https://doi.org/10.1016/j.eswa.2020.114526

MULTI-LEVEL FLEET SIZE OPTIMIZATION FOR CONTAINERS HANDLING USING DOUBLE-CYCLING STRATEGY

By

Mohammed Saeed El-Abbasy[a], Essmeil Ahmed[b], Tarek Zayed[c], Ghasan Alfalah[d], and Sabah Alkass[e]

[a] PhD Graduate (Corresponding Author), Department of Building, Civil and Environmental Engineering, Concordia University, H3G 1M8, Montreal, Quebec, Canada. msksia@yahoo.com

[b] PhD Graduate, Department of Building, Civil and Environmental Engineering, Concordia University, H3G 1M8, Montreal, Quebec, Canada. esm_662003@yahoo.com

[c] Professor, Department of Building and Real Estate (BRE), Hong Kong Polytechnic University, Kowloon, Hong Kong. tarek.zayed@polyu.edu.hk

[d] Assistant Professor, Deptartment of Architecture and Building Sciences, King Saud University, Riyadh, Kingdom of Saudi Arabia. galfalah@ksu.edu.sa

[e] Professor and Dean, College of Engineering, United Arab Emirates University, Alain, United Arab Emirates. alkass@uaeu.ac.ae

ABSTRACT:

Every few years, larger containerized vessels are introduced to the market to accommodate the increase in global trade. Although increasing the capacity of vessels results in maximizing the amount of imported and exported goods per voyage, yet it is accompanied with new challenges to terminal planners. One of the primary challenges is minimizing the vessel turnaround time with the least possible cost. In this context, this paper presents the development of a multi-level optimization model using the elitist non-dominated sorting genetic algorithm (NSGA-II) to determine the optimal or near-optimal fleet size combination of the different container handling equipment used in the terminal. The model aims to minimize two conflicting objective functions, namely, vessel turnaround time and total handling cost. Furthermore, the model considers a double-cycling strategy for the container handling process to achieve increased productivity and eventually more reduction in the vessel turnaround time. The model was implemented on a real-life case study to demonstrate its efficiency and the benefit of employing the double-cycling strategy compared with the traditional single-cycling strategy. The results demonstrated the efficiency of employing the double-cycling strategy by providing a reduction of above 20% in both the vessel turnaround time and the total handling cost and an increase of above 25% in the productivity when compared to the traditional single-cycling strategy.

Keywords: Container Handling, Fleet Size, Multi-level Optimization, NSGA-II, Double-Cycling.

1. INTRODUCTION

Since the 1960s, container terminals have always been the most common form of transshipment points to connect global trades. Global seaborne container trade comprises above 60% of the entire world seaborne trade, which was valued at around US$12 trillion in 2017 (Statista Research

Department 2020). Such transported containers generally come in two standard sizes of 20-foot equivalent units (TEU) or 40-foot equivalent units (2TEU). The quantity of cargo shipped by containers in vessels had increased from approximately 102 million metric tons in 1980 to 1.83 billion metric tons in 2017. Moreover, the global shipping container market was worth approximately US$4.6 billion in 2016 and is expected to reach US$11 billion by 2025 (Statista Research Department 2020). With the increase in the global volume of transported containers, there has been an increase in the complexity of port logistics (Stahlbock and Voβ 2008). This increase has forced shipping and port companies to search for strategies to accommodate such expansion. In addition, an unexpected increase in the demand for global trade requires rapid and efficient alternatives for shipment cycle. Among these alternatives, increasing the capacity of container vessels was one of the potential solutions. The recent generation of container vessels had a capacity of 18,000 TEUs compared to the 2,400 TEUs container vessels used in the 1970s. In 2017, the capacity increased to above 20,000 TEUs, and the latest largest vessel worldwide that was built in 2019 has a capacity of 23,000 TEUs.

It can be claimed that increasing the vessels' capacity can minimize the transportation unit cost as more containers are transported per voyage. In fact, doubling the maximum container vessel capacity over the past decade has reduced the total vessel costs per transported container by roughly a third; however, these cost savings decrease as the capacity of vessels increases (Merk et al. 2015). The reason for this is that larger vessels require adaptations of the handling equipment utilized and result in increased container traffic in ports. Additionally, the vessel turnaround time increases as its capacity increases. To address this issue, researchers started investigating different container handling strategies to minimize such turnaround time by improving the productivity of one or more of the major container handling equipment, namely, quay cranes (QCs), yard cranes (YCs), and yard trucks (YTs). One of the major strategies proposed was considering QCs "double-cycling" rather than the traditional "single-cycling." Improving the handling strategy without deciding upon a suitable balance between the numbers of utilized equipment can result in a loss of opportunity to achieve even further improvement in the productivity. Considering that there is a significant number of QCs, YTs, and YCs in the terminal, an optimum allocation of these resources to serve each arriving vessel becomes essential. Therefore, the main aim of this research is to develop a multi-objective resource allocation multi-level optimization model for container terminal handling using the elitist non-dominated sorting genetic algorithm (NSGA-II). The purpose of this model is to obtain optimal trade-offs between the two conflicting objectives of minimizing both the vessel turnaround time and the total handling cost. The model considers a "double-cycling" strategy for the YTs to achieve more improved productivity.

2. BACKGROUND

2.1 Container Terminals

In general, container terminals are divided into four zones, namely, berth or quay zone, transport zone, yard zone, and land zone. The berth zone is where the vessels are docked so that their containers' unloading and loading can take place by the QCs. Containers on a vessel are stacked into bays along the length of the vessel. Each bay consists of several rows across the vessel's width. Containers in each row are stacked vertically into several tiers above and/or below the vessel's hatch. The yard zone is the place where the imported and exported containers are stacked into what is known as storage yard (SY) by the YCs. The transport zone is the middle zone where the YTs transport the containers between the berth and yard zones. Finally, in the land zone, the imported or exported containers are transferred outside or inside the terminal via external trucks or trains.

QCs are the most expensive equipment for handling containers at the terminals. At the berth zone, a QC unloads an imported container from a vessel and loads it onto a YT or unloads an exported container from a YT and loads it onto a vessel. QCs move parallel to the length of the vessel on a railway, and each QC can lift two 20-foot containers simultaneously or one 40-foot container. YTs are used to transport the containers from/to the berth zone to/from the yard zone. Several types of YTs are available today in different ports, e.g., strudel carriers, truck vehicles, and automated guided vehicles (AGVs). Strudel carriers load the containers from the ground at the quay side and transport them to the SY. Consequently, they self-stack the containers at the SY or have their container unloaded by a YC at the SY. Truck vehicles are operated by drivers and are loaded and unloaded by QCs and YCs, whereas AGVs are automatically operated and controlled. A YC loads and unloads containers from or onto trucks going to or from the SY. YCs are designed to move horizontally along the storage lanes, and their trollies move perpendicular to the lane. They are designed to reach up to seven tiers of containers from the ground level. Two types of YCs are traditionally used, the rubber-tired gantry (RTGCS) and the rail-mounted gantry (RMGCs). RTGCs move on rubber tires and can make 360° turns, whereas RMGCs move along the blocks of a single row on a fixed rail.

2.2 Previous Studies

Minimizing vessels’ turnaround time has attracted the attention of several researchers in the past two decades by solving different assignment/allocation problems and equipment scheduling problems. The assignment/allocation problems include allocating berths to the arriving vessels (i.e., berth allocation problem, BAP), assigning QCs to the vessels (i.e., quay crane assignment problem, QCAP), and allocating containers to specific blocks of the SY (i.e., storage yard allocation problem, SYAP). The equipment scheduling problems include scheduling the different work tasks performed by the QCs, YTs, and YCs, i.e., quay crane scheduling problem (QCSP), yard truck scheduling problem (YTSP), and yard crane scheduling problem (YCSP). All these various problems were investigated either separately or by integrating two or more of them under a single platform.

With respect to the assignment/allocation problems, Correcher et al. (2019) proposed a mixed integer linear model and heuristic for optimizing BAP in terminals with irregular layouts. Schepler et al. (2019) solved the BAP by considering stochastic arrival times of vessels based on iterated tabu search and stochastic dynamic programming. Similarly, uncertainty in vessel arrival times was considered by other researchers to solve the dynamic BAP (Budipriyanto et al. 2015; Golias et al. 2009; Monaco and Sammarra 2007; Imai et al. 2001). Regarding the SYAP, different heuristics and algorithms were applied to optimize the SY layout and the containers' arrangements (Jacomino et al. 2019; Guerra-Olivares et al. 2018; Lin and Chiang 2017; Wang et al. 2014; Chen and Lu 2012; Bazzazi et al. 2009; Zhang et al. 2003). For QCAP, Lajjam et al. (2014) used the ant colony optimization technique to optimize the assignment of QCs to the vessels. A two-phase approach was presented by Karam et al. (2014) to assign QCs considering the availability of the YTs using mixed integer programming (MIP) and dynamic programming. Integration of both BAP and QCAP has also been addressed in the literature (Zheng et al. 2019a; Iris et al. 2015; Xiao and Hu 2014; Zampelli et al. 2013; Raa et al. 2011; Chang et al. 2010). Studies have also addressed the integration of both BAP and SYAP (Al-Hammadi and Diabat 2017; Peng et al. 2015; Safaei et al. 2010). Integration of the three assignment and allocation problems was proposed by Wang et al. (2018), wherein they used a column generation-based heuristic to optimize simultaneously the BAP, QCAP, and SYAP. Moreover, the assignment and allocation problems were integrated with the scheduling problems. Such integrations were investigated in the forms of integrated SYAP-YTSP (Wang et al. 2015; Xue et al. 2013; Lee et al. 2009), integrated SYAP-YCSP (Fan et al. 2017; Tan and He 2016), integrated BAP-QCSP (Jiao et al. 2018; Idris and Zainuddin 2016; Wu et al. 2014; Lee and Wang 2010), integrated QCAP-QCSP (Olteanu et al. 2018; Alsoufi et al. 2018; Diabat and Theodorou 2014), and integrated BAP-QCAP-QCSP (Kasm et al. 2019; Agra and Oliveira 2018; Grubisic and Maglic 2018).

There are also other efforts that were exerted to solve exclusively the scheduling problems of QCs, YTs, and YCs. Beginning with the YCSP, He et al. (2019) proposed a model for optimizing the efficiency of the YC work tasks under uncertainty using GA. An MIP model was developed by Luo et al. (2018) to achieve a flexible schedule for the YCs to minimize the amount of task overflow in loading and unloading operations and the distance covered by all the YCs. A two-stage stochastic programming model using the sample average approximation approach and GA was developed by Zheng et al. (2019b) to minimize the expected total lateness of the YCs work tasks. Sharif and Huynh (2012) compared centralized and decentralized approaches for modeling the YCSP to assess their relative performances and the factors affecting them. For the same problem, other different approaches have also been presented (He et al. 2013; Javanshir et al. 2012; Ng and Mak 2005). With respect to the QCSP, Hu et al. (2019) presented a stochastic programming model using the particle swarm optimization (PSO) algorithm to minimize the makespan of QCs services considering uncertain conditions. In addition, Msakni et al. (2018) proposed two methods to optimize the QCSP using MIP and binary search algorithm. Considering the stability constraints, Zhang et al. (2018) solved the QCSP using the bi-criteria evolutionary algorithm. In another study, Yu et al. (2017) considered tidal impact and fuel consumption to solve the QCSP using the local branching-based solution method and PSO. Several other algorithms and heuristics were also used to solve the QCSP (Al-Dhaheri and Diabat 2015; Sammarra et al. 2007; Ng and Mak 2006). Goodchild and Daganzo (2006) initiated a different approach to solve the QCSP through a double-cycling strategy for the QCs. This double-cycling strategy considers that the loading and unloading tasks of the containers onto and from the vessel by a QC occur consecutively. This strategy was used as an alternative to the traditional single-cycling strategy of starting loading the vessel after the completion of the entire unloading process. Through this strategy, the empty travel time of the QC to unload a new container from the vessel is minimized, which in turn increases its productivity and minimizes the vessel turnaround time. However, for vessels with deck hatches, applying the QC double-cycling strategy is not useful for the containers above a hatch, as all the containers above a hatch must be unloaded before applying double-cycling. Therefore, Zhang and Kim (2009) modified the QC double-cycling strategy in such a manner that it would no longer be limited to the stacks under a hatch but would also work for above-hatch stacks. For the YTSP, Niu et al. (2017) applied the PSO algorithm with a cooperative strategy to minimize the YT unload rate and their makespan. Earlier, Lee (2007) applied the exact dynamic programming algorithm to locate idle vehicles in tandem-loop AGV systems to minimize the maximum response time for all pickup requests. Grunow et al. (2006) proposed a simulation study of AGV dispatching strategies in container terminals where AGVs can be used for single- or double-carrier mode. Similar to the concept of incorporating the double-cycling strategy for the QCs introduced by Goodchild and

Daganzo (2006), Nguyen and Kim (2010) introduced a double-cycling strategy, but this time it was for the YTs. The strategy aimed at minimizing the empty trip times of the YTs with minimum delay for vessel operations. Again, the integration of these scheduling problems was reported in the literature in the forms of integrated YCSP-YTSP (Cao et al. 2017; Chen et al. 2014; Cao et al. 2010a), integrated QCSP-YTSP (Zhen et al. 2019; Kaveshgar and Huynh 2015; Cao et al. 2010b), integrated QCSP-YCSP (Kizilay et al. 2018; Wu and Wang 2018), and integrated QCSP-YTSP-YCSP (Jonker et al. 2019; Yue et al. 2019; Xiao et al. 2016; He et al. 2015).

Apart from the studies conducted to minimize the vessel turnaround times and the handling costs by improving the assignment/allocation and equipment scheduling problems, optimizing the fleet size was another direction to achieve such objectives as summarized in Table 1. For instance, Jingjing et al. (2018) developed an optimization model and a queuing model to minimize the total container handling costs and to determine the optimal number of twin-40ft QCs used considering the random arrival of vessels. Earlier, Pjevcevic et al. (2017) optimized the number of used AGVs using a decision-making approach based on data envelopment analysis. Furthermore, Said and El-Horbaty (2015) had developed a GA optimization model to minimize the container handling time by allocating a suitable number of QCs, YTs, and YCs to each of the arriving vessels. Multiobjective mathematical models were developed by Dkhil et al. (2013) to minimize the vessel turnaround time and to simultaneously minimize the number of AGVs utilized. A simulation model was developed by Azimi and Ghanbari (2011) to optimize the number of YTs used that minimizes the vessel turnaround time and increases the usage of cranes. Similarly, Kulatunga et al. (2011) determined through simulation the most effective number of YTs to minimize the handling process time considering the terminal layout. Bish et al. (2005) developed heuristic algorithms to minimize the vessel turnaround time by allocating a suitable number of YTs. In addition, Koo et al. (2004) used the heuristic tabu search algorithm to determine the minimum number of YTs required and the travel route for each truck while satisfying all the transportation requirements within the planning horizon.

Regarding the fleet size optimization models introduced in the literature, four major limitations were found. First, most of the studies (apart from Said and El-Horbaty 2015) focused only on determining either the optimal number of YTs or QCs to be utilized. Studies optimizing the number of YTs, for example, did not consider the effect of varying the number of QCs and YCs utilized on the vessel turnaround time. In fact, it is essential to examine the effect of varying the number of the three major handling equipment utilized as it could help in determining more cost-effective and productive solutions. Such improved solutions can further help in the better allocation of non-utilized equipment – that are already available in the terminal – to other arriving vessels. Second, the majority of studies (apart from Jingjing et al. 2018, Pjevcevic et al. 2017) did not consider optimizing the handling costs in their model. Handling costs can be reduced while increasing the productivity to a certain limit after which it can increase as more equipment is utilized. Therefore, determining the optimal number of utilized equipment with the aim of minimizing the vessel turnaround time solely cannot guarantee cost-effectiveness. Third, some studies (Pjevcevic et al. 2017; Said and El-Horbaty 2015; Kulatunga et al. 2011; Bish et al. 2005) considered deterministic cycle times for the handling equipment. In practice, the duration of the different work tasks performed by each handling equipment varies from one cycle to the other. Hence, neglecting the effect of such uncertainty on the duration would somehow result in impractical solutions. Finally, to the knowledge of the authors, no study was found in the literature that considered a double-cycling strategy for the handling equipment when optimizing the fleet size. Although determining the optimal number of utilized equipment can improve the productivity, yet incorporating the double-cycling strategy in the optimization process can result in further improvement and eventually a higher reduction in the vessel turnaround time as well as the total handling cost.

To address the abovementioned limitations, this study proposes a multi-objective multi-level optimization model to minimize the vessel turnaround time and the total handling costs. The optimization is achieved by determining the best combination number of QCs, YCs, and YTs to be utilized simultaneously while serving a given vessel. Furthermore, the model considers employing a double-cycling strategy for the YTs to further improve the handling process productivity. The model also considers the uncertainty in the durations of the different work tasks performed by each handling equipment to add practicality.

3. RESEARCH METHODOLOGY

As shown in Figure 1, the methodology followed in this research started by conducting an extensive literature review to identify the major container terminal handling components and the previous studies conducted with respect to the different terminal operations as well as fleet size optimization. Consequently, a mathematical modelling for the main objectives to be optimized, i.e., the vessel turnaround time and the total handling cost, using both the traditional single-cycling and double-cycling strategies was carried out. This was followed by introducing the optimization model formulation to identify the decision variables, the objective functions, and the constraints. Based on that, the development of the multi-level optimization model using NSGA-II was then presented. The NSGA-II goes through three optimization stages, namely, initialization, fitness evaluation, and generation evolution. The optimization takes place at each phase of the handling process individually to identify the set of the optimal or near-optimal solutions. Such a set represents different alternatives for fleet size combination, which maximizes the productivity and minimizes the unit cost at each phase. In the final optimization level, the outcomes of each phase are used as inputs to optimize the complete handling process. After the model development, the process of data collection to implement the model was discussed. The data include the durations of the different work tasks carried by each handling equipment as well as their hourly costs. Thus, the effect of using the double-cycling strategy was then tested against the single-cycling strategy. Such testing aims to demonstrate the capability of reducing both the vessel turnaround time and the total handling cost when using the double-cycling strategy. The model was then implemented on a real-life case study to demonstrate its capability in optimizing the fleet size. A comparison between using the traditional single-cycling and double-cycling strategies was conducted. In addition, another comparison was carried out between utilizing stochastic and deterministic durations. Since the results are always a set of non-dominated solutions, three approaches were adopted from the literature to select the best compromise solution. Finally, the conclusion derived from this study as well as the limitations and future recommendations are discussed.

4. MODELLING OF HANDLING STRATEGIES

This section presents the determination of the two main objectives to be optimized, i.e., the vessel turnaround time and the total handling cost, for both the traditional single-cycling and the double-cycling strategies. In summary, it is necessary to first determine the productivities of each handling equipment used in the handling process to obtain the vessel turnaround time. This is achieved by identifying the different work tasks carried by each equipment to obtain the cycle time. In each cycle, the QC, YT, and YC generally handle either two 20-foot containers simultaneously or one 40-foot container. Thus, each cycle load by any of the handling equipment is defined as 2TEU. By estimating the cycle time and the cycle load, the productivity of each handling equipment can be determined. Since the productivity of each type of equipment differs, the system productivity is defined according to the minimum productivity. Consequently, the vessel turnaround time is determined by estimating the system productivity and the total number of loads to be handled. On the other hand, the total handling cost is determined based on the determined vessel turnaround time in hours together with the estimated hourly cost of the handling process. The following two subsections explain in detail the modelling of the discussed concept. Table 2 shows the notation for all the parameters used to model the objectives.

4.1 Single-Cycling Strategy

Usually in the traditional single-cycling strategy, the arriving loaded vessel is first unloaded completely after which the loading process begins as illustrated in Figure 2a. Hence, the vessel turnaround time can be considered starting with the unloading of the first imported container and ending with the loading of the last exported container. The complete process can be divided into two phases, namely, unloading (phase A) and loading (phase B), as depicted in Figure 3a. As the unloading process precedes the loading process, the YT cycle will start by moving empty from the SY toward the berth side. Simultaneously, the QC starts its cycle by its empty movement toward the targeted container to be unloaded from the vessel. Once the YT arrives at the berth, the QC loads the container onto the YT. Subsequently, the YT moves loaded toward the import SY to be discharged by the YC and then travels back unloaded to the berth side to make another cycle. Meanwhile, the YC moves the container into the lane at the SY. The other YTs repeat this process until the last imported container is unloaded from the vessel. Consequently, the loading process starts by loading the containers on the YTs at the export SY by the YC, to be transported to the berth, where the QC loads the containers onto the vessel. In a manner similar to the unloading cycle, the QCs, YCs, and YTs will move back and forth repeating the loading cycle until the last exported container is loaded onto the vessel.

The cycle time (in minutes) of each equipment type in each phase is considered as the summation of the durations of the different work tasks carried in each cycle as formulated in Equations (1-6). Considering that each cycle load is 2TEU as mentioned earlier, the hourly productivity (in TEUs/hr) for each equipment type in each phase is formulated as shown in Equations (7-12). Accordingly, the system productivity for each phase is determined based on the minimum productivity among the three equipment utilized as formulated in Equations 13 and 14.

$$QC_U = t_{Q1} + t_{Q2} + t_{Q3} + t_{Q4} \quad (1)$$

$$QC_L = t_{Q5} + t_{Q6} + t_{Q7} + t_{Q8} \quad (2)$$

$$YC_U = t_{Y1} + t_{Y2} + t_{Y3} + t_{Y4} \quad (3)$$

$$YC_L = t_{Y5} + t_{Y6} + t_{Y7} + t_{Y8} \quad (4)$$

$$YTS_U = t_{S1} + t_{Q4} + t_{S2} + t_{Y1} \quad (5)$$

$$YTS_L = t_{S3} + t_{Q5} + t_{S4} + t_{Y8} \quad (6)$$

$$PX_A = \frac{120X_A}{QC_U} \quad (7)$$

$$PX_B = \frac{120X_B}{QC_L} \quad (8)$$

$$PY_A = \frac{120Y_A}{YC_U} \quad (9)$$

$$PY_B = \frac{120Y_B}{YC_L} \quad (10)$$

$$PZ_A = \frac{120Z_A}{YTS_U} \quad (11)$$

$$PZ_B = \frac{120Z_B}{YTS_L} \quad (12)$$

$$PV_A = Min(PX_A, PY_A, PZ_A) \quad (13)$$

$$PV_B = Min(PX_B, PY_B, PZ_B) \quad (14)$$

With respect to cost, the total hourly cost ($/hr) of each phase is based on the number of each equipment type utilized as well as the number of operators as formulated in Equations 15 and 16. Thus, the unit handling cost ($/TEU) of each phase can be determined by dividing the respective total hourly cost by the system productivity as formulated in Equations 17 and 18.

$$HC_A = X_A HC_X + Y_A HC_Y + Z_A HC_Z + O_A HC_O \quad (15)$$

$$HC_B = X_B HC_X + Y_B HC_Y + Z_B HC_Z + O_B HC_O \quad (16)$$

$$UC_A = \frac{HC_A}{PV_A} \quad (17)$$

$$UC_B = \frac{HC_B}{PV_B} \quad (18)$$

By estimating both the productivity of each phase and the number of loads to be handled in each phase, the vessel turnaround time using the single-cycling strategy (VT_S) can be determined as depicted in Equation 19. Simultaneously, the total handling cost using the single-cycling strategy (TC_S) can be determined by multiplying the number of loads to be handled in each phase by the respective unit cost as formulated in Equation 20. The VT_S and TC_S are considered as the main two objectives to be optimized from which the overall system productivity (PV_S) and the unit cost

(UC_S) using the single-cycling strategy can be also determined as presented in Equations 21 and 22, respectively.

$$VT_S = \frac{N_A}{PV_A} + \frac{N_B}{PV_B} \qquad (19)$$

$$TC_S = N_A UC_A + N_B UC_B \qquad (20)$$

$$PV_S = \frac{N_I + N_E}{VT_S} \qquad (21)$$

$$UC_S = \frac{TC_S}{N_I + N_E} \qquad (22)$$

4.2 Double-Cycling Strategy

To minimize the number of empty trips travelled by the YTs whether to be loaded or unloaded as in the single-cycling strategy, the main concept of the YT double-cycling strategy proposed in this study is to combine two QCs to work as a single unit with one crane discharging the vessel while the other loading it (Ahmed 2015). In other words, both QCs will serve the same YT where one will be unloading a container from the YT to be loaded onto the vessel and the other will be unloading a container from the vessel to be loaded onto the YT. Each YT will transport containers from the SY to the vessel and from the vessel to the SY in the same cycle. Just as with the QCs, two YCs will load and discharge the trucks at the SY. Accordingly, the first YC (i.e., YC1) starts the cycle by loading the YT at the export lane. The loaded YT then moves to the berth side to be discharged by the first QC (i.e., QC1). After discharging, the YT moves empty to the second QC (i.e., QC2) to be loaded. Next, it returns to the SY to unload the container at the import lane. Thus, the second YC (i.e., YC2) will discharge the YT, which will then depart empty to the export lane to be loaded by the first YC (i.e., YC1), thus starting a new cycle. Based on such complete cycle, the YT double-cycle time (YTD) will be as formulated in Equation 23. As shown in the equation, two new variables are introduced that represent the travel time by the YT between QC1 and QC2 (t_{S5}) and between YC1 and YC2 (t_{S6}). Furthermore, the equation does not include the empty travel times between the SY and QC zones as both unloading and loading processes are performed in the same cycle.

$$YTD = t_{Y8} + t_{S3} + t_{Q5} + t_{S5} + t_{Q4} + t_{S2} + t_{Y1} + t_{S6} \ldots\ldots (26)$$

Depending on the vessel size, in the double-cycling strategy, at least a pair of QCs and a pair of YCs are used and each pair acts as a single unit. Practically speaking, the double-cycling strategy cannot start immediately once a vessel arrives at the terminal. Since the arriving vessel will be usually loaded with imported containers, the exported containers will require some space before being loaded onto the vessel. Thus, the double-cycling strategy starts as a normal unloading single-cycling strategy for a certain time after which the double-cycling strategy will commence ending with a normal loading single-cycling strategy as depicted in Figure 2b. It is worth mentioning that based on experts' opinions, QCs should not cross each other and the clearance between any two adjacent QCs should be at least 40 ft (i.e., two bays). In this study, to add more safety margin, the minimum clearance between two adjacent QCs will be assumed to be three bays.

Three scenarios can be expected in the double-cycling strategy. The first one is when the number of containers to be imported is equal to that of the exported. The second is when the number of containers to be imported exceeds the number of containers to be exported, whereas the third scenario is the vice versa. In the three scenarios, the number of imported and exported containers to be handled in the double-cycling phase is modelled to be equal. If they are not equal, then the phase is not considered as a double-cycle. To explain the handling process in each of these three scenarios, let us assume that a single pair of QCs and YCs is used. Considering the first scenario, as shown in Figure 2b and depicted by a timeline in Figure 3b(i), the process begins with a single-cycle unloading mode (phase A) until the first three bays of the imported containers are unloaded by QC1 from the vessel and loaded at the import SY by YC2. Now, by having three bays' space available in the vessel, the double-cycling (phase C) can begin in which QC1 will change from unloading the imported containers to loading the exported containers on the vessel starting from the first bay to the last bay. Simultaneously, QC2 will begin unloading the imported containers from the fourth bay to the last bay. On the SY side, the YC2 will continue unloading the imported containers while YC1 will start loading the exported containers. Having more than one YT, each YT will make the double-cycling route as explained earlier (i.e., from YC1 to QC1 to QC2 to YC2 and then back to YC1 to start a new double-cycle). The QCs, YTs, and YCs will continue repeating their respective cycles until the last imported container is unloaded and transported to the import SY. At this point, the fleet size will be reduced to one QC (i.e., QC1) and one YC (i.e., YC1) to complete loading the remaining exported containers on the vessel as a normal single-cycle loading mode (phase B).

In the second scenario, the double-cycling phase will be delayed until an additional number of imported loads ($N_{A'}$) are unloaded. Thus, as shown in Figure 3b(ii), an additional time is added in phase A to represent the single-cycle unloading of $N_{A'}$. This is done for a reason to ensure that no conflict occurs in the double-cycling phase due to insufficient space on the vessel. The third scenario, where the number of exported containers is more than that of the imported, is similar to the first scenario, except that there will be an additional number of exported loads ($N_{B'}$) to be loaded toward the end of the process. Thus, as shown in Figure 3b(iii), there is an additional time added to phase B to represent the single-cycle loading of $N_{B'}$.

Irrespective of the double-cycling scenario that is applied, the cycle times, productivities, handling costs, and unit costs formulated in Equations (1-18) remain the same in phases A and B as they represent single-cycling. In phase C, the unloading and loading cycle times of the QCs and YCs also remain the same as formulated in Equations (1-4). However, in this double-cycle phase, each pair of QCs and YCs are utilized as a single unit to complete the loading and unloading process of one load each (i.e., 2TEU loaded and 2TEU unloaded) in one cycle. Accordingly, the productivities of QCs and YCs in phase C are determined as formulated in Equations 27 and 28, respectively. Using the YT double-cycle time in Equation 26, the productivity of YTs in phase C can be determined as formulated in Equation 29. As shown in the equation, the productivity is multiplied by two as two loads are handled in each cycle. To determine the system productivity and unit cost of phase C, the same concept applied in Equations (13-18) is repeated as formulated in Equations (30-32).

$$PX_C = \frac{120X_C}{QC_U} + \frac{120X_C}{QC_L} \quad (27)$$

$$PY_C = \frac{120Y_C}{YC_U} + \frac{120Y_C}{YC_L} \quad (28)$$

$$PZ_C = \frac{2\times120Z_C}{YTD} \quad (29)$$

$$PV_C = Min(PX_C, PY_C, PZ_C) \quad (30)$$

$$HC_C = 2X_CHC_X + 2Y_CHC_Y + Z_CHC_Z + O_CHC_O \quad (31)$$

$$UC_C = \frac{HC_C}{PV_C} \quad (32)$$

To generalize modelling the vessel turnaround time and the total handling cost using any of the three above-discussed scenarios, the additional numbers of loads to be imported ($N_{A'}$) and exported ($N_{B'}$) are first formulated as shown in Equations (33-36).

$$N_{A'} = 0 \qquad if\ N_I = N_E\ or\ N_I < N_E \text{.......(33)}$$

$$N_{A'} = N_I - N_E \qquad if\ N_I > N_E \text{.......(34)}$$

$$N_{B'} = 0 \qquad if\ N_I = N_E\ or\ N_I > N_E \text{.......(35)}$$

$$N_{B'} = N_E - N_I \qquad if\ N_I < N_E \text{.......(36)}$$

Thus, the vessel turnaround time, the total handling cost, the overall system productivity, and the overall system unit cost using the double-cycling strategy are formulated as shown in Equations (37-40).

$$VT_D = \frac{N_A + N_{A'}}{PV_A} + \frac{N_C}{PV_C} + \frac{N_B + N_{B'}}{PV_B} \text{.......(37)}$$

$$TC_D = (N_A + N_{A'})UC_A + N_C UC_C + (N_B + N_{B'})UC_B \text{.......(38)}$$

$$PV_D = \frac{N_I + E}{VT_D} \text{.......(39)}$$

$$UC_D = \frac{TC_D}{N_I + N_E} \text{.......(40)}$$

5. OPTIMIZATION MODEL FORMULATION

Before the development of the optimization model, the decision variables, the objective functions, and the constraints should be identified and formulated for both handling strategies. As discussed in details in the next section, the optimization process will be conducted on two levels. The first level will optimize each handling phase individually. Based on the non-dominated solutions obtained from the first level of optimization, the second level will optimize all phases simultaneously. The complete model formulation of each strategy and each optimization level is summarized in Table 3.

5.1 Decision Variables

Employing the single-cycling strategy, six decision variables that have a direct effect on the optimization objectives will be considered in the first level of optimization. Such decision variables represent the number of resources (i.e. handling equipment) utilized in phase A (i.e., X_A, Y_A, Z_A) and phase B (i.e., X_B, Y_B, and Z_B). The first level of optimization will result in a number of non-dominated solutions for each phase. Each non-dominated solution represents an optimal or near-optimal combination of the resources utilized for each phase. As there are only two phases in the single-cycling strategy, two decision variables will be considered for the second level of optimization. The first and second decision variables will represent the resource combinations optimized in the first level of optimization for phases A and B, respectively. Such resource combinations are defined by integer numbers. For instance, assuming that in the first level of optimization, 50 and 70 non-dominated solutions were obtained for phases A and B, respectively. Thus, the first decision variable of the second level of optimization will range from 1 to 50, and the second will range from 1 to 70. The same concept is applied for the formulation of the double-cycling strategy optimization model. In the first optimization level, there will be nine decision variables (three for each of phases A, B, and C). However, in the second optimization level, three decision variables will be considered representing the resource combinations optimized in the first level of optimization for the three phases.

5.2 Objective Functions and Constraints

As mentioned earlier, the aim of the current model is to minimize both the vessel turnaround time (VT) and the total handling cost (TC). To achieve this aim, the productivities and the costs incurred in each handling phase will be optimized first. As shown in Table 3, in the first optimization level, the main two objectives to be optimized will be the system productivity and the system unit cost in each handling phase; the former is to be maximized, whereas the latter is to be minimized. In the second optimization level, all the handling phases will be optimized simultaneously using the outcomes of the first optimization level to minimize both the VT and the TC.

Usually in any container terminal, the availability of QCs, YCs, and YTs is limited due to space constraints. Moreover, the traffic congestion caused due to the simultaneous use of large number of YTs can affect the productivity and hence increase the costs. In addition, in practice, sometimes more than one vessel can be served at the same time, which requires an appropriate planning for assigning the number of QCs, YCs, and YTs to each vessel. Consequently, the constraints set for the first optimization level will be such that the number of utilized resources in each handling phase does not exceed an assigned maximum number set by the terminal planner as shown in Table 3. On the other hand, the decision variables of the second optimization level depend on the number of non-dominated solutions that were obtained from the first optimization level in each phase as discussed earlier. Thus, the constraints set for the second optimization level will be such that the maximum number of non-dominated solutions obtained from the first optimization level is not exceeded.

6. MULTI-LEVEL OPTIMIZATION MODEL DEVELOPMENT

Two fleet size optimization models are developed using the NSGA-II technique, one for the single-cycling strategy and the other for the double-cycling strategy. The main aim of both models is to identify a set of optimal or near-optimal resource combinations (solutions) to be utilized in each phase that will minimize both the objectives of VT and TC simultaneously. Such a set of optimal or near-optimal solutions is known as the Pareto-optimal front in which they are non-dominated, i.e., no solution is better than the other with respect to both objectives.

Since the targeted two main objectives to be minimized are the VT and the TC, the simultaneous optimization of all the handling phases could have been performed on a single level. However, doing so would significantly increase the search space for the NSGA-II resulting in a possibility of losing the optimal or near-optimal solutions and a higher convergence rate. For instance, considering the double-cycling strategy, let us assume that the maximum number of QCs, YCs, and YTs assigned for phases A, B, and C are (10, 25, 20), (5, 30, 10), and (10, 25, 20), respectively. In that manner, the search space will consist of 37.5 billion possible resource combinations for all the three phases together. However, if each phase would be optimized individually as a first optimization level, the search space for phases A, B, and C will consist of 5000, 1500, and 5000 possible resource combinations, respectively. Such significant reduction in the search space can help in efficiently determining the optimal or near-optimal resource combinations for each phase. Accordingly, the outcomes of the first optimization level can be used as input to the second optimization level to support the findings of the optimal or near-optimal resource combinations for the three phases together with a smaller search space. For example, let us assume that the number of non-dominated solutions obtained from the first optimization level for phases A, B, and

C are 37, 26, and 41, respectively. Thus, the search space for the second optimization level will consist of 39,442 possible resource combinations for the three phases together. For that reason, it is opted in this study to use the discussed multi-level optimization approach as illustrated in Figure 4. As shown in the figure, each phase is first optimized separately to determine the optimal or near-optimal resource combinations that maximize the productivity and minimize the unit cost simultaneously. Such optimized resource combinations are then randomly integrated and used as input to the second optimization level to determine the optimal or near-optimal integrated resource combinations of all the handling phases that minimize both the VT and TC simultaneously.

For any of the optimization levels, the NSGA-II procedure passes through three stages, namely, (1) population initialization, (2) fitness evaluation, and (3) generation evolution. Figure 5 illustrates the detailed procedure of these three stages for the optimization of handling phase A as an example. Beginning with the first stage, the algorithm first identifies the handling phase and the genetic algorithm parameters. The handling phase parameters include the constraints represented by the maximum number of QCs, YCs, and YTs (i.e., x_A, y_A, and z_A, respectively) assigned to such phase as discussed earlier in Table 3. On the other hand, the genetic algorithm parameters include the defined population size (P), the number of generations (G), the crossover rate, and the mutation rate. Consequently, based on the population size defined, the algorithm generates random resource combinations (solutions) by altering the number of QCs, YCs, and YTs. Through this approach, an initial set of parent population for the first generation (PR_1) is created. Such a set evolves later through successive generations to obtain the optimal or near-optimal solutions that maximize the productivity and minimize the unit cost.

In the second stage, for each generated solution, both the objective values of PV_A and UC_A are determined using Equations 13 and 17, respectively. The determined objective values represent the fitness of the resource combinations generated for handling phase A by each solution compared with each other in the generation evolution stage. In the third stage, the non-domination rank and the crowding distance for each of the solutions generated in the parent population (PR_g) are determined. Consequently, a mating population (MT_g) is created by applying the crowded tournament selection. Then, a new child population (CH_g) is created by applying crossover on the MT_g after which mutation is applied on the created CH_g. The fitness of the CH_g is then evaluated as discussed in the second stage (i.e., fitness evaluation stage). At this point, two sets of populations are available, PR_g and CH_g, each of size P. Both PR_g and CH_g are combined to generate a new set of integrated population (IN_g) of size 2P. Next, the non-domination rank and the crowding distance for each of the solutions in the IN_g are determined. Accordingly, the solutions in the IN_g are ranked using the fast non-dominated sorting operation. Based on such ranking, the top P solutions in the IN_g are selected to be considered as the parent population of the next generation (PR_{g+1}). This process is repeated until the defined number of generations (G) is reached.

The expected output of this optimization process is a set of optimized P solutions that are divided into several fronts, which are ranked from 1 to F based on the non-domination concept. As such, all the solutions ranked into front 1 are considered as non-dominated among the full population size and are known as the Pareto-optimal front. These non-dominated solutions comprise the final result in which each solution represents a unique resource combination of QCs, YCs, and YTs in phase A with a maximized productivity and a minimized unit cost. As a reminder, none of these solutions are better than the other with respect to both objectives simultaneously. Finally, the same above-discussed NSGA-II optimization process is repeated for the other optimization levels.

7. DATA COLLECTION

To implement the developed models, different types of data were collected from a container terminal located in Tangier, Morocco, and operated by APM Terminals, which is a worldwide container terminal company based in the Netherlands. The terminal has a strategic location in the southern straits of Gibraltar through which more than 200 cargo vessels pass daily carrying global trade between Asia, Europe, Africa, and the Americas. It is considered as the third busiest container terminal port in Africa with direct services to 170 ports in 67 countries around the world and a capacity of around 1.8 million TEUs/year. The major types of data collected were the actual times of the different work tasks performed by each container handling equipment as well as their costs to be considered as an input for the developed models.

Starting with the times, a breakdown of the work tasks that make a complete cycle of each equipment individually was conducted. For instance, the QC unloading cycle was divided into (1) unloaded forward move toward the vessel, (2) container lifting from the vessel, (3) loaded backward move toward the YT, and (4) container loading on the YT. These four work tasks match the components of Equation 1 discussed earlier. The same concept was applied for the QC loading cycle as well as for the other two equipment's cycles (i.e., YC and YT). Accordingly, over several visits to the terminal, the times of the different work tasks were recorded using a stopwatch for a vessel with a capacity of 16,000 TEUs. The time of each work task is generally inconstant and changes from one cycle to another. Such changes occur due to several reasons such as the container location on the vessel or in the SY that varies in each cycle (different row, above hatch, under hatch, etc.). Human factor is another reason where the proficiency and consistency of equipment operators are considered. Furthermore, the idle times by any of the handling equipment were considered in the time recording process. To take into account such variations, the time recording was conducted more than once for each work task (i.e., over several repeated cycles). Having a set of different times for the same work task, the EasyFit® (Schittkowski 2002) distribution fitting software was used to fit the data. Table 4 summarizes the distribution type and the mean and standard deviation for each work task time for the different equipment and their respective cycle. The times for the YT loading and unloading work tasks carried whether by the QC or the YC are not presented in the table for the YT cycles as these work tasks are common and were already presented in the QC and YC cycles. Moreover, it is worth to mention that the visited terminal applies the traditional YT single-cycling strategy. As such, two additional work tasks were considered for the YT double-cycling strategy, the YT travel from QC1 to QC2 and from YC2 to YC1, i.e., t_{S5} and t_{S6}, respectively. The times of these two additional work tasks were estimated based on the distance travelled and the speed of YT and were considered as deterministic as presented in Table 4. Finally, some work tasks were not considered, such as the movements of the QCs or the YCs from one bay to another due to their minor values compared with the total cycle time.

Based on the collected durations of the different work tasks, the productivity of each equipment and its respective cycle were determined using Equations (7-12) and (27-29). To incorporate uncertainty into the productivities, the stochastic productivities were further determined using the

Monte-Carlo simulation technique. Accordingly, the distribution type and the mean, and standard deviation of the different productivities are summarized in Table 5.

Several cost items contribute to the total cost of the container handling process at the terminal, such as tug services, wharfage charges, berth hire, and the equipment used in handling. Since this study focuses on only the handling process, the costs of the main resources used to load or unload a vessel are considered (i.e., the QCs, YCs, and YTs and the operators). For confidentiality reasons, the financial department at the terminal provided the authors only with an approximate hourly ownership and operating costs for the handling components without the operators. These hourly costs were US$105, US$87, and US$60 for a single QC, YC, and YT, respectively. An additional 25% to these costs will be considered in this study to account for the operators' costs. It should be pointed out that the developed models are flexible to input different costs based on the terminal planner estimate considering the different geographical locations, time factors, and any other unaccounted costs that may contribute to the handling cost.

8. HANDLING STRATEGIES TESTING

Before implementing the developed optimization models, it is necessary to investigate the validity of employing the double-cycling strategy to provide reduction in both the VT and the TC compared with the single-cycling strategy. Thus, the modelling of both handling strategies discussed earlier is applied on three hypothetical case studies. For the three case studies, a vessel with a capacity of 18,000 TEUs is assumed to be served. Moreover, it is assumed that the number of loads to be imported (N_I) and exported (N_E) are equal. Hence, for the single-cycling strategy, both N_A and N_B are equal to 18,000 TEUs, resulting in a total of 36,000 TEUs to be handled during the entire process. For the double-cycling strategy, N_A, N_B, and N_C will be equal to 2400, 2400, and 31,200 TEUs, respectively. Since N_I is equal to N_E, both $N_{A'}$ and $N_{B'}$ will be equal to zero. To ensure fair and consistent comparison between both strategies, the equipment productivities shown in Table 5 will be assumed to be deterministic. Furthermore, the number of utilized equipment in each phase of each strategy in each case study will be assumed to be equal. This is to emphasize on illustrating the effect of employing the different handling strategies rather than the effect of utilizing different fleet sizes. As a reminder, the number of utilized QCs and YCs in phase C of the double-cycling strategy (i.e., X_C and Y_C, respectively) is defined as a pair of units.

Table 6 shows the results of using both strategies on the three case studies. The table shows the number of utilized equipment in each phase and their respective hourly productivity and unit cost. By applying the modelling equations of both strategies, the last four columns of the table present the VT, TC, PV, and UC for each strategy in each case study. It can be observed from the results that employing the double-cycling strategy provided a significant reduction in both the VT and the TC. Such reduction varies from 23 to 99 hrs for the VT (i.e., a reduction of 17%–22%) compared with the single-cycling strategy, given that the same number of equipment were utilized in both strategies. The same improvement trend is noticed when comparing the TC of both strategies where the cost savings varied from US$ 68,705 to 92,186. Furthermore, the productivity improvement reached up to 28% when employing the double-cycling strategy. These results validate the potential of accelerating the handling process while minimizing the costs simultaneously when applying the double-cycling strategy.

9. OPTIMIZATION MODEL IMPLEMENTATION

Three implementations were conducted on a real-life case study to demonstrate the capabilities of the developed optimization models in minimizing both the VT and TC. The first two implementations considered the optimization of each handling strategy using the stochastic productivities presented in Table 5. The third implementation considered optimizing the double-cycling strategy using deterministic productivities for comparison purposes. The case study considered is the 16,000 TEUs vessel from which the required data were collected as explained earlier. In the case study, N_I was equal to N_E (i.e., scenario 1). In any of the three implementations, three types of inputs were required. The first type of inputs are the equipment's productivities and the hourly costs collected. The second type of inputs consist of the genetic algorithm parameters (i.e., population size, number of generations, crossover rate, and mutation rate) for each optimization level as presented in Table 7. The final type of inputs are the constraints of each optimization level as presented in Table 7. As shown in the table, the constraints of the second optimization level depend on the number of non-dominated solutions obtained from each phase in the first optimization level. On the other hand, the output of each implementation will be a set of non-dominated solutions (Pareto-optimal front) that minimizes both the VT and TC. Each non-dominated solution determines the optimal or near-optimal assigned number of utilized equipment in each phase.

9.1 Single-Cycling Vs Double-Cycling

The implementation conducted using the stochastic productivities resulted in 12 and 18 non-dominated solutions for the single- and double-cycling strategies, respectively. The assigned number of equipment to be utilized in each phase for each solution and their corresponding optimized objectives for the single- and double-cycling strategies are shown in Tables 8 and 9, respectively. These results are also plotted in Figure 6 for a better illustration of the Pareto-optimal front of each strategy. At first sight of the figure, the optimization of both strategies resulted into almost a similar range of vessel turnaround times (approximately between 105 and 130 hrs) and system productivities (approximately between 250 and 300 TEUs/hr). This demonstrates the capability of the optimization model in minimizing the VT or maximizing the PV using the single-cycling strategy to a level almost similar to that of the double-cycling strategy. This is despite the fact that the latter strategy is more efficient than the former as tested earlier. To prove such efficiency, on a closer look, it is clear that employing the double-cycling strategy resulted in a significant cost reduction for almost similar vessel turnaround times compared with the single-cycling strategy. This can be explained in the view of using less number of equipment in each phase when employing the double-cycling strategy to achieve similar vessel turnaround times to those of the single-cycling strategy. For example, the non-dominated solution numbers 11 and 18 of the single- and double-cycling strategies, respectively (shown in Tables 8 and 9, respectively), resulted in an identical VT of 127.8 hrs. For these two solutions, the average numbers of QCs, YCs, and YTs utilized among the phases of the single-cycling strategy were 5, 5, and 19, respectively. On the other hand, the approximate average numbers of QCs, YCs, and YTs utilized among the phases of the double-cycling strategy were 4, 4, and 10, respectively. This implies that employing the double-cycling strategy reduced the fleet size by one QC, one YC, and nine YTs while achieving the same VT. Thus, a cost saving of US$ 70,924.3 was achieved. Another merit of reducing the fleet size using the double-cycling strategy is in having the opportunity to assign the additional non-utilized equipment to another arriving vessel while serving the existing vessel.

9.2 Stochastic Vs Deterministic

The third implementation conducted using the deterministic productivities for the double-cycling strategy resulted in 20 non-dominated solutions as shown in Table 10. As such, the Pareto-optimal front comparison between using the stochastic and the deterministic productivities for the double-cycling strategy is depicted in Figure 7. As shown in the figure, it can be observed that using the deterministic productivities resulted in some non-dominated solutions with lower vessel turnaround times or higher productivities than those obtained using the stochastic productivities. This is due to the fact that the use of deterministic productivities does not consider the probable worst-case scenarios that may arise in a certain cycle when the productivities of all or some of the equipment utilized are less than the average. On the other hand, the deterministic productivities also neglect the probable best-case scenarios that could occur when the equipment's productivities are more than average. This can be observed by having lower total handling costs using the stochastic productivities. For instance, solution number 1 using the stochastic productivities and solution number 8 using the deterministic productivities shown in Tables 9 and 10, respectively, provide the same VT of 105.2 hrs. Although the average number of utilized equipment among the three phases using the deterministic productivities is less than that in the stochastic productivities for these two solutions, the latter provides a lower total handling cost. This is because in phase C, the number of utilized equipment was more when using the deterministic productivities. In fact, phase C is the most critical as this is where the double-cycling takes place and hence the majority of loads are handled. Therefore, the stochastic productivities considered in phase C for solution 1 shown in Table 9 were higher than the average productivities considered in phase C for solution 8 shown in Table 10.

The fact of having some solutions with a lower VT using the deterministic productivities and a lower TC using the stochastic productivities cannot be generalized. After all, the Monte-Carlo simulation is a random process where a set of productivity values is available for each handling equipment and in each run a different value is considered. However, using the stochastic productivities can be deemed as a more practical option to consider real-life uncertainties.

9.3 Computational Efficiency

The three implementations were run on a laptop with a processor speed of 2.60 GHz and 6 GB RAM. The running time for implementation 1, 2, and 3 was 28 seconds, 73 seconds, and 46 seconds, respectively. To examine the computational efficiency of applying multi-level optimization, the three implementations were run again, however, as a single level optimization. As discussed before, the search space of applying single level optimization to our problem is huge. Accordingly, the population size and number of generations were increased and assumed to be 5,000 and 10,000, respectively, for the three implementations. The resulted Pareto-optimal fronts of the three implementations using the single level optimization were dominated by their counterparts using the multi-level optimization. Moreover, the number of non-dominated solutions obtained in the three implementations were less due to the high convergence rate. This is despite the fact that the population size and number of generations were increased. In other words, due to the significant large search space, the population size and number of generations still need to be increased to avoid being trapped in local optima. Finally, the running time for implementation 1, 2, and 3 using the single level optimization was 719 seconds, 1317 seconds, and 904 seconds, respectively. This demonstration shows the better and faster performance of the optimization process when it is carried out on multi-level.

9.4 Best Compromise Solution Selection

Since the results of the developed optimization models are a set of non-dominated solutions, the decision-maker has several options to select the solution that will satisfy his/her preference. Should the decision-maker's ultimate preference be minimizing TC, then the solution with the minimum cost among the non-dominated solutions set shall be selected. The same concept is applied if the decision-maker's main concern is minimizing the VT regardless of the cost. Besides these two extreme options, a third option is available that provides the best balance between the two conflicting objectives of VT and TC. This option will be known as the best compromise solution (BCS). Several approaches are available in the literature to rank a set of different non-dominated alternatives (or solutions). Three of these approaches were used in this study, i.e., the technique of order preference by similarity to ideal solution (TOPSIS), the decision index, and the fuzzy approach.

TOPSIS, which was first developed by Hwang and Yoon (1981), ranks a set of alternatives based on the concept that the best alternative would have the shortest and longest geometric distances from the positive and negative ideal solutions, respectively. Hence, for each alternative, a "T-Score" value is determined and the ranking is performed on the basis of this value from the largest to the smallest. The decision index approach that was introduced by Zayed and Halpin (2001) is based on the difference between the unit costs of different solutions and the differences in productivity. If a solution has a unit cost difference that is less than the productivity difference referenced to the lowest unit cost solution, this solution is better than the lowest unit cost solution and vice versa. In this manner, for each solution, a "D-Score" value is calculated and accordingly the solutions are ranked based on such value from the smallest to the largest. Finally, the fuzzy approach was proposed by Dhillon et al. (1993) is based on first determining a normalized membership function value for each objective of each solution and then adding them up to obtain an "F-Score" for each solution. The normalized membership function value measures the relative deviation of the value of each objective in each solution from the maximum objective value among all the solutions. Since our problem is to minimize both the VT and TC, the less the value of any of these two objectives is, the more their corresponding normalized membership function will be and hence the higher the "F-Score" of the solution will be. Therefore, similar to the TOPSIS approach, the solutions are ranked from the largest to the smallest based on the "F-Score" value.

The above-discussed three approaches were applied on the three implementations carried and the score results are presented in Table 11. Accordingly, as shown in the table, the ranking of the non-dominated solution set of each implementation was determined. It is obvious that the three approaches provide almost similar ranking. For the stochastic and deterministic double-cycling implementations, the three approaches agree on the first ranked solutions (BCSs), i.e., solutions 9 and 11, respectively. However, for the stochastic single-cycling implementation, both the TOPSIS and fuzzy approaches consider that solution 6 is the BCS, whereas the decision index approach considers solution 8 as the BCS. Finally, it is obvious that the BCS will always somehow come in a mid-point to satisfy both objectives should the non-dominated solutions be uniformly distributed as shown in Figures 6 and 7.

10. MODEL LIMITATIONS

Although promising results were achieved by the developed optimization model, there is room for further improvement. For instance, the developed optimization model is limited only to the allocation of the fleet size required for serving one vessel at a time. Practically speaking, it may happen that more than one vessel with different capacities arrives simultaneously or at different overlapped times to the terminal. In such cases, the model should be extended to consider the allocation of the handling equipment to serve different vessels arriving simultaneously or at overlapped times. Moreover, to add practicality and consider more uncertainty in the model, additional work tasks should be included that consider the breakdown, repair, and/or periodical minor maintenance for the equipment used in the handling process.

11. CONCLUSIONS

A double-cycling strategy was introduced in this study for improving the container handling productivity. The modelling of the VT and TC was accordingly presented using both the traditional single-cycling and double-cycling strategies. Consequently, for both strategies, a multi-level fleet size optimization model for container terminal handling using the NSGA-II was developed. The optimization model aimed at optimizing the number of QCs, YCs, and YTs used such that both the VT and TC are minimized. The stochastic productivities were considered for the different utilized handling equipment to mimic the real-life situation by considering uncertainty.

Both handling strategies were applied on three hypothetical case studies, and it was found that the double-cycling strategy provided up to 22% reduction in both the VT and TC and up to 28% improvement in PV. The implementation of the optimization model disclosed that the use of the double-cycling strategy significantly saves cost for almost similar VT compared with the single-cycling strategy. This is due to the less number of handling equipment utilized, particularly the YTs, when adopting the double-cycling strategy to achieve VT comparable to that of the single-cycling strategy. This demonstrates the potential of the double-cycling strategy in providing an opportunity to use the additional unneeded handling equipment available at the terminal to serve other arriving vessel(s) simultaneously. Apart from the handling strategy used, the results of the model implementation using the deterministic productivities revealed how considering the uncertainty in the equipment's productivities provides more realistic VT and TC because both the best- and worst-case scenarios are considered throughout the optimization process. Finally, to select the BCS among the set of obtained non-dominated solutions, the TOPSIS, the decision index, and the fuzzy approaches adopted from the literature were applied to rank the different feasible alternatives.

No funding was provided for this research.

REFERENCES

Agra, A., and Oliveira, M. (2018). "MIP approaches for the integrated berth allocation and quay crane assignment and scheduling problem", European Journal of Operational Research, 264(1), 138-148.

Ahmed, E. (2015). "Optimization-Based Simulation of Container Terminal Productivity using Yard Truck Double Cycling", Doctoral dissertation, Concordia University.

Al-Dhaheri, N., and Diabat, A. (2015). "The quay crane scheduling problem", Journal of Manufacturing Systems, 36, 87-94.

Al-Hammadi, J., and Diabat, A. (2017). "An integrated berth allocation and yard assignment problem for bulk ports: Formulation and case study", RAIRO-Operations Research, 51(1), 267-284.

Alsoufi, G., Yang, X., and Salhi, A. (2018). "Combined quay crane assignment and quay crane scheduling with crane inter-vessel movement and non-interference constraints", Journal of the operational research society, 69(3), 372-383.

Azimi, P., and Ghanbari, M.R. (2011). "A Simulation Model for Optimization of the Internal Handling Fleet Size at Shahid Rajaee Container Port Based on Performance Evaluation", Journal of Optimization in Industrial Engineering, 4(8), 19-31.

Bazzazi, M., Safaei, N., and Javadian, N. (2009). "A genetic algorithm to solve the storage space allocation problem in a container terminal", Computers and Industrial Eng., 56(1), 44-52.

Bish, E.K., Chen, F.Y., Leong, Y.T., Nelson, B.L., Ng, J.W.C., and Simchi-Levi, D. (2005). "Dispatching vehicles in a mega container terminal", OR Spectrum, 27, 491-506.

Budipriyanto, A., Wirjodirdjo, B., Pujawan, N., and Gurning, S. (2015). “Berth allocation problem under uncertainty: a conceptual model using collaborative approach”, Procedia Manufacturing, 4, 429-437.

Cao, J.X., Lee, D.H., Chen, J.H., and Shi, Q. (2010a). “The integrated yard truck and yard crane scheduling problem: Benders’ decomposition-based methods”, Transportation Research Part E: Logistics and Transportation Review, 46(3), 344-353.

Cao, J., Shi, Q., and Lee, D. H. (2010b). “Integrated quay crane and yard truck schedule problem in container terminals”, Tsinghua Science and Technology, 15(4), 467-474.

Cao, P., Zhao, H., and Jiang, G. (2017). “Integrated scheduling optimization of Yard Crane and Yard Truck in ship-loading operation”, 2017 4th International Conference on Transportation Information and Safety (ICTIS), 595-599, IEEE.

Chang, D., Jiang, Z., Yan, W., and He, J. (2010). “Integrating berth allocation and quay crane assignments”, Transportation Research Part E: Logistics and Transportation Review, 46(6), 975-990.

Chen, L.H., Gao, Z.J., Wu, C.J., and Cao, J.X. (2014). “The integrated yard truck and yard crane scheduling and storage allocation problem at container terminals”, Applied Mechanics and Materials, 587, 1797-1800.

Chen, L., and Lu, Z. (2012). “The storage location assignment problem for outbound containers in a maritime terminal”, International Journal of Production Economics, 135(1), 73-80.

Correcher, J.F., Van den Bossche, T., Alvarez-Valdez, R., and Berghe, G.V. (2019). “The berth allocation problem in terminals with irregular layouts”, European Journal of Operational Research, 272(3), 1096-1108.

Dhillon, J., Parti, S.C., and Kothari, D.P. (1993). “Stochastic economic emission load dispatch”, Electric Power Systems Research, 26(3), 179-186.

Diabat, A., and Theodorou, E. (2014). “An integrated quay crane assignment and scheduling problem”, Computers and Industrial Engineering, 73, 115-123.

Dkhil, H., Yassine, A., and Chabchoub, H. (2013).” Optimization of container handling systems in automated maritime terminal”, Advanced Methods for Computational Collective Intelligence (pp. 301-312). Springer, Berlin, Heidelberg.

Fan, H., Ma, M., Yao, X., and Guo, Z. (2009). “Integrated optimization of storage space allocation and multiple yard cranes scheduling in a container terminal yard”, Journal of Shanghai Jiaotong University, 51(11), 1367-1373.

Golias, M.M., Saharidis, G.K., Boile, M., Theofanis, S., and Ierapetritou, M.G. (2009). “The berth allocation problem: optimizing vessel arrival time”, Maritime Economics and Logistics, 11(4), 358-377.

Goodchild, A. V., and Daganzo, C.F. (2006). “Double-cycling strategies for container ships and their effect on ship loading and unloading operations”, Transportation Science, 40(4), 473-483.

Grubisic, N., and Maglic, L. (2018). “Optimization process for berth and quay-crane assignment in container terminals with separate piers”, Athens Journal of Technology and Engineering, 5(1), 53-68.

Grunow, M., Günther, H.O., and Lehmann, M. (2006). “Strategies for dispatching AGVs at automated seaport container terminals”, OR spectrum, 28(4), 587-610.

Guerra-Olivares, R., Smith, N.R., Gonzalez-Ramirez, R.G., Garcia-Mendoza, E., and Cardenas-Barron, L.E. (2018). “A heuristic procedure for the outbound container space assignment problem for small and midsize maritime terminals", International Journal of Machine Learning and Cybernetics, 9(10), 1719-1732.

He, J., Tan, C., and Zhang, Y. (2019). "Yard crane scheduling problem in a container terminal considering risk caused by uncertainty", Advanced Engineering Informatics, 39, 14-24.

He, J., Huang, Y., Yan, W., and Wang, S. (2015). "Integrated internal truck, yard crane and quay crane scheduling in a container terminal considering energy consumption", Expert Systems with Applications, 42(5), 2464-2487.

He, J. L., Zhang, W.M., Huang, Y.F., and Yan, W. (2013). "An efficient approach for solving yard crane scheduling in a container terminal", Journal of Shanghai Jiaotong University (Science), 18(5), 606-619.

Hu, H., Chen, X., and Zhang, S. (2019). "Optimisation for quay crane scheduling problem under uncertainty using PSO and OCBA", International Journal of Shipping and Transport Logistics, 11(2-3), 196-215.

Hwang, C.L., and Yoon, K. (1981). *Multiple Attribute Decision Making: Methods and Applications, a state-of-the-art survey*. Berlin: Springer.

Idris, N., and Zainuddin, Z.M. (2016). "A simultaneous integrated model with multiobjective for continuous berth allocation and quay crane scheduling problem", 2016 International Conference on Industrial Eng., Management Science and Application (ICIMSA), 1-5, IEEE.

Imai, A., Nishimura, E., and Papadimitriou, S. (2001). "The dynamic berth allocation problem for a container port", Transportation Research Part B: Methodological, 35(4), 401-417.

Iris, Ç., Pacino, D., Ropke, S., and Larsen, A. (2015). "Integrated berth allocation and quay crane assignment problem: Set partitioning models and computational results", Transportation Research Part E: Logistics and Transportation Review, 81, 75-97.

Jacomino, L., Valdes, D., Morell, C., and Bello, R. (2019). "Solutions to storage spaces allocation problem for import containers by exact and heuristic methods", Computacion y Sistemas, 23(1), 197-211.

Javanshir, H., Ghomi, S., ane Ghomi, M. (2012). "Investigating transportation system in container terminals and developing a yard crane scheduling model", Management Science Letters, 2(1), 171-180.

Jiao, X., Zheng, F., Liu, M., and Xu, Y. (2018). "Integrated berth allocation and time-variant quay crane scheduling with tidal impact in approach channel", Discrete Dynamics in Nature and Society, 2018.

Jingjing, Y., Guolei, T., and Da, L. (2018). "Optimal Number of Quay Cranes in Container Terminals with Twin-40-Feet Quay Cranes", Proceedings of the 10th International Conference on Computer Modeling and Simulation, 162-167.

Jonker, T., Duinkerken, M.B., Yorke-Smith, N., de Waal, A., and Negenborn, R.R. (2019). "Coordinated optimization of equipment operations in a container terminal", Flexible Services and Manufacturing Journal, 1-31.

Karam, A., Eltawil, A.B., and Harraz, N.A. (2014). "An improved approach for the quay crane assignment problem with limited availability of internal trucks in container terminal", 2014 IEEE International Conference on Industrial Engineering and Engineering Management, 112-116, IEEE.

Kasm, O.A., Diabat, A., and Cheng, T.C.E. (2019). "The integrated berth allocation, quay crane assignment and scheduling problem: mathematical formulations and a case study", Annals of Operations Research, 1-27.

Kaveshgar, N., and Huynh, N. (2015). “Integrated quay crane and yard truck scheduling for unloading inbound containers”, International Journal of Production Economics, 159, 168-177.

Kizilay, D., Eliiyi, D.T., and Van Hentenryck, P. (2018). “Constraint and mathematical programming models for integrated port container terminal operations”, International Conference on the Integration of Constraint Programming, Artificial Intelligence, and Operations Research, 344-360, Springer, Cham.

Koo, P.H., Lee, W.S., and Jang, D.W. (2004). “Fleet sizing and vehicle routing for container transportation in a static environment”, Or Spectrum, 26(2), 193-209.

Kulatunga, A., Mekala, R.A.D.S., Luthfi, M.A.L., Dharmapriya, U.S.S., Wijesundara, A.S.W., and Jayasundara, A. (2011). “Determining the best fleet sizing of a container terminal for a given layout”, Proceedings of the 2011 International Conference on Industrial Engineering and Operations Management.

Lajjam, A., El Merouani, M., Tabba, Y., and Medouri, A. (2014). “An efficient algorithm for solving quay-crane assignment problem”. International Journal of Research in Manufacturing Technology and Management, 2(1), 13 – 18.

Lee, S. (2007). “Locating idle vehicles in tandem-loop automated guided vehicle systems to minimize the maximum response time”, IEMS, 6(2), 125-135.

Lee, D.H., Cao, J.X., and Shi, Q.X. (2009). “Synchronization of yard truck scheduling and storage allocation in container terminals”, Engineering Optimization, 41(7), 659-672.

Lee, D.H., and Wang, H.Q. (2010). “Integrated discrete berth allocation and quay crane scheduling in port container terminals”, Engineering Optimization, 42(8), 747-761.

Lin, D.Y., and Chiang, C.W. (2017). “The storage space allocation problem at a container terminal”, Maritime Policy and Management, 44(6), 685-704.

Luo, T., Chang, D., and Gao, Y. (2018). “Optimization of gantry crane scheduling in container sea-rail intermodal transport yard”, Mathematical Problems in Engineering, 2018.

Martinez, J.C. (2001). “EZStrobe-general-purpose simulation system based on activity cycle diagrams”, Proceeding of the 2001 Winter Simulation Conference (Cat. No. 01CH37304), 2, 1556-1564, IEEE.

Merk, O., Busquet, B., and Aronieti, R.A. (2015). “The impact of mega-ships”, International Transport Forum, OECD, Paris.

Monaco, M.F., and Sammarra, M. (2007). “The berth allocation problem: a strong formulation solved by a Lagrangean approach”, Transportation Science, 41(2), 265-280.

Msakni, M.K., Diabat, A., Rabadi, G., Al-Salem, M., and Kotachi, M. (2018). “Exact methods for the quay crane scheduling problem when tasks are modeled at the single container level”, Computers and Operations Research, 99, 218-233.

Ng, W.C., and Mak, K.L. (2006). “Quay crane scheduling in container terminals”, Engineering Optimization, 38(6), 723-737.

Ng, W.C., and Mak, K.L. (2005). “Yard crane scheduling in port container terminals”, Applied mathematical modelling, 29(3), 263-276.

Nguyen, V.D., and Kim, K.H. (2010). “Minimizing empty trips of yard trucks in container terminals by dual cycle operations”, Industrial Engineering and Management Systems, 9(1), 28-40.

Niu, B., Zhang, F., Li, L., and Wu, L. (2017). “Particle swarm optimization for yard truck scheduling in container terminal with a cooperative strategy”, Intelligent and Evolutionary Systems, 8, 333-346.

Olteanu, S., Costescu, D., Ruscă, A., and Oprea, C. (2018). "A genetic algorithm for solving the quay crane scheduling and allocation problem", IOP Conference Series: Materials Science and Engineering, 400(4), 042045, IOP Publishing.

Peng, J., Zhou, Z., and Li, R. (2015). "A collaborative berth allocation problem with multiple ports based on genetic algorithm", Journal of Coastal Research, 73(sp1), 290-297.

Pjevcevic, D., Nikolic, M., Vidic, N., and Vukadinovic, K. (2017). "Data envelopment analysis of AGV fleet sizing at a port container terminal", International Journal of Production Research, 55(14), 4021-4034.

Raa, B., Dullaert, W., and Van Schaeren, R. (2011). "An enriched model for the integrated berth allocation and quay crane assignment problem", Expert Systems with Applications, 38(11), 14136-14147.

Safaei, N., Bazzazi, M., and Assadi, P. (2010). "An integrated storage space and berth allocation problem in a container terminal", International Journal of Mathematics in Operational Research, 2(6), 674-693.

Said, G.A.E.N.A., and El-Horbaty, E.S.M. (2015). "An optimization methodology for container handling using genetic algorithm", Procedia Computer Science, 65, 662-671.

Sammarra, M., Cordeau, J.F., Laporte, G., and Monaco, M.F. (2007). "A tabu search heuristic for the quay crane scheduling problem", Journal of Scheduling, 10(4-5), 327-336.

Schepler, X., Absi, N., Feillet, D., and Sanlaville, E. (2019). "The stochastic discrete berth allocation problem", EURO Journal on Transportation and Logistics, 8(4), 363-396.

Schittkowski, K. (2002). "EASY-FIT: a software system for data fitting in dynamical systems", Structural and Multidisciplinary Optimization, 23(2), 153-169.

Sharif, O., and Huynh, N. (2012). "Yard crane scheduling at container terminals: A comparative study of centralized and decentralized approaches", Maritime economics and logistics, 14(2), 139-161.

Stahlbock, R., and Voβ, S. (2008). "Operations research at container terminals: a literature update", OR Spectrum, 30(1), 1-52.

Statista Research Department (2020). "Container shipping – statistics and facts", < https://www.statista.com/topics/1367/container-shipping/ > (March 05, 2020)

Tan, C., and He, J. (2016). "Integrated Yard Space Allocation and Yard Crane Deployment Problem in Resource-Limited Container Terminals", Scientific Programming, 2016.

Wang, K., Zhen, L., Wang, S., and Laporte, G. (2018). "Column generation for the integrated berth allocation, quay crane assignment, and yard assignment problem", Transportation Science, 52(4), 812-834.

Wang, L., Zhu, X., and Xie, Z. (2014). "Storage space allocation of inbound container in railway container terminal", Mathematical Problems in Engineering, 2014.

Wang, Z.X., Chan, F.T., Chung, S.H., and Niu, B. (2015). "Minimization of delay and travel time of yard trucks in container terminals using an improved GA with guidance search", Mathematical Problems in Engineering, 2015.

Wu, C.J., Chen, L.H., Zhao, Q.Y., and Cao, J.X. (2014). "The integrated berth and quay crane scheduling problem in container terminals", Applied Mechanics and Materials, 587, 1793-1796.

Wu, L., and Wang, S. (2018). "Joint Deployment of Quay Cranes and Yard Cranes in Container Terminals at a Tactical Level", Transportation Research Record, 2672(9), 35-46.

Xiao, L., and Hu, Z.H. (2014). "Berth allocation problem with quay crane assignment for container terminals based on rolling-horizon strategy", Mathematical Problems in Engineering, 2014.

Xiao, Y., Zheng, Y., and Li, P. (2016). “Modeling of integrated quay cranes, yard trucks and yard cranes scheduling problem for outbound containers”, Proceedings of the 2016 International Conference on Artificial Intelligence and Engineering Applications, Atlantis Press.

Xue, Z., Zhang, C., Miao, L., and Lin, W.H. (2013). “An ant colony algorithm for yard truck scheduling and yard location assignment problems with precedence constraints”, Journal of systems science and systems engineering, 22(1), 21-37.

Yu, S., Wang, S., and Zhen, L. (2017). “Quay crane scheduling problem with considering tidal impact and fuel consumption”, Flexible Services and Manufacturing Journal, 29(3-4), 345-368.

Yue, L., Fan, H., and Zhai, C. (2019). “Joint configuration and scheduling optimization of a dual-trolley quay crane and automatic guided vehicles with consideration of vessel stability”, Sustainability, 12(1), 1-16.

Zampelli, S., Vergados, Y., Van Schaeren, R., Dullaert, W., and Raa, B. (2013). “The berth allocation and quay crane assignment problem using a CP approach”, International Conference on Principles and Practice of Constraint Programming, 880-896, Springer, Berlin, Heidelberg.

Zayed, T.M., and Halpin, D. (2001). “Simulation of concrete batch plant production”, ASCE, Journal of Construction Engineering and Management, 127(2), 132-141.

Zhang, C., Liu, J., Wan, Y., Murty, K.G., and Linn, R.J. (2003). “Storage space allocation in container terminals”, Transportation Research Part B: Methodological, 37(10), 883-903.

Zhang, H., and Kim, K. H. (2009). “Maximizing the number of dual-cycle operations of quay cranes in container terminals”, Computers and Industrial Engineering, 56(3), 979-992.

Zhang, Z., Liu, M., Lee, C.Y., & Wang, J. (2018). “The quay crane scheduling problem with stability constraints”, IEEE Transactions on Automation Science and Engineering, 15(3), 1399-1412.

Zhen, L., Yu, S., Wang, S., and Sun, Z. (2019). “Scheduling quay cranes and yard trucks for unloading operations in container ports”, Annals of Operations Research, 273(1-2), 455-478.

Zheng, F., Li, Y., Chu, F., Liu, M., and Xu, Y. (2019a). “Integrated berth allocation and quay crane assignment with maintenance activities”, International Journal of Production Research, 57(11), 3478-3503.

Zheng, F., Man, X., Chu, F., Liu, M., and Chu, C. (2019b). “A two-stage stochastic programming for single yard crane scheduling with uncertain release times of retrieval tasks”, International Journal of Production Research, 57(13), 4132-4147.

LIST OF TABLES:

LIST OF FIGURES:

Table 1: Fleet Size Optimization Literature Summary

Citation	Technique Used	Vessel Turnaround Minimized	Handling Cost Minimized	Number of Yard Trucks Optimized	Number of Quay Cranes Optimized	Number of Yard Cranes Optimized	Uncertainty Considered	Double-Cycling Strategy
Jingjing et al. (2018)	Queueing Modelling	Yes	Yes	No	Yes	No	Yes	No
Pjevcevic et al. (2017)	Data Envelopment Analysis	Yes	Yes	Yes	No	No	No	No
Said and El-Horbaty (2015)	Genetic Algorithm	Yes	No	Yes	Yes	Yes	No	No
Dkhil et al. (2013)	Mathematical Modelling	Yes	No	Yes	No	No	Yes	No
Azimi and Ghanbari (2011)	Simulation	Yes	No	Yes	No	No	Yes	No
Kulatunga et al. (2011)	Simulation	Yes	No	Yes	No	No	No	No
Bish et al. (2005)	Heuristic Algorithms	Yes	No	Yes	No	No	No	No
Koo et al. (2004)	Heuristic Tabu Search Algorithm	Yes	No	Yes	No	No	Yes	No
Current Research	Elitist Non-dominated Sorting Genetic Algorithm	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 2: Notations used in Handling Strategies Modelling

Notation	Description
QC_U	QC unloading cycle time
QC_L	QC loading cycle time
t_{Q1}	Time for QC to make an unloaded forward move towards the vessel
t_{Q2}	Time for QC to lift the container from the vessel
t_{Q3}	Time for QC to make a loaded backward move towards the YT
t_{Q4}	Time for QC to load the container on the YT
t_{Q5}	Time for QC to lift the container from the YT
t_{Q6}	Time for QC to make a loaded forward move towards the vessel
t_{Q7}	Time for QC to load the container on the vessel
t_{Q8}	Time for QC to make an unloaded backward move towards the YT
X_A and X_B	Number of QCs utilized in phases A and B, respectively
X_C	Number of QC pairs utilized in phase C
PX_A, PX_B, and PX_C	Productivity of the QCs utilized in phases A, B, and C, respectively
YC_U	YC unloading cycle time
YC_L	YC loading cycle time
t_{Y1}	Time for YC to lift the container from the YT
t_{Y2}	Time for YC to make a loaded forward move towards the SY
t_{Y3}	Time for YC to load the container in the SY
t_{Y4}	Time for YC to make an unloaded backward move towards the YT
t_{Y5}	Time for YC to make an unloaded forward move towards the SY
t_{Y6}	Time for YC to lift the container from the SY
t_{Y7}	Time for YC to make a loaded backward move towards the YT
t_{Y8}	Time for YC to load the container on the YT
Y_A and Y_B	Number of YCs utilized in phases A and B, respectively
Y_C	Number of YC pairs utilized in phase C
PY_A, PY_B, and PY_C	Productivity of the YCs utilized in phases A, B, and C, respectively
YTS_U	YT unloading single-cycle time
YTS_L	YT loading single-cycle time
YTD	YT double-cycle time
t_{S1}	Time for YT to travel unloaded from the SY area to the QC area
t_{S2}	Time for YT to travel loaded from the QC area to the SY area
t_{S3}	Time for YT to travel loaded from the SY area to the QC area
t_{S4}	Time for YT to travel unloaded from the QC area to the SY area
t_{S5}	Time for YT to travel unloaded from QC1 to QC2
t_{S6}	Time for YT to travel unloaded from YC2 to YC1
Z_A, Z_B, and Z_C	Number of YTs utilized in phases A, B, and C, respectively
PZ_A, PZ_B, and PZ_C	Productivity of the YTs utilized in phases A, B, and C, respectively
PV_A, PV_B, and PV_C	System productivity of phases A, B, and C, respectively
O_A, O_B, and O_C	Number of operators utilized in phases A, B, and C, respectively
HC_X, HC_Y, HC_Z, and HC_O	Hourly cost of one QC, one YC, one YT, and one operator respectively
HC_A, HC_B, and HC_C	Hourly cost of phases A, B, and C, respectively
UC_A, UC_B, and UC_C	Unit cost of phases A, B, and C, respectively
N_A, N_B, and N_C	Number of loads handled in phases A, B, and C, respectively
$N_{A'}$ and $N_{B'}$	Number of additional imported and exported loads, respectively
N_I and N_E	Total number of imported and exported loads, respectively
VT_S and VT_D	Vessel turnaround time using the single-cycling and double-cycling strategies, respectively
TC_S and TC_D	Total handling cost using the single-cycling and double-cycling strategies, respectively
PV_S and PV_D	Overall system productivity using the single-cycling and double-cycling strategies, respectively
UC_S and UC_D	Overall system unit cost using the single-cycling and double-cycling strategies, respectively

Table 3: Optimization Model Formulation

Optimization Level	Single-Cycling Strategy	Double-Cycling Strategy
Level 1A	*Decision Variables:* $A = \{X_A, Y_A, Z_A\}$ *Maximize/Minimize:* $f_1 = PV_A$ $f_2 = UC_A$ *Subject to:* $1 \leq X_A \leq x_A$ $1 \leq Y_A \leq y_A$ $1 \leq Z_A \leq z_A$	*Decision Variables:* $A = \{X_A, Y_A, Z_A\}$ *Maximize/Minimize:* $f_1 = PV_A$ $f_2 = UC_A$ *Subject to:* $1 \leq X_A \leq x_A$ $1 \leq Y_A \leq y_A$ $1 \leq Z_A \leq z_A$
Level 1B	*Decision Variables:* $B = \{X_B, Y_B, Z_B\}$ *Maximize/Minimize:* $f_3 = PV_B$ $f_4 = UC_B$ *Subject to:* $1 \leq X_B \leq x_B$ $1 \leq Y_B \leq y_B$ $1 \leq Z_B \leq z_B$	*Decision Variables:* $B = \{X_B, Y_B, Z_B\}$ *Maximize/Minimize:* $f_3 = PV_B$ $f_4 = UC_B$ *Subject to:* $1 \leq X_B \leq x_B$ $1 \leq Y_B \leq y_B$ $1 \leq Z_B \leq z_B$
Level 1C	NA	*Decision Variables:* $C = \{X_C, Y_C, Z_C\}$ *Maximize/Minimize:* $f_5 = PV_C$ $f_6 = UC_C$ *Subject to:* $1 \leq X_C \leq x_C$ $1 \leq Y_C \leq y_C$ $1 \leq Z_C \leq z_C$
Level 2	*Decision Variables:* $S = \{nd_A, nd_B\}$ *Minimize:* $f_5 = VT_S$ $f_6 = TC_S$ *Subject to:* $1 \leq nd_A \leq ND_A$ $1 \leq nd_B \leq ND_B$	*Decision Variables:* $D = \{nd_A, nd_B, nd_C\}$ *Minimize:* $f_7 = VT_D$ $f_8 = TC_D$ *Subject to:* $1 \leq nd_A \leq ND_A$ $1 \leq nd_B \leq ND_B$ $1 \leq nd_C \leq ND_C$

Where; A, B, and C = number sets of handling equipment utilized in phases A, B, and C, respectively; f_i = ith objective; x_A, y_A, and z_A = maximum number of QCs, YCs, and YTs, respectively, assigned in phase A; x_B, y_B, and z_B = maximum number of QCs, YCs, and YTs, respectively, assigned in phase B; x_C, y_C, and z_C = maximum number of QCs, YCs, and YTs, respectively, assigned in phase C; S = number sets of non-dominated solutions obtained individually for phases A and B using the single-cycling strategy; D = number sets of non-dominated solutions obtained individually for phases A, B, and C using the double-cycling strategy; nd_A, nd_B, and nd_C = non-dominated solutions obtained in phases A, B, and C, respectively; ND_A, ND_B, ND_C = maximum number of non-dominated solutions obtained in phases A, B, and C, respectively.

Table 4: Work Tasks' Times Collected Data

Handling Component	Cycle Type	Work Task	Distribution	Mean Time (min)	Standard Deviation (min)
Quay Crane	Unloading	Unloaded forward move (t_{Q1})	Normal	0.84	0.22
		Container lifting from the vessel (t_{Q2})	Normal	0.36	0.30
		Loaded backward move (t_{Q3})	Normal	0.87	0.33
		Container loading on the YT (t_{Q4})	Normal	0.30	0.36
	Loading	Container lifting from the YT (t_{Q5})	Normal	0.20	0.11
		Loaded forward move (t_{Q6})	Normal	0.64	0.25
		Container loading on the vessel (t_{Q7})	Normal	0.21	0.16
		Unloaded backward move (t_{Q8})	Normal	0.66	0.11
Yard Crane	Unloading	Container lifting from the YT (t_{Y1})	Normal	0.34	0.13
		Loaded forward move (t_{Y2})	Normal	0.77	0.25
		Container loading in the SY (t_{Y3})	Normal	0.28	0.21
		Unloaded backward move (t_{Y4})	Normal	0.62	0.28
	Loading	Unloaded forward move (t_{Y5})	Normal	0.67	0.16
		Container lifting from the SY (t_{Y6})	Normal	0.18	0.07
		Loaded backward move (t_{Y7})	Normal	1.12	0.33
		Container loading on the YT (t_{Y8})	Normal	0.23	0.11
Yard Truck	Unloading (Single-Cycle)	Unloaded travel from SY to QC (t_{S1})	Normal	4.43	1.04
		Loaded travel from QC to SY (t_{S2})	Normal	4.38	0.53
	Loading (Single-Cycle)	Loaded travel from SY to QC (t_{S3})	Normal	4.79	1.06
		Unloaded travel from QC to SY (t_{S4})	Normal	3.65	0.54
	Double-Cycle	Unloaded travel from QC1 to QC2 (t_{S5})	Deterministic	0.16	-
		Unloaded travel from YC2 to YC1 (t_{S6})	Deterministic	0.75	-

Table 5: Stochastic Productivity Rates

Handling Equipment	Statistical Parameter	Single-Cycling Productivity Rate (TEUs/hr)		Double-Cycling Productivity Rate (TEUs/hr)
		Unloading	Loading	
Quay Crane	Distribution	Normal	Normal	Normal
	Mean	55.33	68.03	110.86
	Standard Deviation	15.53	9.58	30.37
Yard Crane	Distribution	Normal	Normal	Normal
	Mean	61.86	53.59	113.11
	Standard Deviation	13.93	13.24	27.85
Yard Truck	Distribution	Normal	Normal	Normal
	Mean	12.85	13.81	17.84
	Standard Deviation	3.43	3.91	4.38

Table 6: Handling Strategies Testing Results

Case #	Strategy	Number of Utilized Equipment									Productivity and Unit Cost						Vessel Turnaround Time (hrs)	Total Handling Cost (US$)	Overall System Productivity (TEUs/hr)	Overall System Unit Cost (US$/TEU)
		Phase (A)			Phase (C)			Phase (B)			Phase (A)		Phase (C)		Phase (B)					
		X_A	Y_A	Z_A	X_C	Y_C	Z_C	X_B	Y_B	Z_B	PV_A (TEUs/hr)	UC_A (US$/TEU)	PV_C (TEUs/hr)	UC_C (US$/TEU)	PV_B (TEUs/hr)	UC_B (US$/TEU)				
1	Single-Cycling	2	2	6	-	-	-	2	2	6	77.1	12.1	-	-	82.9	11.2	450.7	419,148	79.9	11.64
	Double-Cycling	2	2	6	1	1	6	2	2	6	77.1	12.1	107.0	8.7	82.9	11.2	351.6	326,963	102.4	9.08
	Improvement	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	99.1 (22%)	92,186 (22%)	22.5 (28%)	2.56 (22%)
2	Single-Cycling	4	4	13	-	-	-	4	4	13	167.1	11.6	-	-	179.5	10.8	208.0	402,507	173.1	11.18
	Double-Cycling	4	4	13	2	2	13	4	4	13	167.1	11.6	221.7	8.7	179.5	10.8	168.5	325,957	213.7	9.05
	Improvement	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	39.6 (19%)	76,550 (19%)	40.6 (23%)	2.13 (19%)
3	Single-Cycling	6	6	20	-	-	-	6	6	20	257.0	11.4	-	-	276.2	10.6	135.2	397,515	266.3	11.04
	Double-Cycling	6	6	20	3	3	20	6	6	20	257.0	11.4	332.6	8.8	276.2	10.6	111.8	328,809	321.9	9.13
	Improvement	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	23.4 (17%)	68,705 (17%)	55.6 (21%)	1.91 (17%)

Table 7: Model Implementation Inputs

Input Type	Parameter	Optimization Level			
		Level 1A	**Level 1B**	**Level 1C**	**Level 2**
Genetic Algorithm	**Population Size**	500	500	500	1000
	No. of Generations	1000	1000	1000	2000
	Crossover Rate	0.9	0.9	0.9	0.9
	Mutation Rate	0.1	0.1	0.1	0.1
Constraints	**Maximum QCs**	6	6	3	NA*
	Maximum YCs	10	10	5	NA*
	Maximum YTs	30	30	30	NA*
	Maximum ND_A	NA*	NA*	NA*	TBD**
	Maximum ND_B	NA*	NA*	NA*	TBD**
	Maximum ND_C	NA*	NA*	NA*	TBD**

*Not Applicable
**To be determined from the first optimization level

Table 8: Single-Cycling Strategy Non-dominated Solutions (Stochastic Productivities)

Non-Dominated Solution #	Number of Utilized Equipment						Vessel Turnaround Time (hrs)	Total Handling Cost (US$)	Overall System Productivity (TEUs/hr)	Overall System Unit Cost (US$/TEU)
	Phase (A)			Phase (B)						
	X_A	Y_A	Z_A	X_B	Y_B	Z_B				
1	6	30	10	6	25	10	106.9	424,597.2	299.4	13.27
2	6	22	10	6	30	6	108.8	390,982.6	294.1	12.22
3	6	22	10	6	23	7	110.6	378,155.5	289.2	11.82
4	6	22	10	6	22	6	112.8	376,118.5	283.8	11.75
5	6	21	9	5	21	6	115.1	361,044.8	278.0	11.28
6	6	18	4	6	30	6	116.8	350,991.3	274.0	10.97
7	5	17	4	6	25	10	119.6	342,862.6	267.6	10.71
8	6	18	4	6	22	6	120.8	336,127.1	265.0	10.50
9	6	18	4	5	21	6	123.1	332,736.7	259.9	10.40
10	6	18	4	5	20	5	125.8	330,643.0	254.3	10.33
11	5	17	4	5	21	6	127.8	329,142.6	250.3	10.29
12	5	17	4	5	20	5	130.6	327,048.9	245.1	10.22

Table 9: Double-Cycling Strategy Non-dominated Solutions (Stochastic Productivities)

Non-Dominated Solution #	Number of Utilized Equipment									Vessel Turnaround Time (hrs)	Total Handling Cost (US$)	Overall System Productivity (TEUs/hr)	Overall System Unit Cost (US$/TEU)
	Phase (A)			Phase (C)			Phase (B)						
	X_A	Y_A	Z_A	X_C	Y_C	Z_C	X_B	Y_B	Z_B				
1	6	19	6	3	17	4	6	30	7	105.2	313,865.9	304.2	9.81
2	6	16	5	3	17	4	6	30	7	105.9	312,287.0	302.2	9.76
3	5	16	5	3	16	4	6	30	7	107.2	307,406.3	298.5	9.61
4	5	15	4	3	16	4	5	25	6	108.4	304,596.6	295.3	9.52
5	5	13	4	3	15	4	5	28	6	109.6	300,437.9	292.1	9.39
6	5	15	4	3	15	4	4	19	5	110.0	296,426.8	290.9	9.26
7	5	15	4	3	15	4	3	14	4	111.0	292,348.1	288.2	9.14
8	5	16	5	3	15	3	4	19	4	112.5	284,245.3	284.6	8.88
9	4	11	3	3	15	3	5	23	5	113.6	280,962.6	281.7	8.78
10	4	10	3	3	15	3	4	19	5	115.2	278,077.5	277.9	8.69
11	4	13	4	3	14	3	3	17	4	115.9	275,352.3	276.1	8.60
12	6	16	5	3	14	3	2	10	3	117.9	272,184.2	271.4	8.51
13	4	12	4	3	13	3	3	14	3	119.5	269,812.2	267.7	8.43
14	3	9	3	3	13	3	3	17	4	120.9	267,609.0	264.6	8.36
15	6	19	5	3	11	3	2	10	3	122.7	265,234.2	260.8	8.29
16	3	9	3	3	12	3	3	13	3	124.6	261,978.8	256.9	8.19
17	2	6	2	3	12	3	5	24	6	126.5	259,685.9	253.0	8.12
18	5	13	4	3	12	3	2	6	2	127.8	258,218.3	250.3	8.07

Table 10: Double-Cycling Strategy Non-dominated Solutions (Deterministic Productivities)

Non-Dominated Solution #	Number of Utilized Equipment									Vessel Turnaround Time (hrs)	Total Handling Cost (US$)	Overall System Productivity (TEUs/hr)	Overall System Unit Cost (US$/TEU)
	Phase (A)			Phase (C)			Phase (B)						
	X_A	Y_A	Z_A	X_C	Y_C	Z_C	X_B	Y_B	Z_B				
1	6	19	8	3	26	5	6	25	7	98.5	366,845.4	324.7	11.46
2	6	18	5	3	28	4	6	25	8	99.1	359,598.4	322.9	11.24
3	4	16	8	3	30	3	6	25	7	100.4	355,799.2	318.7	11.12
4	5	16	5	3	29	3	6	23	7	101.0	348,323.2	316.8	10.89
5	4	17	3	3	23	5	5	22	6	102.7	345,387.3	311.6	10.79
6	4	16	6	3	28	3	4	18	5	103.1	340,545.8	310.4	10.64
7	4	16	4	3	22	5	4	17	5	103.7	337,383.2	308.7	10.54
8	6	16	5	3	27	3	3	15	4	105.2	335,851.1	304.2	10.50
9	3	13	4	3	21	5	4	18	7	105.9	333,569.9	302.3	10.42
10	4	12	3	3	26	3	5	18	5	107.0	329,051.9	299.1	10.28
11	4	17	4	3	18	5	3	14	4	108.1	321,066.7	296.0	10.03
12	4	14	3	3	19	5	3	12	3	110.0	319,379.9	290.8	9.98
13	5	13	3	3	24	3	3	11	3	111.9	317,446.0	285.9	9.92
14	3	12	3	3	23	3	3	11	3	113.1	308,400.5	282.9	9.64
15	4	13	3	3	18	4	3	11	4	114.9	307,132.9	278.6	9.60
16	4	12	3	3	19	4	3	9	3	116.6	306,227.6	274.3	9.57
17	4	12	3	3	21	3	3	8	3	119.1	302,445.8	268.8	9.45
18	4	11	3	3	20	3	2	8	2	121.2	293,049.9	264.1	9.16
19	4	11	3	3	18	3	2	9	2	124.1	290,691.5	257.9	9.08
20	2	9	3	3	19	3	2	9	2	125.8	287,500.3	254.3	8.98

Table 11: Best Compromise Solution Selection

Implementation	Non-Dominated Solution #	T-Score	D-Score	F-Score	TOPSIS Rank	Decision Index Rank	Fuzzy Approach Rank
Single-Cycling (Stochastic Productivities)	1	0.423	1.063	1.000	12	12	11
	2	0.531	0.996	1.263	11	10	6
	3	0.585	0.980	1.317	8	7	3
	4	0.569	0.993	1.248	10	9	8
	5	0.635	0.973	1.304	5	5	4
	6	0.668	0.960	1.335	1	3	1
	7	0.660	0.960	1.301	3	4	5
	8	0.666	0.951	1.320	2	1	2
	9	0.643	0.959	1.256	4	2	7
	10	0.614	0.974	1.162	6	6	9
	11	0.597	0.985	1.094	7	8	10
	12	0.577	1.000	1.000	9	11	12
Double-Cycling (Stochastic Productivities)	1	0.496	1.000	1.000	17	17	16
	2	0.494	1.002	0.997	18	18	18
	3	0.499	0.999	1.027	15	14	14
	4	0.497	1.000	1.026	16	16	15
	5	0.503	0.997	1.049	14	13	12
	6	0.525	0.988	1.101	10	10	9
	7	0.538	0.983	1.129	8	8	8
	8	0.582	0.968	1.212	3	3	3
	9	0.587	0.967	1.220	1	1	1
	10	0.577	0.970	1.203	4	4	4
	11	0.583	0.967	1.218	2	2	2
	12	0.564	0.972	1.187	5	5	5
	13	0.549	0.977	1.157	6	6	6
	14	0.539	0.981	1.135	7	7	7
	15	0.527	0.986	1.101	9	9	10
	16	0.520	0.989	1.076	11	11	11
	17	0.510	0.995	1.032	12	12	13
	18	0.504	1.000	1.000	13	15	17
Double-Cycling (Deterministic Productivities)	1	0.496	0.999	1.000	20	19	19
	2	0.514	0.985	1.071	15	14	16
	3	0.513	0.987	1.072	16	16	15
	4	0.539	0.972	1.144	10	6	10
	5	0.529	0.980	1.119	12	11	12
	6	0.549	0.970	1.165	6	4	6
	7	0.559	0.967	1.184	3	3	3
	8	0.542	0.977	1.147	9	10	9
	9	0.545	0.976	1.151	7	9	8
	10	0.553	0.973	1.167	5	7	5
	11	0.584	0.959	1.226	1	1	1
	12	0.559	0.971	1.177	4	5	4
	13	0.536	0.982	1.132	11	13	11
	14	0.566	0.964	1.202	2	2	2
	15	0.545	0.975	1.154	8	8	7
	16	0.523	0.987	1.101	14	15	14
	17	0.510	0.995	1.060	17	17	17
	18	0.526	0.981	1.102	13	12	13
	19	0.507	0.997	1.023	18	18	18
	20	0.504	1.000	1.000	19	20	20

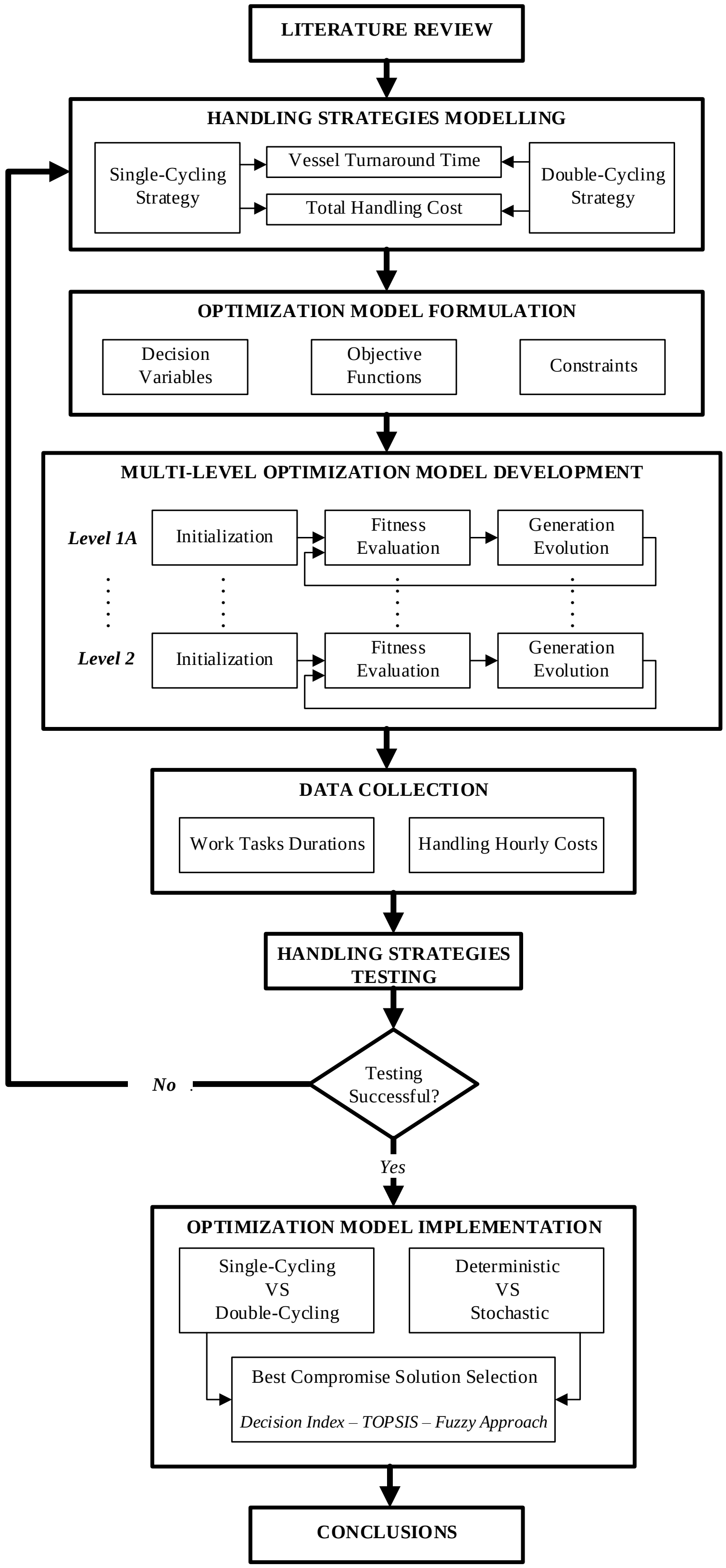


Figure 1: Research Methodology Framework

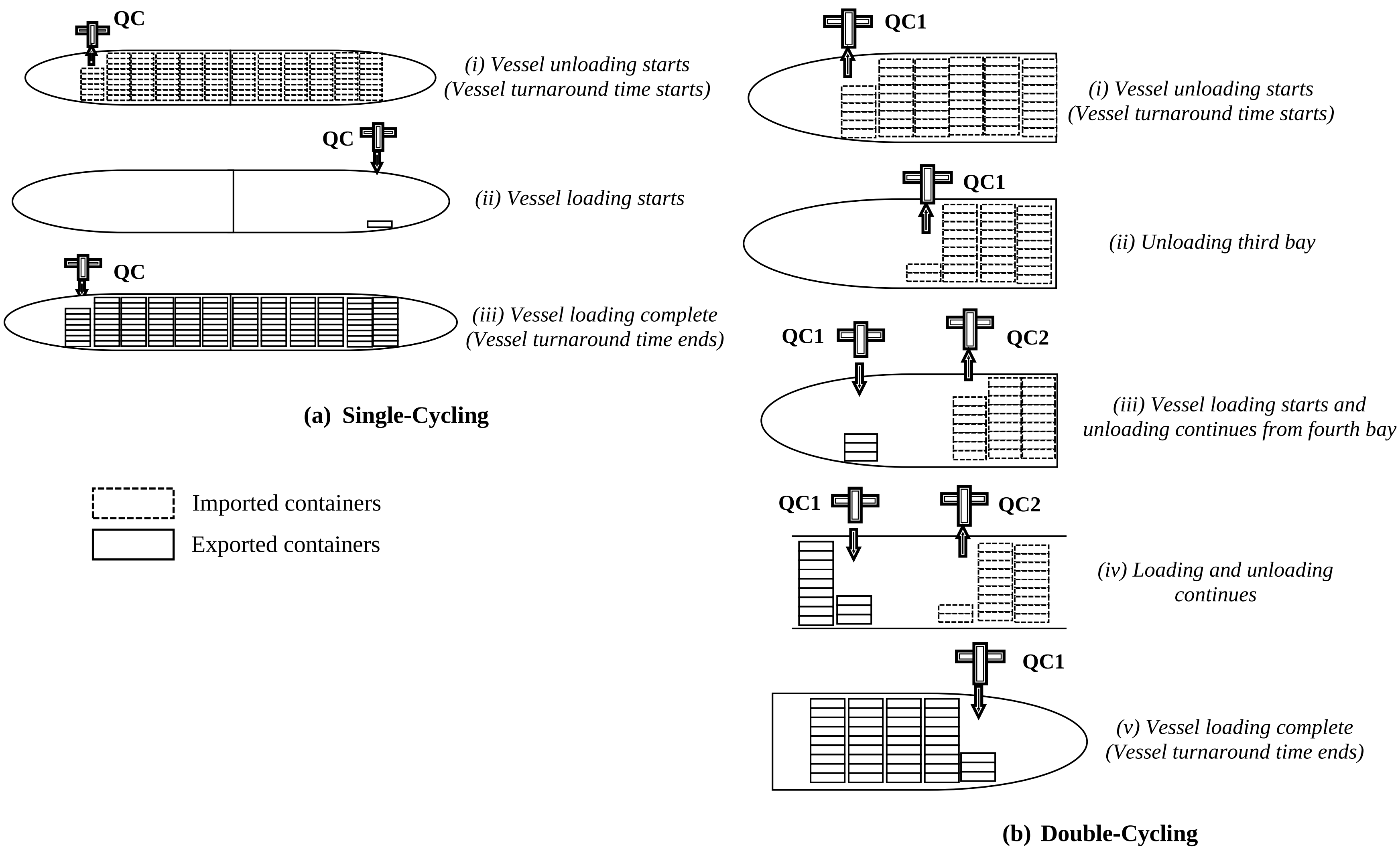
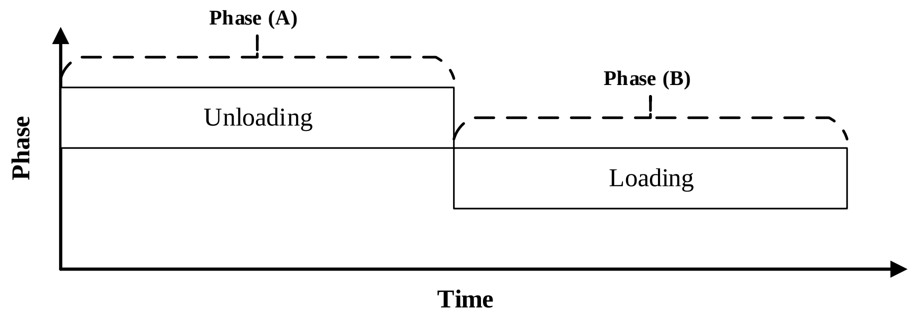
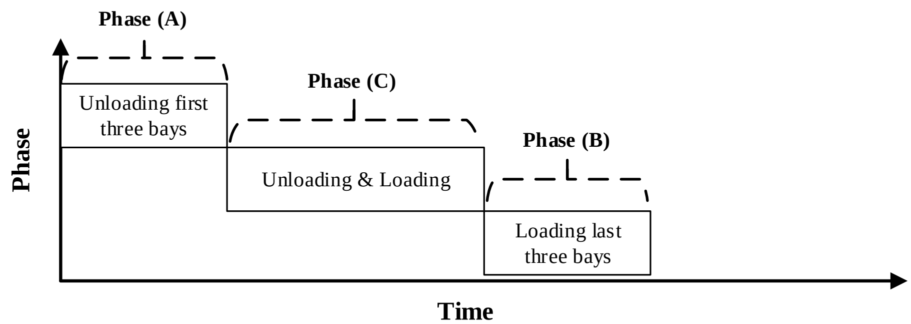


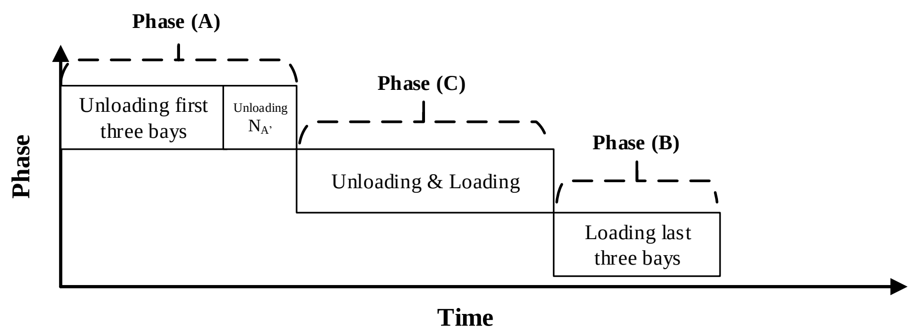
Figure 2: Single- and Double-Cycling Handling Sequence



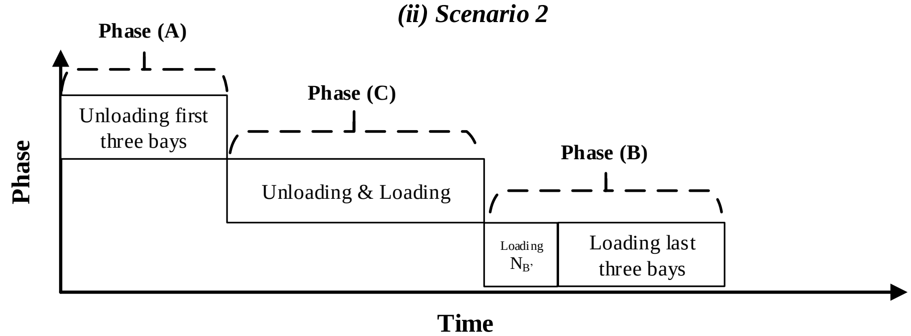
(a) Single-Cycling



(i) Scenario 1



(ii) Scenario 2



(iii) Scenario 3

(b) Double-Cycling

Figure 3: Single- and Double-Cycling Handling Timeline

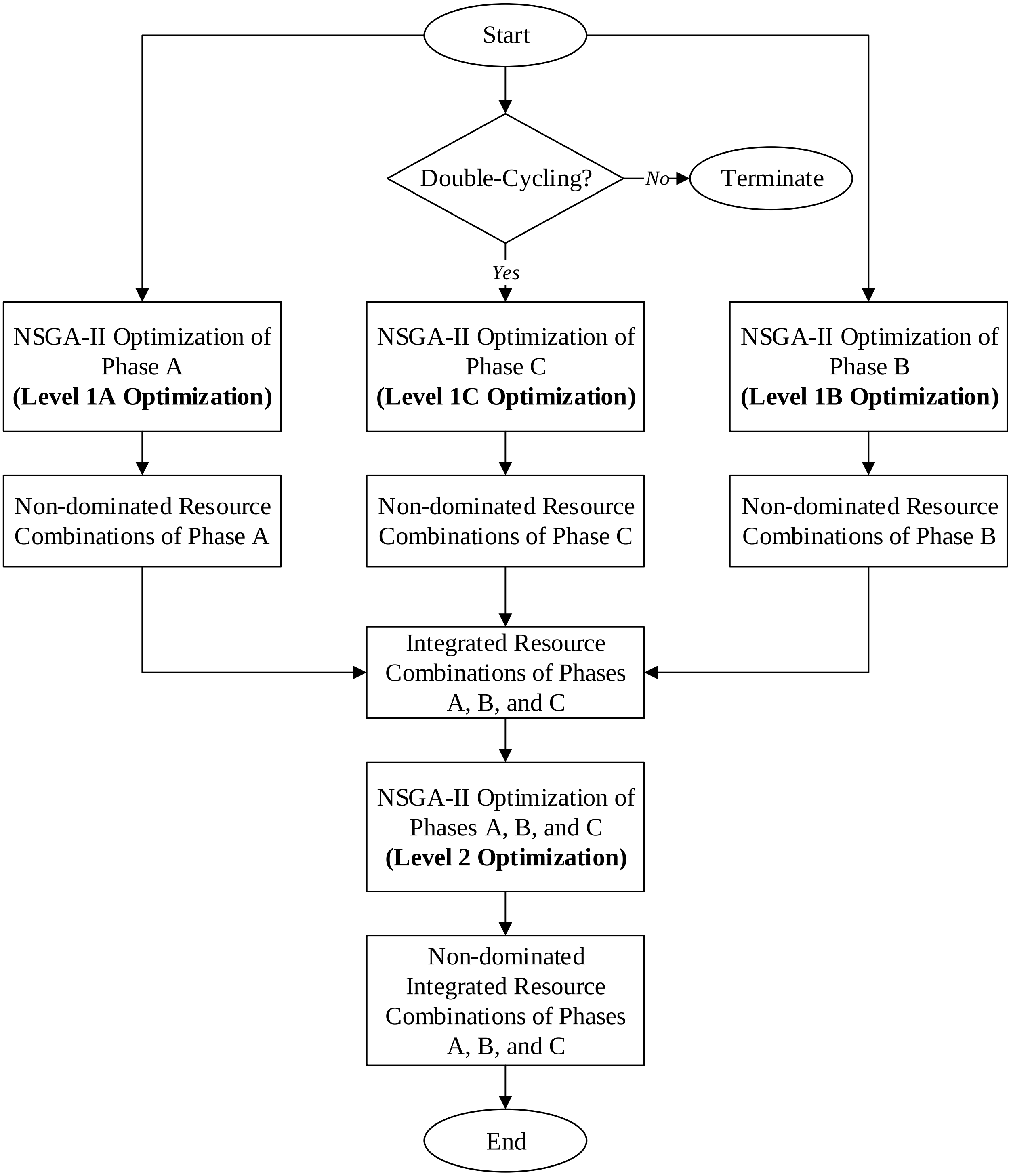


Figure 4: Multi-level Optimization Framework

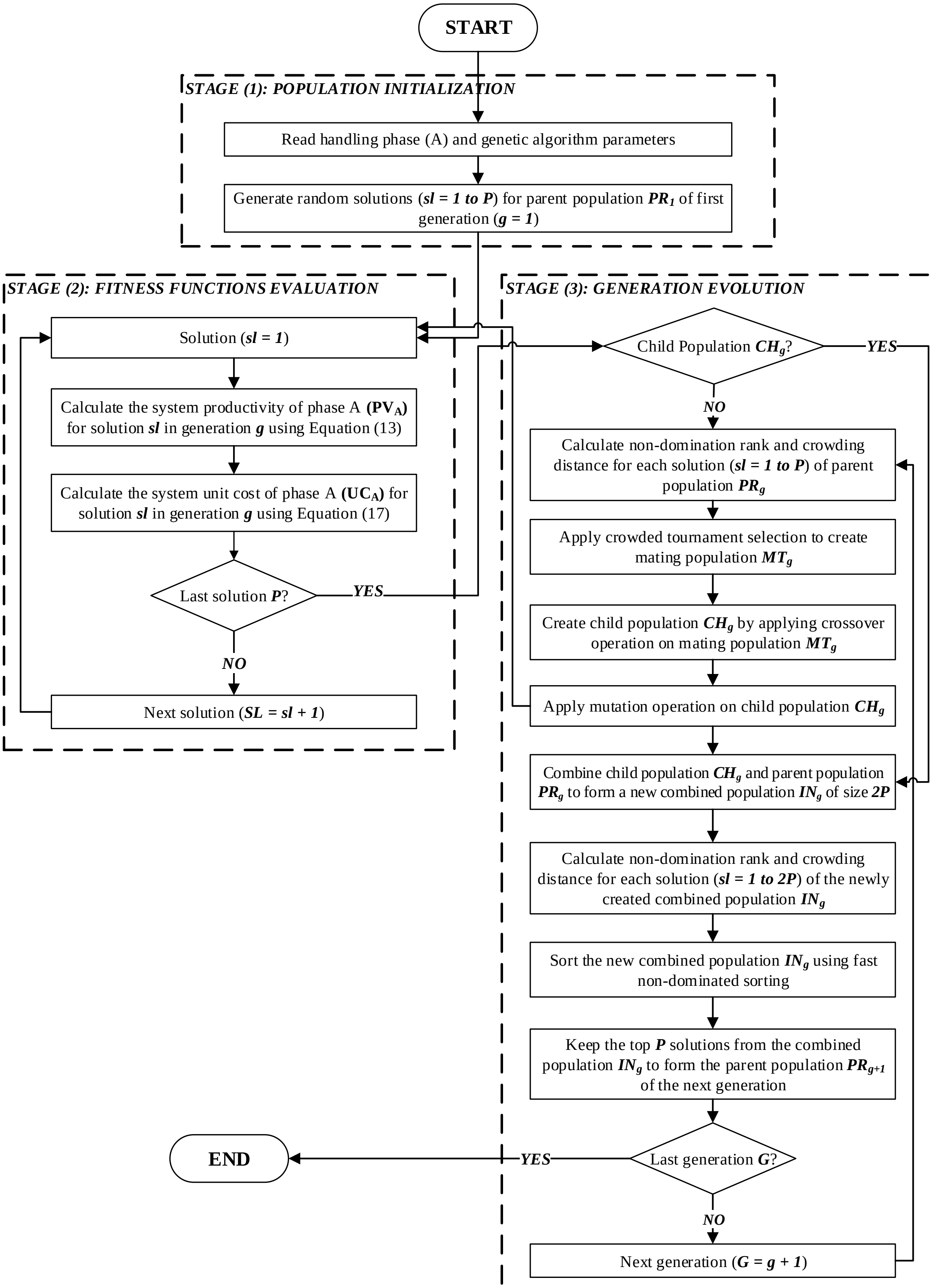


Figure 5: NSGA-II Optimization Process for Phase (A)

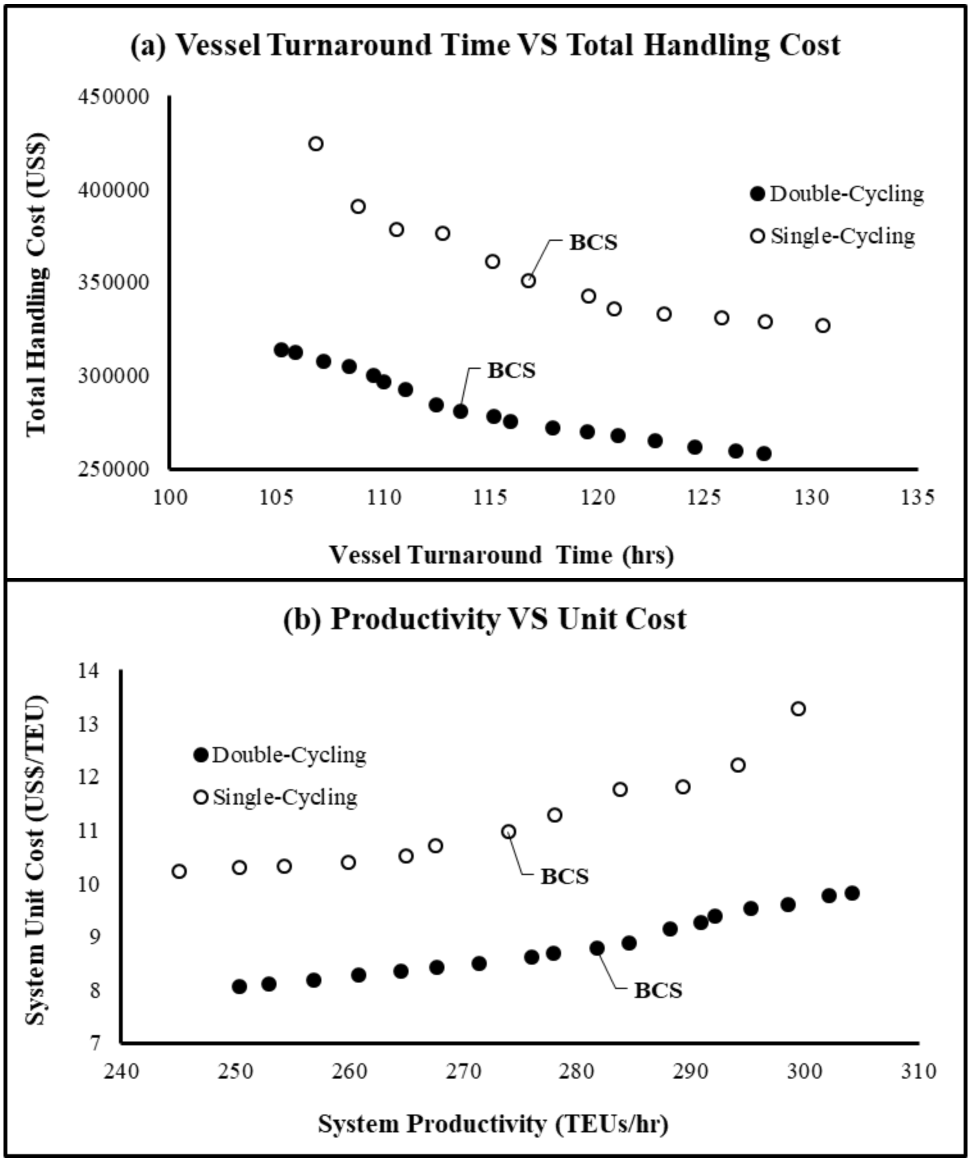


Figure 6: Single-Cycling VS Double-Cycling Pareto-Optimal Front

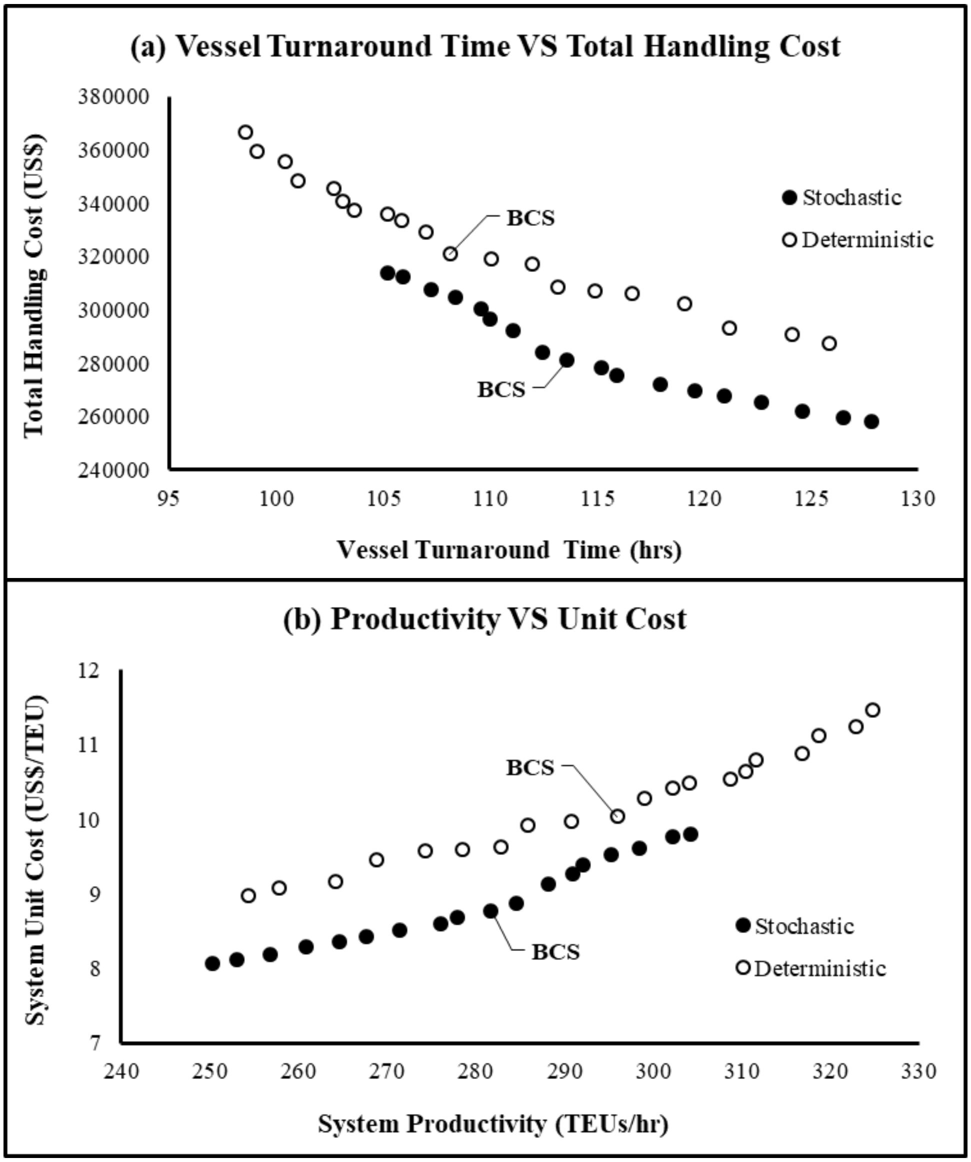


Figure 7: Stochastic VS Deterministic Pareto-Optimal Front