Decision Science Letters 13 (2024) 1007–1026

Contents lists available at GrowingScience

Decision Science Letters

homepage: www.GrowingScience.com/dsl

A simultaneous time and fuel minimization robust possibilistic multiobjective programming approach for truck-sharing scheduling in container terminals under uncertainty

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C H R O N I C L E

Article history:
Received: February 20, 2024
Received in the revised format:
May 8, 2024
Accepted: June 23, 2024
Available online:
June 23, 2024

Keywords:
Container terminal
Operation scheduling
Multi-objective
Robust optimization
Time parameters uncertainty
Fuel consumption reduction
Epsilon-constraint

A B S T R A C T

The issue of integrated scheduling and sequencing operation of unloading and loading equipment in container ports has been one of the most important issues concerning time efficiency. In addition, with the emergence of green harbor concepts, the inclusion of criteria for minimizing energy consumption, fuel and emission reduction are among the other issues that have been noticed by planners in the field of energy efficiency. Furthermore, due to the complexity and scope of activities of a container terminal, uncertainty in operational parameters such as transportation time, time of readiness and entry of work into the system and the velocity of the transportation fleet are inevitable in this operational environment. Therefore, this research with the aim of sharing trucks among loading and unloading equipment, proposes a robust multi-objective integer programming model for the synchronized scheduling of truck operations with other handling equipment to decrease the fuel consumption of trucks and the flow time of containers, considering the uncertainty in operational parameters as fuzzy numbers. To find the Pareto solutions for this model, the ε-Constraint technique is employed. Finally, the performance of the model in deterministic and uncertain modes is evaluated, compared and analyzed employing the inputs gathered from Shahid Rajaei port. The findings demonstrate that using this model will result in a substantial decrease in both fuel consumption and flow time of containers in comparison to the current procedure. Additionally, results will demonstrate the extent to which the terminal's fuel and time consumption will increase under conditions of uncertainty in operational parameters when the optimal plans derived from the robust model are implemented.

1. Introduction

Among the strategic goals of container ports, the two goals of reducing service time to customers and reducing consumption and optimal use of energy resources have higher priorities for container terminal managers. The priority of the first objective is due to the existence of competition between ports, because a slight delay in serving customers, which are often shipping lines, will push them to other competitors in neighboring ports and impose the cost of lost opportunities on the ports. However, the second purpose takes importance for two reasons. Firstly, these resources, particularly fossil fuels, are finite. Secondly, their utilization results in the release of greenhouse gas emissions and environmental impacts. Consequently, in recent times, effectively managing fuel and energy consumption has become a worldwide challenge. This necessitates governments establish policies and incorporate this issue into its underlying legislation, including regulations pertaining to maritime transportation.

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doi: 10.5267/dsl.2024.6.002

The main sources of energy and fuel consumption in container ports are: 1. Yard Cranes (YCs), which handle the operation of pick up and placing containers to and from the storage yard, 2. Quay cranes (QCs) are accountable for the container handling operations in the berth area and on the ship. 3. Yard trucks (YTs) perform container transportation operations between the berth and the storage yard. Research on equipment performance, such as the study conducted by Yu et al. (2017), has demonstrated that over 50% of the emitted pollutants are associated with YTs. Furthermore, as the allocation of QCs and YCs is done at the tactical level planning and later the issue of scheduling and sequencing of YTs operations stands out, this study just considered the fuel consumption of YTs. A study conducted by Barth et al. (2005) revealed that various factors, including manufacturer nominal technical specifications, functional characteristics, and environment conditions, affect the calculation of fuel consumption for heavy goods vehicles. The nominal technical specifications include various factors such as weight, engine speed, engine displacement, acceleration, and frontal area surface. Additionally, the functional parameters and environmental conditions include load weight, average loaded and unloaded velocity, gravity, road gradient, drag, rolling resistance, and air density. Consequently, due to the utilization of various models of YTs in container ports, their fuel consumption will vary based on their specifications.

In the literature, different criteria have been suggested for reducing service time. These include minimizing the sum of completion times, minimizing the makespan ($C_{\max}$), minimizing the time between the arrival and departure of the ship, and minimizing the tardiness of the works based on their due date. However, since $C_{\max}$ only focuses on the maximum completion time and does not address the specifics of task waiting time, there is a possibility of having two schedules with the same $C_{\max}$, which in one of these schedules, the waiting time for containers (i.e., the duration between the moment when a task is ready and the moment when its operation begins.) may be longer compared to the other schedule. Thus, in this study, we have focused on reducing the flow time of tasks as one of the time criteria, which is the duration from a task's readiness to its finish time in the system.

Given that the two objectives mentioned earlier, namely minimizing fuel consumption of YTs and minimizing flow time of containers in the system, are in conflict with each other. If we seek time efficiency, the fuel objective function may be negatively affected due to differences in truck technical and functional parameters. Conversely, if we focus on reducing fuel consumption, time efficiency may not be achieved. Hence, employing multi-objective planning methodologies is an appropriate remedy for such issues, as they have capability to provide Pareto solutions, thereby enhancing decision-making flexibility for planners and facilitating the tradeoff between minimizing two objectives.

Moreover, the uncertainty in the operational parameters of the planning models leads to disruption in the implementation of a plan derived from the deterministic approach. The literature discusses many strategies for addressing uncertainty. For instance, Rodrigues & Agra (2021) classify these strategies into three categories: reactive, proactive, and reactive-proactive. In reactive approaches, a program is created after observing the occurrence of uncertainty and decisions are made according to what happened. Proactive approaches are approaches that, taking into account the worst case, present a risk-averse plan for implementing the program from the very beginning. Proactive-reactive approaches also present a plan with regard to uncertainty in the parameters, and in case of uncertainty, alter the plan once more and fix it. Therefore, in this research, in order to face the uncertainty in operational parameters such as the container's ready time for being transported, the travel time and the velocity of the YTs, which are affected by many unforeseen and beyond control factors, such as the skill of the equipment operator, breakdown in the operation of the equipment and route congestion, a robust optimization approach is utilized which is considered as a proactive approach.

Analysis of the pertinent literature on scheduling loading and unloading operations in container ports indicates that there hasn't been any previous analysis and optimization of truck fuel usage when YTs with various technological specifications are in use. Furthermore, considering the requirement to ensure time efficiency and the fact that the primary objective of scheduling and sequencing operations is to complete the work in the minimum possible time, it is imperative that these two criteria be taken into account simultaneously. Nevertheless, a review of the literature reveals that no multi-objective model considering the aforementioned two objectives is presented. Furthermore, to address the uncertainty in the parameters, the existing approaches are either scenario-based or stochastic programming. In scenario-based approaches, there may be so many scenarios that they add to the complexity of the problem, or some scenarios may be ignored. In stochastic programming, when non-deterministic parameters follow a probability distribution other than the uniform distribution, converting the non-deterministic model into a deterministic equivalent becomes challenging due to the complexity of the problem. In such cases, either average case models or scenario-based models with discrete probability distributions for each scenario are commonly employed. Consequently, the absence of methods that incorporate the uncertainty set directly into the model without turning it into discrete scenarios is readily apparent. Therefore, in the first stage of this research, a bi-objective is presented to determine the optimum schedule and sequence of operations. The objective is to reduce both the containers' flow time and the fuel usage of YTs in a synchronized and integrated manner with QCs and YCs, which in addition to the mentioned objectives leads to the implementation of the policy of sharing YTs between QCs with the aim of reducing the empty trip of YTs. The next step involves presenting the uncertain model of this problem as a robust possibilistic programming model. This model uses the possibility distribution by using fuzzy numbers and the possibility and necessity measures to face the uncertainty of the parameters. An advantage of this model is its ability to consider the entire uncertainty set, rather than limiting it to a specific number of scenarios. It can also control the confidence level of crisp equivalent constraints, which include uncertain parameters, and determine the minimum value of their confidence levels. Additionally, the ε-Constraint approach is utilized to address the robust bi-objective programming model. Once the preferred solution is chosen from the collection of Pareto front, the model's performance is evaluated in both deterministic and non-deterministic modes. Furthermore, the realization model compares the quality of the solutions derived from several versions of the uncertain model.

In summary, the distinctive aspect of this research can be stated based on the following:

- A conceptual framework is put forward to determine an optimal sequence of operations that simultaneously minimizes the waiting time of containers in the system and the fuel consumption of YTs.
- Uncertainty in operational parameters is considered and a robust multi-objective possibilistic programming framework is presented for the uncertain state of the problem.
- The ε-Constraint approach is adapted to deal with the proposed framework and identify Pareto front.
- Provides an estimate of fuel consumption for YTs based on the number of containers moved.
- It is determined how much increase in the waiting time of containers and fuel consumption will be imposed on the terminal in the presence of uncertainty.
- The performance of the solutions achieved in non-deterministic mode is evaluated and contrasted under real settings using the realization model.

According to what was mentioned in this introduction, the upcoming component of this research will examine the literature review pertaining to the consideration of uncertainty in parameters across several domains of container terminal problems. Section 3 outlines the operating environment in the container terminal. It also presents the mathematical program of the problem being studied, both in deterministic and non-deterministic modes. Section 4 outlines the procedure for resolving the model. Section 5 covers the experimental outcomes from implementing the model and the subsequent improvements achieved. In Section 6, the research outcomes and accomplishments are discussed as a tool for container terminal managers to make informed decisions. Additionally, potential areas for future research are identified.

2. Literature review

In general, the challenges related to planning operations in the container port are mostly centered around three specific areas, which are then classified accordingly. The berth side issues pertain to the allocation of berths and scheduling QCs operations. The yard and storage area problems involve the allocation of storage space and scheduling of YCs. Additionally, there are issues concerning the scheduling of transportation equipment between the berth and the storage area. This article examines the inclusion of uncertainty in decision-making models for container terminals' operating parameters in these three specific domains. It also reviews the various techniques used to address this uncertainty in these models.

When it comes to berth allocation and QC operation scheduling, there are many more research studies focused on these areas, considering the uncertainty in the parameters, compared to the other two. Regarding this matter, Rodrigues & Agra (2022) conducted a comprehensive evaluation of 66 works that address non-deterministic parameters in this particular sector and highlighted “stochastic programming, robust optimization and fuzzy programming” as the three main modeling techniques for dealing with uncertainty. A two-stage mixed integer stochastic programming approach was formulated by Ma et al. (2021) for scheduling the operation of QCs that can only move in one direction. The approach takes into account the uncertainty in the unloading and loading time parameters by considering different scenarios with varying probabilities of occurrence. To solve the model, they suggested a decomposition method known as the L-shaped integer method for small-scale problems, and a simulated annealing algorithm (SA) for larger-scale problems. In the analysis of the proposed model, two measures concerned to stochastic programming were utilized: the stochastic solution value and the expected value of full information. The former demonstrates the cost reduction resulting from considering uncertainty, particularly in conditions with a high degree of uncertainty. The latter quantifies the extent to which having perfect information about a parameter's future reduces the costs associated with uncertainty. In their study, Wu & Miao (2020) addressed the berth allocation problem by incorporating uncertainty in ship arrival time and operation time as a uniform distribution. They proposed a two-stage stochastic mathematical programming framework that included design variables and control variables. The objective was to develop a robust berth scheduling strategy for vessels, with the goal of minimizing the average port time of ships and reducing the cost of robustness. To solve the model, they devised a simulation-based genetic algorithm (GA). Shang et al. (2016) examined the combined issue of assigning berths and QCs in order to minimize the weighted sum of the time taken for unloading and loading operations, as well as the waiting time for all vessels. They took into account the uncertainty in the productivity of QCs and the processing time regarding uncertainty set and proposed a risk-averse and entirely conservative robust linear programming model. Additionally, to control the robustness, they introduced an alternative model derived from Bertsimas & Sim (2004)’s work. By taking into account the price of robustness, this model can control the level of conservatism and reduce the degree of disruption in the program. Rodrigues & Agra (2021) proposed a model that combines berth allocation and QC allocation and scheduling, considering the uncertainty of ship arrival times. They developed a two-stage robust mixed integer programming with the goal of reducing the time it takes to complete the operations. In their model, the allocation of berths is considered as the design variables, while the allocation and scheduling of QCs’ operations are considered as the control variables. The control variables are decided once the uncertainty parameters, namely the berth allocation, are realized. The model was solved by introducing a decomposition algorithm, and for larger-scale problems, a rolling horizon algorithm was employed.

In another research Chargui et al. (2023) addressed the issue of allocating berths and scheduling QCs while taking into account the uncertainty of renewable energy resources through various scenarios. They presented a robust optimization programming framework with multiple objectives to maximize the utilization of renewable energy resources and minimize operational costs, which include energy consumption and penalties for delays in servicing ships. Considering the intricate nature of solving the model due to the high number of scenarios, they proposed an exact decomposition algorithm. In another research, Chargui et al. (2023) tackled this problem by incorporating the uncertainty in the time of QC operations as well as the arrival time of ships in a scenario-based manner. Their objective was to minimize two key factors: the penalty for late vessel services and the cost associated with the electricity usage of QCs. The aforementioned decomposition algorithm was once again utilized to solve this model. Zheng et al. (2023) introduced a mixed integer programming problem to address the allocation of berths and QCs, considering the volatile nature of ship arrival times and the possibility of unscheduled arrivals. The objective was to reduce the deviation in the ship's time window and the operation time of unscheduled vessels. In this model, contrary to using robust proactive approaches and stochastic programming, they adopted a reactive approach based on rescheduling, which involved the utilization of the rolling horizon strategy. Within this framework, there are three methods to respond to uncertainty: 1. Immediate rescheduling method that is done as soon as uncertainty occurs, 2. Rescheduling at fixed time points that takes place at the end of each time interval, and 3. The combined method, if the intensity of the effect is high, the timing is immediate and if not, it is re-scheduled in time intervals, and a GA algorithm was also applied to solve the model. Zhang et al. (2024) proposed a robust linear programming model for the problem of ship traffic scheduling by considering the uncertainty budget in the condition of uncertainty in the arrival and departure time of vessels as an uncertainty set, which aims to minimize the waiting time of the ships. They proposed a hybrid algorithm of memetic algorithm (MA) and variable neighborhood search (VNS) to solve the model. Once again, Rodrigues & Agra (2024) examined the issue of scheduling QCs in the presence of unidirectional QC movement and uncertain operation times. Their objective was to minimize the duration between a ship's arrival and departure, in order to determine the sequence of bay operations for each QC. They proposed a distributionally robust optimization model, and a decomposition algorithm was presented to solve it. This model assumes that the non-deterministic parameter follows an unknown probability distribution within an ambiguity set. By adjusting a parameter that constrains the size of the ambiguity set, this approach can generate solutions that fall within the framework of stochastic programming and robust optimization. The ambiguity set is defined as the collection of all probability distributions whose distance from the nominal probability distribution (which is a uniform discrete distribution in this model) is less than or equal to the control parameter. If the control parameter has a value of zero, the problem is transformed into stochastic programming, where a stochastic distribution is used for the uncertain parameter. On the other hand, if the maximum value is assigned to the control parameter, the problem becomes robust optimization, which takes into account uncertainty sets for the uncertain parameters.

In the area of storage space allocation and scheduling of YCs in terms of uncertainty in parameters, Liu et al. (2021) developed a proactive conservative stochastic programming approach to address uncertainty in storage space allocation and scheduling of YCs. The approach considers uncertainty in two parameters: the arrival time of external trucks and the volume of operations allocated to YCs. The objective is to minimize the expected makespan of YCs and the total waiting time of all jobs. The approach takes into account all possible scenarios to determine the optimal sequence of YC operations. A heuristic algorithm and a GA algorithm were also used to solve the model. In this proposed model, 20 scenarios were generated for the YTs' arrival time parameter, which subsequently increases the computational complexity of the model even in small-scale problems. Uncertainty in the clustering of exported containers by considering different bay configuration scenarios in the yard as well as uncertainty in loading sequence was considered by Yu et al. (2021). They presented a bi-objective programming model by considering the minimization of the transportation distance and the number of containers' rehandles in order to allocate export containers to storage area. Additionally, Wang et al. (2023) by taking into account the uncertainty in the quantity of arriving containers at yard based on different scenarios and the flexibility in the capacity of the storage sub-blocks, presented a two-stage stochastic optimization model for determining the allocation of blocks and their length to each vessel in the initial stage, as well as the number of active YCs in each time period and the number of stored containers in each sub-block in the subsequent stage. The model evaluated three objective functions: minimizing the total distances to allocated sub-blocks for each ship, minimizing the operating cost of YCs, and penalizing deviations from the capacity of the sub-blocks and assigned YCs in each scenario. In addition, they suggested two algorithms to solve the model: one based on column creation and the other based on tabu search.

In connection with the scheduling of transportation equipment, working between the berth and storage area with regard to the uncertainty in the parameters, Jian et al. (2021) developed a multi-objective scheduling optimization model with the objective functions of minimizing the risk of delay in QCs' operation and the transportation time of Automated Guided Vehicles (AGVs), in order to assign containers to AGVs as well as to their storage location, considering the uncertainty in the operation time of AGVs using triangular fuzzy numbers. This model demonstrated that taking uncertainty into account resulted in the reduction of the risk of delays in QC operations and the overall completion time of tasks. Furthermore, this study employed fuzzy number theory for handling fuzzy numbers and transforming them into crisp equivalents. Zhong et al. (2022) developed a method to integrate the scheduling of QCs and AGVs. They considered the uncertainty in the handling time of containers by QCs, which follows a normal distribution, as well as the uncertainty in the ship's stowage plan. They initially modeled the process as a Markov decision process and then used a real-time scheduling approach based on Reinforcement Learning to minimize the finish time of vessels. Zhang et al. (2022) investigated the problem of AGV's double cycling operation and presented a stochastic mixed integer programming model under the uncertainty in QCs operation time with Gaussian distribution. The objective was to minimize the waiting time of AGVs, decrease their empty trip duration, and increase the rate of their loaded trips. To solve this, a hybrid algorithm from PSO and GA was proposed. Given the uncertainty of the YTs travel time, Liu et al. (2021) proposed a mixed integer programming model with the objective of minimizing the YTs travel time and determining the shortest path. This uncertainty, according to their model, is a result of both yard congestion and congestion brought on by YT joining from nearby paths and following a normal distribution. Subsequently, three scenarios were estimated based on the operator's attitude, namely risk taking, neutral risk, and risk averse. These scenarios were determined by setting three values for the confidence level of a normal distribution. To solve the model, two heuristic algorithms, namely the Shuffled Complex Evolution Approach and A*, were presented.

In a recent study, Cai et al. (2024) examined the combined scheduling of QCs, YTs, and YCs as a bi-directional hybrid flow shop. They considered the nondeterministic time of equipment operation and proposed a mixed integer programming model to minimize finish time and maximize robustness. They developed a novel robust proactive scheduling procedure, where the schedule is viewed as a complex network. To deal with uncertainty, they proposed a new evaluation measure regarding the entropy of the complex network structure to estimate the robustness of the schedule. In their model, scheduling plans with more gap time slots and more distributed gaps have higher robustness and reduce the effect of disruptions caused by time perturbations. Table 1 provides a thorough overview of the indicated research studies, categorizing them with respect to the problem they explored, the objective functions they focused on, the uncertain parameters they considered, the type of uncertainty representation used, the uncertainty programming model employed, and the algorithm utilized to solve the model.

Table 1
Literatures related to uncertainty in container terminal operations

Authors	Problem	Objectives	Uncertainty Parameter	Uncertainty Representation	Uncertainty Model	Solution Algorithm
Ma et al. (2021)	Unidirectional QCs scheduling and sequencing	Min Makespan	- Loading and unloading time	Scenarios	Scenario-based Stochastic Programming	Integer L-shaped method /SA
Wu and Miao (2020)	Berth allocation	- Min Total stay time of vessels - Min Robustness cost	- Vessel's arrival time - Operation time	Uniform distribution	Two stage Stochastic Programming	Simulation based GA
Shang et al. (2016)	Integrated Berth allocation and QC assignment	- Min weighted sum of loading and unloading operation time - Min Waiting time of all vessels	- QC's productivity and processing time	Uncertainty Set	Robust Programming	GA/ Insertion heuristic algorithm
Rodrigues and Agra (2021)	Integrated Berth allocation QCs allocation and scheduling	- Min Makespan	- Vessel's arrival time	Scenarios	Two stage scenario-based robust optimization	decomposition algorithm
Chargui et al. (2023)	Berth allocation QCs allocation and scheduling	- Max renewable energy usage rate - Min Energy cost and Tardiness penalty of vessel services	- Renewable energy resources	Scenarios	Scenario-based robust optimization	Exact decomposition algorithm
Chargui et al. (2023)	Berth allocation QCs allocation and scheduling	- Min QCs' electricity usage - MinTardiness penalty of vessel services	- QCs' operation time - Vessel's arrival time	Scenarios	Scenario-based robust optimization	Exact decomposition algorithm
Zheng et al. (2023)	Berth allocation QCs allocation	- Min deviation in vessels' time window - Min Unscheduled vessels' operation	- Vessel's arrival time - Unscheduled vessels' arrival	Uncertainty Set	Rescheduling	GA
Zhang et al. (2024)	Vessels' traffic scheduling	- Min vessels' waiting time	- Vessel's arrival and departure time	Uncertainty Set	Linear robust programming	Hybrid MA and VNS
Rodrigues and Agra (2024)	Unidrection QCs scheduling	- Min time between vessels' arrival and departure	- QCs' operation time	Random distribution Uncertainty Se	Distributionally Robust Optimization	Decomposition Algorithm
Liu et al. (2021)	YCs scheduling and sequencing	- Min Average completion time of YCs - Min Total jobs waiting time	- Arrival time of external truck - Handling volume of YCs	Scenarios	Scenario-based Stochastic Programming	A heuristic GA
Yu et al. (2021)	Storage space allocation to export containers	- Min transportation distance - Min Containers rehandles	- Cluster of export containers - Loading sequence	Scenarios	Scenario-based Stochastic Programming	A heuristic
Wang et al. (2023)	Storage block and YC assignment	- Min Total distance of vessels to sub-blocks - Min YCs operational costs - Min Penalty cost of deviations from capacity of sub-blocks and allocated YCs	- Quantity of arriving containers - Flexibility in capacity of storage sub-blocks	Scenarios	Two stage scenario-based Stochastic Programming	A heuristic column generation/ Tabu search
Jian et al.(2021)	AGV's Task allocation and storage space allocation to container	- Min QC's delay risk - Min AGVs' operational time	- AGVs' operation time	Fuzzy numbers	Fuzzy programming	An improved GA
Zhong et al. (2022)	Integrated scheduling of QCs and AGVs	- Min Makespan of vessels	- QCs' handling time - Vessels' stowage plan	Normal distribution	Real-time scheduling	Reinforcement learning
Zhang et al. (2022)	AGVs' Double cycling scheduling	- Min AGVs' waiting time - Min AGVs' empty trip	- QCs' operation time	Gaussian distribution	Stochastic Programming	Hybrid PSO
Liu et al. (2021)	Shortest path for YTs	- Min YTs' travel time	- YTs' travel time	Normal distribution Scenarios	scenario-based robust optimization	Shuffled complex evolution approach/ A*
Cai et al. (2024)	Integrated scheduling of QCs, YTs and YCs	- Min Makespan - Max Robustness	- Operational time of equipment	Uncertainty Set	Robust proactive scheduling	NSGA II

Therefore, the findings of the literature review reveal a study deficiency in the domain of YT operation scheduling, which not only fuel consumption optimization has not been considered yet, but this issue has not been investigated in a multi-objective manner along with time efficiency objective functions. Furthermore, due to the intricate nature of port processes and the multitude of unforeseen factors in terminal operations, uncertainty in operational parameters can cause disruptions and interruptions in the execution of a baseline plan. Therefore, it is necessary to employ uncertain programming approaches to address this uncertain problem. In this research, the robust possibilistic programming concept will be utilized.

3. Problem Description and mathematical formulation

The details of the operational procedure of the container port considered in this research are in accordance with Fereidoonian et al. (2024), which is summarized below. This problem assumes that the assignment of QCs for unloading and loading containers on ships, as well as YCs for storing and retrieving containers from the storage area, has been prearranged at the tactical decision-making level and it is evident which QCs and YCs are responsible for handling specific sets of containers. This assumption stems from the fact that, six hours prior to the ship's arrival at the port, shipping agencies systematically upload and send the list and specifications of the containers to be loaded or unloaded as well as the ship's stowage plan. Based on this received information, equipment allocation is carried out. A container terminal's schema is displayed in Fig. 1.

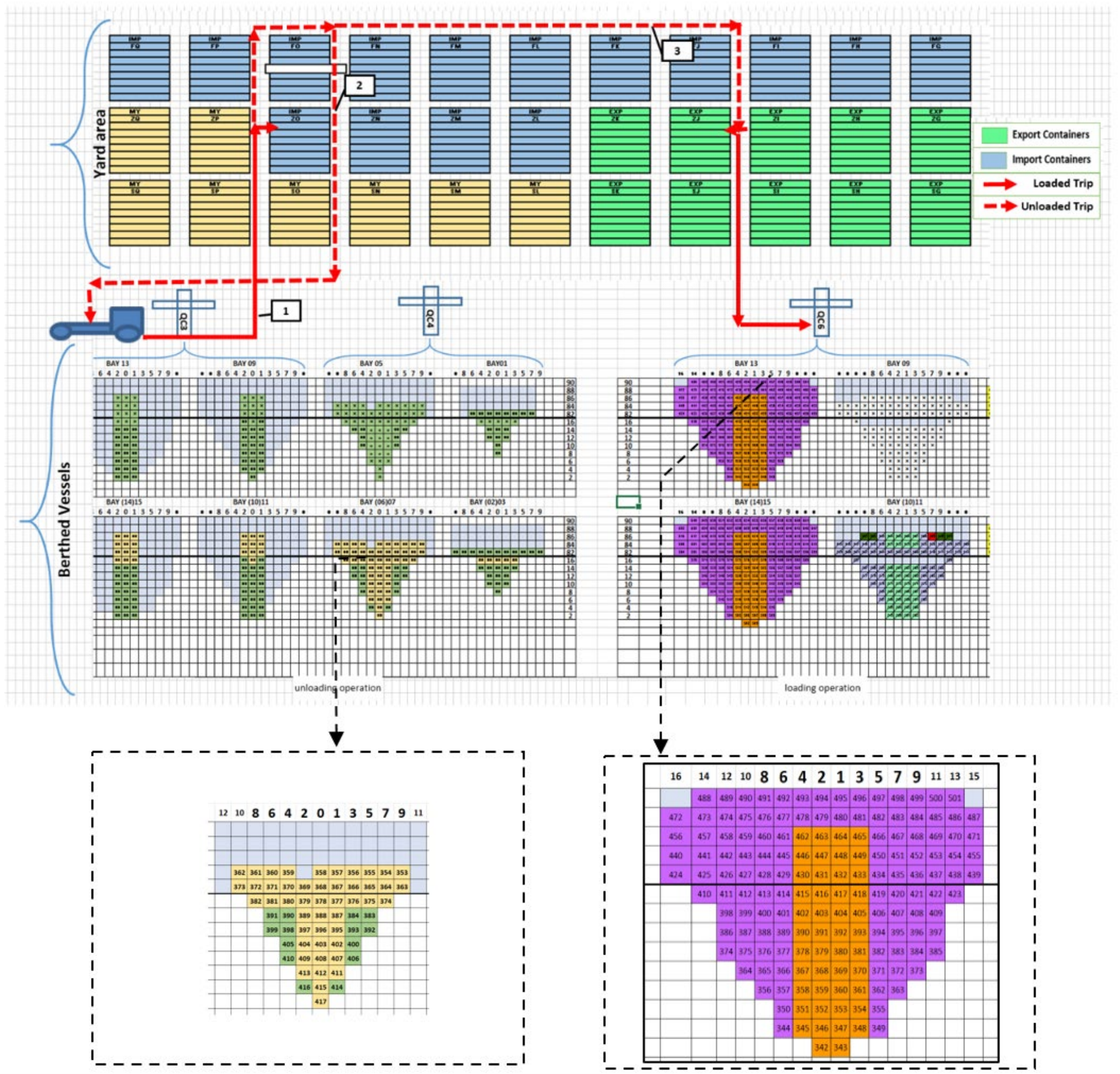

Fig. 1. A schema of container terminal including storage yard and berthed ship at quayside

The storage blocks are visible in the upper portion of the image, while the lower portion displays sections of two berthed ships, the left ship is loading, and the right ship is discharging. The cross-sectional image of the ships displays the arrangement of their bays and the sequential of unloading and loading containers, as indicated by the numbers assigned to each container. Within this view, the left ship designates QC3 to handle bays 9 to 15, while QC4 is responsible for bays 1 to 7. On the right ship, QC6 is allocated to bays 9 to 15. Unloading typically occurs from the stern to the bow of the ship, or in other words, in descending sequence from the bays, while across the ship is done from the berth to the sea. The opposite is true for loading containers onto the ship.

The current procedure for assigning YTs to QCs involves allocating a specific quantity of YTs to each QC. These YTs only handle and transport containers belonging to their allocated QC. They consistently return to the QC to carry out the operation of its next container. However, this research specifically examines the scheduling and sequencing of YTs operations with the aim of sharing them between QCs in order to reduce their empty trip. For instance, in Fig. 1, the truck that moves the unloading container from QC3 to its storage area via route 1, can then either take route 2 to transport another unloading container or take route 3 to transport a loading container from the storage area of export containers to QC6.Which route to choose in this problem, is done in the optimization model, taking into account the travel time of the trucks and the time when the containers are ready, which is equivalent to the finish time of container's pick up process by QCs for unloading containers and the finish time of container's pick up process by YCs for loading containers. Consequently, the two objective functions of the problem, decreasing the containers' flow time and minimizing fuel consumption of YTs are achieved

It is worth mentioning that considering completion time of jobs on QCs for unloading containers and YCs for loading containers facilitates problem modeling in several ways. Firstly, it ensures that the sequence of operations is synchronized and coordinated with the operations of QCs and YCs. Secondly, it considers the order of jobs in the scheduling model. For instance, in the unloading operation, the lower container cannot be operated on until the upper container has been transported. By utilizing this numerical parameter, we satisfy this condition and eliminate the need to incorporate precedence relationships in the index of decision variables, which would otherwise result in an increase in the number of decision variables.

Based on the provided explanations, this operational process could be considered as a scheduling and sequencing problem involving parallel machines that have the same speed but differ in other technical characteristics that impact fuel consumption. Meanwhile, there are additional conditions related to the ready time of jobs in the system and the sequence dependent set up time between jobs. The objective is to reduce both the flow time and fuel consumption of the jobs.

In order to calculate fuel usage, the model presented by Barth et al. (2005) and Demir et al. (2011) is used. In this model, the initial step involves calculating the tractive power requirements (P_{tract}) in (*kw*), using the following method:

$$P_{tract} = (Ma + Mg\sin\theta + 0.5c_d \rho A v + Mgc_r \cos\theta)v / 1000 \quad (1)$$

where:

M Mass of YT (kg)
A frontal surface of YT's (m^2)
v Speed (m/s)
a Estimated acceleration of YT (m/s^2)
ρ Environment density (1.2 (kg/m^3) in 30 $°C$)
g Gravitational acceleration (9.8 (m/s^2))
θ Route slope (here is 0)
c_d Drag coefficient (0.7)
c_r Rolling coefficient (0.01)

In the second step, the engine power output (*P*) in (*kw*) is estimated on a second-by-second basis using the following formula:

$$P = \frac{P_{tract}}{\varepsilon} + P_{acc} \quad (2)$$

In the above equation, (P_{acc}) refers to the power demand of the engine that is required to compensate for the energy losses during operation, as well as to power the car accessories such as air conditioning. In most cases, this demand is thought to be negligible or zero. ε represents the efficiency of the drive train, which is commonly assumed to be 0.4. Ultimately, the fuel consumption in (g/s) is determined by employing the subsequent equation:

$$FR = \frac{\varphi}{44}(KNV\eta + P) \quad (3)$$

$$\varphi = 1 + 10^{-4}.(N - 30\sqrt{\frac{3}{V}})^2 \quad (4)$$

In the above relationships, φ is the ratio of the mass of fuel to the mass of air, which is calculated based on Eq. (4), K is the engine friction factor, usually is considered 0.2. N is equivalent to the engine speed and is usually mentioned between 1600 and 4800 revolutions per minute (rpm) and V represents the engine displacement, measured in (*liters*), both of which can be extracted from the technical specifications of the trucks. The efficiency parameter for diesel engines has been shown by η which is usually considered to be 0.4.

Therefore, in the following the bi-objective programming model to optimize the fuel usage and flow time of containers in the mentioned process is delineated in the subsequent section in deterministic and non-deterministic states.

3.1 Notations

Model formulation is conducted employing the following notations in the subsequent sections of this document:

Indices definition:

u	Index for working YTs ranging 1,…, U
i, j	Index for unloading and loading containers in scheduling time frame ranging 1,…, N

Parameters:

r_j	Container's ready time for being transported by YTs
ve	Unloaded YTs' Velocity of YTs (m/s)
ae	Unloaded YTs' acceleration rate (m/s^2) (m/s^2)
vl	Loaded Velocity of YTs (m/s)
al	Loaded YTs' acceleration rate (m/s^2)
de_{ij}	Empty transportation distance from the delivery point of container i to pick up point of container j
$S_{ij} = \frac{de_{ij}}{ve}$	Empty transportation time from the delivery point of container i to pick up point of container j

dl_j	loaded transportation distance from pick up point of container *j* to its delivery point
$t_j = \frac{dl_j}{vl}$	loaded transportation time from pick up point of container *j* to its delivery point
mt_u	Mass of YT *u* (*kg*)
mc_j	Mass of container *j* (*kg*)
φ_u	The ratio of the mass of fuel to the mass of air of YT *u*
N_u	Engine speed of YT *u*
V_u	Engine displacement of YT *u*
L	A large positive number
tw	The allowed Containers' waiting time for arriving YTs
τ	Weight of minimizing deviation between maximum and minimum value of objective function Flow time (FT)
μ	The penalty unit of the completion time constraint violation (the difference between the maximum value of nondeterministic parameters r_j, t_j and their value taken in chance constraint)
τ'	Weight of minimizing deviation between maximum and minimum value of objective function Fuel usage (FL)
δ	The penalty unit of the precedence

	relationship constraint disruption (the difference between maximum value of nondeterministic parameter t_j , s_{ij} and their value taken in the crisp equivalent constraint)

Decision variables:

x_{iju}	Takes 1 if YT u transport container i before container j , otherwise 0
y_{ju}	Takes 1 if YT u transport container j , otherwise 0
c_j	The completion time of container j 's transportation by YTs
α	Confidence level for completion time constraint satisfaction
β	Confidence level for precedence relationship constraint satisfaction

$$\min FT = \sum_{j \in J} c_j - r_j \qquad (5)$$

$$\min FL = [\sum_{u=1}^{U} 0.08\varphi_u N_u V_u + \sum_{u=1}^{U}\sum_{i=1}^{N}\sum_{j=1}^{N} 0.0025\varphi_u .ve(mt_u .ae + 0.42ve.A_u + 0.098mt_u)s_{ij} x_{iju}$$
$$+ \sum_{u=1}^{U}\sum_{j=1}^{N} 0.0025\varphi_u .vl((mt_u + mc_j).al + 0.42vl.A_u + 0.098(mt_u + mc_j))t_j y_{ju}]/44 \qquad (6)$$

subject to

$$\sum_{u=1}^{U} y_{ju} = 1 \quad \forall j \in \{1,\ldots,N\} \qquad (7)$$

$$\sum_{\substack{i=1 \\ i \neq j}}^{N} x_{iju} \le y_{ju} \quad \forall j \in \{1,\ldots,N\}, u \in \{1,\ldots,U\} \qquad (8)$$

$$\sum_{\substack{j=1 \\ i \neq i}}^{N} x_{iju} \le y_{iu} \quad \forall i \in \{1,\ldots,N\}, u \in \{1,\ldots,U\} \qquad (9)$$

$$\sum_{i=1}^{N}\sum_{j=1}^{N} x_{iju} = \sum_{i=1}^{N} y_{iu} - 1 \quad \forall u \in \{1,\ldots,U\} \qquad (10)$$

$$c_j \ge r_j + t_j \quad \forall j \in \{1,\ldots,N\} \qquad (11)$$

$$c_i + s_{ij} + t_j \le L.(1 - x_{iju}) + c_j \quad \forall i,j \in \{1,\ldots,N \mid r_i + t_j + s_{iju} \le r_j + tw\ ,\ i \neq j\}\ ,\ u \in \{1,\ldots,U\} \qquad (12)$$

$$x_{iju} \in \{0,1\} \quad \forall i,j \in \{1,\ldots,N \mid r_i + t_j + s_{ij} \le r_j + tw\ ,\ i \neq j\}\ ,\ u \in \{1,\ldots,U\} \qquad (13)$$

$$y_{ju} \in \{0,1\} \quad \forall j \in \{1,\ldots,N\}, u \in \{1,\ldots,U\} \qquad (14)$$

$$c_j \ge 0 \quad \forall j \in \{1,\ldots,N\} \qquad (15)$$

Objective function (5) minimizes the sum of flow time of all containers, which implicitly assure the minimization of waiting time of containers after their completion time by QCs and YTs and ready to be loaded by YTs. The objective function (6) which intends to minimize the fuel consumption by YTs consists of two parts, fuel consumption during empty trips of YTs to the origin of assigned containers and fuel consumption during loaded trips when YTs carry containers from their origin to their destination. Constraints 7 to 10 are assignment constraints which (7) guarantees that each container is assigned to a YT, (8) and (9) indicate only one container can be processed before or after a container in a sequence. Constraints (10) ensures that a loop does not occur in the acquired sequence and determine the initial and final job on the YTs. Constraints (11) and (12) are time relevant constraints, which (11) accounts ready time and process time of a container in its completion time, whereas constraint (12) assures the precedence relationship among jobs. Constraints (13) to (15) specify the range of values that the decision variables can take.

Subsequently, in order to model the above problem with non-deterministic parameters, we use robust possibilistic programming. The introduction of this approach was done by Pishvaee et al. (2012). This model utilizes the chance constrained programming (CCP) approach to address parameter uncertainty by employing fuzzy numbers, their expected value, possibility and necessity measures, which are based on possibility distributions. This approach allows the decision maker to regulate the confidence level of the constraints' violation, while also minimizing the potential risks associated with executing a plan in the presence of uncertainty.

In this model, the two parameters of job's processing time (which depends on the velocity and distance between the pickup and delivery points of containers) and the readiness of containers due to being affected by various factors, including the utilization of trucks with varying technical characteristics, the congestion of routes, the operator's skill, and choosing alternative routes, have an uncertain nature. The terminal management only has information about the interval fluctuations of these parameters. Therefore, in this research, these uncertain parameters are represented as triangular fuzzy numbers. Specifically, $\tilde{t}_j = (t_j^1, t_j^2, t_j^3)$ represents the loaded travel time of a container *j*, $\tilde{s}_{ij} = (s_{ij}^1, s_{ij}^2, s_{ij}^3)$ represents the empty trip time from the destination of the container *i* to the origin of container *j*, and $\tilde{r}_j = (r_j^1, r_j^2, r_j^3)$ represents the ready time of tasks in the system.

Hence, the bi-objective robust possibilistic programming model in order to minimize the fuel usage and flow time of containers in the system, which is denoted as RTFL1, is defined as follows:

RTFL1:

$$\min FT = \sum_{j \in J} c_j - \left(\frac{r_j^1 + r_j^2 + r_j^3}{3}\right) + \tau(FT_{\max} - FT_{\min}) + \mu((r_j^3 + t_j^3) - (1-\alpha)(r_j^2 + t_j^2) - \alpha(r_j^3 + t_j^3)) \tag{16}$$

$$\begin{aligned} \min FL = & \\ & [\sum_{u=1}^{U} 0.08\varphi_u N_u V_u + \sum_{u=1}^{U}\sum_{i=1}^{N}\sum_{j=1}^{N} 0.0025\varphi_u .ve(mt_u .ae + 0.42ve.A_u + 0.098mt_u)\left(\frac{s_{ij}^1 + s_{ij}^2 + s_{ij}^3}{3}\right)x_{iju} \\ & + \sum_{u=1}^{U}\sum_{j=1}^{N} 0.0025\varphi_u .vl((mt_u + mc_j).al + 0.42vl.A_u + 0.098(mt_u + mc_j))\left(\frac{t_j^1 + t_j^2 + t_j^3}{3}\right)y_{ju}] / 44 \\ & + \tau'(FL_{\max} - FL_{\min}) + \delta \sum_{i=1}^{N}\sum_{j=1}^{N} (t_j^3 + s_{ij}^3) - (1-\beta)(t_j^2 + s_{ij}^2) - \beta(t_j^3 + s_{ij}^3) \end{aligned} \tag{17}$$

subject to

Constraints (7) to (10)

$$c_j \geq (1-\alpha)(r_j^2 + t_j^2) + \alpha(r_j^3 + t_j^3) \quad \forall j = 1,\ldots,N \tag{18}$$

$$c_i + (1-\beta)(s_{ij}^2 + t_j^2) + \beta(s_{ij}^3 + t_j^3) \leq L.(1 - x_{iju}) + c_j \quad \forall i,j \in \{1,\ldots,N \mid r_i^1 + t_j^1 + s_{ij}^1 \leq r_j^3 + tw,\ i \neq j\},\ u \in \{1,\ldots,U\} \tag{19}$$

$$x_{iju} \in \{0,1\} \quad \forall i,j \in \{1,\ldots,N \mid r_i^1 + t_j^1 + s_{ij}^1 \leq r_j^3 + tw,\ i \neq j\},\ u \in \{1,\ldots,U\} \tag{20}$$

Constraints (14) - (15)

$$0.5 < \alpha, \beta \leq 1 \tag{21}$$

According to Pishvaee et al. (2012) "a solution is robust if it assures optimality robustness and feasibility robustness". Optimal robustness of a solution minimizes the undesirable deviation between realized objective value and its optimal value obtained from a robust model considering all the values in the uncertain set of a nondeterministic parameter. In addition, feasibility robustness minimizes the disruption of constraints including operational uncertain parameters. In this respect robust approaches could be considered in three categories: 1. Full pessimistic robust programming, 2. Semi pessimistic robust programming and 3. Realistic robust programming approach. The first approach is so conservative therefore in respect to optimality robustness minimizes the worst case i.e. maximum value of the objective function and in respect to feasibility robustness does not allow for any violation in the constraints. The second approach is still strict for optimal robustness but somewhat allows for a degree of violation in the constraint. However, the third approach looks for a tradeoff between optimality robustness and feasibility robustness.

In the above formulation, objective function (16) consists of three terms. The first term is the minimization of expected value of the flow time which is calculated based on fuzzy numbers, the second term is concerned with optimality robustness by minimizing the gap between the maximum and minimum value of the flow time and the third term assures the feasibility robustness by minimizing the difference between pessimistic value of ready time parameter and the value it would take in the chance constraints. In this case we consider equal weight importance for optimality robustness and feasibility robustness by setting the value of τand μ to 0.5. The objective function (17) consists of five parts. The first two parts minimize the expected fuel consumption empty trips and loaded trips of YTs based on fuzzy numbers. The third part aimed to minimize the gap between the maximum and minimum value of the fuel consumption and keeps them close to its expected value in order to achieve optimality robustness. The fourth and fifth parts of this relation are feasibility robustness relevant terms. The fourth part minimizes the gap between the pessimistic value of the processing time and its value in the chance constraint, similarly the fifth part provide tradeoff between the worst value of sequence dependent set up time and the value it would take according to chance constraint (19). Additionally, we set equal importance for optimality robustness and feasibility robustness by setting their coefficients' values to 0.5. Furthermore, $FT_{\max}$ and $ET_{\max}$ ($FT_{\min}$ and $ET_{\min}$) are optimum objective function value of definite model when maximum (minimum) value of uncertain parameters are considered.

Constraints (18) and (19) are crisp equivalent of the following constraints from CCP:

$$Nes\{c_j \geq \tilde{r}_j + \tilde{t}_j\} \geq \alpha$$

$$Nec\{c_i + \tilde{s}_{ij} + \tilde{t}_j \leq L.(1 - x_{iju}) + c_j\} \geq \beta$$

Since the necessity measure is stricter and pessimistic than possibility measure, due to focusing on worst cases, this measure is used to represent our chance constraints. Additionally, since in the definite state of this problem, we limit the number of x_{iju} variable by eliminating those which take the value 0 due to the nature of the problem with respect to precedence relationship among jobs, which is considered in the condition $r_i + t_j + s_{ij} \leq r_j + tw$, so that in the uncertain mode in order to account all possible x_{iju}, the limit of this condition is set to minimum value for the left hand side and maximum value for the right hand side of this inequality, which is applied in constraint 19 and 20. In the CCP literature it has been proven that the crisp equivalent of chance constraints are valid when confidence level is greater than 0.5. Hence the scope of confidence level decision variables is considered as in (21).

The RTFL1 model tries to perform minimization in a way that provides solutions with less variation and concentrated towards the Expected value. Since solutions with less than the expected value are desirable for terminal manager, so that in the following two variant of above model's objective function, called RTFL2 and RTFL3, are introduced, which specifically target worst-case scenarios and seek to minimize the maximum value.

RTFL2:

$$\min FT = \sum_{j\in J} c_j - (\frac{r_j^1 + r_j^2 + r_j^3}{3}) + \tau(FT_{\max} - E(FT)) + \mu((r_j^3 + t_j^3) - (1-\alpha)(r_j^2 + t_j^2) - \alpha(r_j^3 + t_j^3)) \tag{22}$$

$$\begin{aligned} \min FL = \\ &[\sum_{u=1}^{U} 0.08\varphi_u N_u V_u + \sum_{u=1}^{U}\sum_{i=1}^{N}\sum_{j=1}^{N} 0.0025\varphi_u .ve(mt_u .ae + 0.42ve.A_u + 0.098mt_u)(\frac{s_{ij}^1 + s_{ij}^2 + s_{ij}^3}{3})x_{iju} \\ &+\sum_{u=1}^{U}\sum_{j=1}^{N} 0.0025\varphi_u .vl((mt_u + mc_j).al + 0.42vl.A_u + 0.098(mt_u + mc_j))(\frac{t_j^1 + t_j^2 + t_j^3}{3})y_{ju}]/44 \\ &+\tau'(FL_{\max} - E(FL)) + \delta\sum_{i=1}^{N}\sum_{j=1}^{N}(t_j^3 + s_{ij}^3) - (1-\beta)(t_j^2 + s_{ij}^2) - \beta(t_j^3 + s_{ij}^3) \end{aligned} \tag{23}$$

subject to

Constraints (7) - (10), (14) - (15), (18) - (21)

In the RTFL2 model, the goal is to minimize the solutions more than the average and to find the solutions close to the expected value of the objective function.

RTFL3:

$$\min FT = \sum_{j\in J} c_j - (\frac{r_j^1 + r_j^2 + r_j^3}{3}) + \tau FT_{\max} + \mu((r_j^3 + t_j^3) - (1-\alpha)(r_j^2 + t_j^2) - \alpha(r_j^3 + t_j^3)) \tag{24}$$

$$\begin{aligned}\min FL = & \\ & [\sum_{u=1}^{U} 0.08\varphi_u N_u V_u + \sum_{u=1}^{U}\sum_{i=1}^{N}\sum_{j=1}^{N} 0.0025\varphi_u .ve(mt_u.ae + 0.42ve.A_u + 0.098mt_u)(\frac{s_{ij}^1 + s_{ij}^2 + s_{ij}^3}{3})x_{iju} \\ & + \sum_{u=1}^{U}\sum_{j=1}^{N} 0.0025\varphi_u .vl((mt_u + mc_j).al + 0.42vl.A_u + 0.098(mt_u + mc_j))(\frac{t_j^1 + t_j^2 + t_j^3}{3})y_{ju}]/44 \\ & + \tau' FL_{\max} + \delta \sum_{i=1}^{N}\sum_{j=1}^{N} (t_j^3 + s_{ij}^3) - (1-\beta)(t_j^2 + s_{ij}^2) - \beta(t_j^3 + s_{ij}^3)\end{aligned} \tag{25}$$

subject to

Constraints (7) - (10), (14) - (15), (18) - (21)

In the RTFL3 model, there is no centralization of the answers towards the average, and only the pessimistic value of the objective functions is minimized.

To assess the answers derived from this robust optimization model, it is important to analyze the model in real conditions. Therefore, the realization model of the problem is as follows:

$$\min FT = \sum_{j\in J} c_j^* - r_j^{real} + \mu R_j^{rt} \tag{26}$$

$$\begin{aligned}\min FL = & \\ & [\sum_{u=1}^{U} 0.08\varphi_u N_u V_u + \sum_{u=1}^{U}\sum_{i=1}^{N}\sum_{j=1}^{N} 0.0025\varphi_u .ve(mt_u.ae + 0.42ve.A_u + 0.098mt_u)s_{ij}^{real} x_{iju}^* \\ & + \sum_{u=1}^{U}\sum_{j=1}^{N} 0.0025\varphi_u .vl((mt_u + mc_j).al + 0.42vl.A_u + 0.098(mt_u + mc_j))t_j^{real} y_{ju}^*]/44 + \delta R_{ij}^{st}\end{aligned} \tag{27}$$

subject to

Constraints (7) to (10)

$$c_j^* + R_j^{rt} \geq r_j^{real} + t_j^{real} \quad \forall j = 1,\ldots,N \tag{28}$$

$$c_i^* + s_{ij}^{real} + t_j^{real} \leq L.(1 - x_{iju}^*) + c_j^* + R_{ij}^{st} \quad \forall i,j \in \{1,\ldots,N \mid r_i^1 + t_j^1 + s_{ij}^1 \leq r_j^3 + tw \ , \ i \neq j\}, \ u \in \{1,\ldots,U\} \tag{29}$$

$$R_j^{rt}, R_{ij}^{st} \geq 0 \quad \forall i,j \in \{1,\ldots,N\} \tag{30}$$

In the given model, r_j^{real}, t_j^{real} and s_{ij}^{real} represent the realized values of non-deterministic parameters. These values are randomly generated within the range defined by the uncertainty set, using a uniform distribution. x_{iju}^*, y_{ju}^*, And c_j^* are the values of the decision variables acquired from the robust possibilistic programming model replace the decision variables in the aforementioned model. Furthermore, R_j^{rt}, R_{ij}^{st} are the decision variables represent the disruption of constraints with non-deterministic parameters when implementing the solution generated from the robust model of the problem.

4. Solution approach

Given that the model discussed in the preceding part is a bi-objective programming model, it is imperative to employ multi-objective planning approaches to solve the model. Typically, these methods can be classified into two main groups: a priori methods and a posteriori method. In a priori techniques, the decision maker must present weights to each objective function to indicate their priority. The objectives are then combined using these weights to create a single objective problem, resulting in a single solution. Nevertheless, a posteriori technique does not require prior preferences from the decision maker, instead, they present a collection of Pareto solutions to the decision maker, who can then select one based on their preferences. In this research, the ε-Constraint method is employed to find the solution of this model. This method is the only posteriori approach that provides exact Pareto optimal solutions. According to Mavrotas (2009), the summary of the steps of this method is as follows. This method involves optimizing the value of each objective function individually to reach their respective minimum values. Next, one of the objective functions, in this research FT, is chosen, while the other function, FL, is incorporated into the constraints by considering its upper and lower limits. Its lower Min FL, while the upper limit is FL (Min FL), which represents the value of FL in the optimum solution of FT.

$$\min FT$$

$$\min \ FL \leq FL \leq FL(\min \ FT) - \varepsilon$$

Other Constraints

The value of ε is obtained from the relation $\varepsilon = \frac{FL(\min \ FT) - \min \ FL}{nbPareto} \times \text{iteration}$ in which $nbPareto$ is equivalent to the number of Parato solutions, ε is also updated based on the values of $iteration = 1, ..., nbPareto$.

To facilitate the selection process of Parato solutions and enable performance comparison of the different models discussed earlier, we utilize the ideal solution displacement approach proposed by Zelany (1974). This method helps in choosing a solution from a collection of Parato solutions. The aim of this method is to select a solution with lower distance to the ideal solution. It involves calculating the distance between each of the Pareto solutions and the ideal solution, and then choosing the solution with the highest closeness value to the ideal solution.

5. Experimental Implementation

To evaluate the efficacy of the proposed models in both deterministic and non-deterministic modes with respect to the actual operation conditions in the container terminal, the model was implemented using data acquired from Shahid Rajaei port, the largest container port in Iran. In this port, a specific time has been considered to gather data on the implementation of the model. During this time, two vessels have berthed as shown in Fig. 1. Based on this, different instance problems have been examined, that include variations in the number of containers, YTs, QCs, and YCs. The input data for the given problem consists of the vehicle specs, the distance matrix between the origin and destination locations of the containers, the information matrix of the containers, the truck's speed and acceleration, and the number of Pareto solutions. Table 2 presents the specifications of the YTs carrying containers between the berth and the storage area.

Table 2
YTs Technical features

No	Model	Mass of YT (kg)	Frontal Surface Area (m^2)	Engine speed (N) of YT (RPM)	Engine displacement (V) (lit)	Fuel to air mass ratio (φ)
1	Dafran	7800	3.81	1900	12.15	356.358
2	Dima	7400	3.95	1900	12	356.323
3	Volvo	7592	3.75	1900	12.8	356.502
4	Foton	8150	3.79	1900	11.8	356.275
5	Scania G460	10000	3.80	1900	13	356.544
6	Amico	6900	3.78	1900	11.5	356.201
7	Man	7080	3.83	1900	12.8	356.502

The container information matrix, exemplified by Table 3 for 25 containers, contains data regarding the containers' origin and destination, weight, ready time in the system, and transportation time from origin to destination.

Table 3
A sample of container information matrix for 25 container

Container	Pick up location	Deliver location	Delivery distance	Mass of container (kg)	Ready Time (min)			Transportation time (min)		
					r^1	r^2	r^3	t^1	t^2	t^3
1	Crane1	ZM	544.87	4500	2.5	3	4	0.82	1.09	2.18
2	Crane1	ZM	544.87	19305	5.5	6	7	0.82	1.09	2.18
3	Crane1	ZM	544.87	23000	8.5	9	10	0.82	1.09	2.18
4	Crane1	ZM	544.87	22264	11.5	12	13	0.82	1.09	2.18
5	Crane1	ZM	544.87	23000	14.5	15	16	0.82	1.09	2.18
6	Crane2	ZO	544.87	23131	2.5	3	4	0.82	1.09	2.18
7	Crane2	ZO	544.87	30000	5.5	6	7	0.82	1.09	2.18
8	Crane2	ZO	544.87	30210	8.5	9	10	0.82	1.09	2.18

9	Crane2	ZO	544.87	30210	11.5	12	13	0.82	1.09	2.18
10	Crane2	ZO	544.87	30210	14.5	15	16	0.82	1.09	2.18
11	Crane3	ZS	529.87	3800	2.5	3	4	0.79	1.06	2.12
12	Crane3	ZS	529.87	3800	5.5	6	7	0.79	1.06	2.12
13	Crane3	ZS	529.87	29740	8.5	9	10	0.79	1.06	2.12
14	Crane3	ZS	529.87	28585	11.5	12	13	0.79	1.06	2.12
15	Crane3	ZS	529.87	27480	14.5	15	16	0.79	1.06	2.12
16	SG	Crane5	264.94	29250	1.5	2	3	0.40	0.53	1.06
17	SG	Crane5	264.94	19305	3.5	4	5	0.40	0.53	1.06
18	SG	Crane5	264.94	31300	5.5	6	7	0.40	0.53	1.06
19	SG	Crane5	264.94	5100	7.5	8	9	0.40	0.53	1.06
20	SG	Crane5	264.94	3750	9.5	10	11	0.40	0.53	1.06
21	SH	Crane6	264.94	25800	1.5	2	3	0.40	0.53	1.06
22	SH	Crane6	264.94	19305	3.5	4	5	0.40	0.53	1.06
23	SH	Crane6	264.94	25470	5.5	6	7	0.40	0.53	1.06
24	SH	Crane6	264.94	23131	7.5	8	9	0.40	0.53	1.06
25	SH	Crane6	264.94	26250	9.5	10	11	0.40	0.53	1.06

The ready time and transportation time, which are estimated based on truck speed and distance, are subject to uncertainty and are represented by triangular fuzzy numbers. The nominal values of these uncertain parameters, denoted as r_j^2 and t_j^2, substitute for the values of these parameters in the definite model. Furthermore, Table 4 displays the distance matrix that represents the distances between the container destinations and the starting point of the truck's next container shipment. Additionally, the main diameter of this table represents the distance travelled from the pickup point of a container to its delivery destination. The YTs' velocity during unloaded empty trips is expected to be 50 *km/h*, whereas during loaded trips it is estimated to be 30 *km/h*. In addition, their acceleration during the empty and loaded trips is measured at 0.463 *m/s*^{2} and 0.278 *m/s*^{2}, respectively.

Table 4
Matrix of distances between delivery and pick up location of containers (m)

		Pick up location					
		Unloading area				Retrieval Block	
Delivery location		Crane1	Crane2	Crane3	Crane4	SG	`SH
Storage Block	ZM	544.87	569.26	587.54	599.74	429.94	399.94
	ZO	544.87	544.87	563.16	575.35	489.94	459.94
	ZS	566.45	548.16	529.87	542.06	609.94	579.94
	ZT	554.26	542.06	529.87	529.87	639.94	579.94
berth Loading area	Crane 5	62.67	87.06	105.34	111.44	264.94	279.94
	Crane 6	38.29	62.67	80.96	87.06	279.94	264.94

The imprecise values of the transportation time for unloaded YTs from the destination of one container to the origin of its subsequent container $\tilde{s}_{ij}$, referred to as the precedence relationship set up time in the model, are also treated as fuzzy numbers. These values are calculated based on the distances in Table 4, the empty velocity of YTs, and the uncertainty range provided by terminal experts. The triangular fuzzy numbers are displayed in three square matrices, each with several rows and columns equal to the number of containers. However, we did not provide the matrices here because of limited space and their large dimensions. This research examines 12 instance problems according to the information in Table 5. These problems are divided into 4 categories, each with a different number of containers: 25, 30, 50, and 100. The model's results are achieved by varying the number of assigned YTs.

Table 5
Instance Problems

Instance No	Number of Container	Total weight (ton)	Number of QC	Number of Truck
1	25	537.90	5	4
2	25	537.90	5	5
3	25	537.90	5	6
4	30	655.47	6	5
5	30	655.47	6	6
6	30	655.47	6	7
7	50	1207.70	6	6
8	50	1207.70	6	7
9	50	1207.70	6	8
10	100	2507.13	6	6

11	100	2507.13	6	7
12	100	2507.13	6	8

To implement the ε-Constraint procedure, the algorithm of this method is scripted and implemented in ILOG CPLEX Optimization Studio 12.6. The acquired results are as follows. Initially, the outcomes derived from the deterministic model have been compared with the current procedure in the terminal. Subsequently, the results for uncertain mode from robust programming models are compared. Ultimately, the effectiveness of the solutions derived from robust models is investigated by generating random values of non-deterministic parameters in the realization model.

Table 6 presents a comparison between the existing procedure in the terminal and the deterministic planning model with respect to the results obtained for the flow time of containers in the system, the fuel usage, and the fuel usage per ton of load movement. The data shown in this table demonstrates that using this strategy will lead to a 5% decrease in container flow time and a 28% reduction in fuel usage. Additionally, the average fuel usage per ton of load movement can be expected to be 1.1 liters. This outcome is one of the excellences of this approach, since it enables us to quantify and estimate the fuel consumption based on the weight of load transported.

Table 6
The computational result of current practice and definite model

Instance No	Current practice			Definite				
	Flow Time (min)	Fuel (litr)	Fuel usage per tonne (litr)	Flow Time (min)	Flow Time Improvement	Fuel (litr)	Fuel Improvement	Fuel usage per tonne (litr)
1	25.87	974.52	1.81	23.52	9%	598.54	39%	1.11
2	24.97	812.10	1.51	22.63	9%	585.70	28%	1.09
3	23.80	784.45	1.46	22.06	7%	566.18	28%	1.05
4	30.15	1168.04	1.78	28.56	5%	769.22	34%	1.17
5	29.72	1001.18	1.53	27.93	6%	750.97	25%	1.15
6	28.99	993.30	1.52	26.79	8%	724.41	27%	1.11
7	49.05	1763.75	1.46	47.91	2%	1353.03	23%	1.12
8	47.05	1767.50	1.46	45.95	2%	1295.88	27%	1.07
9	46.05	1732.00	1.43	45.62	1%	1278.22	26%	1.06
10	98.04	3645.75	1.45	95.99	2%	2714.44	26%	1.08
11	95.04	3675.38	1.47	92.38	3%	2681.11	27%	1.07
12	92.04	3624.38	1.45	91.04	1%	2678.49	26%	1.07
	Average		**1.53**		**5%**		**28%**	**1.10**

Furthermore, Table 7 displays the flow time of containers in the system, the amount of fuel used, and the fuel usage per ton of load movement based on the robust planning model. It also indicates the percentage increase in these criteria due to uncertainty. Based on this table, in the case of uncertainty in the parameters, the terminal will experience a 90% increase in flow time and a 25% increase in fuel consumption. Additionally, the average fuel consumption will be 1.38 liters per ton of load movement. Fig. 2 displays the Pareto solutions obtained for each instance problem in the deterministic model. According to this information, while determining the ideal number of YTs, the third instance problem identifies the most suitable number of trucks in each group. This is because any more increase in the number of YTs does not result in any additional improvement in FT.

Table 7
The computational result of RTF1 model

RTFL1					
Instance No	Flow Time (min)	FT Increase over Definite	Fuel (litr)	Fuel Increase over Definite	Fuel usage per tone (litr)
1	47.03	100%	741.08	24%	1.38
2	44.15	95%	730.21	25%	1.36
3	41.44	88%	711.48	26%	1.32
4	54.69	91%	935.05	22%	1.43
5	53.79	93%	920.76	23%	1.40
6	51.42	92%	912.60	26%	1.39
7	86.89	81%	1664.90	23%	1.38
8	85.37	86%	1654.60	28%	1.37
9	84.36	85%	1612.86	26%	1.34
10	173.46	81%	3554.07	31%	1.42
11	170.98	85%	3533.18	32%	1.41
12	168.51	85%	3480.11	30%	1.39
Average		**88%**		**26%**	**1.38**

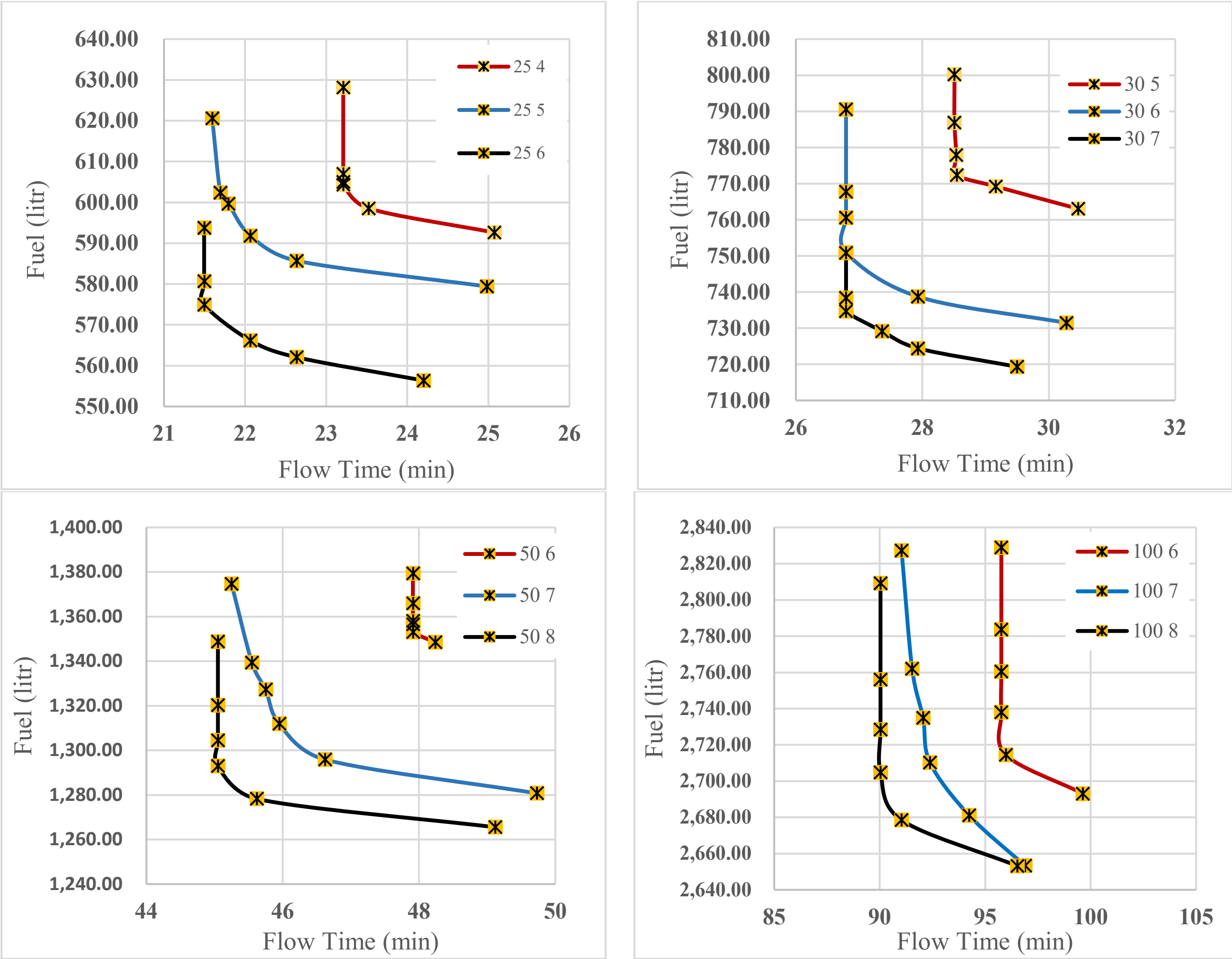

Fig. 1. The Pareto solutions of instance problems from ε-Constraint

In addition, Fig. 3 displays a comparison diagram of fuel usage of three modes: the current procedure, deterministic model, and non-deterministic model. It is evident that even though the fuel consumption in the current procedure has been calculated using uncertain parameters' nominal values and without considering their worst-case scenario, the fuel consumption resulting from the robust planning model is still lower than the current situation.

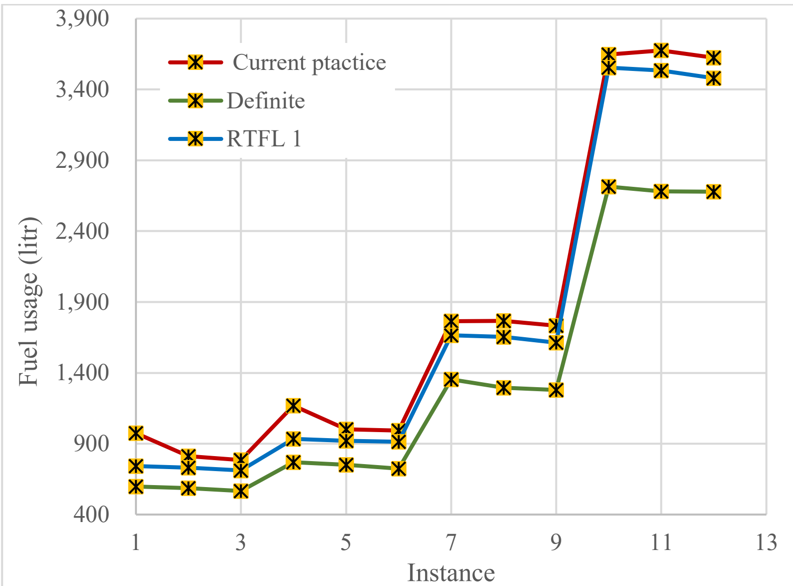

Fig. 2. The comparison of results from current practice, definite model and Robust model

Table 8
Results of random realization of proposed models

Realization Number	RTFL1		RTFL2		RTFL3	
	Flow Time (min)	Fuel (litr)	Flow Time (min)	Fuel (litr)	Flow Time (min)	Fuel (litr)
1	38.30	757.85	36.17	792.73	39.23	803.26
2	36.68	740.21	38.20	833.94	35.44	778.47
3	37.27	794.97	37.83	777.71	37.49	820.05
4	34.52	839.49	38.34	795.19	39.84	817.42
5	41.18	803.58	37.06	747.79	42.01	814.74
6	39.49	787.24	36.53	824.45	39.88	827.86
7	40.36	790.69	40.00	770.41	40.80	831.10
8	37.45	719.04	36.95	736.83	38.21	725.51
9	34.97	835.80	38.22	768.25	40.34	858.55
10	33.55	740.12	40.10	796.61	38.33	765.68
Average	37.38	780.90	37.94	784.39	39.16	804.26
Standard Deviation	2.53	40.79	1.34	30.73	1.87	38.17

To evaluate the model's performance in practical situations, we consider the instance problem with 25 containers and 6 trucks. The solutions obtained from any of the three robust possibilistic programming models are then replaced in the realization model. We conduct ten random realizations of these models, and the results are presented in Table 8 and Fig. 4. To assess the performance of the three models, we utilize two criteria: average performance and standard deviation. Based on Fig. 4, it is evident that the RTFL1 model offers superior solutions with the lowest average values of the objective functions. In the RTFL2 model, while the average performance is close to that of RTFL1, the standard deviation of the answers is lower compared to other models. Due to its emphasis on worst cases, the RTFL3 model exhibits a higher average in comparison to the other two models. Therefore, to determine which model to adopt, the decision-maker can select one based on the preference of each model in comparison to the others, as outlined in the provided Table 9.

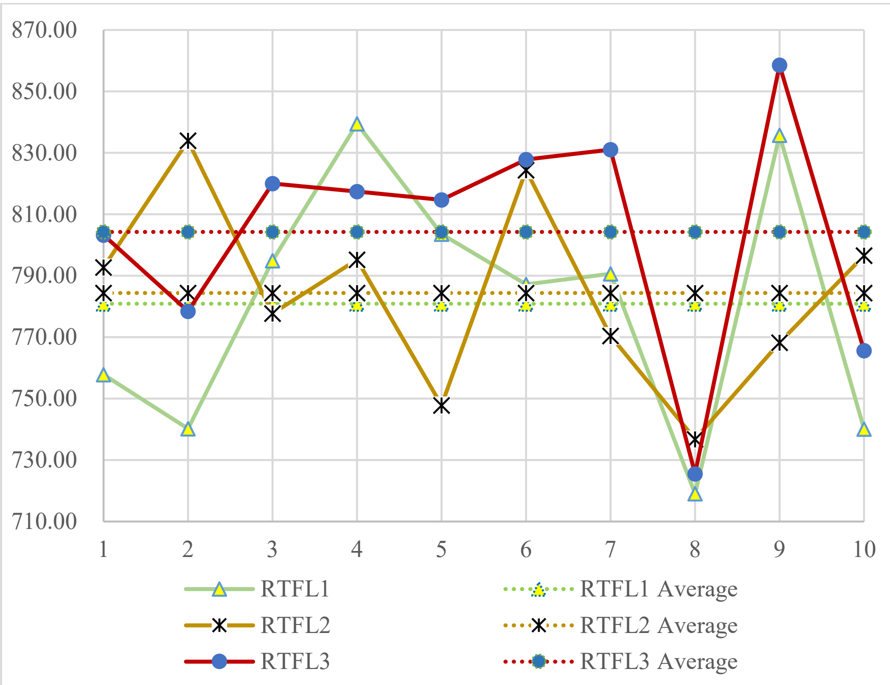

Fig. 3. comparison of the random realization of proposed models

Table 9
The preferences of proposed models

Robust Model	Superiority
RTFL1	Minimum average performance
RTFL2	Minimum Standard Deviation-Minimizing worst cases - Close average to RTFL1
RTFL3	Minimizing worst cases

6. Conclusion and future research

This study was conducted to address the absence of a model for sharing trucks between QCs during container unloading and loading operations, to satisfy two criteria of minimizing both the flow time of containers in the system and fuel consumption through optimizing the schedule and sequence of truck operations. The goal was to enhance the container terminal planning software by incorporating this functionality. Furthermore, since the terminal utilizes trucks with varying technical specifications, it was imperative to calculate fuel consumption based on their respective specifications. Moreover, given the numerous unforeseen factors that impact operations in this environment, it was necessary to account for the uncertainty in operational parameters. As the managers of the container terminal were only aware of the range of fluctuations in those parameters, employing robust programming approaches was deemed an appropriate solution to address these fluctuations.

In this regard, initially a two-objective mixed-integer programming model was proposed to minimize both the waiting time in the system and fuel consumption simultaneously. Subsequently, to incorporate uncertainty in the parameters, three robust optimization models were presented under the titles RTFL1, RTFL2, and RTFL3. The ε-Constraint procedure was employed to generate Pareto front from these bi-objective models.

One of the important achievements of this research for container terminal managers is that it provides an optimal sequence of YT operations, resulting in minimal waiting time for containers and fuel consumption. Compared to the current situation, it will lead to an average 5% reduction in FT and a 28% reduction in fuel consumption.

Moreover, the sequence obtained from the robust programming model takes into account the uncertainty in the parameters of the ready time in the system, loaded and unloaded travel time of trucks, and provides a sequence that guarantees both optimality robustness and feasibility robustness. Another implicit outcome of this research is that it provides a pattern for managers to determine the optimal number of YT's based on the number of containers. By increasing the number of YTs, we reach a point where no more reduction in FT is observed, and this may be chosen as the optimal number of YT's.

The findings of this study also indicate that the average fuel consumption per ton of load movement is 1.1 litres in the deterministic model and 1.38 liters in the non-deterministic model. This estimation provides quantitative information for terminal managers and offers two advantages: firstly, it can be calculated in the total cost of services, and secondly, it provides a precise and quantitative criterion for targeting fuel consumption reduction in future.

The findings from the realization model robust optimization programming model indicate that if one is seeking solutions with lower average performance, the RTFL1 model is suitable. Conversely, if one is looking for a model that generates solutions with lower standard deviation but acceptable average performance, the RTFL2 model is recommended. Finally, if one is specifically interested in a plan with lower risk and greater conservatism, the RTFL3 model appears to be appropriate.

One of the limitations of this study is that the allocation of QC to ships and YC to the storage area is a prerequisite for this model, and it is necessary to determine its information prior to implementation. Furthermore, despite considering a combined approach to loading and unloading operations, it is assumed that the loading of a ship takes place after its unloading, and double cycling mode is not considered for QC operations.

The future development of this research could involve adapting this model to more advanced terminals that use manless equipment such as AGVs instead of trucks for transportation, which is still required to optimize energy consumption and operational sequences. In this case, the calculation of fuel consumption specific to that equipment would replace the calculation of fuel consumption for heavy goods vehicle. Considering the uncertainty in the number of transportation and loading/unloading equipment is another proposed area for future research. The implementation of other robust planning methods and comparing them with the proposed model, as well as considering budget uncertainty and partial uncertainty in the problem, where not all parameters are uncertain but only a percentage of them, are topics that can be investigated in the future.

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