert}^f$ }, a vector consisting of all container free days at all depots
X	**X**= { $X_{i,j}^k, Y_{i,j}, Z_{i,j}^k, W_{i,j}^k$ }, which denotes all the decision variables at stage two

Objective function of this two-stage model is given below (Eq. (5.1)). The first term of the right-hand-side is the total fleet size investment cost per period, and the second term is the profits made per period:

$$\textbf{P0}:\ \max Z(B,\mathbf{C},\boldsymbol{T_f},\mathbf{X}) = -B\cdot C_c + \frac{1}{T}E_{\Omega}Q(B,\mathbf{C},\boldsymbol{T_f},\mathbf{X},\omega) \tag{5.1}$$

At the first stage of the model, three factors are determined. The TC free days and TC overholding charge are determined which can consequently decide the TC customer holding time at each depot in Stage 2. The TC fleet size is also determined so that the fleet size investment can be minimized at the first stage. The second stage is to maximise the expectation of job profits and TC over-holding profits after considered shipment transportation costs, leasing costs, cleaning costs, inventory costs, penalty costs and ETCR costs with respect to random container cleaning duration. For a given realized container cleaning durations ω, $Q(B,\mathbf{C},\boldsymbol{T_f},\hat{\mathbf{X}},\omega)$ is the optimal value of a mixed integer programming problem. When $B,\mathbf{C},\boldsymbol{T_f}$ are given, Eq. (5.2) below is to find the most profitable arrangements for all job fulfilments and ETCR activities.

$$\begin{aligned} Q(B,\mathbf{C},\boldsymbol{T_f},\mathbf{X},\omega) &= \sum_{k\in K}\sum_{(i,j)\in A_V}(X_{i,j}^k + Z_{i,j}^k)\cdot r_k + \sum_{k\in K}\sum_{(i,j)\in A_V}\sum_{\mathbb{Q}(k)=m_p} X_{i,j}^k\cdot t_p^h\cdot C_p^h \\ &-\sum_{k\in K}\sum_{(i,j)\in A_V} X_{i,j}^k\cdot(t_{ij}\cdot C_{ij}+C_n) - \sum_{k\in K}\sum_{(i,j)\in A_c} Z_{i,j}^k\cdot t_{ij}\cdot(C+C_{ij}) \\ &-\sum_{k\in K}\sum_{(i,j)\in A_V} W_{i,j}^k\cdot C_p - \sum_{r\in R}\sum_{(i,j)\in A_E} Y_{i,j}\cdot t_{ij}\cdot C_{ij} - \sum_{t\in T}\sum_{p\in P} S(p^t)\cdot C_h \end{aligned} \tag{5.2}$$

It can also be seen that the first term on the right-hand side in Eq. (5.2) represents the total revenue made in this period. The second term is the profit made from customer over-holding revenue. The third term is the transportation costs for self-container jobs. The fourth term is the transportation costs and leasing costs for leased container jobs. The fifth term is the penalty costs for rejected jobs. The sixth term is the ETCR costs. The last term is the inventory holding costs.

Constraints

Constraint 1: the customer over-holding time is determined by predefined TC hire free days and TC over-holding charge for all depots. We use function $J(C_p^h, t_p^f)$ to illustrate how customer over-holding time can be determined. In reality, $J(C_p^h, t_p^f)$ could be written in many ways, such as $t_p^h = (t_{LH} - t_p^f) * \theta$, where θ is a constant and $\theta \geq 0$. But for the purpose of simplifying the underlying model, it is kept as the simple form until the experiment section. In addition, all customer holding time is no longer than the longest customer holding time.

$$t_p^h = J(C_p^h, t_p^f),\ t_p^h + t_p^f \leq t_{LH},\ \forall p \in P \tag{5.3}$$

Constraint 2: for any customer demand, it cannot be split into several sub-orders. Namely, it can be fulfilled in only one way.

$$\begin{cases} X_{i,j}^k \in \{d_k, 0\} \\ Z_{i,j}^k \in \{d_k, 0\} \\ W_{i,j}^k \in \{d_k, 0\} \\ X_{i,j}^k + Z_{i,j}^k + W_{i,j}^k = d_k, (i,j) = (O_k, D_k), \forall k \in K \\ X_{i,j}^k = Z_{i,j}^k = W_{i,j}^k = 0, i = O_k, j \neq D_k \end{cases} \tag{5.4}$$

Constraint 3: represents the flow balancing at any depot node i considering laden, empty and inventory TC movements.

$$\sum_{k \in K} \sum_{(j,i) \in A_C} \sum_{i = p^t} F_{j,i}^k + \sum_{(j,i) \in A_E} \sum_{i = p^t} Y_{j,i} + S(p^t) = \sum_{k \in K} \sum_{(i,j) \in A_V} \sum_{i = p^t} X_{i,j}^k + \sum_{(i,j) \in A_E} \sum_{i = p^t} Y_{i,j} + S(p^{t+1}), \forall t \in T \tag{5.5}$$

Constraint 4: the initial inventory for every depot is equally distributed.

$$S(p^t) = B / |P|, \forall p \in P, t = 0 \tag{5.6}$$

Constraint 5: the sum of available self-owned TCs for all depots at any time are smaller than the predefined total fleet size with considering returned TCs from job-finishing, ETCR arrival and self-owned TC inventory.

$$\sum_{k \in K} \sum_{(j,i) \in A_C} \sum_{p \in P, i = p^t} F_{j,i}^k + \sum_{(j,i) \in A_E} \sum_{p \in P, i = p^t} Y_{j,i} + \sum_{p \in P} S(p^t) \leq B \ , \ \forall t \in T \tag{5.7}$$

Constraint 6: the self-owned TC flow arrived at any customer site node i should all return to the corresponding depot.

$$\sum_{(j,i) \in A_V} \sum_{i = m_p^t} X_{j,i}^k = \sum_{(i,j) \in A_C} \sum_{i = m_p^t} F_{i,j}^k \ , \ \forall k \in K \tag{5.8}$$

Finally, there are non-negative integers below.

$$X_{i,j}^k, \ Y_{i,j}, Z_{i,j}^k, W_{i,j}^k, \ S_i(t), F_{i,j}^k \in \mathbf{Z}^{\geq} \tag{5.9}$$

5.3 Problem solution

In response to stochastic programming problems, SAA (Sample Average Approximation) is a mature method which addresses the whole stochastic population by taking a certain number of realized sample processes of the uncertain parameters. Based on the law of Large Numbers, results obtained from SAA will converge to the optimal value of the real problem if the number of samples are large enough (Dong et al., 2015). However, evidences from rich studies show that a typical SAA is not suitable for problems with large scale of variables and constraints (e.g. Santoso et al., 2005; Crainic et al., 2011; Long et al., 2012). In this study, if the researched network consisting 10 nodes with 100 days, the number of decision variables would potentially to be 2,497,522 (22+5* C_{1000}^2). Since the number of samples is required to be sufficiently large to ensure the convergence of the results, the problem can easily go up to a very large scale when more demands and larger network are considered. Next:

Proposition 1. P0 is a NP-complete problem.

Proof. According to Pia et al. (2017), mixed-integer quadratic programming is in NP and proved as NP-complete. It is formed as:

$$\min \; x^{\mathrm{T}} H x + c^{\mathrm{T}} x$$

$$\text{s.t. } x \in P$$

$$x \in \mathbb{Z}^{p} \times \mathbb{R}^{q} \tag{5.10}$$

Where $H \in \mathbb{Q}^{n\times n}$, and it is symmetric. $c \in \mathbb{Q}^{n}$ and P is a polyhedron $p = \{x : Ax \le b\}$. For the second term in equation (5.2), if we replace t_p^h by $J(C_p^h, t_p^f)$ according to the equation (5.3), it can be re-written as $\sum_{k\in K} \sum_{(i,j)\in A_V} \sum_{Dp(m_p)=p} \sum_{\mathbb{Q}(k)=m_p} X_{i,j}^{k} \cdot J(C_p^h, t_p^f) \cdot C_p^h$. Therefore, give any forms of function (non-reciprocal) to $J(C_p^h, t_p^f)$, maximisation (equals to negative minimisation) the second term in equation (5.2) will be no simpler than $\max \mathbf{M}^{\mathrm{T}} H \mathbf{M} + c^{\mathrm{T}} \mathbf{M}$ where $\mathbf{M} = (\mathbf{X}(\omega_n), \boldsymbol{T_f}(\omega_n), \mathbf{C}(\omega_n))$ $H \in \mathbb{Q}^{(2|P|+|K|)\times(2|P|+|K|)}$ and $c \in \mathbb{Q}^{2|P|+|K|}$, $|P|$ is the total number of TC depots, $|K|$ is the total number of commodities. Compare to the standard form of mixed-integer quadratic programming, it follows the similar format but no simpler than the standard mixed-integer quadratic programming. Hence, the objective function **P0** is no simpler than the standard mixed-integer quadratic programming and **P0** is an np-complete problem. This completes the proof.

Hence, using SAA method indicates a combination of a large number of mixed-integer quadratic programming problem to be solved together. Realistically, it is not efficient and when the scale of the problem increases, computation complexity of this problem will limit SAA method obtaining a result in polynomial time. Alternatively, Progressive Hedging Algorithm (PHA) method is introduced to decrease the computation complexity and increase the efficiency of the solution method. Following the same principle, Progressive Hedging Algorithm (PHA) is transformed from SAA (Long et al., 2012) which tries to obtain the optimal value for its addressed problem through a series of realised sampling processes. Different from solving all realised samples jointly by SAA, PHA decreases the mathematical complexity by decomposing stochastic problems such as **P0** in to a number of smaller problems that are easier to solve. Specifically, as described in Chapter 3.2, PHA decompose **P0** into N independent scenario based problems while each of the scenario based problem models the time-space network for a given sample process (i.e. ω_n, and $1 < n < N$). Similarly, there are other methods such as L-shaped method (Slyke and Wets, 1969) and Benders decomposition (Santoso et al., 2005), but PHA is more appropriate for this model as the overall model is a two-stage one and the second stage is a mixed integer programming (Dong et al., 2015).

However, even though computation complexity can be largely decreased through PHA to decompose the large-scale problem into scenario-based one, every scenario-based problem is still hard to be solved mathematically. This is because, the decomposed sub-problems eliminated the disruption of sample difference caused by random parameters, but the structure of the time-space network at the lower level is still hard to be fixed due to the uncertain of the decision variables (C_p^h, t_p^f) at the upper level. Specifically, the self-owned TC return arc (i.e. A_C) set is dependent on the known of the customer holding policy related decision variables, and then the lower level decision variables are able to be solved but the upper level decision variables (as it is relevant to cost) can only be decided if the following lower level decision variables can result in the best operational profit. Thus, the upper level decision variables and lower level decision variables are hard to be jointly optimised but need to be solved sequentially. Therefore, instead of using mathematical solutions to jointly optimise both the upper and lower decision variables for each scenario-dependent optimisation, a math-heuristic technique is incorporated after **P0** is decomposed by PHA method. Particularly, we use Genetic Algorithm to randomly decide the value of upper level decision variables and optimise them according to a profit-based mathematical result from the optimisation of lower level (it will be elaborated later in section 5.3.2). By doing so, the PHA method is able to be implemented and lead to the overall optimisation for this stochastic mixed-integer multivariate optimisation problem. Figure 5.4 below shows the overall structure of the proposed solution method.

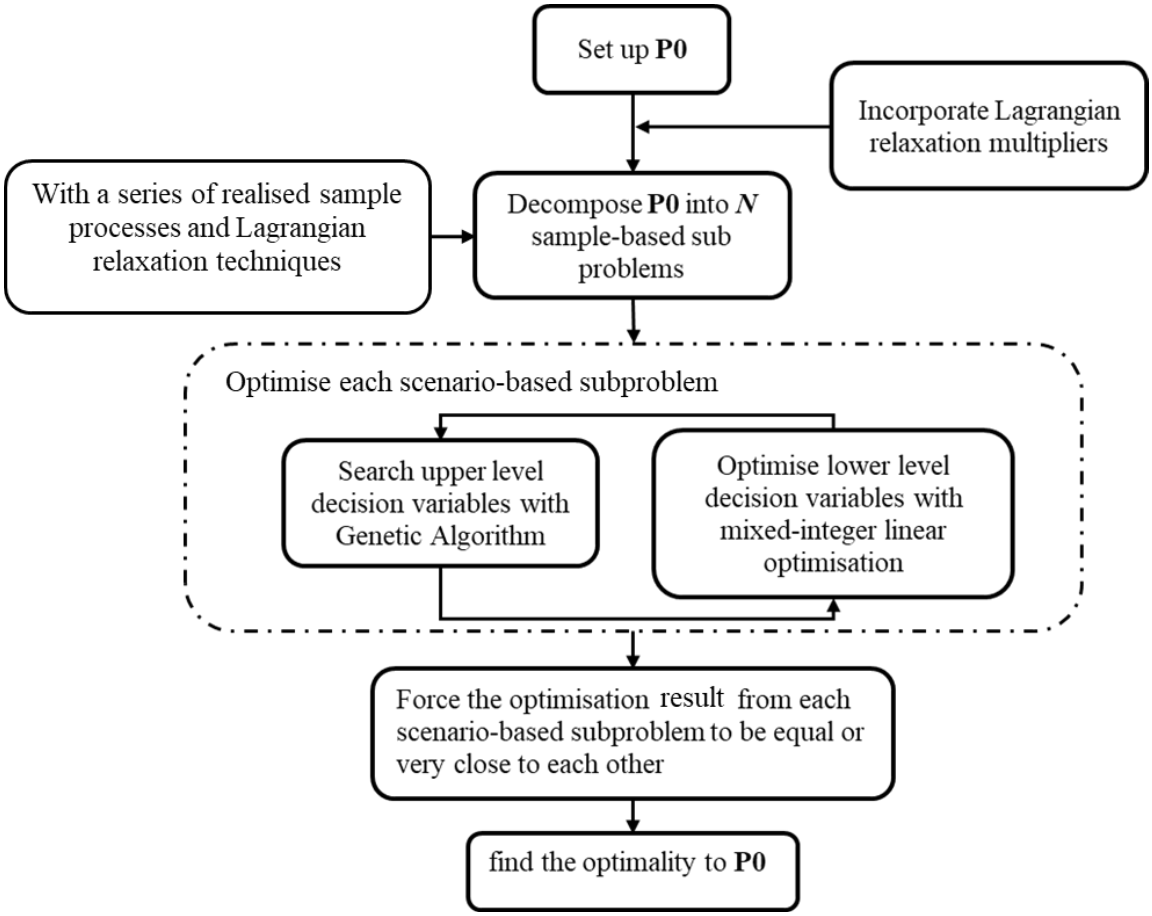

Figure 5.4 the overall structure of the designed solution method

In comparison with the PHA-based mathheuristic solution, a GA-based solution is also implemented to find the optimised TC fleet size and customer holding policies. Differently, instead of progressively approaching the optimality of the underlying decision variables with the help of Lagrangian multipliers, the GA-based solution is searching the optimalities (or near-optimality) through evolving the decision variables iteratively regarding the evaluation of the average profit across all samples.

Next, the designs of the PHA-based meth-heuristic solution and the GA-based solution are discussed respectively.

5.3.1 Progressive Hedging Algorithm (PHA)

In PHA, Lagrangian relaxation is employed to decompose the problem. Prior to the application of PHA algorithm, the scenario-dependent decision variables are introduced first. $\boldsymbol{T}_f(\omega_n) = \{t_1^f(\omega_n), \ldots t_p^f(\omega_n), \ldots t_{|P|}^f(\omega_n)\}(1 < n < N)$,

$\mathbf{C}(\omega_n)=\{C_1(\omega_n),...C_p(\omega_n),...C_{|P|}(\omega_n)\}(1<n<N)$, $B(\omega_n)(1<n<N)$, and **P0** can be substituted as following,

P1:
$$\max_{B,\mathbf{C},\boldsymbol{T}_f,B(\omega_n),\mathbf{C}(\omega_n),\boldsymbol{T}_f(\omega_n),\mathbf{X}(\omega_n)} Z(B,\mathbf{C},\boldsymbol{T}_f,B(\omega_n),\mathbf{C}(\omega_n),\boldsymbol{T}_f(\omega_n),\mathbf{X}(\omega_n))=$$
$$\frac{1}{N}\sum_{n=1}^{N}\left[-B(\omega_n)\cdot C_c+\frac{1}{T}Q(B(\omega_n),\mathbf{C}(\omega_n),\boldsymbol{T}_f(\omega_n),\mathbf{X}(\omega_n),\omega_n)\right] \tag{5.11}$$

s.t.

$$\mathbf{AX}(\omega_n)=\mathbf{B}(B(\omega_n),\mathbf{C}(\omega_n),\boldsymbol{T}_f(\omega_n),\omega_n)\ \forall n \tag{5.12}$$

$$B(\omega_n)=B\ \forall n \tag{5.13}$$

$$C_p(\omega_n)=C_p\ \forall n,p \tag{5.14}$$

$$t_p^f(\omega_n)=t_p^f\ \ \forall n,p \tag{5.15}$$

Eq. (5.10) above is the objective function to maximise the profits by taking customer overholding policies, TC fleet size and average of operational profits related to N different cleaning realisation. Eq. (5.12) comprises N copies of Eqs. (5.3) - (5.9). Eqs (5.13) - (5.15) represents that the first stage decision variables become scenario-dependent decision variables, which related to the given sample process of container cleaning ω_n. If we drop the constant coefficient $\frac{1}{N}$ and move the non-anticipativity constraints into the objective function based on Lagrangian relaxation method, we can have

P2:
$$\max_{\lambda_1,\lambda_2,\lambda_3}\max_{B,\mathbf{C},\boldsymbol{T}_f,B(\omega_n),\mathbf{C}(\omega_n),\boldsymbol{T}_f(\omega_n),\mathbf{X}(\omega_n)} Z(B,\mathbf{C},\boldsymbol{T}_f,B(\omega_n),\mathbf{C}(\omega_n),\boldsymbol{T}_f(\omega_n),\mathbf{X}(\omega_n),\lambda_1,\lambda_2,\lambda_3)=$$
$$\sum_{n=1}^{N}\left[-B(\omega_n)\cdot C_c+\frac{1}{T}Q(B(\omega_n),\mathbf{C}(\omega_n),\boldsymbol{T}_f(\omega_n),\mathbf{X}(\omega_n),\omega_n)\right]-$$
$$\sum_{n=1}^{N}\left\{\lambda_1(n)\cdot\left|B(\omega_n)-B\right|+\sum_{p=1}^{|P|}\left[\lambda_2(n,p)\cdot\left|C_p(\omega_n)-C_p\right|+\lambda_3(n,p)\cdot\left|t_p^f(\omega_n)-t_p^f\right|\right]\right\} \tag{5.16}$$

s.t.

$$\lambda_1(n)\geq 0,\lambda_2(n,p)\geq 0,\lambda_3(n,p)\geq 0\ \ \forall p,n \tag{5.17}$$

Eqs (5.12) -(5.15) (5.18)

To relax the non-anticipativity constraints, we use the Lagrangian multipliers times the absolute value of the difference between scenario-dependent variables and their corresponding first stage decision variables. The same method is used in the study of Dong et al. (2005), Long et al. (2012) for the purpose of simplifying the computer programming.

Followed, since **P2** comprises N different scenarios, each of the individual scenario can be indexed by $n \in (1, N)$ and write with the following form,

P3:
$$\max_{\lambda_1,\lambda_2,\lambda_3} \max_{B,\mathbf{C},\boldsymbol{T_f},B(\omega_n),\mathbf{C}(\omega_n),\boldsymbol{T_f}(\omega_n),\mathbf{X}(\omega_n)} Z_n(B,\mathbf{C},\boldsymbol{T_f},B(\omega_n),\mathbf{C}(\omega_n),\boldsymbol{T_f}(\omega_n),\mathbf{X}(\omega_n),\lambda_1,\lambda_2,\lambda_3) =$$
$$-B(\omega_n)\cdot C_c + \frac{1}{T}Q(B(\omega_n),\mathbf{C}(\omega_n),\boldsymbol{T_f}(\omega_n),\mathbf{X}(\omega_n),\omega_n) \tag{5.19}$$
$$-\lambda_1(n)\cdot\left|B(\omega_n)-B\right| - \sum_{p=1}^{|P|}\left[\lambda_2(n,p)\cdot\left|C_p(\omega_n)-C_p\right| + \lambda_3(n,p)\cdot\left|t_p^f(\omega_n)-t_p^f\right|\right]$$

s.t.

$$\mathbf{AX}(\omega_n) = \mathbf{B(}B(\omega_n),\mathbf{C}(\omega_n),\boldsymbol{T_f}(\omega_n),\omega_n\mathbf{)} \tag{5.20}$$

$$\lambda_1(n)\geq 0, \lambda_2(n,p)\geq 0, \lambda_3(n,p)\geq 0 \ \forall p \tag{5.21}$$

Further, as the third term and fourth term in Eq. (5.19) are non-linear, we introduce auxiliary variables α, α', $\boldsymbol{\beta}=\{\beta_p \mid p\in P\}$, $\boldsymbol{\beta}'=\{\beta'_p \mid p\in P\}$, $\boldsymbol{\gamma}=\{\gamma_p \mid p\in P\}$ and $\boldsymbol{\gamma}'=\{\gamma'_p \mid p\in P\}$ to linearise the two terms and **P3** can be re-written as,

P4:
$$\max_{\lambda_1,\lambda_2,\lambda_3} \max_{B,\mathbf{C},\boldsymbol{T_f},B(\omega_n),\mathbf{C}(\omega_n),\boldsymbol{T_f}(\omega_n),\mathbf{X}(\omega_n)} Z_n(B,\mathbf{C},\boldsymbol{T_f},B(\omega_n),\mathbf{C}(\omega_n),\boldsymbol{T_f}(\omega_n),\mathbf{X}(\omega_n),\lambda_1,\lambda_2,\lambda_3,\alpha,\alpha',\boldsymbol{\beta},\boldsymbol{\beta}',\boldsymbol{\gamma},\boldsymbol{\gamma}') =$$
$$-B(\omega_n)\cdot C_c + \frac{1}{T}Q(B(\omega_n),\mathbf{C}(\omega_n),\boldsymbol{T_f}(\omega_n),\mathbf{X}(\omega_n),\omega_n)$$
$$-\lambda_1(n)\cdot(\alpha+\alpha') - \sum_{p=1}^{|P|}\left[\lambda_2(n,p)\cdot(\beta_p+\beta'_p) + \lambda_3(n,p)\cdot(\gamma_p+\gamma'_p)\right] \tag{5.22}$$

s.t.

$$\mathbf{AX}(\omega_n) = \mathbf{B(}B(\omega_n),\mathbf{C}(\omega_n),\boldsymbol{T_f}(\omega_n),\omega_n\mathbf{)} \tag{5.23}$$

$$B(\omega_n) - B = \alpha - \alpha' \tag{5.24}$$

$$C_p(\omega_n) - C_p = \beta_p - \beta'_p \ \forall p \tag{5.25}$$

$$t_p^f(\omega_n) - t_p^f = \gamma_p - \gamma'_p \ \forall p \tag{5.26}$$

$$\alpha \geq 0, \alpha' \geq 0 \tag{5.27}$$

$$\beta_p \geq 0, \beta'_p \geq 0 \ \forall p \tag{5.28}$$

$$\gamma_p \geq 0, \gamma'_p \geq 0 \ \ \forall p \tag{5.29}$$

$$\lambda_1(n) \geq 0, \lambda_2(n,p) \geq 0, \lambda_3(n,p) \geq 0 \ \forall p \tag{5.30}$$

Then we use $Z(B, \mathbf{C}, \boldsymbol{T_f}, \mathbf{X}(\omega_n))$ or Z to denote an approximated profit solution for **P1**, and Z can be calculated by the solution to **P4** as,

$$Z(B, \mathbf{C}, \boldsymbol{T_f}, \mathbf{X}(\omega_n)) = Z(B, \mathbf{C}, \boldsymbol{T_f}, B(\omega_n), \mathbf{C}(\omega_n), \boldsymbol{T_f}(\omega_n), \mathbf{X}(\omega_n), \lambda_1, \lambda_2, \lambda_3) =$$
$$\frac{1}{N}\sum_{n=1}^{N} Z_n(B, \mathbf{C}, \boldsymbol{T_f}, B(\omega_n), \mathbf{C}(\omega_n), \boldsymbol{T_f}(\omega_n), \mathbf{X}(\omega_n), \lambda_1, \lambda_2, \lambda_3, \alpha, \alpha', \boldsymbol{\beta}, \boldsymbol{\beta}', \boldsymbol{\gamma}, \boldsymbol{\gamma}') \tag{5.31}$$

Proposition 2. (1) if $\lambda_1(n) = 0, \lambda_2(n,p) = 0 \,\&\, \lambda_3(n,p) = 0$ ($\forall p$), then $\frac{1}{N}\sum_{n=1}^{N} Z_n(B, \mathbf{C}, \boldsymbol{T_f}, B(\omega_n), \mathbf{C}(\omega_n), \boldsymbol{T_f}(\omega_n), \mathbf{X}(\omega_n), \lambda_1, \lambda_2, \lambda_3)$ is the upper bound to Z in **P1**; (2) $\frac{1}{N}\sum_{n=1}^{N} Z_n(B, \mathbf{C}, \boldsymbol{T_f}, B(\omega_n), \mathbf{C}(\omega_n), \boldsymbol{T_f}(\omega_n), \mathbf{X}(\omega_n), \lambda_1, \lambda_2, \lambda_3)$ converges to a lower bound to Z if $\lambda_1(n), \lambda_2(n,p) \,\&\, \lambda_3(n,p)$ are sufficiently large. Therefore, their relationship can be written as below:

$$\frac{1}{N}\sum_{n=1}^{N} \max\{Z_n(B, \mathbf{C}, \boldsymbol{T_f}, B(\omega_n), \mathbf{C}(\omega_n), \boldsymbol{T_f}(\omega_n), \mathbf{X}(\omega_n), 0, 0, 0)\} \geq Z \geq$$
$$\frac{1}{N}\sum_{n=1}^{N} \max\{Z_n(B, \mathbf{C}, \boldsymbol{T_f}, B(\omega_n), \mathbf{C}(\omega_n), \boldsymbol{T_f}(\omega_n), \mathbf{X}(\omega_n), \lambda_1, \lambda_2, \lambda_3)\} \tag{5.32}$$
$(\lambda_1, \lambda_2, \lambda_3$ represent suffciently large $\lambda_1, \lambda_2, \lambda_3)$

Proof. When $\lambda_1(n) = 0, \lambda_2(n,p) = 0 \,\&\, \lambda_3(n,p) = 0$ ($\forall p$), each scenario chooses their best customer overholding policies and TC fleet sizes, hence, the sum of the maximised profits over all scenarios are more than it from the original problem **P1** which requires all scenarios should have the same customer overholding policy and TC fleet size. Therefore, it is the upper bound of the optimality to **P1**. Conversely, when $\lambda_1, \lambda_2, \lambda_3$ are sufficiently large, $\lambda_1(n) \cdot (\alpha + \alpha')$, $\sum_{p=1}^{|P|} \lambda_2(n,p) \cdot (\beta_p + \beta'_p)$ and $\sum_{p=1}^{|P|} \lambda_3(n,p) \cdot (\gamma_p + \gamma'_p)$ are forced to be zero respectively. Thus, when $\lambda_1(n)\cdot\left|B(\omega_n)-B\right|$, $\sum_{p=1}^{|P|}\lambda_2(n,p)\cdot\left|C_p(\omega_n)-C_p\right|$ and $\sum_{p=1}^{|P|}\lambda_3(n,p)\cdot\left|t_p^f(\omega_n)-t_p^f\right|$ are equal to zero respectively, it is a feasible solution to **P1**, and it also leads to the lower bound. This completes the proof. This idea is inspired by the study of Dong et al. (2015).

According to **Proposition 2**, we can design two algorithms to update $\lambda_1, \lambda_2(n,p)$ and $\lambda_3(n,p)$. Such designs are based on the study of Long et al. (2012) and Dong et al. (2005). Notably, as there's no effective mathematical solutions to Z, the GA-based solution can only obtain a near-lower-bound and near-upper-bound through the updating of Lagrangian multipliers. Since the solution (Z') obtained from GA-based math-heuristic at each iteration is a feasible solution to the scenario-dependent problems, the lower bound (LB') and (UB') are satisfy the following equation (5.33), and so the two algorithms are detailed as follow.

$$\begin{aligned}&\frac{1}{N}\sum_{n=1}^{N}\max\{Z_n(B,\mathbf{C},\boldsymbol{T}_f,B(\omega_n),\mathbf{C}(\omega_n),\boldsymbol{T}_f(\omega_n),\mathbf{X}(\omega_n),0,0,0)\}\geq UB'\geq Z'\geq LB'\geq\\&\frac{1}{N}\sum_{n=1}^{N}\max\{Z_n(B,\mathbf{C},\boldsymbol{T}_f,B(\omega_n),\mathbf{C}(\omega_n),\boldsymbol{T}_f(\omega_n),\mathbf{X}(\omega_n),\lambda_1,\lambda_2,\lambda_3)\}\end{aligned}\tag{5.33}$$

($\lambda_1,\lambda_2,\lambda_3$ represent suffciently large $\lambda_1,\lambda_2,\lambda_3$)

Algorithm 1

First, we set $\lambda_1, \lambda_2(n,p)$ and $\lambda_3(n,p)$ as 0. $B(\omega_n)$, $\boldsymbol{C}(\omega_n)$ and $\boldsymbol{T}_f(\omega_n)$ can be obtained depending on each sample, and so as the average value $\hat{B}$, $\hat{\boldsymbol{C}}$ and $\hat{\boldsymbol{T}}_f$ across all samples. Followed, the λ_1, $\lambda_2(n,p)$ and $\lambda_3(n,p)$ increase independently depending on the absolute value of the difference between the sample results and average values from previous round respectively. Iteratively, this algorithm can be terminated when certain criteria are satisfied. The detailed step-by-step of this algorithm is as follows.

Step 1: Initialise λ_1, $\lambda_2(n,p)$ and $\lambda_3(n,p)$ as 0 ($\forall n,p$). Set iteration number k=1, constant ρ_B^k, ρ_C^k, ρ_T^k ($\rho_B^1 = \rho_C^1 = \rho_T^1$) and another constant α ($\alpha > 1$).

Step 2: Solve **P4** for each scenario and obtain the average value as $\hat{B}^{(k)}$, and $\hat{\boldsymbol{T}}_{\boldsymbol{f}}^{(k)}$ at kth iteration. Specifically, $\hat{\boldsymbol{C}}^{(k)} = \{C_p^{h(k)}\omega(n) \mid p = 1,2,\ldots,|p|\}$, $\hat{\boldsymbol{T}}_{\boldsymbol{f}}^{(k)} = \{t_p^{f(k)}\omega(n) \mid p = 1,2,\ldots,|p|\}$, where $\hat{B} = \frac{1}{n}\sum_{n=1}^{N} B(\omega_n)$, $\hat{\boldsymbol{C}}^{(k)} = \frac{1}{n}\sum_{n=1}^{N}\hat{\boldsymbol{C}}^{(k)}(\omega_n)$ and $\hat{\boldsymbol{T}}_{\boldsymbol{f}}^{(k)} = \frac{1}{n}\sum_{n=1}^{N}\boldsymbol{T}_f^{(k)}(\omega_n)$.

Step 3: Stop the current algorithm if either of the following criteria is satisfied:

(1) all $\sum_{n=1}^{N} |B^{(k)}(\omega_n) - \hat{B}^{(k-1)}| \le \xi$, $\sum_{p=1}^{|P|}\sum_{n=1}^{N} |C_p^{h(k)}(\omega_n) - \hat{C}_p^{h(k-1)}| \le \xi$, and $\sum_{p=1}^{|P|}\sum_{n=1}^{N} |t_p^{f(k)}\omega(n) - \hat{t}_p^{f(k-1)}| \le \xi$, ξ is a pre-defined very small positive number;

(2) There is no improvement for all three variables in L steps, L is a pre-defined positive integer;

Step 4: Update the Lagrangian multipliers from the second iteration with the follow rule: $\lambda_1^{(k+1)}(n) = \lambda_1^{(k)}(n) + \rho_B^{(k+1)} |B^{(k)}(\omega_n) - \hat{B}^{(k-1)}|$, $\lambda_2^{(k+1)}(n,p) = \lambda_2^{(k)}(n,p) + \rho_C^{(k+1)} |C_p^{h(k)}(\omega_n) - \hat{C}_p^{h(k-1)}|$, $\lambda_3^{(k+1)}(n,p) = \lambda_3^{(k)}(n,p) + \rho_T^{(k+1)} |t_p^{f(k)}\omega(n) - \hat{t}_p^{f(k-1)}|$ and $\rho_B^{(k+1)} = \alpha\rho_B^k, \rho_C^{(k+1)} = \alpha\rho_C^k, \rho_T^{(k+1)} = \alpha\rho_T^k$

Step 5: $k = k+1$, and then go to Step 2;

According to above description, $\lambda_1, \lambda_2(n,p)$ and $\lambda_3(n,p)$ are updated incrementally by the pre-defined parameters ρ_B^k, ρ_C^k, ρ_T^k. In order to increase the convergence speed, the value of ρ_B^k, ρ_C^k, ρ_T^k are increased with the same and a fixed positive slope α at each iteration. Alternatively, we can design a new algorithm to dynamically increase the pre-defined parameters ρ_B^k, ρ_C^k, ρ_T^k according to the largest difference among all the scenario-dependent best optimal values of objective function at iteration k. Since the ultimate goal of the optimisation is to force all the feasible scenario-dependent solutions are the same, so we update the Lagrangian multipliers with larger parameters when the current variations of the best optimal values are great among all samples, and we update the Lagrangian multipliers with smaller ones when the occasion is opposite. In this regard, the detail of Algorithm 2 is as follows:

Algorithm 2

Step 1: Initialise λ_1, $\lambda_2(n,p)$ and $\lambda_3(n,p)$ as 0 ($\forall n,p$). Set iteration number k=1, constant ρ_B^k, ρ_C^k, ρ_T^k ($\rho_B^1=\rho_C^1=\rho_T^1$) and another constant α ($\alpha>1$).

Step 2: Solve **P4** for each scenario and obtain the average value as $\hat{B}^{(k)}$, and $\hat{\boldsymbol{T}}_{\boldsymbol{f}}^{(k)}$ at kth iteration. Specifically, $\hat{\boldsymbol{C}}^{(k)}=\{C_p^{h(k)}\omega(n)\,|\,p=1,2,\ldots,|p|\}$, $\hat{\boldsymbol{T}}_{\boldsymbol{f}}^{(k)}=\{t_p^{f(k)}\omega(n)\,|\,p=1,2,\ldots,|p|\}$, where $\hat{B}=\frac{1}{n}\sum_{n=1}^{N}B(\omega_n)$, $\hat{\boldsymbol{C}}^{(k)}=\frac{1}{n}\sum_{n=1}^{N}\hat{\boldsymbol{C}}^{(k)}(\omega_n)$ and $\hat{\boldsymbol{T}}_{\boldsymbol{f}}^{(k)}=\frac{1}{n}\sum_{n=1}^{N}\boldsymbol{T}_f^{(k)}(\omega_n)$. Also, obtain the upper bound value (UB^k) and lower bound value (LB^k) at this iteration from all optimal values of objective functions for all samples. In particular, $UB^k=\max(Z_n^k)$ and $LB^k=\min(Z_n^k)$.

Step 3: Stop the current algorithm if either of the following criteria is satisfied:

(1) all $\sum_{n=1}^{N}|B^{(k)}(\omega_n)-\hat{B}^{(k-1)}|\le\xi$, $\sum_{p=1}^{|P|}\sum_{n=1}^{N}|C_p^{h(k)}(\omega_n)-\hat{C}_p^{h(k-1)}|\le\xi$, and $\sum_{p=1}^{|P|}\sum_{n=1}^{N}|t_p^{f(k)}\omega(n)-\hat{t}_p^{f(k-1)}|\le\xi$, ξ is a pre-defined very small positive number;

(2) There is no improvement for all three variables in L steps, L is a pre-defined positive integer;

Step 4: Update the Lagrangian multipliers from the second iteration with the follow rule:

$$\lambda_1^{(k+1)}(n)=\lambda_1^{(k)}(n)+\rho_B^{(k+1)}\,|B^{(k)}(\omega_n)-\hat{B}^{(k-1)}|,$$

$$\lambda_2^{(k+1)}(n,p)=\lambda_2^{(k)}(n,p)+\rho_C^{(k+1)}\,|C_p^{h(k)}(\omega_n)-\hat{C}_p^{h(k-1)}|,$$

$$\lambda_3^{(k+1)}(n,p) = \lambda_3^{(k)}(n,p) + \rho_T^{(k+1)} \,|\, t_p^{f(k)}\omega(n) - \hat{t}_p^{f(k-1)} \,|$$ and

$$\rho_B^{(k+1)} = \alpha\left(\frac{UB^k\text{-}LB^k}{\frac{1}{n}\sum_{n=1}^{N}|\,B^{(k)}(\omega_n) - \hat{B}^{(k-1)}\,|}\right)\rho_B^k, \quad \rho_C^{(k+1)} = \alpha\left(\frac{UB^k\text{-}LB^k}{\frac{1}{n}\sum_{p=1}^{|P|}\sum_{n=1}^{N}|\,C_p^{h(k)}(\omega_n) - \hat{C}_p^{h(k-1)}\,|}\right)\rho_C^k,$$

$$\rho_T^{(k+1)} = \alpha\left(\frac{UB^k\text{-}LB^k}{\frac{1}{n}\sum_{p=1}^{|P|}\sum_{n=1}^{N}|\,t_p^{f(k)}\omega(n) - \hat{t}_p^{f(k-1)}\,|}\right)\rho_T^k$$

Step 5: $k = k+1$, and then go to Step 2;

Next, the detailed description of the adopted math-heuristic method is going to be introduced for solving each scenario-dependent problem.

5.3.2 The adopted Math-Heuristic technique

According to the definition and characteristics of Math-Heuristic mechanism in previous chapter (Section 4.4.1), the overall solution design of this research is pinned down in the same category. Specifically, regarding the illustration of figure 5.4, the PHA method is firstly used to decompose the overall problem into a series of smaller scenario-dependent problems, then for each scenario-dependent problem, the GA search solution is used for finding solutions for upper level decisions variables (i.e. $B(\omega_n)$, $\boldsymbol{C}(\omega_n)$ and $\boldsymbol{T_f}(\omega_n)$) and the lower level decisions variables (i.e. $X_{i,j}^k$, $Y_{i,j}^t$, $Z_{i,j}^k$, $W_{i,j}^k$) are solved by integer optimisation techniques. In addition to the two algorithms used for updating the Lagrangian multipliers, figure 5.5 below illustrates how the math-heuristic method is applied to find the optimality for each scenario-based decomposed problems.

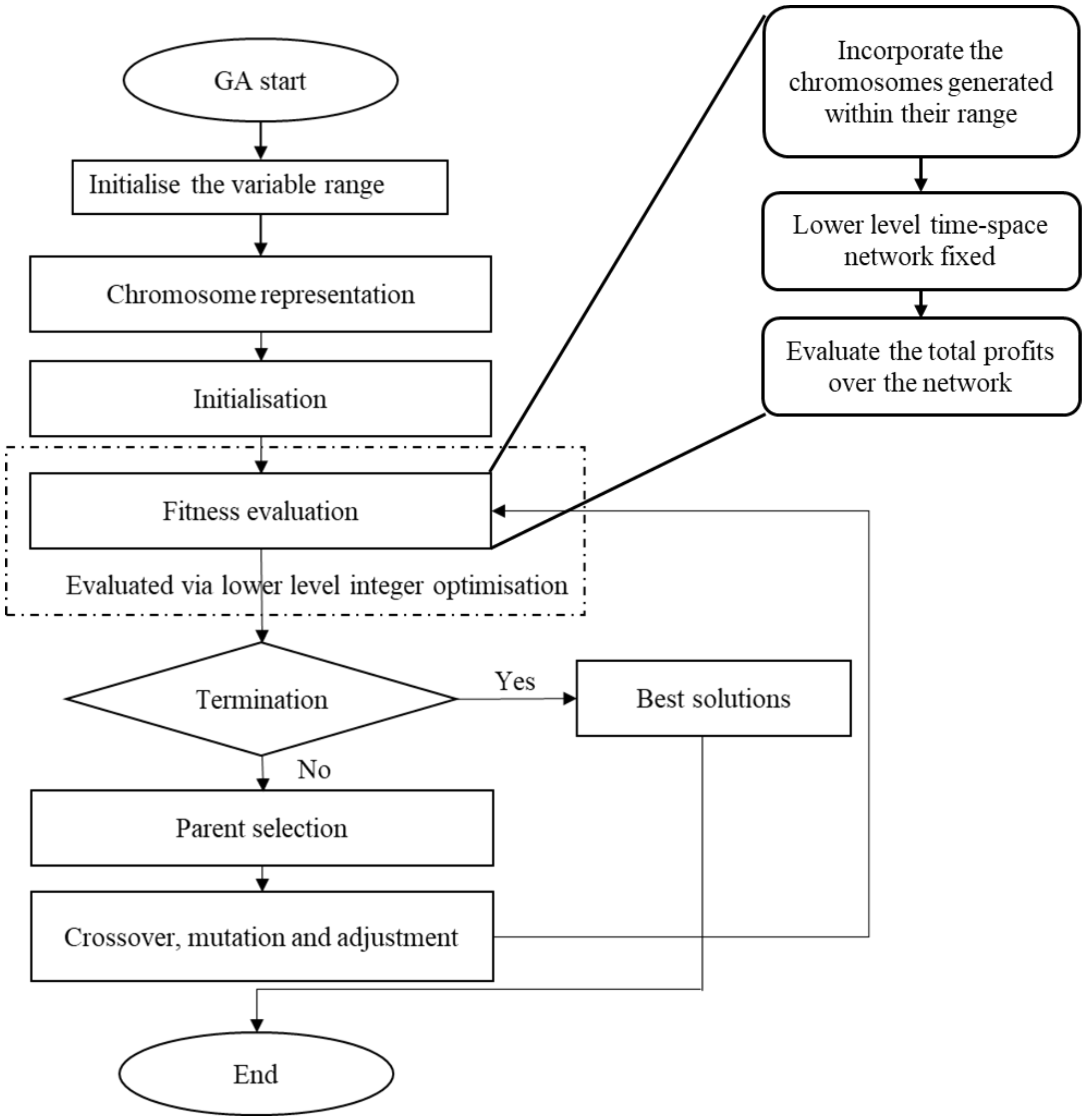

Figure 5.5 The solution for scenario-dependent problem

To start the GA search, the chromosome representation is firstly initialised. The candidate solutions consisting of values for overall fleet size (i.e. $B(\omega_n)$), values of free customer holding days and customer overholding charge for every depot. In particular, the later two are coded as vectors respectively. Also, constraints to define the valid chromosomes are designed as well. For the fleet size chromosome, same idea can be borrowed from the term LCCNO$_i$ in section 4.4.3 and a valid fleet size chromosome should be in the range $[0, \sum_{i \in P} \text{LCCNO}_i]$. For free days and overholding rates, the range of them are developed from industrial practice. The initial population of solutions is generated randomly. Since the optimization is to maximize profit, the higher the objective function value (profit), the higher the solution fitness value should be. To achieve this, $E(q)$ is used to represent the total profits under the solution represented by chromosome q, then the fitness value of chromosome q is defined as $F_q = E(q) - \min\{E(q): 1 \le q \le N_p\}$, where N_p is the population size. For the parent selection process, roulette wheel sampling is used; each of two parents is selected from a binary tournament, which randomly picks two individuals from the entire population and retains the fittest. The two selected parents generate a child using scattered crossover. Fourth, probabilities are selected for crossover and mutation, they are 0.8 and 0.05 respectively. Finally, all the parent and offspring chromosomes are sorted into descending fitness order and only the chromosomes with sequence numbers less than or equal to N_p are carried into the next generation. At last, the solution needs to be terminated when it runs up to 50 generations or the improvement in best fitness is smaller than 1/1000 for 10 consecutive generations. This setting is acquired from several pilot tests. Next, a series of numerical tests will be carried to highlight the insights of the underlying research problems.

5.3.3 The brief of the GA-based solution

In this section, how the formulated problem can be solved by the GA-based solution is going to be described. Since the procedure for this solution is very standard, and there are many discussions about processes of GA are presented previously (e.g. section 5.3.2 or section 4.4), only the key steps of this solution with respect to this problem and the associated parameter settings are introduced.

First, the upper level decision variables (TC fleet size and customer holding policies) are initialised with proper chromosome representations. Second, a certain series of samples will be realised and then chromosomes at the current generation will be incorporated to evaluate how much profit they can generate with respect to each realised sample and the deterministic time-space network. Third, all the obtained profits over all the samples will be averaged and then it will be regarded as the fitness result to determine how the current

GA process is going to be evolved or terminated. Figure 5.6 below shows the simple flow chart of this GA solution.

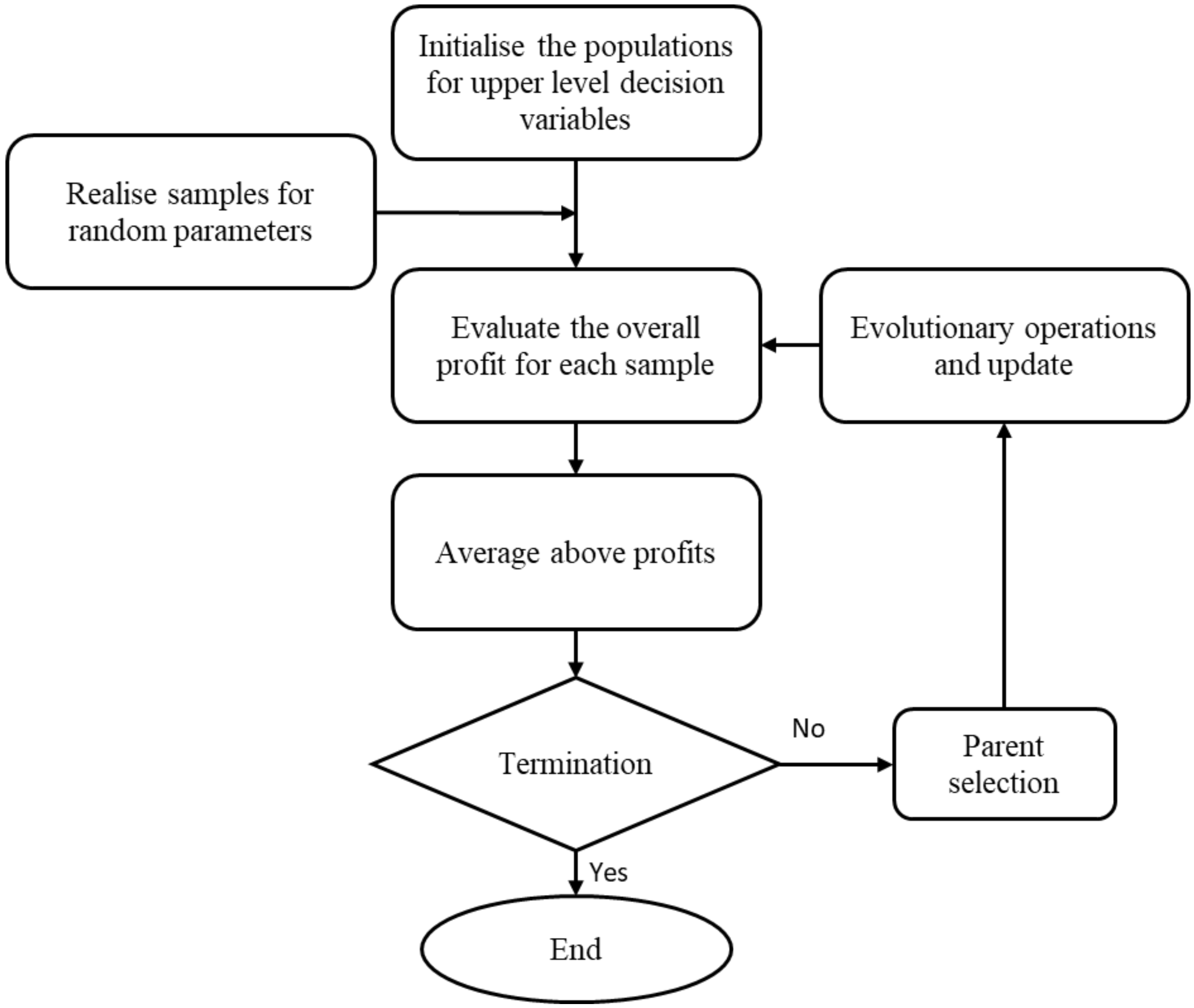

Figure 5.6 the GA-based solution

In addition, we set 15 as the initial population size for all three decision variables, termination criteria are either the solution runs up to 75 generations or there's not changes from the evaluation for 10 consecutive generations. Other settings for the GA solution is the same as section 4.4.2.

5.3.4 Verification &Validation (V&V) for the computerised model formulation and results

Similar to the V&V implementation process in Section 4.4.5, V&V activities in this chapter are implemented within the same paradigm discussed in Section 3.3.

First, since data used in this chapter is the same set as used in Section 4.4.5, therefore, the data validity activity is not going to be repetitively implemented.

Then, a full picture of TC network flow under a time-space manner is prepared. Alongside this, the overall structure of the two-stage model is conceptualised with both qualitative description and quantitative description (i.e. the mathematical equations). They are all approved by industrial experts for the representation of the real-time system as well as the feasibility of its intended purpose. Moreover, assumptions and abstraction of the real-system proposed in this Chapter is double validated, which refers to credibility of the conceptual model is coming from both existing studies and industrial voices.

To verify the computerised model based on the conceptual model, similar mechanisms used in Section 4.4.5 are employed. The computerised model is designed modularly based on different functions and addressed sub-problems. Walk-through analysis is conducted with the help of Matlab Debugger and manual calculation. Pilot tests are conducted with the some sample data, and then their results are compared across different proposed solution methods. Different from Section 4.4.5, the computerised model in this section is not simulation but analytical based, the solution part can be worked out with different solvers, therefore, both Cplex and Gurobi are used to compare the computation results.

At last, to verify the operational validity of the computerised model, industrial practitioners are again involved to validate the output behaviours, the rationale of different sensitivity analyses and the obtained implications.

5.4 Numerical tests

In this section, several experiments are carried to firstly compare the efficiency and quality of different solutions (GA-based one and the PHA-based ones) with given region, depot and customer site information. By varying the size of samples, a more suitable solution is chosen to conduct a series of further sensitivity analyses. Specifically, the sensitivity experiments are designed to unfold insights that affect the effectiveness and performance of TC customer holding policies and the potential solutions for improving customer over-held behaviour when external environment changes.

Data to be used in this section are derived from real-time operational records, which including, route network information, revenue for customer demands, journey duration and various cost components (Table 5.2). Also, according to the recent new TC purchase cost (£6,000+/TC) (Alibaba, 2018), the capital cost of holding TC is calculated by dividing the new unit purchase cost over the average unit life time (normally 20 years according to industrial practice) in days and round up to £1/day. This dataset is modelled in a hypothetical shipping network which consisting 3 regions, 9 depots and 21 different customer sites (Table 5.1).

Region Name	Depot Name	Customer Sites
Region A	Depot A1	Customer Site A1-1
		Customer Site A1-2
	Depot A2	Customer Site A2-1
		Customer Site A2-2
	Depot A3	Customer Site A3-1
		Customer Site A3-2
		Customer Site A3-3
Region B	Depot B1	Customer Site B1-1
		Customer Site B1-2
	Depot B2	Customer Site B2-1
		Customer Site B2-2
	Depot B3	Customer Site B3-1
		Customer Site B3-2
		Customer Site B3-3
Region C	Depot C1	Customer Site C1-1
		Customer Site C1-2

	Depot C2	Customer Site C2-1
		Customer Site C2-2
	Depot C3	Customer Site C3-1
		Customer Site C3-2
		Customer Site C3-3

Table 5.1 the regions, depots and customer sites network

According to the region and route difference of each demand, the job revenue is ranged from £250 to £700. The length of the planning horizon is 133 days, and 3,939 customer demands received. In line with the industrial practice, each self-container job will be associated with a random cleaning time which takes value uniformly from range [3,7] days. The model is coded by Matlab 2017b, and all the solutions for the lower (operational) level are implemented in IBM CPLEX and the solutions for the upper (strategic) level are solved by standard GA optimisation implemented in Matlab 2017b. The computer used to run the programme has an INTEL I7 3.6HZ 8 cores and 16 GB RAM.

Inventory cost per TC	**Self-container cost per TC**	**Leasing-container cost per TC**	**Cleaning cost per TC**	**Capital cost per TC**	**Penalty cost per job**
£3/day	£30/day	£80/day	£40	£1/day	£500

Table 5.2 the main cost components of TC operation

Furthermore, by borrowing the basic price and demand function from Burkett (2006), we assume the overholding duration (t_p^h) and overholding charge (C_p^h) follow the behaviour $t_p^h = M - t_p^f - \theta * C_p^h, \forall p \in P$, where M and θ are two control parameters. According to industrial practice and statistics from realistic data, we set M as 20 (which means no matter how cheap the overholding cost is, customers would overheld the container for more than 20 days), and θ is 0.2. Also, t_p^h and t_p^f should satisfy the constraint that $t_p^h + t_p^f \le 20$.

First, results (TC fleet size and customer holding policies) to each solution are demonstrated in table 5.3a (sample size is 15). Followed, we have varied the sample size

(N_S) to compare the efficiency of the two algorithms. Also, results from the two different PHA algorithms are compared to GA-based solution as well (table 5.3b).

	GA-based		**Algorithm 1 (PHA-based)**		**Algorithm 2 (PHA-based)**	
	Free days	TC overholding charge (£/day)	Free days	TC overholding charge (£/day)	Free days	TC overholding charge (£/day)
DepotA1	4	38	5	55	3	48
DepotA2	7	57	4	68	5	62
DepotA3	2	79	4	71	3	72
DepotB1	3	72	5	74	4	68
DepotB2	5	68	2	67	3	71
DepotB3	3	74	3	71	1	89
DepotC1	4	67	7	69	6	58
DepotC2	2	49	4	58	5	63
DepotC3	4	67	3	79	2	87
TC fleet size	207		189		216	

Table 5.3a the solutions to the problem from three algorithms when sample size is 15

N_S	**GA-based**		**Algorithm 1 (PHA-based)**			**Algorithm 2 (PHA-based)**		
	Obj. result	**Time (s)**	**Obj. result**	**diff. to GA (%)**	**Time (s)**	**Obj. result**	**diff. to GA (%)**	**Time (s)**
10	£1.69M	2,677	£1.86M	10.06%	15,337	£1.85M	9.47%	10,259
15	£1.72M	3,897	£1.89M	9.88%	21,365	£1.87M	8.72%	17,920
20	£1.77M	5,218	£1.89M	6.78%	28,784	£1.86M	5.08%	23,472
30	£1.74M	8921	£1.88M	8.05%	42,061	£1.88M	8.05%	34,637
40	£1.78M	13124	£1.90M	6.74%	74,315	£1.89M	6.18%	51,247

Table 5.3b the efficiency and results for SAA, PHA Algorithm 1 and PHA Algorithm 2 (M:million)

As table 5.3a indicated, the GA-based solution tends to have lower average customer holding cost (£63.4/day) and larger TC fleet size while the PHA-based solution tends to have lower average customer holding cost (£68.7/day) but smaller TC fleet size. Followed, in table 5.3b we can see, using the GA-based algorithm is more efficient but the optimisation results are much lower compare to PHA-based algorithms (PHA-based Algorithm 1 is 8.3% higher than GA and PHA-based Algorithm 2 is 7.5% higher than GA on average) when the sample size varies. One of the reasons lead to lower solution quality for GA-based algorithm is because the search of GA-based solution is less efficient within the range of the variables but the PHA-based one tends to provide better guide when updating the solutions iteratively. Even though the GA-based solution might have the chance to reach the same quality level of optimisation results (or even higher) as PHA-based ones if they can run to the same amount of time, they all terminated before they reached the maximal generations indicated such chance is very small. Moreover, comparing to the objective result of Algorithm 1, Algorithm 2 has slightly lower quality than Algorithm 1 (0.54% lower when sample size is 10, 1.06% lower when sample size is 15, and 1.59% lower when sample size is 20), however, the computation efficiency is much better especially when the sample size increased incrementally. The main reason of the better efficiency for Algorithm 2 is result by the faster convergence speed and the fewer iterations required to update the Lagrangian multipliers corresponding to the nonanticipativity constraints (Algorithm 2 takes 28% fewer iterations averagely than Algorithm 1). When sample size increased, this advantage become more significant. Due to the better efficiency provided by Algorithm 2 and the corresponding quality is also acceptable, it is used for carrying the rest of the experiments with sample size 15.

In order to seek the effectiveness of the joint optimisation for fleet size and TC customer holding policies, the optimised one is compared to the one with the current practice. Since the data used for this experiment are extracted and modified from realistic company's records. By averaging free days and the overholding charge for each depot. It can be regarded the current practice for customer holding policy. In addition, the current fleet size before optimisation is 252 in total and evenly distributed in 9 depots. With the built model, these two practices are compared by different metrics and summarised in table 5.4 below

	The current practice	The optimised model	
Items	**Results**	**Results**	**Difference to the current practice (%)**

Profits	£1.72M	£1.87M	+8.7%
Revenue	£2.27M	£2.30M	+1.3%
Overholding revenue	£1.43M	£1.32M	-7.7%
Self-container job cost	£1.01M	£1.24M	+22.8%
Leasing cost	£0.59M	£0.21M	-64.4%
Penalty cost	£68,000	£11,000	-83.8%
ETCR cost	£0.20M	£0.17M	-15.0%
Inventory cost	£1,321	£1,535	+16.2%
Capital cost	£33,516	£28,728	+14.2%

Table 5.4 the optimisation model vs. the current practice (M:million)

As above table illustrated, with the optimisation model, the profit is improved by 8.7% and it is majorly contributed by the increase of self-owned container jobs (22.8% increase in cost) and decrease of job rejections (83.8% decrease in cost). The optimisation model increased the overall fleet size to 901 and the associated costs increased by 25.3%, yet the inventory cost makes no significant increase, which is only £214 difference. As a result, the new practice is able to better satisfy the market with self-owned containers, therefore the notable increase of self-owned container cost (22.8%) and decrease of penalty cost (83.8%). Moreover, after adjusting the customer holding policy (customer holding free days + overholding charge rate), the new overholding revenue decreased by 7.7% but the overall profit is improved by 8.7%, which implies, it is worth evaluating the effectiveness of TC customer holding policy and it is possible that some revenue made by customer overholding would hamper the asset profitability as overall.

In order to take a further investigation about the customer holding policy, some deductions and sensitivity analyses are carried as well. Based on the optimised results from previous test, we have listed the changes (table 5.5) between the current customer holding policy and the old one for each depot and included the overall TC flow for the corresponding depot as well.

Depot	TC flow(TEU)			Changes of customer holding policy	
	Inflow	Outflow	Net flow	Free days	Overholding charge
Depot A1	434	365	69	3→3	£54/day→£48/day
Depot A2	425	391	34	4→5	£48/day→£62/day
Depot A3	449	527	-78	4→3	£58/day→£72/day
Depot B1	444	371	73	5→4	£64/day→£68/day
Depot B2	444	357	87	6→3	£66/day→£71/day
Depot B3	378	601	-223	4→1	£53/day→£89/day
Depot C1	476	391	85	4→6	£48/day→£58/day
Depot C2	451	367	84	3→5	£54/day→£63/day
Depot C3	410	541	-131	4→2	£72/day→£87/day

Table 5.5 the changes of customer holding policy with respect to TC flow

According to table 5.5, the first thing need to be pointed out is almost all the optimised overholding charges have gone up regardless the magnitudes. Which means, the optimised one is in favour of promoting a faster TC return to speed up the TC turnover. Especially, with respect to the TC flow situation for each depot, it is more significant of reducing the over-customer holding days for net-export depots (i.e. Depot A3, B3 and C3) than net-import depots. That is to say, the design of the customer holding policies is closely linked to the overall TC flows. Moreover, in Region A, B and C, the overall net regional TC flow can be further calculated out as 25, -63 and 38, and since TCOs can only carry intra-regional ETCR activities, the ability of re-balancing the intra-regionally inventory distribution through ETCR is thereby ranked as Region C > Region A > Region B. Accordingly, we can see it is more heavily to reduce the TC return duration for net-export depot in region B (free days reduced by 3 days and the overholding charge increased by £36/day) than the other two and the net-import depots in region B are also tweaked for faster TC turnover (both Depot B1 and B2 have reduced free days and increased overholding charge), so that more empty TCs can be ready for self-container jobs and

ETCR deployments. To further verify above conclusion, table 5.6 below illustrated the comparison between the performance of using uniform policy and location-based policy. It can be seen that the location-based on demonstrate better revenue-making in both job revenue (0.9% higher) and overholding-revenue (3.1% higher) while a great reduction in leasing cost (70.4% reduced) and penalty cost (80% reduced).

Items	The uniform policy	The location-based policy	
	Results	**Results**	**Difference to the current practice (%)**
Profits	£1.74M	£1.87M	+7.4%
Revenue	£2.28M	£2.30M	+0.9%
Overholding revenue	£1.28M	£1.32M	+3.1%
Self-container job cost	£1.15M	£1.24M	+7.8%
Leasing cost	£0.71M	£0.21M	-70.4%
Penalty cost	£55,000	£11,000	-80.0%
ETCR cost	£0.23M	£0.17M	-26.1%
Inventory cost	£1,438	£1,535	+6.8%
Capital cost	£0.11M	£0.12M	+9.1%

Table 5.6 Uniform TC customer holding policy vs. Location-based one (M:million)

In addition, by varying the price difference (between self-containers and leasing containers) and the sensitivity that customer overholding duration over overholding charges (i.e. different θ), more insights about the design of customer holding policy can be extracted.

Price difference	θ	Profit	Job Rev.	Overholding Rev.	Over. Rev./Job Rev. (%)
30	0.1	£2.01M	£2.32M	£1.98M	85.3%
30	0.2	£1.97M	£2.31M	£1.66M	71.9%
30	0.4	£1.91M	£2.31M	£1.48M	64.1%

50	0.1	£1.93M	£2.30M	£1.81M	78.7%
50	0.2	£1.87M	£2.31M	£1.57M	67.9%
50	0.4	£1.85M	£2.31M	£1.09M	47.2%
80	0.1	£1.89M	£2.18M	£1.67M	76.6%
80	0.2	£1.78M	£2.23M	£1.44M	64.5%
80	0.4	£1.81M	£2.26M	£1.09M	48.2%

Table 5.7 the sensitivity analysis (M:million)

Above table demonstrates three essential implications. First, in a long-term the effectiveness of customer holding policy is greatly influenced by the price fluctuation (market condition) of the leasing market. To be more explicitly, when leasing price is high in the market, the model tends to reduce the weight of the overholding job revenue, so that the self-owned TCs have a higher job turnover, and as a result, the overall profit can still maintain at a high level. For example, we can see when the cost of using leased TCs increased from £30/day more expensive to £80/day more expensive (+167%), the overall profit is only dropped by 5.7% (from £1.94m average to £1.83m average). This explains as the faster TC return increased the utilisation of self-owned TCs, hence the operational costs are less influenced by the increased price difference of using leased TCs. Regarding the weight ratio that overholding revenue versus job revenue, a significant decrease can be spotted along the increase of leasing cost, which means, the total overholding duration is reduced even though the overholding price is increased. Second, different values for θ indicates that how sensitive the price mechanism can influence demand pattern. A larger θ means customers are very sensitive to price changes which implies that customers' dependence on TCs as storage equipment are no longer that critical. This could be the emergence of new storage solution or other cheaper substitutions. While a smaller θ means the dependence from customers are essential and unreplaceable. As the test result indicated, when θ is low, increase the customer overholding price and decrease customer free days can greatly contribute to overall profit, as it provides the possibility to increase overholding revenue without compromising self-owned container utilisation (e.g. when θ is 0.1, the high percentage of overholding revenue over job revenue). While θ increases, it will be more competitive to make revenue from customer overholding, instead, they can consider lower down the customer overholding revenue to reduce inefficient TC flow caused cost increase and maintain the good performance of overall profitability (e.g. when

θ is 0.4, the corresponding profit). Third, in dealing with the fluctuated leasing market with dynamic TC storage dependence, matrix below illustrates the corresponding strategies (table 5.8).

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="2">Dependence on TC as storage</td></tr>
<tr><td>High</td><td>Low</td></tr>
<tr><td rowspan="2">Cost difference between using self-owned TC and leased-TC</td><td>High</td><td>Balance the policy for better TC flow efficiency</td><td>Use to policy to make the best TC flow efficiency</td></tr>
<tr><td>Low</td><td>Use the policy for best overholding revenue</td><td>Balance the policy for better TC overholding revenue</td></tr>
</table>

Table 5.8 the strategy matrix

According to implication 1 and 2, when the price difference is high, but the dependence is low, the key to maintain a good asset profitability is to largely reduce the overholding occurrence and increase the job-related profits. Conversely, the low-level price difference and high TC storage dependence provides the best opportunity that TC can be used for making both job and overholding revenue. When both the dependence and price difference is low, the cost for using non-self-owned TCs is low but it is very competitive for TC used as storage equipment. In this sense, it will be difficult for TCOs making high revenue from customer overholding because a little cost increase for overholding will largely reduce the overholding duration. For example, in table 5.6, when the price difference is 30 and θ is changed from 0.1 to 0.4, the profit dropped notably (from £2.01m to £1.91m) due to the overholding revenue decrease. Hence, strategy for this scenario has the goal of maintaining the overall profitability with optimal overholding income. Meanwhile, when the dependence and price difference are both high, over generating TC overholding revenue will hamper the job-related profits. For example, in table 5.6, when price difference increased from £30/day increased to £80/day while θ remain at 0.1, the total profit decreased significantly due to more expensive operational cost and rejected jobs. Hence, it is intrinsic to balance the policy that can reduce cost and contribute to better TC flow efficiency.

In addition, similar to actions carried in Chapter 4.5, Table 5.9 below has included the min and max results for each parameter change, which can further indicate that the quality of obtained solution and findings from Table 5.8 are enhanced with stronger evidence. For each parameter change, with respect to each random sample, the whole results (indicated by the range) have the same trend as their average result. Also, the difference for those results comparing to their corresponding average results are very small (less than 5%). In turn, the quality of the solution and observations are reinforced.

Price difference	θ	**Profit**		**Job Rev.**		**Overholding Rev.**		**Over. Rev./Job Rev. (%)**	
		min	**max**	**min**	**max**	**min**	**max**	**min**	**max**
30	0.1	£1.99M	£2.02M	£2.30M	£2.35M	£1.94M	£2.01M	83.2%	86.5%
30	0.2	£1.95M	£1.99M	£2.29M	£2.35M	£1.62M	£1.68M	68.9%	72.3%
30	0.4	£1.90M	£1.94M	£2.28M	£2.34M	£1.43M	£1.53M	63.6%	64.8%
50	0.1	£1.91M	£1.97M	£2.28M	£2.32M	£1.79M	£1.84M	78.2%	79.7%
50	0.2	£1.85M	£1.91M	£2.30M	£2.34M	£1.55M	£1.62M	66.3%	68.9%
50	0.4	£1.83M	£1.88M	£2.29M	£2.33M	£1.04M	£1.13M	46.2%	48.8%
80	0.1	£1.85M	£1.91M	£2.17M	£2.19M	£1.64M	£1.72M	75.4%	77.9%
80	0.2	£1.76M	£1.81M	£2.20M	£2.25M	£1.41M	£1.48M	62.8%	65.3%
80	0.4	£1.78M	£1.84M	£2.23M	£2.27M	£1.05M	£1.14M	47.5%	49.4%

Table 5.9 Highlights of ten-experiment with respect to each parameter change

5.5 Summary for this chapter

In this chapter, pricing policy for TC customer holding behaviour and TC fleet sizing are jointly investigated and optimised. In order to address the strategic/tactic level of management issues, a corresponding model is designed accordingly. With the designed numerical experiments, the PHA-based algorithm is shown better optimisation quality comparing to GA-based one within a reasonable computation time. In addition, some insights are obtained through different sensitivity analyses which revealed the negative influence of TC overholding phenomenon to the overall performance of TC asset management, the more effective way of designing the customer overholding policies, and how TC customer holding policies can be influenced by leasing market and customers' requirements. As a result, the associated strategies are proposed to fit the designed policies with different scenarios.

6. Conclusion, limitation and future research

In this section, the main findings with respect to the proposed research objectives and the overall journey of this PhD research are going to be concluded and presented. Followed, the limitations that might affect the quality, accuracy and effectiveness of this research are analysed and discussed as well. In the end, regarding what has been reached; what has been identified but not reached yet; and what could be touched but not significant now, the future research directions are pointed out with some initial research approaches.

6.1 Main findings

This thesis reflected the authors' four years PhD research efforts and outcomes in the TC asset management domain. As a highly specialised industry with great uncertainties, challenges such as unbalanced global trade, TC "quotation-booking", uncertain TC return and unreliable FFs are throughout TC asset management agenda and heavily limited TCOs' ability of increasing their TC asset management performance. To cope with those issues, the author is motivated to construct an improved **TC asset management that can support better decision-making, comprehensive evaluation and effective planning with thorough consideration of TCs' features and uncertainties.** Follow this motivation, this thesis identified its research gaps based on extensive literature review. Especially, by reviewing the existing studies about DCs and other relevant asset management researches, the research objectives are identified with appropriate development of its rationale. With respect to the constructed conceptual framework, the proposed research objectives are grouped into different planning levels and addressed with selected methodologies. At the operational level, the thesis constructed a two-stage simulation model that comprehensively emulated the key features of TC "quotation-booking" process with an inventory-control fashion. With the designed optimisation mechanisms, the proposed system is proven to increase TCs' profitability and utilisation while TCOs cope with daily job fulfilment, ETCR and FF choices decision-makings despite different kinds of uncertainties. Through various numerical and sensitivity analyses, this research has not only demonstrated its effectiveness in respond to the research objectives, but also revealed a number of research insights from TCOs' interests:

(1) The benefits of optimizing with respect to profits the choice of FF for empty TC repositioning (ETCR), rather than always using the most reliable and therefore expensive FF, have been demonstrated. From a strategic management perspective, this has important advantages beyond just profits as it means that the TCO is not dependent on just the most reliable FF. Even if the profit differences are small, having a feasible alternative opens up competition that could drive costs down and service quality up.

(2) The importance of including stochastic TC cleaning times has been demonstrated, as this is a source of uncertainty that leads to emergent leasing when TCs are held up. Experiments have shown that increased reliability (reduced variation) in cleaning times results in higher profits due to reduced emergent leasing due to increased certainty in planning. This means that TCOs should aim for more reliable (less variable) cleaning times and not just shorter cleaning times.

(3) Taking into consideration a demand forecast in the optimization can reduce excessive ETCR that would cause higher costs and less profits. Experiments with ETCR guided by regional average inventory levels (ETCR with RAIL), which emulates a natural industrial practise, have revealed that not taking a longer-term perspective in planning and simply repositioning TCs based on current inventory levels results in hugely excessive repositioning, as well as more emergent-leasing and this tends to be for expensive, longer distance jobs. The greatly reduced repositioning, and thereby greater profits, achieved with ETCR with adapted GA (AGA) using demand forecasts, demonstrates the validity of the novel approach presented here, and in particular the value of taking a longer-term perspective of net flows and inventory levels in planning ETCR. To this end TCOs should aim to develop their forecasting capabilities to achieve more accurate forecasts. Results have shown that the forecast horizons should correspond to the typical TC job plus cleaning times for best results, and it is recommended that TCO's monitor their average job plus cleaning times with a view to revising forecast horizons accordingly.

At the tactical and strategic planning level, this thesis designed a two-stage time-space network flow model to address TC fleet sizing and customer overholding issues with the consideration of unbalanced trade pattern and uncertain container return. With the constructed model, TCOs are able to optimise their fleet sizing and container overholding policies, and in turn, it can contribute to improved TC profitability and TC flow efficiency compare to general practice in a long run. Through the presentation of numerical experiment results, the proposed novel algorithm shows the ability of returning good quality results with acceptable computer time consuming. Also, the sensitivity analyses discovered:

(1) At the current situation, TC overholding phenomenon does generate juicy profits for TCOs, but it also covers the cons that how it can negatively influence self-asset utilisation and profitability as whole. Since customer overholding delays TC return duration and worsen the associated uncertainties, the revenue made from customer overholding is made from more chances of rejecting jobs or more expensive job cost because of TC leasing. As a result, the built model shows the great ability to improve the asset profitability and utilisation through adjusting TC fleet sizing and TC customer holding policy at depot level. By doing so, the strategy aims to promote the balance of maintaining high performance in making job-related profits as well as securing the profitable customer overholding business. In addition, the journey for TC return can be better monitored, controlled and evaluated with the proposed model even when environment changes.

(2) By linking the adjustment of customer holding policies with overall container flow network, it is spotted that the design of customer holding police is worth being more sophisticated with respect to different depots or even customer sites. Because different policies will directly influence the inward speed of TC flow for their corresponding locations, thus different demand pattern at different location can interplay with tailored location-based policy to determine the TC flow performance of each point. Due to unbalanced trade pattern, the location-based policy can be more effective in adapting the local demands and contributing to overall efficiency and profitability.

(3) Apart from local flow situation, customer holding policy also needs to be well adapted with the external market characteristics. Particularly, how much more expensive when using a leased TC for jobs or how likely customers will keep holding TCs when overholding charge varies. Regarding the numerical test results, the difference in cost of

using leased containers would decide whether the current customer holding policy is in favour of more overholding revenue or less operational cost. Specifically, when using leased containers is every expensive, the holding policy is moving to support better TC flow turnover and reduce the leasing-related cost. While the cheap leasing cost provides opportunity for making good customer overholding revenue in addition to the core business. However, since customers' dependence on TC as storage equipment will not remain unchanged, the dynamic about this dependence will affect the effectiveness of customer holding policy in pursuing its strategic interests. Specifically, a high dependence allows easier revenue making while a lower one makes it more effective for cost reduction.

In addition, table 6.1 below is created to have a better view of how the propose research objectives are achieved and what the main findings are respectively.

Planning levels	Research objectives	Response to research objectives	Key findings
Operational level	To build a model that can simulate, evaluate and optimise the TC "*quotation-booking*" process under various uncertainties, as well as giving decision support to job-fulfilment, ETCR arrangements and selection of freight forwarders	A two-stage inventory-control simulation model is created with featuring TC "quotation-booking" process and industry characteristics	1. Inventory control plays a key role in maintaining good TC asset management performance under various uncertainties; 2. Optimising FF choices enables more cost economic way of conducting ETCR activities; 3. It is worth investing in improving reliability of TC cleaning, where a more effective TC flow planning can be obtained, and higher asset profitability is thereby yielded; 4. Forecast ability is a key factor to TC asset management performance.
	To form the systematic way of setting up inventory control policies that can help TC operators cope with uncertainties and manage more efficient TC flow;	The inventory control policies are optimised with consideration of uncertain container cleaning and "quotation-booking" process	
Tactical/strategic level	To design TC flow network that meets both customer delivery and holding demand with optimised TC profitability at strategic viewpoint;	A two-stage TC time-space network model is constructed.	1. Instead of being the more customer overholding, the better asset profitability, TC container overholding needs to be

	To jointly optimise TC fleet size and TC customer holding pricing strategy which can control and lead the overall TC network flow with increased efficiency and profitability	TC fleet sizing and customer holding pricing policies are jointly optimised which can lead the time-space network model with improved profitability	well managed to achieve better TC asset management; 2. Instead of having uniform TC customer holding policy, a location-based one seems more suitable; 3. Effectiveness of TC customer holding policy is highly influenced by the price dynamics of leasing market and customers' reliance on TC as storage equipment.

Table 6.1 the response to research objectives and main findings

6.2 Limitations

Due to both subjective and objective reasons, there are several limitations existed in the whole research process. The author has concluded five main limitations, which include data limitation, method limitation, time limitation, verification limitation and industry limitation respectively.

Data limitation

Even though some V&V processes are carried for each subtopic study (see Chapter 4 and 5), data validity problem is still existed. Specifically, apart from manually screening out error and abnormal data, the rest of the available records are hard to be guaranteed their reflection of reality. Also, the available data can only reflect the operational situation in one company. Findings obtained, and conclusions made through this thesis may lose their application in other companies in the same industry, therefore, it is worth further efforts to validate them with more case studies.

Method limitation

To acquire the research outcomes, the chosen methods for model formulation and solution have their own limitations, in turn, application of research outcomes from this thesis could be reduced. For example, several assumptions are defined when both models are formulated in Chapter 4 and 5; the adaptive GA solution used in Chapter 4 can only return the near-optimal results; and the designed solution algorithm for Chapter 5 will still have computation intractability issue when the researched problem scale increased above a certain level. Moreover, heuristic solutions are proposed in Chapter 4 and 5 for evaluating the effects of changing input parameters. Since the proposed solutions to their corresponding formulation can only obtain the near-optimal result, they could have the possibility that the quality of the near-optimal solution may influence the confidence of the corresponding conclusions. For example, Figure 6.1 below shows the near-optimal solution decreased largely from Setting 1 (S1) to Setting 2 (S2), whereas the exact solution actually increased from S1 to S2. Even though, we have further included the solution range from all samples for each changing input parameters, it can only enhance the quality of the near-optimal solution not eliminating the risk of the risk mentioned above. Therefore, only if method is incorporated to find the exact solution, such risks cannot be avoided otherwise. In another words, the current research outcomes may not be effective enough.

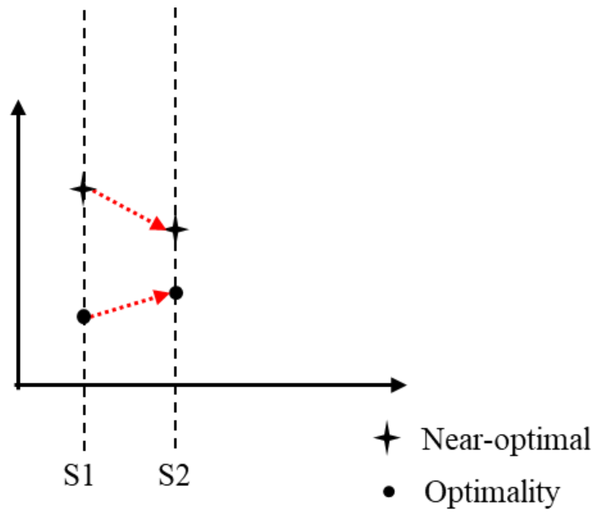

Figure 6.1 an example of sensitivity analysis for near-optimal solution and optimal solution

Time limitation

The whole research has been carried over 3 years including literature reviewing, data collection, model formulation, solution design, and experiments five main components. Due to the complexity and the scale of the fundamental knowledge body of the researched subject, some of the research components are very time consuming and time is not enough to cover everything. For example, due to time limit, only certain subtopics are focused and researched within the whole container asset management domain; it takes time for the author to learn and master different model techniques to get this research achieved, however, there are still a lot of other model and solution mechanisms that the author is not be able to learn and try but they could be performing better; Some of the experiment process is very time consuming so that the author is not be able to carry more dimensions and larger scale experiments. Therefore, the total available time is a constraint which limit the coverage, depth and performance of the overall research outcomes.

Access limitation

Even though this is an industrial-based research, the whole thesis is finished with open data without access to the case company. As a result, problems such as the data validity issues cannot be verified with people from the case company. Meanwhile, without an effective access, the author is hard to appreciate more company details such as some practices of the case company, customer characteristics or its supply chain configuration. This is also the reason that some of the methodologies only can be constructed upon some assumptions.

Industry limitation

The last limitation is coming from this particular industry. Although those test results, optimisation models can be good for the case company, it requires a lot of changes as well. Companies may need to change their governances and structures to implement some applications from the research outcomes. If the petrochemical industry is so dynamic that TCOs are too conservative to make a move, it will limit the feasibility of the research outcomes from this thesis. Also, if some of the optimisations may take time to reveal their contributions, it will be hard to draw TCOs attention, and they may feel less motivated to apply what are obtained from this research.

6.3 Future research opportunities

Due to above mentioned limitations, some of the issues mentioned during the research process are either not fully addressed or unaddressed. In addition, throughout the PhD research journey, more ideas are inspired during literature reviewing, model formulation and experiments as well. Therefore, three main directions are summarised below to illustrate how this thesis can be expanded in the future.

First, due to the large variety of commodities that TCs serving, types of TCs are also highly diversified. According to T-code classification (defined by TC pressure and shell thickness) (Exsif, 2018), there are more than 20 types of different TCs with different physical features and used for different purposes. Considering the complex TC "quotation-booking" and the uncertain TC cleaning caused by different commodities, it is worth researching heterogenous TC fleet management with consideration of type differences. Based on the research results from this study (especially Chapter 4), it then requires a more complicated simulation model that is able to deal with different demand pattern with the "quotation-booking" process, more constrained ETCR and different TC cleaning uncertainties regarding the features of different TC types.

Second, at the operational level and in respect of demand fulfilment, the current simulation model assigns different job types in a rule-based fashion. Instead, decisions on self-container jobs, planned-leasing jobs and rejected jobs could be optimized simultaneously and solved by mathematical programming techniques.

Third, at the strategic level, the current designed optimisation solution still has its limitation in addressing larger and more complex TC network model (e.g. time consuming and potential computational intractability). As a result, its practical application is limited accordingly especially if more detail is included by that time-space network model. Hence, it will be nice to have more efficient and powerful optimisation algorithms that can counter more complex and larger networks with quality results.

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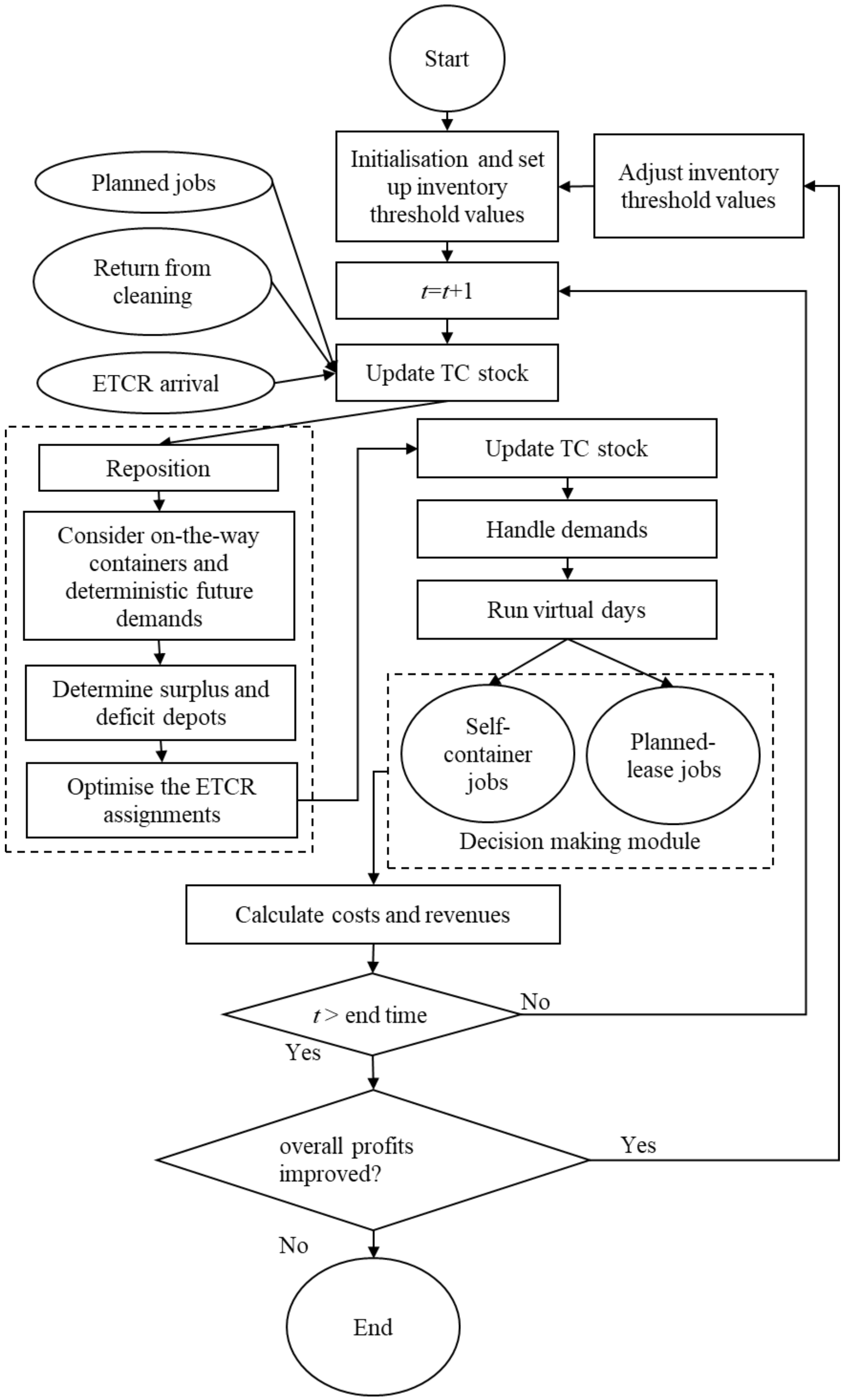
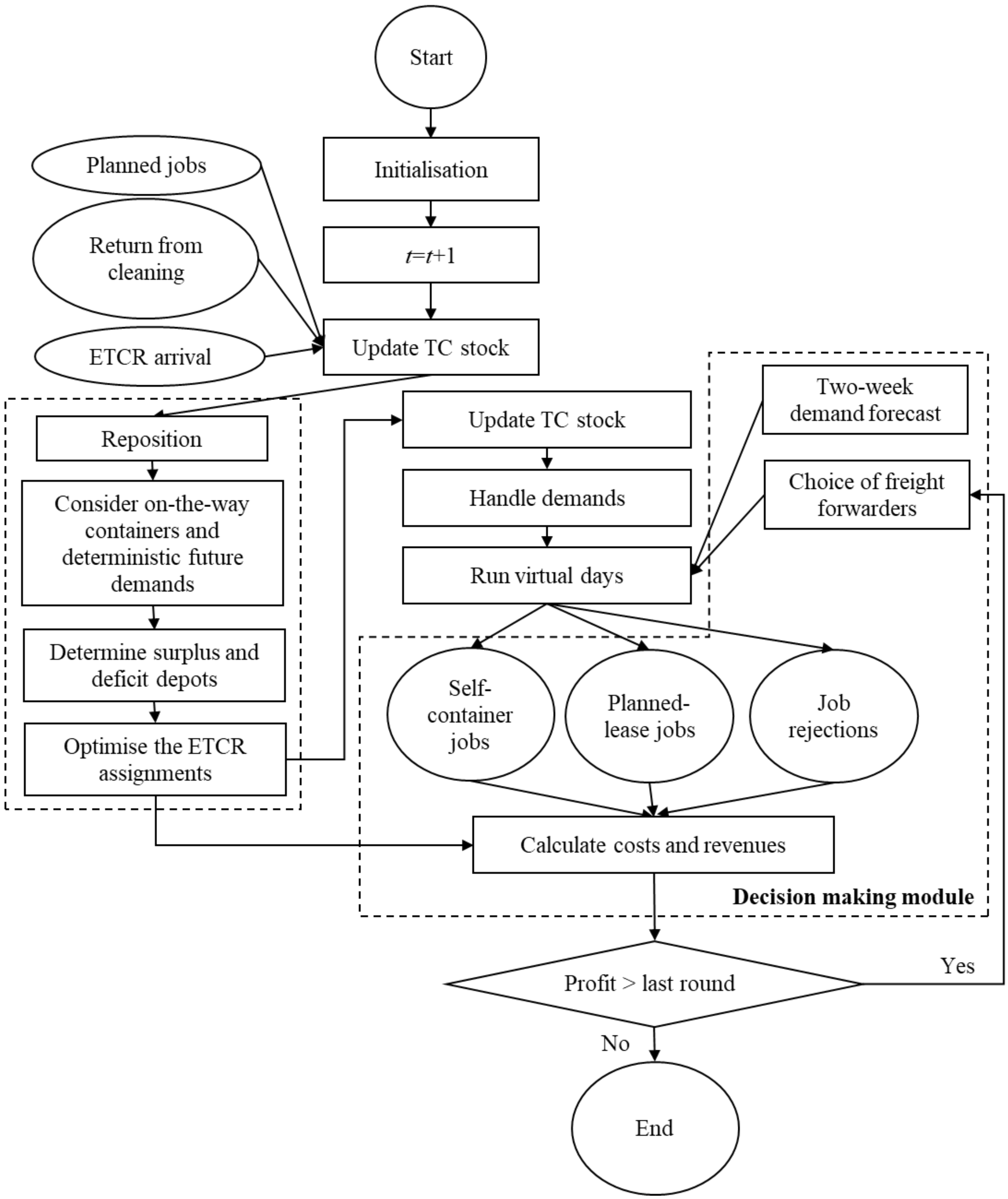
Appendix 1. The Simulation Module in Stage 1

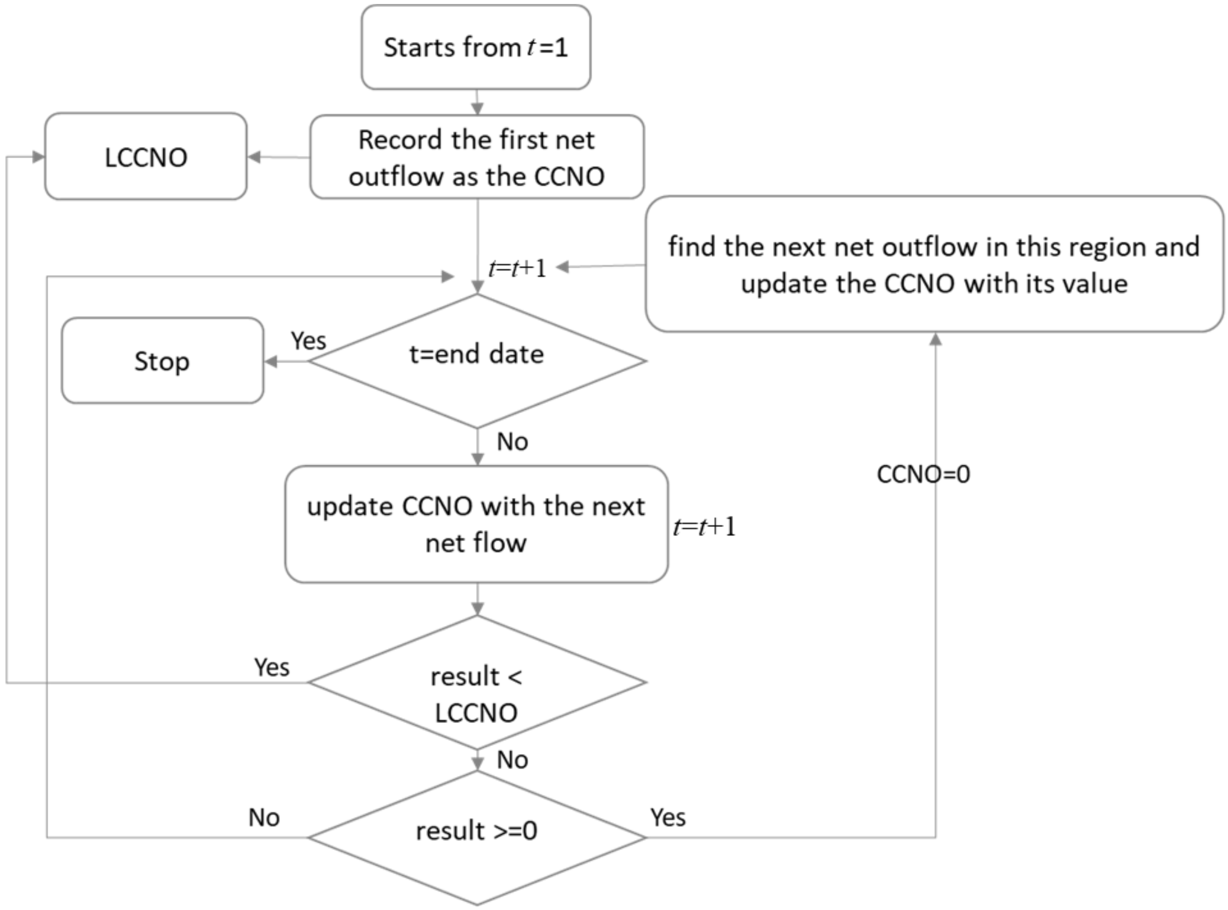


Start
Initialisation and set up inventory threshold values
Adjust inventory threshold values
Planned jobs
Return from cleaning
ETCR arrival
t=t+1
Update TC stock
Reposition
Consider on-the-way containers and deterministic future demands
Determine surplus and deficit depots
Optimise the ETCR assignments
Update TC stock
Handle demands
Run virtual days
Self-container jobs
Planned-lease jobs
Decision making module
Calculate costs and revenues
t > end time
No
Yes
overall profits improved?
Yes
No
End

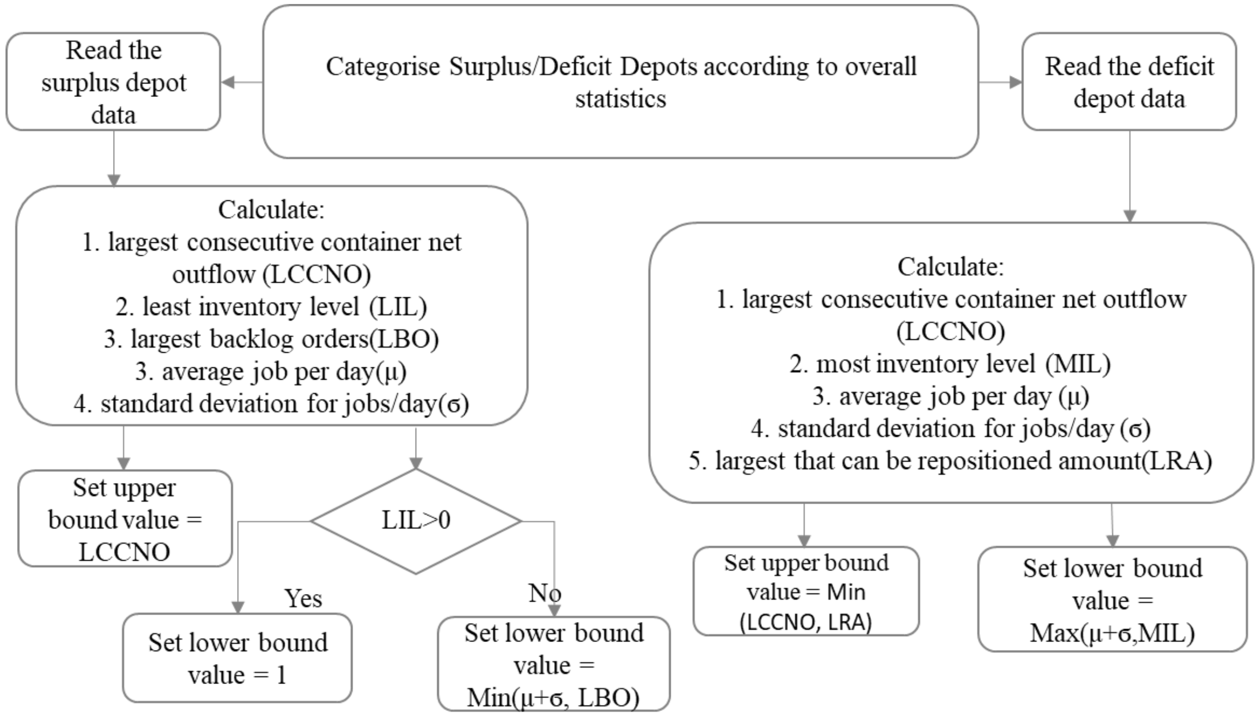
Appendix 2. The Simulation Module in Stage 2



Appendix 3. Process of obtaining LCCNO value



Appendix 4. The Heuristic Search Method



Appendix 5. The flow chart of AGA