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Bi-objective Recoverable Berth Allocation and Quay Crane Assignment Planning under Environmental Uncertainty

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Abstract. This study discusses the development of tactical-level integrated planning at seaport container terminals in an uncertain environment. The suggested approach seeks to strike a balance between the cost-effectiveness of a robust baseline schedule and recovery plan and the required quality of customer service in order to enhance the competitive edge of container ports. Integrated planning for a tactical level at the container terminal synchronizes the decisions of berth allocation and quay crane assignment planning by taking into account the unpredictability of the vessel's arrival time and handling time caused by a variety of unforeseen factors such as unfavorable weather conditions, instability in the productivity rate of the quay cranes, the uncertainty of the quantity of loading and discharging containers, and other unpredictable events. The proposed optimization model produces a robust and proactive baseline schedule with a recoverable reactive plan for each scenario that occurs by utilizing buffer times and quay cranes that anticipate fluctuations in uncertain parameters. The proposed bi-objective recoverable robustness optimization model is solved by applying a hybrid method, namely the Rolling Horizon-based Optimization Algorithm (RHOA) and the Preemptive Goal Programming approach, using Gurobi-Python Optimization. The proposed bi-objective recoverable robust optimization model demonstrates superior solution quality in terms of service level and total costs, as well as a more efficient computational time when compared to an optimization model that minimizes total costs for tactical level planning decisions in seaside container terminals.

Keywords: Bi-objective optimization model; Container terminal; Environmental uncertainty; Recoverable robustness; Rolling horizon-based optimization algorithm

1. Introduction

The tactical level planning decisions in resources planning that have the most influence on container terminal performance are the berth and quay cranes as the primary resources at seaport container terminals (Carlo et al., 2015). The Tactical Berth Allocation Problem (TBAP) dictates the timetable and placement of each incoming vessel's berth. This decision is heavily influenced by the Quay Crane Assignment Problem (QCAP) decision, which determines the number of quay cranes assigned to each vessel, and vice versa. Since TBAP and QCAP decisions are intertwined, these two issues should be considered as a whole (Prayogo et al., 2018).

The essential factor in getting ahead of the intense competition in container terminals

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is to improve service quality through a well-balanced combination of robust resource planning, recoverable planning in an uncertain environment, and operational cost-efficiency (Iris & Lam, 2019). Maximization of the service level is required to increase the competitive advantage of container terminals. However, maximizing the service level will increase the expected total operating and recovery costs. Therefore, this study offers a bi-objective recoverable robust optimization model for integrated tactical planning that considers two objectives, i.e., maximization of minimum service levels for all vessels served and minimization of total operational and recovery costs at a seaside container terminal. To obtain a compromise solution between these two conditions. Non-Polynomial/NP-hard problem characterizes the integrated model (Li et al. 2015; He 2016; Gutierrez et al. 2018; Homayouni & Fontes 2018; Yu et al. 2019), that becomes more complex when considering the uncertain environment. When there is uncertainty, it is extremely challenging to compute the global optimal solution of the TBAP and QCAP integration models using the exact method, and if it is even feasible, it takes an extremely long time. Therefore, in this study, we apply a hybrid solution methodology using the Rolling Horizon-based Optimization Algorithm (RHOA) of Xiang et al. (2018), adapted with Pre-emptive Goal programming to solve the proposed bi-objective recoverable robust optimization model to get good quality solution with efficient computation time. In the case of complex problems, RHOA's solution methodology provides various advantages. The computation time can be reduced by subdividing the problem into multiple subproblems. We shall obtain the optimal solutions while tackling sub-problems utilizing the exact method. In addition, the rolling horizon-based optimization will let the subproblems be linked together, which will make for a smooth transition and the best solution overall. The following are the main contributions of this study:

- The proposed model of bi-objective recoverable robust optimization for integrated tactical planning decisions at a seaside container terminal in an uncertain environment aims to increase the competitive advantage of the container terminal by maximizing the service level and balancing total cost efficiency, robustness, and recoverable planning. This is different from a single-objective optimization model, which only tries to minimize expected total costs.
- We describe a hybrid method that combines the RHOA and Preemptive Goal Programming approaches to get a high-quality solution in a reasonable amount of computing time. This method is used to solve the proposed bi-objective recoverable robust optimization model.
- Moreover, by maximizing the minimum service level of all vessels served as the first objective function, which is solved by the Preemptive Goal Programming approach, and then using the solution result as a goal constraint to minimize the total cost, this is in addition to being able to produce a better quality solution as well as more efficient computational time compared to the single-objective model, which has a greater computational burden to achieve the same result.

This paper will henceforth be arranged as described below. In Section 2, there is a review of the research on the deterministic and probabilistic TBAP and QCAP integrated planning models. In Section 3, the construction of a bi-objective optimization model is discussed. The Rolling Horizon-based Optimization approach is proposed as a solution method for this study in Section 4. The proposed model and solution approach are evaluated in Section 5 through numerical experiments and analysis of the findings. Finally, Section 6 concludes with conclusion thoughts and some research directions.

2. Literature Review

This section focuses on a literature review about the development of a bi-objective, recoverable integrated model in the presence of environmental uncertainty. In container terminals at seaports, unexpected things happen often, which can make it hard to carry out operational planning. It results in decreased service levels and inefficient use of resources at container terminals. In latest years, some scholars have recognized the importance of including unpredictability in container terminal operational planning. In tactical planning, there are two strategies for dealing with uncertainty: proactive and reactive strategies. In the proactive strategy, a baseline plan is constructed by incorporating a degree of uncertainty anticipating (Xu et al., 2012; Liu et al., 2016a; Liu et al., 2016b; Nourmohammadzadeh & Voß, 2021) In the meantime, the reactive strategy changes the baseline plan to account for realistic events that have a certain chance of happening (Li et al. 2015; Umang et al. 2017).

Furthermore, only a few researchers have explored a robust optimization approach to tactical planning at container terminals in the presence of uncertainty. Zhou and Kang (2008) were pioneers in developing a proactive technique for Berth Allocation and Quay Crane Assignment Problem (BACAP) with unforeseeable vessel arrival and service times. They established a Genetic Algorithm as a method for finding solutions. Han et al. (2010) used a simulation-based Genetic Algorithm to construct a robust, proactive strategy for discrete berth allocation and quay crane scheduling under unpredictability of vessel arrival and container handling times. For numerous disruption situations, Zhen et al. (2011) worked on a reactive technique to resolve the integrated planning of Berth Allocation Problem (BAP) and QCAP using a Tabu Search-based approach. Rodriguez et al. (2014) studied the time-invariant robust BACAP under handling times uncertainty. They devised a proactive Genetic Algorithm heuristic-based solution method with two objectives: maximization of vessel-specific buffer times and minimization of the baseline plan's total cost. Li et al. (2015) established a reactive technique for incorporating BAP and QCAP in the presence of disturbances, such as a service interruption or a vessel delay. They tackled this problem using a heuristic technique based on Squeaky Wheel Optimization (SWO). Shang et al. (2016) used a Genetic Algorithm and an insertion heuristic algorithm to tackle the problems proactively and offered two robust optimization techniques for BACAP of Meisel and Bierwirth (2009) and Iris et al. (2015) to handle data uncertainties in quay crane productivity. Liu et al. (2016c) split the challenge into two parts by using a behavior perception-based reactive technique for combined BAP and QCAP planning. As a solution methodology, they used a Mixed Integer Programming (MIP)-based relax-and-fix method and a dynamic programming approach. Umang et al. (2017) focused on the real-time recovery of the BAP under uncertain vessel arrival and service hours. They developed a rolling horizon heuristic to minimize the overall real expenses of the updated baseline plan.

Xiang et al. (2018) established the Berth Allocation and Specific Quay Crane Assignment Problem (BACASP) with four classes of disruptions that can arise: uncertainty of vessel arrival and handling delays, quay crane productivity rate instability, and unscheduled vessel calling. They applied a reactive strategy to minimize the total recovery costs, solved by a Rolling Horizon-based Optimization Algorithm (RHOA). Iris and Lam (2019) provided a recoverable optimization technique for the robust BACAP that encompasses both proactive and reactive strategies to deal with vessel arrival and handling time unpredictability. An adaptive large neighborhood search heuristic has been used to resolve this problem in a two-stage heuristic framework.

Several researchers have tackled integrated planning at the container port by analyzing the precision of forecasts for the demand for reefer containers and energy usage (Budiyanto

& Shinoda, 2017; Pradita et al., 2020); integrating quay crane and internal truck assignment with preventive maintenance activities solved by applying a bi-objective optimization model (Liu et al., 2016c; Vahdani et al., 2019; Li et al., 2020); estimation of CO2 emissions and their effect on vessel energy efficiency management plan development (Budiyanto et al., 2019; Dawangi & Budiyanto, 2021); and the application of Swarm-based Algorithms to solve the stochastic optimization problem in container terminal design (Zukhruf et al., 2020).

This research examines a bi-objective recoverable robust optimization model for TBAP and QCAP integration based on a model proposed by Iris and Lam (2019). It also applies a hybrid method that combines a Rolling Horizon-based Optimization Algorithm and Preemptive Goal Programming approaches to obtain good quality results in reasonable computational time.

3. Model Development

Before discussing the formulation of a bi-objective optimization model for recoverable robust BACAP in a Mixed Integer Linear Programming (MILP), the initial stage is to identify the current problem. The problem characteristic of recoverable robust BACAP with the uncertainty of vessel arrival and handling times is continuous berth allocation for the tactical planning horizon. The vessel i is allowed to moor at any available place along the quay wharf area with a length of L meters. The continuous berth is divided into equal berth sections, b, and the planning horizon, H, is also divided into equal time steps, t. A set of quay cranes, Q, is assigned to serve each vessel's loading and unloading processes with time-variant quay cranes assignment while complying with interferences or non-crossing constraints and safety space allowance between quay cranes. In this study, the relationship between the tactical planning of the seaside container terminal, and the land-side container terminal, storage container yard planning, in the proposed bi-objective optimization model for recoverable robust BACAP is stated by the expected berth location for each vessel, b_i^0, which is the ideal berthing location, resulting in a minimum internal transport distance between the vessel berthing position and the container allocation location at the reserved storage container yard.

Productivity losses at container terminals are significantly influenced by interference among QCs with a exponential coefficient, and an increase of the internal transport workload due to deviations, Δb, between the actual berthing location of the vessel, b_i, and the expected berthing location, b_i^0, (Meisel & Bierwirth, 2009). Each vessel's estimated arrival, a_i^e, and total workload, m_i, are known. However, because quay crane productivity rates may be disrupted or unstable within the planning horizon, vessel arrival and total workload are unpredictable and represented in discrete scenarios. The recoverable robust BACAP model produces a robust baseline schedule and recovery plan to anticipate uncertainty by applying buffer times and QCs.

A bi-objective robust optimization model is developed based on the single-objective recoverable model of Iris and Lam (2019). In addition to minimizing the total cost as in the single-objective model of Iris and Lam (2019), To boost the container terminal's competitive advantage, we create a first objective function that maximizes the minimal service level for all vessels served during the planning horizon. Furthermore, the maximum of the minimum service level of all vessels served will positively impact efforts to minimize the waiting cost before berthing and the departure delay cost, both of which are cost components in the baseline schedule cost. Thus, the bi-objective optimization model is constructed to (a) maximize the minimum service level of all vessels served and (b) balance the cost efficiency of a robust, proactive baseline schedule with a recoverable reactive plan.

The first objective is to maximize the minimum service level of all vessels in the integrated plan, as shown in (1).
Maximize the minimum service level of all vessels served.

$$Max.\ SL = \min_{i\in V}\{SL_i\} \tag{1}$$

The service level of each vessel, SL_i, is defined in (2),

$$SL_i = 1 - \frac{\tau_i^{a+} + \tau_i^{b+}}{b_i^e - a_i^e} \qquad \forall i \in V \tag{2}$$

where τ_i^{a+} and τ_i^{b+} are waiting time before the vessel i begins mooring and tardiness of vessel i 's mooring finish time in the baseline plan, respectively, and the expected handling time of vessel i is $b_i^e - a_i^e$ for $i \in V$.

The cost efficiency is expressed as the second objective, namely, to minimize the total cost of the baseline schedule, TC_b, the total recovery cost from the baseline schedule for each scenario, TC_r, and the expected total cost for all scenario solutions, TC_s.

$$Min.TC = TC_b + TC_r + TC_s \tag{3}$$

The total cost of the baseline schedule, TC_b, constitutes the waiting cost before berthing, the departure delay cost, and the assigned QCs operational cost to all vessels in the integrated planning, as shown in (4).

$$TC_b = \sum_{i\in V} c_{1i}.\tau_{is}^{a+} + \sum_{i\in V} c_{1i}.\tau_{is}^{b+} + \sum_{i\in V}\sum_{q\in q_i}\sum_{t\in T} c_2 q X_{it}^q \tag{4}$$

where: c_{1i} and c_2 are penalty cost for waiting of mooring start time of vessel i from its expected start handling time or delay of completion time of vessel i from its designed departure time and QC operational cost rate per time step, respectively. The decision variable, X_{it}^q, is set to 1, if vessel i is served by allocated q QCs at time step t in the baseline plan and 0 otherwise; for $i \in V, q_i \in \left[0, q_i^{min}, \ldots, q_i^{max}\right], t \in T$.

Total recovery costs, TC_r, consist of the total cost of postponement due to recovery plan, the total cost of operations lateness after the end of buffer time, and the total cost of QC setup due to recovery plan, as shown in (5).

$$TC_r = \sum_{s\in S} p_s\{\sum_{i\in V} c_{1i}(\gamma_{is} + \delta_{is}) + \sum_{i\in V}\sum_{t\in T} c_3\lambda_{its}\} \tag{5}$$

where: c_3 is the setup cost of additional QC assigned to the recovery plan. The decision variables, γ_{is}, δ_{is}, and λ_{its} are vessel i's relative tardiness in comparison to the baseline plan in scenario s, vessel i's handling time duration exceeds the buffer time in scenario s, and number of additional QCs setup for a vessel i at time step t as a recovery plan in scenario s compared to the baseline plan for $i \in V$, $t \in T, s \in S$, respectively.

The total expected cost of all scenarios, TC_s, consists of the expected cost of waiting time before berthing costs, the departure delay costs, and the QC operation costs for all scenarios as shown in (6).

$$TC_s = \sum_{s\in S} p_s\left\{\sum_{i\in V} c_{1i}.\tau_{is}^{a+} + \sum_{i\in V} c_{1i}.\tau_{is}^{b+} + \sum_{i\in V}\sum_{q\in q_i}\sum_{t\in T} c_2 q X_{its}^q\right\} \tag{6}$$

where: p_s is the scenario's probability of being realized, for scenario $s \in S$.

Some constraints are considered in the proposed model. Each vessel must moor along with the quay wharf range and within its feasible time windows, without overlapping each other in the berth plan. The number of allocated QCs must fulfil the QC capacity requirements and consider the QC productivity losses caused by the discrepancy, Δb, between berthing location, b_i and its expected berthing location, b_i^0, with β coefficient and QC interferences, with α exponential coefficient. The total number of allocated QCs and buffer QCs for each vessel cannot exceed the maximum allowable number of allocated QCs. In addition, the total amount of allocated QCs included buffer QC for all vessels cannot exceed the total available QCs in each time step. The recovery plan occurs if there is a delay after the end of the buffer time and the minimum setup QCs are carried out in addition to the allocated QCs in the baseline plan. The complete model and its explanation of the proposed bi-objective recoverable robust BACAP optimization model are presented in the Supplementary Material (https://bit.ly/3b6VEC0).

4. Rolling horizon-based Optimization Algorithm

We apply a rolling horizon-based optimization algorithm based on the RHOA developed by Xiang et al. (2018) with some adjustments to obtain computational time efficiency in solving large-scale problems. Xiang et al. (2018) applied RHOA using the ut and gt parameters as time durations after the expected arrival time of the last vessel and before the expected arrival time of the first vessel in a sub-problem, as the overlapping time between iterations, where each iteration may consist of a different number of vessel arrivals. Each sub-problem consists of nv vessel arrivals being scheduled. Thus, each iteration has a different number of vessel arrivals with a fixed overlapping time range. While in this study, each iteration i has a fixed number of vessel arrivals, namely $nv + overlap$, where the overlap parameter is expressed as a number of vessel arrivals from the next sub-problem ($overlap \leq nv$), which is considered in optimizing the sub-problem with different time ranges among iterations. In addition, Xiang et al. (2018) used RHOA to solve a single objective optimization problem, while in this study, RHOA was combined with the Pre-emptive Goal Programming approach for solving the proposed bi-objective optimization model by using the optimal solution result of the first objective function as a goal constraint to solve the second objective function in each iteration. The following explanation discusses the detailed steps of the Rolling Horizon-based Optimization algorithm for solving the bi-objective optimization model for a recoverable robust BACAP model.

1. **Step 1: Initialize model parameters**
2. nv ← the number of new vessels to be considered in each iteration
3. $niter$ ← number of iterations, $niter = \lceil V/nv \rceil$ V = number of vessels
4. $overlap$ ← number of vessels to be considered to the next iteration
5. **Step 2: sort total vessels in ascending order of vessel arrival time expectation**
6. Sort all vessels by expected arrival times in ascending order.
7. **Step 3: optimize the first iteration with $nv + overlap$, as the number of vessels**
8. Solve the first iteration using the first objective function to obtain the optimal schedule for the first $(nv + overlap)$ vessels, then use the value of the first objective function as a goal constraint for optimizing the second objective function (apply Pre-emptive Goal Programming approach).
9. **Step 4: Fix optimal schedule of the first nv vessels**
10. Fix the optimal schedule of the first nv vessels
11. **Step 5: Iterative process**
12. For $iter == 2 : niter - 1$, **do:**
13. Solve the $iter\text{-}th$ iteration to get the optimal schedule of the first $(iter \times nv + overlap)$ vessels using a fixed optimal schedule of the first $(iter - 1) \times nv$ vessels.
14. Fix the optimal schedule of the first $iter \times nv$ vessels.
15. **end**

16. **Step 6: solve the last iteration**
17. For the last iteration ($niter\text{-}th$ iteration), optimize the schedule of all vessels, V, using a fixed optimal schedule of the first $(niter - 1) \times nv$ vessels.

In addition, the steps of the rolling horizon-based optimization algorithm can be described in Figure 1, where "fix" means that all decision variables in these time steps use the optimal results from the previous iterations. Meanwhile, "optimize" is referred to as the decision variables in these time steps are optimized by considering the fixed optimal values from the previous iterations. "Release" is defined as the values of the decision variables in these time steps, that are still free.

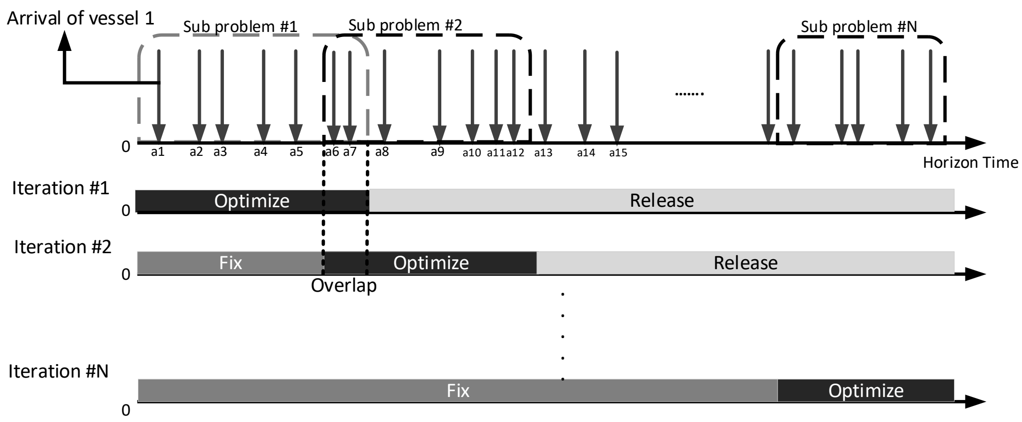


Figure 1 The steps of the rolling horizon based optimization algorithm

5. Experimental Setting, Results, and Discussion

The proposed bi-objective recoverable robust optimization model for integrated tactical planning in seaside container terminals under environmental uncertainty is applied to 30 cases. Each case has 10 discrete scenarios that have an equal probability of occurrence. The parameter settings, data generation, and scenario uncertainty information for numerical experiments are based on Iris and Lam (2019).

Numerical experiments are performed using a combination of the number of calling vessels (V = 20, 30, and 40 vessels), the length of quay wharf (L = 1000 m and 1500 m), and the number of available QCs (Q = 10 QCs). Quay wharf is divided into equal length of berth section with a length of 20 m. The planning horizon is a weekly period that is divided into time steps (ts) of 4 hours (H = 42-time steps). There are two scenarios of uncertainty level (UL), namely highly uncertain (HU) and slightly uncertain (SU). In highly uncertain (HU) cases, vessel arrival times and QC capacity demand can vary significantly from the expected parameters of the initial schedule, while in slightly uncertain cases, delays from expected arrival times are up to 1 time-step (ts). The QC capacity demand for each vessel is in the range of 0 to 2 QC-ts difference between the two scenarios' uncertainty levels. We randomly generate 5 datasets for each scenario of uncertain level (UL) of the slightly and highly uncertain QC capacity demand (SU and HU). In each case, three-vessel types consist of Feeder, Medium, and Jumbo vessels with a composition of 90%, 30%, and 10%, respectively. The vessels' length, l_i, QCs capacity demand, m_i, the minimum and the maximum number of assigned QCs, q_i^{min}, q_i^{max}, QCs capacity demand for each scenario of uncertain level, m_{is}, and the penalty cost per time step for waiting and delay times, c_2 are shown in Table 1. Table 2 presents the parameters setting of the expected and feasible arrival and depart times and their uncertain times for each vessel type.

Table 1 Data for each of vessel type

Vessel Type	Proportion	l_i (m)	m_i (QC-ts)	$[q_i^{min}, q_i^{max}]$ (QCs)	m_{is} (QC-ts) SU	HU	c_{1i}
Feeder	60%	U[70,200]	U[2,5]	[1,3]	U[2,7]	U[3,9]	4
Medium	30%	U[200,300]	U[6,14]	[2,4]	U[6,17]	U[7,19]	8
Jumbo	10%	U[300,400]	U[15,20]	[3,6]	U[15,23]	U[16,24]	12

Table 2 Parameters setting of the expected vessel arrival and depart times and their uncertainties

Vessel Type	a_i^e	b_i^e	a_{is}^e	b_{is}^e
Feeder	U[1,H-U[2,4]]	$\min\{H, a_i^e + U[4,8]\}$	$a_i^e + U[0,3]$	$\min\{H, a_{is}^e + U[4,8]\}$
Medium	U[1,H-U[3,5]]	$\min\{H, a_i^e + U[5,9]\}$	$a_i^e + U[0,3]$	$\min\{H, a_{is}^e + U[5,9]\}$
Jumbo	U[1,H-U[4,6]]	$\min\{\mathrm{H}, a_i^e + U[6,10]\}$	$a_i^e + U[0,3]$	$\min\{H, a_{is}^e + U[6,10]\}$

Parameters setting of the feasible vessel arrival and departure times are generated using $a_i^f = \max\{1, a_i^e - U[2,6]\}$ and $b_i^f = \min\{H, b_i^e + U[2,6]\}$. Furthermore, their associated time in each scenario s are obtained from $a_{is}^f = \max\{1, a_{is}^e - U[2,6]\}$ and $b_{is}^f = \min\{H, b_{is}^e + U[2,6]\}$. The expected berthing location of each vessel i is obtained from $b_i^o = U[\frac{l_i}{2}, L - \frac{l_i}{2}]$ meters. Productivity losses of QCs use coefficients of $\alpha = 0.9$ and $\beta = 0.01$. The cost of QC operational per time step and QC setup cost are $c_2 = 0.4$, and $c_3 = 0.06$, respectively, as used in Iris and Lam (2019). The numerical experiment was accomplished with the following RHOA setting parameters: each iteration is comprised of sub-problems with the number of vessels, $nv = 5$, and the number of vessels from the next sub-problem, $overlap = 2$. The numerical experiments are conducted on processor Intel core i7-8550U, 1.80GHz, and 8 GB RAM. Python programming-Gurobi 9.0 optimization with the configuration of eight threads is applied to the proposed rolling horizon-based optimization algorithm as the solution methodology for solving the recoverable robust optimization model.

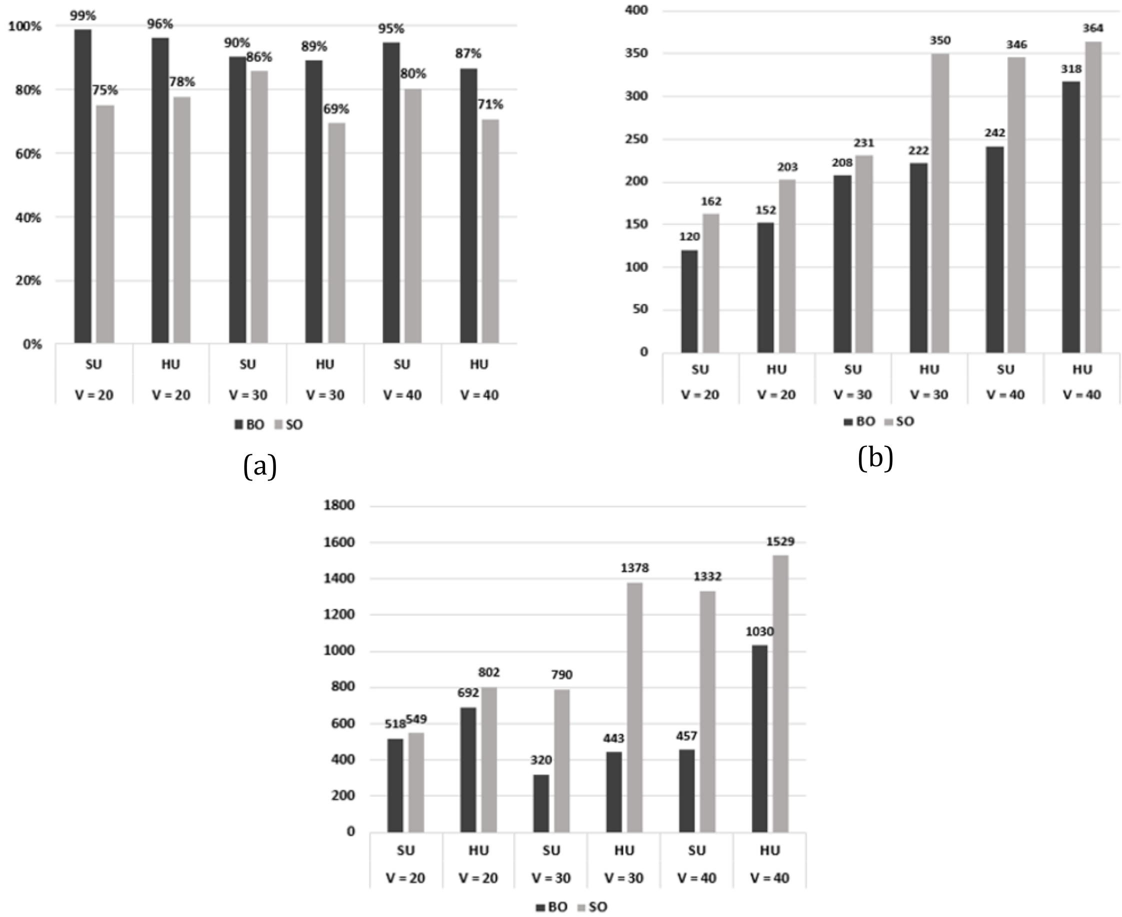
In addition to minimizing the total cost as in the single-objective model of Iris and Lam (2019), we add an objective function to maximize the minimum service level of all vessels served in the planning horizon as the first objective function to increase the competitive advantage of the container terminal. Furthermore, the maximum of the minimum service level of all vessels served will positively impact efforts to minimize the waiting cost before berthing and the departure delay cost, both of which are cost components in the baseline schedule cost. Moreover, the application of the RHOA and Pre-emptive Goal Programming approaches by using the optimal solution results from the first objective function, namely, maximizing the minimum service level of all vessels served as a goal constraint in minimizing the total cost, can help ease the burden of calculations to minimize the total costs, which, in the end, will shorten the computation time, as shown in the comparison of the solution results between the bi-objective and single-objective optimization models in Table 3, as follows.

Table 3 demonstrates that the bi-objective optimization model is superior to the single-objective optimization model in terms of both the quality of the solution results and the solution's runtimeIn terms of service level, overall cost-efficiency, and average runtime, the findings of the bi-objective optimization model appear to be superior to those of the single-objective optimization model in 90 percent of all cases for both low and high uncertainty level situations. This is because the solution result from the bi-objective optimization model uses lower buffer times allocation and higher buffer QCs than the solution from the single-objective optimization model. The average runtime completion for the bi-objective optimization model is more efficient because the completion of the bi-objective optimization model using the Pre-emptive Goal Programming approach generates a lower calculation burden than combining the objective functions into a single-objective optimization model. In addition to providing a more efficient average runtime solution, the bi-objective optimization model for recoverable robust BACAP under unpredictable vessel arrival time and service time yields a higher quality solution.

Table 3 The results comparison between bi-objective and single-objective optimization models for the recoverable robust BACAP that are solved using RHOA

No.	V	L (m)	UL	Bi-objective model			Single-objective model		
				SL	TC	Runtime (s)	SL	TC	Runtime (s)
1	20	1000	SU	100%	84.66	264.95	100%	84.66	181.67
2				100%	133.18	541.16	17%	251.03	772.64
3				94%	165.22	1224.23	59%	255.30	1200.71
4				100%	100.05	170.21	100%	100.05	183.97
5				100%	119.02	391.06	100%	121.43	403.88
6			HU	100%	100.13	987.78	100%	99.72	990.59
7				88%	203.47	927.96	56%	299.86	908.13
8				100%	162.86	646.52	33%	368.23	1200.83
9				92%	158.28	479.62	100%	113.98	221.18
10				100%	136.09	416.23	100%	131.26	690.22
11	30	1000	SU	100%	151.44	41.88	100%	151.85	387.78
12				100%	171.92	146.50	100%	179.12	618.54
13				75%	274.19	816.31	80%	234.88	1323.06
14				82%	263.06	457.72	60%	396.87	944.91
15				94%	178.12	137.14	88%	191.72	675.42
16			HU	100%	167.88	71.20	69%	259.88	1451.66
17				100%	188.84	234.17	47%	539.99	1990.29
18				73%	238.88	691.65	80%	373.85	1419.86
19				78%	317.95	1116.67	78%	341.69	1366.82
20				94%	196.36	99.50	73%	235.57	662.80
21	40	1500	SU	89%	241.48	198.23	85%	291.61	713.18
22				100%	219.13	908.91	95%	224.34	1517.04
23				83%	327.39	672.62	63%	532.81	1765.88
24				100%	194.05	160.85	88%	256.84	843.22
25				100%	227.62	342.83	71%	423.49	1820.16
26			HU	95%	260.61	603.01	85%	358.81	1323.98
27				100%	233.85	655.49	73%	254.67	1707.29
28				39%	626.21	2756.60	22%	667.78	2030.17
29				100%	218.57	479.28	94%	237.49	965.85
30				100%	248.94	657.77	80%	302.46	1619.79

Figure 2 shows the comparison between the results of the bi-objective optimization model for recoverable robust BACAP and the single objective optimization model to minimize the total costs. In the bi-objective optimization model, the objective function to maximize the service level is more priority than minimizing the total cost. Therefore, the average service level in the bi-objective optimization model is higher than in the single-objective optimization model. In addition, the average total cost in the bi-objective optimization model is more efficient than the single-objective optimization model for the various number of calling vessels in slightly and highly uncertain conditions. This is due to the cost weights of the waiting time for berthing and the lateness in operating time, which significantly contributes to the expected total cost.



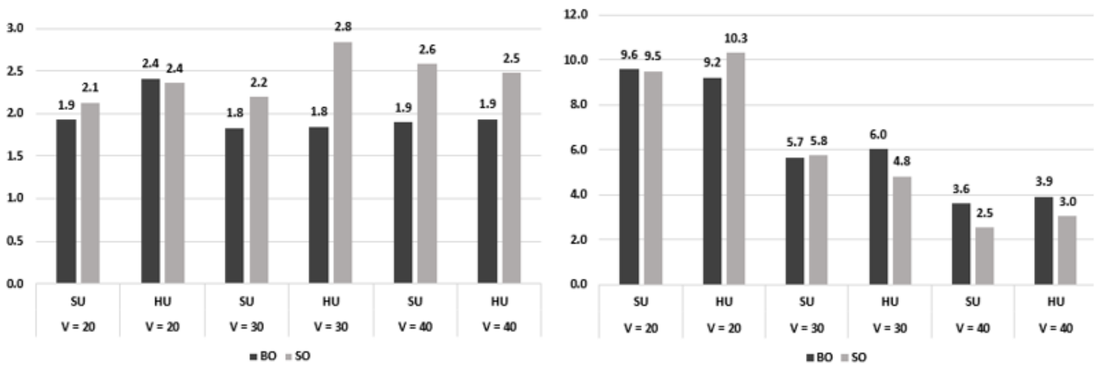
(a) (b)

(c)

Figure 2 Comparison between bi-objective (BO) and single objective (SO) results for: (a) average of the service level, (b) average of the total cost, and (c) average of the runtime for various in the number of vessels and the uncertainty levels

The experimental results show that the bi-objective optimization model results in an increase in the average service level under conditions of slightly uncertainty - SU by 5% to 25% and for highly uncertainty - HU by 16% to 20% for cases with 20 to 40 vessels. While the comparison of the total costs between the results of the bi-objective solution and the single-optimization model shows the total cost-efficiency generated by the bi-objective optimization model for conditions of slightly uncertainty - SU of 10% to 30% and for highly uncertainty - HU of 13% to 37%. for cases with 20 to 40 vessels.

Figure 3 demonstrates that the bi-objective optimization model reduces the need of buffer times to predict the uncertainty of the vessel's arrival and handling time by an average of 19 percent compared to the single-objective optimization model. In contrast, the use of buffer QCs in the bi-objective optimization model solution is 6 percent higher on average than in the single-objective optimization model solution.



(a) (b)

Figure 3 Comparison between bi-objective (BO) and single objective (SO) results for: (a) average of the buffer times, and (b) average of the buffer QCs for various in the number of vessels and the uncertainty levels

Bi-objective optimization models typically require less time to solve than single-objective optimization models.This is because the computational time for the first objective function, which is to maximize service levels, has a lower computational burden compared to the objective function of minimizing total costs. Consequently, when we solve the second objective function, which is to minimize the total costs in the bi-objective optimization model by using maximum service levels as goal constraint will give more efficient computational time compared to the single-objective optimization model. The example of a berth plan of the baseline plan for 20 vessels in the highly uncertain condition is shown in Figure 4.

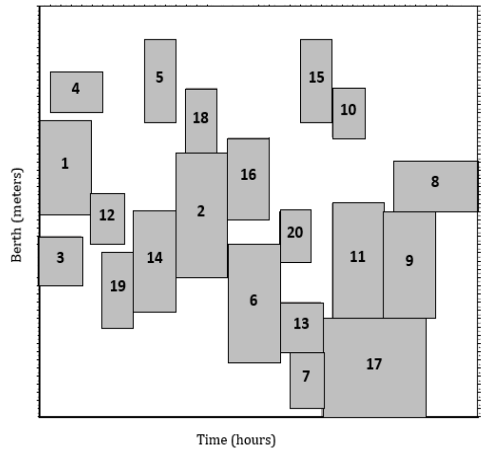


Figure 4 Illustration for berth plan for 20 vessels in the highly uncertain condition

The proposed bi-objective recoverable and robust BACAP model's solution can be used as a reference for container terminal operators, shipping liner owners, and logistics service providers in making decisions to increase competitive advantage and balance cost efficiency, recoverability, and robustness planning in seaside container terminal operations. In uncertain conditions, a baseline schedule resulting from proactive and reactive strategies with optimal buffer times and buffer QCs allocation can produce recoverable, robust planning for container port management in providing reliable logistics services.

6. Conclusions

This paper presents a proposed bi-objective recoverable robust optimization model for integrated tactical planning in seaside container terminals with uncertain vessel arrival and handling times. We consider two objectives: maximizing the minimum service level of all vessels served and minimizing the total costs of the baseline schedule, recovery plan, and expected total costs for all scenarios such that the container terminal has a competitive advantage. The rolling horizon-based optimization algorithm and Pre-emptive Goal Programming approaches are proposed as a solution method to solve the bi-objective recoverable robust BACAP model, resulting in good quality solution for a large-scale problem in reasonable computation time. For further research development, recoverable robust optimization can be considered for integrated planning with storage container yards under uncertainty and effective solution methods for real-time disruption recovery.

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