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Container storage space assignment problem in two terminals with the consideration of yard sharing

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ABSTRACT

Facing the shortage of storage space of container terminal yard, a yard sharing strategy that uses dry port's surplus storage space to ease container congestion is proposed. This novel strategy can address the container storage space assignment problem for inbound containers. The problem is studied based on the storage yard of the combined container terminal and dry port. First, a multiple-objective mixed integer programming model that considers yard sharing strategy with the objectives of minimizing total travel distance, minimizing imbalance in number of containers, maximizing shared storage space of the dry port is formulated to obtain optimal solutions. Second, a non-dominated sorting genetic algorithm II (NSGA-II) is proposed. Next, the performance of the algorithm is verified by a set of instances. Numerical experiments are conducted to elucidate the problem with yard sharing strategy intuitively. Furthermore, the performance of the model in four aspects proclaims the advantages of yard sharing strategy and certifies the comprehensiveness. Finally, sensitivity analysis is conducted by two aspects which are weight coefficient and feasible distance to verify the efficiency of the proposed method.

1. Introduction

With the increase of international trade volume year by year, container transportation has undertaken most of the transportation tasks with the advantage of large volume and low cost. However, the scale of container terminals has been fixed in the early stage of construction. Limited site resources and equipment resources make many container terminals unable to meet the increasing volume of container freight. In view of this, storage space is the main factor affecting the capacity of existing container terminals. However, the expansion of the existing yard involves land acquisition, construction cost and time of storage yard, and purchase of equipment resources. Considering the high cost of expansion, other terminals with surplus storage space are selected. Hence, finding a suitable yard for container operation can not only solve the actual situation of limited yard, but also promote the sustainable development of the maritime transportation. The strategy of yard sharing is for container terminals and inland dry ports, that means dry port is sharing the yard with container terminal.

Obviously, yard sharing, i.e., improving the utilization of dry port yard, is an excellent approach to solve the shortage of container terminal yard resources. Nevertheless, to apply the yard sharing strategy in practice, two major problems need to be solved: first, how to define the location of the dry port storage yard needs to focus on the actual constraints such as distance, yard availability, etc.; second, how to ensure the smooth implementation of scheduling tasks between two storage yards on condition that available yard resources.

Consequently, to address the concerns, the main researches focus on setting up a tactical schedule plan to meet the requirements of vessel operation under the consideration of sea-rail multimodal transport. Yan et al. [35] studied train schedule template and transshipment plan of inbound containers to handle the sea-rail transshipment operation problem of seaport rail terminals. They took limited resources and time constraints into account to help operators decide the operating time of trains, so that it can coordinate with vessels' unloading time and the transshipment plan of inbound containers. The mode of sea-rail multimodal transport is a reasonable way to use the resources of both storage yards. However, fully considering the availability of storage yard is the basic factor to meet the requirements of shipping schedule, discharge plan of vessels and schedule template of trains, ensure the continuity of operation.

Another feasible way is to maximize the utilization of storage yard blocks. Tan et al. [28] investigated the problem of yard template

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regeneration for container port, which contains multiple container terminals. They adopted space sharing strategy aiming at sharing part of storage space of a sub-block by its neighboring sub-blocks, so that the container space can be shared by two different shipping liners as long as their containers do not occupy the space at the same time. Although yard sharing strategy improve the block utilization and operation efficiently, it cannot meet the increasing container freight volume with the international trade. In combination with the dry port storage yard to help the container terminal to stack and lift containers, it can also increase the utilization of the dry port storage yard. In the later stage, the location sharing within the container block will be considered in detail to improve the overall container freight efficiency.

More specifically, for the aforementioned two problems, this paper studies dry port configuration for container terminals to solve the shortage of storage yard capacity of the container terminals. It contains the following two key decisions: (1) determining the number of containers will be stored in blocks of container terminal and dry port, respectively; (2) determining whether containers are stacked in the container terminal or dry port. Accordingly, main contributions of current paper can be summarized as: (1) a strategy of yard sharing that combines container terminal and dry port is proposed; (2) a programming model allows to identify the number of containers to be stocked in container terminal or dry port is established, the distinctive features from previous work can be listed as below:i) from the perspective of abstraction of research problem, minimizing total travel distance and the imbalance in number of containers while maximizing shared storage space of the dry port in the storage space assignment under the container terminal operation is considered in the multi-objective problem formulation; ii) from the techniques of simplifying the model, fuzzy theory and triangle weighting are introduced to convert the multi-objective function into single-objective evaluation function; (3) to address multiple-objective mixed integer programming, a novel approach that combines the model optimization and meta-heuristics algorithm NSGA-II with elitist strategy is proposed and demonstrated in detail.

The remainder of this paper is organized as follows: Literature reviews are provided in Section 2. Section 3 gives a detailed description of storage space assignment problem with the consideration yard sharing strategy. The mathematical model is designed in Section 4. In order to solve the problem effectively, a NSGA-II with elitist strategy is proposed in Section 5. Section 6 presents numerical experiments and analyses. Finally, the conclusion is drawn in Section 7.

2. Literature review

Recently, the issue of container terminals sustainability has attracted more and more scholar's interest., Especially under the trend of mega-vessels and deep-sea terminals, maritime transportation confronts the shortage of container yard resources. The research interests contain yard space assignment, multi-terminal maritime transportation, shared yard mode and solution method. Specific scientific contributions of existing researches on these topics are introduced as follows.

2.1. Yard space assignment

In the study of yard space assignment field, scholars' researches mainly focus on the assignment of container storage location, whether the container is mixed or not, the modeling method of the problem, and the solution algorithm.

To our knowledge, the space assignment problem was proposed by Taleb-Ibrahimi [31] and Teleb-Ibrahimi et al. [30], who analyzed this problem with a constant or cyclic space requirement in container terminals. They focused on determining the amount of space to be allocated to each vessel. Later, many scholars made in-depth research in this field. To allocate storage space for outbound containers, Kim and Park [14] suggested two heuristic algorithms respectively based on the duration-of-stay of containers and the sub-gradient optimization technique. Zhen et al. [38] studied two tactical level decisions and provided an integrated model for berth template and yard template planning in transshipment hubs that the latter tactical level is concerned with assigning yard storage locations to vessels. Chen and Lu [1] addressed the storage location assignment problem, which is decomposed into two stages for outbound containers. Therein, the first stage determined the amount of locations that was assigned to the containers bounded for different vessels in each yard bay, while the second stage determined the exact storage location for each container. For the block space assignment problem, Yu and Qi [36] focused on three optimization models under different strategies of storing inbound containers, i.e., a non-segregation model, a single-period segregation model, and a multiple-period segregation model. Tan et al. [27] investigated an integrated optimization model which simultaneously considered the space assignment and yard crane deployment for tactical storage yard management. Tan et al. [28] worked on the yard template which determined the space assignment in a container terminal yard for all the arriving shipping liners. Lin et al. [16] proposed a bi-level programming location-allocation model for the multi-classification-yard location problem.

2.2. Multi-terminal maritime transportation

In the research of multi-terminal maritime transportation field, the main concerns are integration of multi-terminal container transportation plan by the optimization of handling operations. However, they do not take the availability of container space assignment under yard-sharing as a constraint into consideration.

Xie and Song [34] mentioned a container pre-staging problem arising in sea-rail terminal. The cost of the intermodal container transportation can be significantly reduced, which was confirmed by a stochastic dynamic programming model with uncertain scenarios and numerical experiments. Liu and Yang [18] considered demand uncertainties for joint slot allocation and dynamic pricing of multi-node container sea-rail multimodal transport by the means of a two-stage optimal model based on revenue management. Yan et al. [35] focused on the sea-rail transshipment operation problem of sea-rail intermodal container transportation, which included train schedule template and transshipment plan of inbound containers. Li et al. [17] investigated intermodal freight transport planning problems among container terminals and inland terminals in hinterland haulage for a horizontally fully integrated intermodal freight transport. Wiercx et al. [32] developed a tailor-made new model based on the maritime container terminal literature combined with the specificities of Inland Waterway Terminals. Facchini et al. [7] adopted the strategy of a dry port configuration for container terminals which can lead to benefits on terminal congestion and can also attract resources and investments for the transportation between container terminals and dry port. They defined a mathematical model to decide the number of containers to be stocked in port and/or in dry port.

2.3. Shared yard mode

Recently, yard space-sharing problem has attracted researcher's great interest. With the limited resources of container storage yard, it is practical that improves the utilization rate of yard, in which the container storage plan of terminals is optimized for operators.

Jin et al. [13] presented the possibility of sharing container storage space for different container handling companies in a container terminal. Zhou et al. [39] first integrated the impact of container reshuffling into space planning so that overall space allocation and yard template planning were realized. Jiang et al. [11] considered two space-sharing approaches for the aim of improving on the land utilization of storage space for different vessels during different shifts. Zhen et al. [37] studied a yard template to determine the assignment of spaces (subblocks) in a yard for arriving vessels. He et al. [10] proposed a two-level space sharing strategy. The space sharing strategy is utilized based on the pairing of vessels with different container collection patterns. Tan et al. [28] considered maximum the space utilization of container yard as one objective of a multiple-objective mixed integer programming model. They adopted the space sharing strategy so that part of storage space of a sub-block can be shared by its adjacent sub-blocks.

2.4. Solution method

Another important stream not mentioned in the above literature is the solution method for yard space assignment problem of multi-terminal container transportation. The solution methods for container terminal operation research, especially yard operation research can be categorized into two major groups: i.e., exact approach and approximate approach. It is known that the exact approach refers the frequent approach to optimize CO models. As for approximate approach, especially meta-heuristics, has become more favored for searching for a good solution with a reasonable computation time.

Dekker et al. [4] compare different stacking strategies by the way of simulation. The results show that the performance of category stacking considering the expected departure time is better to reduce the number of reshuffles. Zhou et al. [39] developed a simulation model to look into the insight behind container reshuffling. Facchini et al. [7] introduced the way of numerical simulations to evaluate the efficiency and the reliability of dry port strategy by model. Jiang and Jin [12] presented a branch-and-price method for integrated yard crane deployment and container allocation in transshipment yards. Different scales of numerical experiments proved that the method can solve the problem efficiently. A GA-based framework combined with three-stage algorithm is proposed by He et al. [9] to solve the yard crane scheduling problem under uncertainty. Li et al. [17] considered a receding horizon intermodal container flow control approach to control and to reassign intermodal container flows in a receding horizon way. Xiang et al. [33] attempted a rolling horizon heuristic to solve the discrete berth allocation and quay crane assignment problem by dividing the entire horizon time problem into several iterations while each iteration corresponds to a subproblem. Tao and Lee [29] developed a novel three-stage heuristic solution approach to show the benefit of the multi-cluster stacking strategy which splits each transshipment flow into a number of container clusters, and then stacks each cluster in different yard blocks. Niu et al. [20] described Swarm intelligence algorithms, namely, particle swarm optimization and bacterial colony optimization are originally designed for yard truck scheduling and storage assignment problems. Cordeau et al. [2] developed a metaheuristic algorithm based on the adaptive large neighborhood search framework to optimize yard assignment in an automotive transshipment terminal. Ng et al. [22] presented a novel swarm intelligence algorithm, which significantly reduces the computational effort in iterative relaxation procedure for min–max regret optimization. In the aspect of method innovation, Nguyen et al. [24] proposed a method which is a hybridization of Least Squares Support Vector Machine (LSSVM) and Particle Swarm Optimization (PSO). The PSO algorithm, a swarm intelligence-based meta-heuristic, is utilized to optimize the LSSVM prediction model. The literature survey of the use of meta-heuristics algorithms in airside research proposed by Ng et al. [21] is also applicable to container terminal operation research. The research methodology using meta-heuristics is importance to the development of sophisticated modelling in yard operations. The main studies about storage space assignment are shown in Table 1. It can be seen intuitively from table 1 that most studies have not been carried out from the perspective of multi-objective, and less meta-heuristic method is used to solve the model.

As for multi-objective formulations, which are realistic models for many complex engineering optimization problems. A reasonable solution to a multi-objective problem is to investigate a set of solutions, each

Table 1
The main studies listed in this paper [15].

Research Topic	Authors (year)	Mathematical Model	Method	Journal Publisher or Proceeding
Flexible space allocation problem	Zhou et al. [39]	A mix integer programming model which integrates macro-level impact of container reshuffling is derived from discrete event simulation	• Improved empirical allocation algorithm • Hybrid particle swarm optimization	Transportation Research Part E
Storage space allocation problem	Yu and Qi [36]	• Non-segregation space allocation model • Single-period segregation space allocation model • Multiple-period segregation space allocation model	• Convex cost network flow algorithm • Dynamic programming	European Journal of Operational Research
Sea-rail transshipment operation problem (includes train schedule template and transshipment plan of inbound containers)	Yan et al. [35]	An integer programming model for maximizing the number of direct-transshipment containers while minimizing the storage time and dwell time of inbound containers	A tailored rolling horizon approach with the adaptive horizon and backtracking strategy	Computers & Industrial Engineering
Storage location assignment problem	Chen and Lu [1]	A mixed integer programming model for the yard bay allocation for outbound containers	A hybrid sequence stacking algorithm	International Journal of Production Economics
Storage shared space allocation problem	Jin et al. [13]	A linear programming model: one using dual variables of the LP model and the other using the Lagrangian multipliers of the relaxed LP model	Coopetitive space sharing	Transportation Research Part E
Container assignment problem in two terminals	Facchini et al. [7]	A non-linear model allowing to identify the number of containers to be stocked in port and/or in dry port	A computational algorithm	International Journal of Production Economics
Yard management problem	Cordeau et al. [2]	An integer linear programming model for minimizing the total handling time	A metaheuristic algorithm based on the adaptive large neighborhood search framework	European Journal of Operational Research
Yard template planning	Tan et al. [28]	A mixed integer programming model considering the minimum transportation cost, minimum template disturbance and maximum space utilization	CPLEX	Advanced Engineering Informatics
Yard template planning	Zhen et al. [37]	A mixed integer programming model for minimizing the transportation cost of moving containers around the yard	• CPLEX • Local branching-based solution method • PSO	Transportation Research Part B
Storage space allocation problem	Kim and Park [14]	A mixed-integer linear programming model for minimizing the total travel distance between the apron and the storage location	Two heuristic algorithms: • the least duration-of-stay rule • sub-gradient optimization heuristic algorithm	European Journal of Operational Research

of which satisfies the objectives at an acceptable level without being dominated by any other solution [15]. Table 2 references part of summary of multi-objective algorithm. As can be seen in Table 2, NSGA-II is a more suitable algorithm for solving multi-objective problems. There are also related researches in other fields that use NSGA-II to solve the problem. Favuzza et al. [8] studied crowded comparison operators for constraints handling in NSGA-II for optimal design of the compensation system in electrical distribution networks. In order to obtain the optimal solutions without considering the various assumptions, Chang et al. [3] proposed a heuristic bi-level nested parallel solution algorithm with hybrid NSGA-II and GA. The NSGA-II is applied to optimize the upper level's multi-objective problem, while the GA is used to determine the lower level's Nash equilibrium solution in parallel. Rahimi-Vahed et al. [25] researched a multi-objective sequencing problem, and designed a new multi-objective scatter search (MOSS) for searching locally Pareto-optimal frontier for the problem.

Based on the review of previous contributions in scientific literatures on the yard space assignment, it can be concluded that multi-terminal yard space-sharing strategy has attracted more attention of operators and scholars to improve the efficiency of container handling operations and transportation. In this paper, the dry port configuration of container terminals is be attempted to satisfy the shortage of space resources in terminal yard and improve utilization rate of dry port yard. Moreover, a mathematical model that identifies the number of containers to be stocked in container terminal or dry port has been defined. The actual constraints, such as distance, yard availability, etc. are also considered in this work to define the location of the dry port. In order to solve the problem effectively, a meta-heuristics algorithm as NSGA-II with elitist strategy is proposed.

3. Problem description

This paper solves the storage space assignment problem arising in two terminals, which considers yard sharing for inbound containers. More specific, the problem integrates the optimization of total travel distance for assignment between two yards, imbalance of two yard and shared storage space of the dry port yard. Details of the problem are discussed as follows.

In the storage space assignment problem, with the current situation of insufficient storage space resources and the lack of space in the operational area often significantly reduce the terminal productivity, so container terminal operators need to increase the storage capacity by means of a physical expansion. In this paper, the storage yard of dry port is regarded as a part of the storage yard of container terminal, and shared by the storage yard.

General layout of container terminal and dry port is shown in Fig. 1. In container terminal, vessels are operated in wharf apron, while inbound containers and outbound containers are loaded and unloaded from vessels, respectively. Container storage yard store the inbound and outbound containers. As for dry port, the terminal connects container terminal and hinterland as the corresponding logistics facilities, so it can complete the logistics services including loading, unloading, storage and transfer. It should be noted that there is no vessel berthing in dry port. The function of the transport passage shown in Fig. 1 is used to connect the wharf and the dry port.

The unloading process of inbound containers shown in Fig. 2 can be divided into several stages. In the first stage, the inbound containers are taken from the vessel by the quay crane, and then placed at the wharf apron. In the second stage, to allocate the storage yards with different terminals, the terminal operators take the space utilization of the two terminals, transportation cost, imbalance containers of the storage yard and the terminal of the customer's suitcase into consideration. Therefore, one part of the containers is directly transported to the storage yard of the container terminal by the automatic guided vehicles, while the other part of the containers is transported by the container trucks through the transport passage to the storage yard of the dry port. In the third stage, in the storage yard of the container terminal and storage yard of the dry port, the containers are respectively handled by the automatic stacking crane and the gantry crane. In the last stage, the containers of both terminals are finally transported to the customers by container trucks.

Different to the traditional storage space assignment, the container storage space assignment shared by storage yards of two terminals can fundamentally change the traditional container operation process. In the majority of cases, the dry port plays an important role as it is an effective interface for hinterland operators. The main task of dry port is to transport containers from congested transfer nodes to inland areas after stacking and sorting, so it makes more space available. The storage space assignment based on yard sharing not only makes the optimal use of storage yards between two terminals to reduce the congestion of the port area effectively, but also helps to extend the hinterland of the port.

In summary, to promote the sustainable development of container shipping, a configuration of the dry port in a container terminal is proposed. It realizes storage space assignment in multiple container terminals with the consideration of yard sharing. A mathematical model has been defined to identify the number of containers to be stocked in container terminal or dry port. It minimizes the total travel distance for assignment between two yards, which can simultaneously minimize the total travel distance for assignment between two yards and imbalance of two yards, and maximizes shared storage space of the dry port storage yard. On the basis of this model, the number of containers will be stored in blocks of container terminal and dry port storage yards determined. Meanwhile, it also determines the containers are stacked in the container terminal or dry port storage yard.

Table 2
A list of a part of well-known multi-objective algorithm.

Algorithm	Fitness assignment	Diversity mechanism	Elitism	External population	Advantages	Disadvantages
VEGA	Each subpopulation is evaluated with respect to a different objective	No	No	No	First MOGA Straightforward implementation	Tend converge to the extreme of each objective
MOGA	Pareto ranking	Fitness sharing by niching	No	No	Simple extension of single objective GA	Usually slow convergence Problems related to niche size parameter
PESA	No fitness assignment	Cell-based density	Pure elitist	Yes	Easy to implement Computationally efficient	Performance depends on cell sizes Prior information needed about objective space
NSGA	Ranking based on non-domination sorting	Fitness sharing by niching	No	No	Fast convergence	Problems related to niche size parameter
NSGA-II	Ranking based on non-domination sorting	Crowding distance	Yes	No	Single parameter (N) Well tested Efficient	Crowding distance works in objective space only

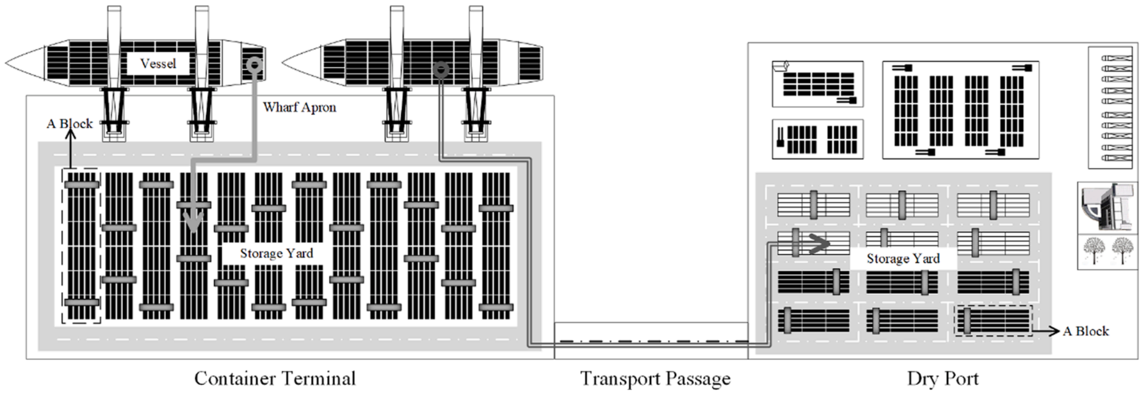


Fig. 1. General layout and transport flow for sharing-yard.

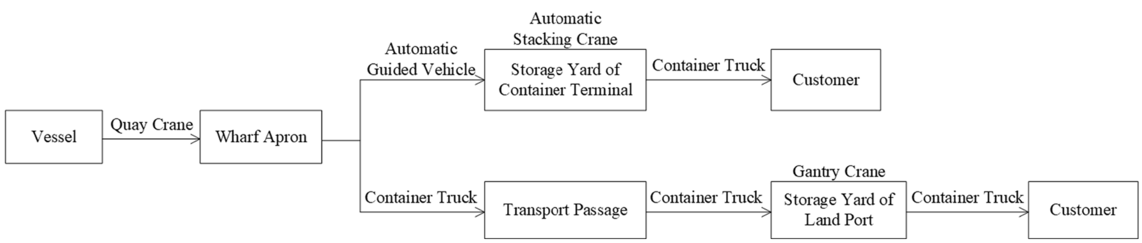


Fig. 2. Container flows.

4. Mathematical model

This section discusses a multiple-objective mixed integer programming model for container storage space assignment problem. This model is constructed to evaluate the number of inbound containers to be respectively stocked in container terminal and dry port. The framework for solution is shown in Fig. 3.

4.1. Assumptions

The model is developed under the following assumptions:

(1) The berth allocation of vessels is assumed to be known, so the distance between the vessel and the designated yard block is a known parameter.
(2) The research object of this question is inbound containers, so it is assumed that all the containers to be transported and stored are inbound containers.
(3) In order to simplify the research, this paper does not consider the case of mixed stacking, so it is assumed that the inbound containers and outbound containers are not mixed up in one block.
(4) This paper studies the impact of transportation distance with yard sharing strategy, so the number of container trucks is not limited and the number is assumed to be sufficient.
(5) The size of the containers is Twenty-feet Equivalent Unit (TEU). Because TEU is an important statistical and conversion unit of container and port throughput.

4.2. Notations definitions

4.2.1. Indices

v	index of vessels;
a	index of blocks in the yard of container terminal;
b	index of blocks in the yard of dry port.

4.2.2. Parameters

V	the set of vessels for which inbound containers should be unloaded during the planning horizon;
A	the set of yard blocks should be allocated in the container terminal, $A = \{1, 2, \cdots, N^a\}$;
B	the set of yard blocks should be allocated in the dry port, $B = \{1, 2, \cdots, N^b\}$;
N^v	the total number of vessels for which inbound containers should be unloaded during the planning horizon;
N^a	the total number of blocks for storing inbound containers in the container terminal;
N^b	the total number of blocks for storing inbound containers in the dry port;
C_a	the storage capacity of block a;
C_b	the storage capacity of block b;
m_{av}	the number of containers that can be stacked into block a for vessel v;
m_{bv}	the number of containers that can be stacked into block b for vessel v;
n_a	the number of containers in block a at the beginning of the planning horizon;
n_b	the number of containers in block b at the beginning of the planning horizon;
d_{av}	the travel distance of container trucks between block a and the berth location of vessel v;
d_{bv}	the travel distance of container trucks between block b and the berth location of vessel v;
p_v	the total number of inbound containers for vessel v;
q	the storing parameter of yard blocks;
φ	the sharing space of blocks in the yard of dry port, and $\varphi \in [0, 1]$.
c_1	the unit transportation cost
c_2	the unit imbalance cost

4.2.3. Decision variables

x_{av}	the number of inbound containers for vessel v, which will be stores in block a;
y_{bv}	the number of inbound containers for vessel v, which will be stores in block b;
δ_{av}	=1, if inbound containers of vessel v be stored in block a; =0, otherwise;
γ_{bv}	=1, if inbound containers of vessel v be stored in block b; =0, otherwise.

4.3. Model formulation

4.3.1. Objective function

The objective for the problem of yard space assignment between two

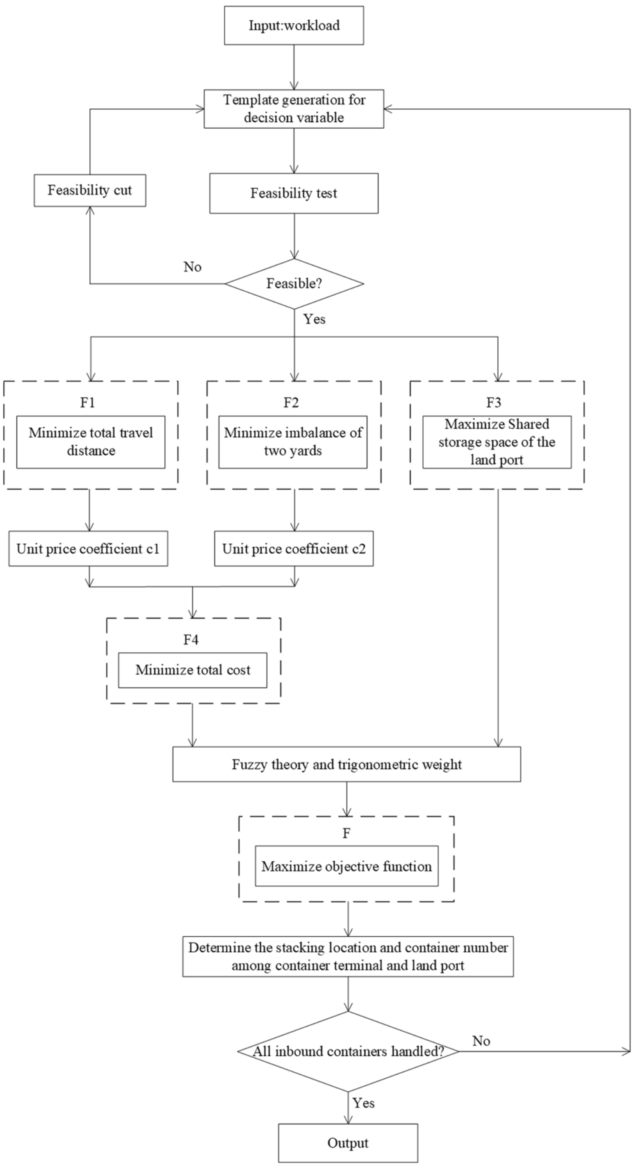


Fig. 3. Flow chart of the computational process.

terminals is much more complex than conventional container assignment problem. The port operators need to consider minimizing travel distance between two terminals, minimizing the imbalance of the number of containers stacked in each yard and improving shared storage space. The objective function for this problem is modeled from the following three elements:

(1) The total travel distance for assignment

The total travel distance for assignment that is consists of the travel distance between the berth location of vessel with the yard block a and the travel distance between the berth location of vessel with the yard block b mainly depends on decision variable x_{av} and y_{bv}, which can be calculated by Eq. (1).

$$F_1 = \sum_{v\in V}\sum_{a\in A} x_{av}\bullet d_{av} + \sum_{v\in V}\sum_{b\in B} y_{bv}\bullet d_{bv} \tag{1}$$

(2) Imbalance of two yards

Due to the different stacking assignment of inbound containers, the container operation in the yard blocks will be interfered, and causes the imbalance of the number of containers in blocks, which will affect the operation efficiency of the yard. The imbalance of two yards equals to the sum of the gap between maximum and minimum number of containers in blocks in the yard of container terminal and in blocks in the yard of dry port. The specific formulation is shown as Eq. (2).

$$F_2 = \frac{max}{a}\sum_{v\in V} x_{av} - \frac{min}{a}\sum_{v\in V} x_{av} + \frac{max}{b}\sum_{v\in V} y_{bv} - \frac{min}{b}\sum_{v\in V} y_{bv} \tag{2}$$

(3) Shared storage space of the dry port

For the sake of using the limited yard resources efficiently, especially the storage space, so as to improve the operation capacity of the whole container terminal. At the same time, we assume that the inbound containers will be handled as soon as possible and efficiently. On the one hand, it is necessary to ease the container congestion. On the other hand, it is essential to improve the utilization of the storage yard of the dry port. The shared storage space of the dry port is formulated as:

$$F_3 = \sum_{v\in V}\sum_{b\in B} y_{bv}\cdot\gamma_{bv} \tag{3}$$

4.3.2. Constraints

$$n_a + \sum_{v\in V} x_{av} \le qC_a, \forall a \in A \tag{4}$$

$$n_b + \sum_{v\in V} y_{bv} \le qC_b, \forall b \in B \tag{5}$$

$$\sum_{a\in A} x_{av} + \sum_{b\in B} y_{bv} = p_v, \forall v \in V \tag{6}$$

$$x_{av} \le p_v\delta_{av}, \forall a \in A, \forall v \in V \tag{7}$$

$$y_{bv} \le p_v\gamma_{bv}, \forall b \in B, \forall v \in V \tag{8}$$

$$\sum_{a\in A}\delta_{av} \le m_{av}, \forall v \in V \tag{9}$$

$$\sum_{b\in B}\gamma_{bv} \le m_{bv}, \forall v \in V \tag{10}$$

$$\sum_{v\in V}\delta_{av} \le N^v, \forall a \in A \tag{11}$$

$$\sum_{v\in V}\gamma_{bv} \le N^v, \forall b \in B \tag{12}$$

$$\sum_{v\in V}\sum_{a\in A}\delta_{av} \le N^a \tag{13}$$

$$\sum_{v\in V}\sum_{b\in B}\gamma_{bv} \le N^b \tag{14}$$

$$\sum_{a\in A}\sum_{b\in B}(\delta_{av} + \gamma_{bv}) \ge 1, \forall v \in V \tag{15}$$

$$q\varphi\sum_{b\in B} C_b\bullet\gamma_{bv} \ge \sum_{b\in B} y_{bv}\bullet\gamma_{bv}, \forall v \in V \tag{16}$$

$$x_{av}, y_{bv} \ge 0, \forall a \in A, \forall b \in B, \forall v \in V \tag{17}$$

$$\delta_{av} \in \{0,1\}, \forall a \in A, \forall v \in V \tag{18}$$

$$\gamma_{bv} \in \{0,1\}, \forall b \in B, \forall v \in V \tag{19}$$

Constraints in (4) and (5) guarantee the density of each yard block in container terminal and dry port will not exceed the allowable level.

Constraint (6) ensures that the space requirement of each vessel during the planning horizon must be satisfied. Constraint (7) defines the decision variable δ_{av}. Such as $\delta_{av} = 1$,the inbound containers of vessel v are stored in yard of container terminal. Similarly, constraint (8) defines the decision variable γ_{bv} for dry port. The number of inbound containers that can be stacked into block a for vessel v is controlled by constraint (9). Constraint (10) ensures the number of block b. Constraints (11) and (12) indicate that block a and b can stack inbound containers from different vessels. Constraints (13) and (14) guarantee that the number of blocks stored by inbound containers of vessel v cannot exceed the maximum number in container terminal and dry port. The inbound containers only can be stacked in the block of container terminal or dry port, which is controlled by constraint (15). Constraint (16) limits the shared storage space of the dry port to the vessel must not exceed its maximum shareable capacity. Constraint (17) ensures the non-linear values of the decision variables. Constraints (18) and (19) specify the binary decision variables.

4.3.3. Model optimization process

The function of F_2 involves the non-linear expression ($\underset{a}{max}\sum_{v\in V}x_{av}$, $\underset{a}{min}\sum_{v\in V}x_{av}$, $\underset{b}{max}\sum_{v\in V}y_{bv}$, $\underset{b}{min}\sum_{v\in V}y_{bv}$),which makes the solution of this model difficulty. In order to convert it to a linear model, we give that x_{av} and y_{bv} are positive integer and $F_2 = \underset{a}{max}\sum_{v\in V}x_{av} - \underset{a}{min}\sum_{v\in V}x_{av} + \underset{b}{max}\sum_{v\in V}y_{bv} - \underset{b}{min}\sum_{v\in V}y_{bv}$.

We define new coefficients.

$$e = \underset{a}{max}\sum_{v\in V}x_{av} \tag{20}$$

$$f = \underset{a}{min}\sum_{v\in V}x_{av} \tag{21}$$

$$g = \underset{b}{max}\sum_{v\in V}y_{bv} \tag{22}$$

$$h = \underset{b}{min}\sum_{v\in V}y_{bv} \tag{23}$$

Then we can get the following inequalities.

$$e \geq \sum_{v\in V}x_{av}, \forall a \in A \tag{24}$$

$$f' \geq -\sum_{v\in V}x_{av}, \forall a \in A \tag{25}$$

$$f \geq -f' \tag{26}$$

$$g \geq \sum_{v\in V}y_{bv}, \forall b \in B \tag{27}$$

$$h' \geq -\sum_{v\in V}y_{bv}, \forall b \in B \tag{28}$$

$$h \geq -h' \tag{29}$$

$$e, f, g, h \geq 0 \tag{30}$$

Therefore, the function of F_2 can be rewritten as:

$$F_2 = e - f + g - h \tag{31}$$

Base on the equations above, it is obvious that this multi-objective optimization problem is needed to convert into a single-objective one. Here, c_1 and c_2 as the unit price coefficient are used to transform container transportation and imbalance of containers into cost. Therefore, we consider F_1 and F_2 together by integrated Eq. (32), which is defined as:

$$F_4 = c_1F_1 + c_2F_2 \tag{32}$$

In order to solve the dimension problems of multi-objective, fuzzy theory and triangle weighting are introduced to convert the multi-objective function into single-objective evaluation function. In addition, θ within the coefficient of $\frac{cos\theta}{cos\theta+sin\theta}$ and $\frac{sin\theta}{cos\theta+sin\theta}$ are the weight of the shared storage space of the dry port and of the merged element. Therefore, the objective function is formulated as:

$$maxF = \frac{cos\theta}{cos\theta + sin\theta}\cdot\frac{F_3 - F_3^{min}}{F_3^{max} - F_3^{min}} + \frac{sin\theta}{cos\theta + sin\theta}\cdot\frac{F_4^{max} - F_4}{F_4^{max} - F_4^{min}} \tag{33}$$

where F_3^{min} and F_3^{max} represent the minimum and maximum of F_3 respectively. It is the same that F_4^{min} and F_4^{max} represent the minimum and maximum of F_4 respectively. Eqs. (34)–(37) are given to obtain the boundary values of these parameters. Moreover, the value range of θ is $\left[0, \frac{\pi}{2}\right]$. In order to obtain the value of coefficient θ of the optimal objective function, dynamic random assignment is proposed. First, we determine an initial value of θ_0, which is $\theta_0 = \frac{\pi}{4}$. Then, we define α as a randomly generated random parameter and request $|\alpha| < 1$. Besides, we find out the corresponding θ_j with randomly generated α by $\theta_j = \theta_0\cdot(1+\alpha), j = 1, 2, \cdots, z$. So that we can get z different angles of θ_j, and $\theta_j \in \left[0, \frac{\pi}{2}\right]$.

$$F_3^{min} = 0 \tag{34}$$

$$F_3^{max} = q\varphi C_b \tag{35}$$

$$F_4^{min} = \sum_{a\in A}\underset{v\in V}{min}d_{av} + \sum_{b\in B}\underset{v\in V}{min}d_{bv} \tag{36}$$

$$F_4^{max} = \sum_{a\in A}\underset{v\in V}{max}d_{av} + \sum_{b\in B}\underset{v\in V}{max}d_{bv} + \beta eg \tag{37}$$

As can be seen, Eq. (34) represents all the blocks of the dry port cannot be shared with container terminal. Instead, Eq. (35) denotes the maximum storage space of the dry port, which can store containers from container terminal. As for Eq. (36), it shows the sum of minimum travel distance for storing inbound containers in container terminal and minimum travel distance for storing inbound containers in dry port. Similarly, the first and second parts of Eq. (37) represent the sum of maximum travel distance for storing inbound containers in container terminal and maximum travel distance for storing inbound containers in dry port, while the third part represents the maximum imbalance distance.

4.3.4. Computational process

The flowchart related to the computing process of the proposed model is displayed in Fig. 3. As we can see, the solving process of the container storage space assignment problem for inbound containers is started by inputting workload data into the template generation for decision variable. In the second step, the feasibility test is an important part carried out to test whether it is feasible to get template generation with decision variable in this computation. If the template generation is not feasible, then cut the feasibility to remove the value of the decision variable. Conversely, if feasibility is passed, then enter next step. In the next step, the container storage space assignment problem for inbound containers is formulated by considering constraints such as the allowable level of each yard block, the space requirement of each vessel, the storage capacity of container terminal and dry port, constraints of decision variables x_{av}, y_{bv}, δ_{av}, γ_{bv} and now decision making. After this, three objectives, which are aiming at minimizing total travel distance, minimizing imbalance in number of containers, maximizing shared storage space of the dry port, should be considered at the same time. In order to simplify the calculation, unit price coefficients c_1 and c_2 are respectively used in F1/F2 and integrated into F4. Then, fuzzy theory and trigonometric weight are used to convert the multi-objective function into single-objective evaluation function. Next, determine the stacking location and container number among container terminal and dry port according to the optimization result. Finally, make sure that all inbound containers handled. If not, regenerate template generation. On the contrary, if all inbound containers handled, the storage location and quantity of the inbound containers correspond to the container terminal and dry port, respectively.

5. Methodology

5.1. Pareto optimality criteria

Pareto optimality, also known as Pareto improvement, is named after Italian economist Vilfredo Pareto. Pareto optimal concept is widely used in the field of engineering and economics. A situation in which it is impossible to make one better off without making the another one worse off is defined as Pareto optimal or Pareto efficient [23].

A multi-objective minimization problem can be formulated as follows:

$$f = min(f_1(x), f_2(x), \cdots, f_n(x))$$

where $x \in X$, X represent a feasible set of decision vectors.

(1) Pareto dominance relations

For any two decision vectors a', b', $a' \prec b'$ (a' dominates b'), if the following two conditions are satisfied.

i) $f_i(a') \leq f_i(b'), \forall i \in \{1, 2, \cdots, N\}$
ii) $f_j(a') < f_j(b'), \exists j \in \{1, 2, \cdots, N\}$

If any of the above conditions is violated, decision vector a' does not dominate decision vector b'. If a' dominates b', a' is called the non-dominated solution.

(2) Pareto optimal solutions

The decision vector x^* is called Pareto optimal solution if and only if the following formula holds.

$$\nexists x \in \mathbb{R}^D : x \prec x^*$$

Pareto optimal solution is also called Pareto non-dominated solution.

(3) Pareto optimal set

The set of all Pareto optimal solutions is called Pareto optimal set of the problem.

$$P^* = \{x^* \in \mathbb{R}^D | \nexists x \in \mathbb{R}^D : x \prec x^* \}$$

(4) Pareto front

The set of objective vectors corresponding to all Pareto optimal solutions is called the Pareto optimal front or simply the Pareto front of the problem. Fig. 4 depicts a Pareto set for a two-objective minimization problem [6].

$$Paretofront = \left\{ \overrightarrow{f} = [f_1(x^*), f_2(x^*), \cdots, f_n(x^*)] | x^* \in P^* \right\}$$

Therefore, Pareto optimal criteria is utilized to produce a set of non-dominating solutions from the two conflicting objective functions considered in this paper.

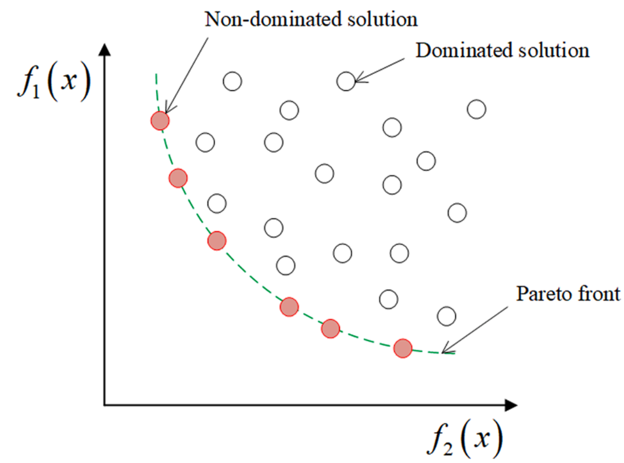


Fig. 4. Pareto optimal front.

5.2. NSGA-II

Non-dominated sorting genetic algorithm II(NSGA-II) is an improvement of the original NSGA [26]. Deb et al. [5] proposed a fast NSGA-II with elitist strategy. It is superior to NSGA: i) NSGA-II uses a fast non dominated sorting algorithm, which greatly reduces the computational complexity compared with NSGA. ii) It introduces the concept of crowding degree. Using crowding distance comparison operator to replace the original fitness sharing strategy by setting the sharing radius makes the algorithm more practical. Moreover, the individuals on the front of Pareto can be evenly extended to the whole Pareto domain, effectively ensuring the population diversity. iii) The elitist strategy is introduced to combine the parent population and the offspring population, which expands the sampling space. Meanwhile, to prevent the loss of the best individual, select the better individual as the next generation parent. These improvements improve the operation speed, convergence speed and robustness of the algorithm and keep the diversity of results.

In this paper, we designed a two-dimensional NSGA-II. Chromosome encoding is in the form of two-dimensional matrix. In order to construct the non-dominated solution set, we used a fast sorting method proposed by Konak et al. [15]. In addition, the crowding distance is sorted, and the elite strategy is introduced. At the same time, binary tournament selection, simulated binary crossover and polynomial mutation are used to effectively obtain optimal solutions. The flow of NSGA-II multi-objective programming optimization designed in this paper is shown in Fig. 5.

(1) Input and initialization of basic data

Read the data of vessel unloading containers, as well as the initial data such as the quantity of existing containers, storage capacity and container area distance of the blocks.

(2) Encoding

Due to the assignment of container volume related to two terminals, we adopt a real-coded combining two-dimensional matrix encoding method. Each chromosome has two lines in total, and each line has two parts. The first part of the first line is the number of inbound containers for vessels stored in each yard block of the container terminal. And the second part is the number of inbound containers for vessels stored in each yard block of the dry port. The first part of the second line is whether the inbound containers of vessels will be stored in block of the container terminal, that is 0 or 1. The second part of the second line is whether the inbound containers of vessels will be stored in block of the dry port, that is 0 or 1. The length of chromosome is $a \cdot v + b \cdot v$. For

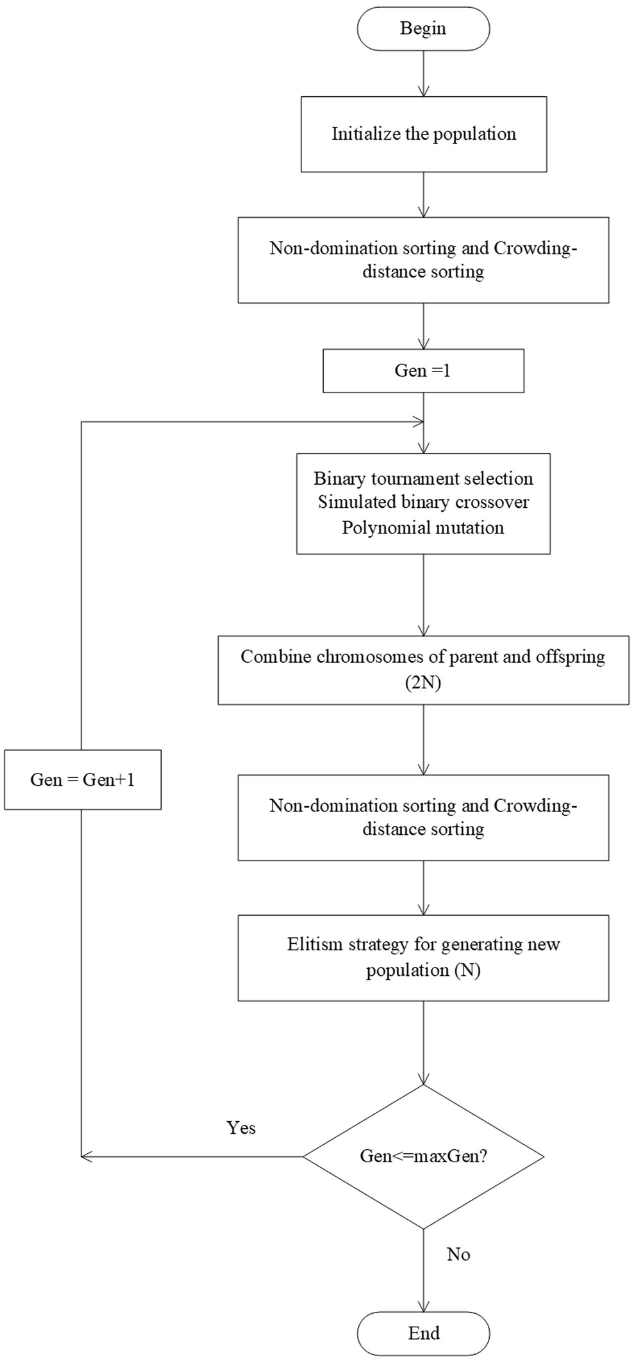


Fig. 5. NSGA-II calculation flow chart.

example: there are only one vessel for inbound containers, 6 blocks in container terminal and 4 blocks in dry port. The specific initial solution for assignment is generated as shown in Fig. 6.

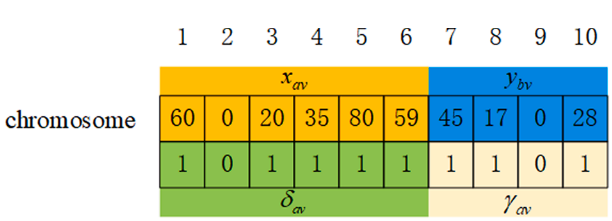


Fig. 6. The specific initial solution of containers by chromosome.

(3) Non-dominated sorting

The objective function F1/F2/F3 can be non-dominated sorted. For any two chromosomes u and k in the population can establish a relationship as follows: if $Fu1 < Fk1$, $Fu2 < Fk2$ and $Fu3 > Fk3$, u dominates k, that is, u is better than k for all objective functions; and if the solution of u is not dominated by k, then u is not dominated by k, that is, u and k are solutions on Pareto.

The NSGA-II of non-dominated sorting for chromosomes in the population is as follows.

Step1: Initialization. Let $i = 1$for the i[th] Pareto front. Let $S_u = \varnothing$, representing all chromosome sets dominated by chromosome u. Let$n_u = 0$, indicating the number of other chromosomes dominated by chromosome u. Let$F_i = \varnothing$, indicating the chromosome set of the i[th] Pareto front.

Step2: For each chromosome k in the population, if u dominates k, then $S_u = S_u \cup \{k\}$. If k dominates u, then $n_u = n_u + 1$.

Step3: If $n_u = 0$, there is no chromosome dominates u, then u is the best individual in the population and belongs to the first Pareto front. Let $u_{rank} = 1$, and update the set of the first Pareto front, that is, $F_1 = F_1 \cup \{u\}$.

Step4: If $F_i \neq \varnothing$, make $K = \varnothing$, which is used to store the chromosome corresponding to the $(i+1)^{th}$ pareto front, otherwise the algorithm will end.

Step5: Traverse each chromosome u in Pareto front set F_i, for each chromosome k in set S_u, let $n_k = n_k - 1$. If $n_k = 0$, it means that there is no individual dominating u in the next Pareto front, then let $k_{rank} = i + 1$, $K = K \uplus \{k\}$.

Step 6: Let $i = i + 1$, $F_i = K$, return to Step4.

(4) Crowding-distance sorting

The crowding degree is calculated by the local crowding distance between each point in the target space and two adjacent points in the same layer, which can keep the diversity of individuals. The process is as follows:

Step1: Initial crowding distance $n_d = 0$, $n = 1, \cdots, N$.

Step2: For each objective function f_m, the individuals of this rank are sorted according to the objective function. Note that f_m^{max} is the maximum value of individual objective function f_m, and f_m^{min} is the minimum value of individual objective function f_m. Give the maximum distance value to the individual of the boundary after crowding distance sorting, that is, $1_d = \infty$ and $N_d = \infty$.

Step3: Find the crowding distance for the individuals in the middle of the sorting. The performance distance is: $n_d = n_d + \frac{f_{m(i+1)} - f_{m(i-1)}}{f_m^{max} - f_m^{min}}$. $f_{m(i+1)}$ is the objective function value of the rank of the next individual.

(5) Genetic operator (selection, crossover, and mutation)

The purpose of selection operation is to prevent the loss of effective genes and filter out ineffective individuals. The optimization process is carried out in the direction of Pareto front solution, keeping excellent individuals and making them evenly distributed. Thus, we adopted the tournament selection with high utilization rate. In the iterative evolution process of NSGA-II, the alternation of crossover and mutation is helpful to improve the search performance of the algorithm. After the comparation through using different methods of crossover and mutation, and characteristics of chromosome, we adopt a simulated binary crossover and polynomial mutation operation to effectively obtain optimal solutions.

(6) Elitist strategy

The elitist strategy is to keep the excellent individuals in the parent generation and enter the offspring directly. It is a necessary condition for

NSGA-II to converge with probability 1. According to the Pareto rank and crowding distance of the individuals, the population recombined by the parents and the offspring is screened again to form a population for the next generation evolution. The process is as follows:

Step1: Combine parent population W_i and offspring population D_i into population R_i.

Step2: According to the order of Pareto rank from low to high, the eligible whole layer population in R_i is put into parent population W_{i+1} until the individuals in one layer of R_i can not all be put into parent population W_{i+1}.

Step3: The individuals in this layer are arranged from large to small according to the crowding distance, and then put the individuals into the parent population W_{i+1} in turn until the parent population W_{i+1} is full.

Step4: Then a new parent population W_{i+1} can be generated from population R_i.

The overall procedure of NSGA-II is illustrated as follows:

As mentioned above, NSGA-II uses a fast non dominated sorting algorithm, which greatly reduces the computational complexity compared with NSGA. The algorithm complexity of NSGA-II is $O(mN^2)$. In order to rank the population with m number of optimization objects and N population size, every individual must be compared with other individuals in the population to determine whether the individual is dominated or not. For each iteration, Steps 3 and 5 in (3) above require N calculations, so the maximum computational complexity of the entire iteration process is N^2. Therefore, the computational complexity of the whole algorithm is $O(mN^2)$.

6. Numerical experiments

In this section, several sets of computational instances are conducted to elucidate the storage space assignment problem with yard sharing intuitively and certify the effect of the proposed method. Then, the performance of the model is illustrated, which is compared with random stacking strategy. The above-mentioned NSGA-II is programmed on MATLAB R2014a platform. In addition, all the computational experiments are conducted to validate the proposed mathematical model and the optimal value of objective function obtained by the GAMS software in a computer with a CPU of 1.8 GHz and a RAM size of 8.0 GB.

The parameter settings of NSGA-II approach include population size, maximum evolutionary iterations, crossover rate and mutation rate. Different selection of parameter settings will have a great impact on the performance of NSGA-II. How to determine the optimal parameter setting has always been the goal of NSGA-II researchers. To solve this difficulty, we have used the IRACE package [19] to selects the best setting of parameters in our approach. These are selected in IRACE through an iterated racing procedure, which starts by generating a set of candidate configurations. Then compare their performance on training instances and select elite configuration to generate more other configurations in the next iteration. Repeat the process until the tuning budget given by the maximum number of configurations to check is reached and the current optimal combination of parameters is returned. We use Pop,

Table 3
Best combination of parameters setting.

Parameter	Range	Best value
Pop	[20,100]	100
Maxgen	[100,500]	500
Pc	[0.4,0.99]	0.9
Pm	[0.0001,0.1]	0.09

Algorithm 1 NSGA-II for yard space assignment in two terminals with the consideration of yard sharing

Input: Problem data; NSGA-II parameters, Pop, $Maxgen$, pc, pm, f_{num}, x_{num}, min_{range}, max_{range};
Output: The best solution;
for each individual p **do**
  initialize the x_{num} ranges from 0 to 1;
  evaluate $object_{functions}$;
end for
evaluate n_p and S_p for each individual p of Pop;
put the individual p with the parameter $n_p = 0$ in the Pop into the set F_1;
while $F_1 = \emptyset$ **do**
  for each individual j in F_1 **do**
    for each individual k in S_j **do**
      $n_k = n_{k-1}$;
      until $n_{k=0}$ and put the individual k in F_2;
    end for
  end for
end while
$n_{d=0}$;
the n ranges from 1 to N;
for each h of $object_{function}$ fm **do**
  sort the individuals of this rank by fm;
  find f_{min} and f_{max} of fm;
  set $1_d = \infty$ and $N_d = \infty$ after sorting;
  $n_d = n_d + (fm\,(h+1) - fm\,(h-1))\,/\,(f_{max} - f_{min})$;
end for
for $i = 0$; $i \le Maxgen$; $i++$ **do**
  for all individual in Pop **do**
    execute binary tournament selection to find $chromo_{parent}$;
  end for
  for all $chromo_{parent}$ in Pop **do**
    execute simulated binary crossover and polynomial mutation to find $chromo_{offspring}$;
    combine $chromo$ and $chromo_{offspring}$ to get $combine_{chromo}$;
    execute non-dominated sorting for $combine_{chromo}$ to get F_2 of $combine_{chromo1}$;
    execute crowding-distance sorting for individuals in $combine_{chromo1}$ to get $combine_{chromo2}$;
  end for
  for all individual of $combine_{chromo2}$ in Pop **do**
    sort $combine_{chromo2}$ by pareto rank and get chromo rank;
  end for
  for all rank of $combine_{chromo2}$ in Pop **do**
    put the entire population of rank into chromo;
  end for
  for all individual of the certain rank **do**
    execute crowding-distance sorting;
    put the individuals into chromo;
  end for
end for

Maxgen, Pc, Pm to represent the population size, maximum evolutionary iterations, crossover rate and mutation rate respectively. Table 3 shows the results of each parameter tuned in the NSGA-II approach, and the tuning budget is set to 2500 experiments.

6.1. Test instances

The numerical experiments in this subsection select 30 vessels specific information of a container terminal in Shanghai China. Detailed information is given in Table 4. In order to evaluate the efficiency and the reliability of the yard sharing strategy between container terminal (CT) and dry port (DP) by the model, the computational instances can be groups in three sets with 50 blocks in CT and 20 blocks in DP (shown in Table 5). It is assumed that there is a DP with 20 blocks 30 km away from the CT. The capacity of a block in CT and DP are 1200 TEU containers and 450 TEU containers, respectively. Other important parameters adopted in numerical experiments are collected as follows: (1) the sharing space of blocks in the yard of DP is set to 0.5; (2) the storing parameter of yard blocks is set to 80%; (3) the container to be handled is the 20-foot equivalent units (TEU). In addition, the unit transportation cost and the unit imbalance cost are equal to 40 CNY/TEU·km and 30 CNY/TEU, respectively. The parameter α set to 0 makes coefficient $\theta = \pi/4$ in this test balances the shared storage space of the dry port and the cost combined with container transportation and imbalance of containers. The initial situation of stacking blocks of the CT and the DP are shown in Appendices A and B.

6.2. The effectiveness of proposed method

Fig. 7 shows the distribution of Pareto solution under NSGA-II after 500 iterations. Although we can see that the solution is distributed in a curved surface through the three-dimensional image, the relationships between the three objective functions are hard to come by obviously. Combined with the results of Fig. 8, it is easily to find that the increase of sharing rate will lead to the increase of the total travel distance for assignment and the imbalance of two yards.

Table 4
The information of vessels.

Vessel	Preferred berth	Inbound containers	Handling window
vessel 1	1#	410	Mar.1 16:00
vessel 2	1#	1600	Mar.3 5:00
vessel 3	1#	440	Mar.5 13:00
vessel 4	1#	858	Mar.7 13:00
vessel 5	2#	1177	Mar.1 16:00
vessel 6	2#	393	Mar.3 17:00
vessel 7	2#	1540	Mar.5 21:00
vessel 8	2#	888	Mar.7 20:00
vessel 9	2#	503	Mar.9 2:00
vessel 10	3#	256	Mar.1 17:00
vessel 11	3#	1537	Mar.3 21:00
vessel 12	3#	617	Mar.6 5:00
vessel 13	3#	675	Mar.8 9:00
vessel 14	4#	1332	Mar.1 17:00
vessel 15	4#	1071	Mar.4 21:00
vessel 16	4#	904	Mar.6 17:00
vessel 17	4#	1505	Mar.8 9:00
vessel 18	4#	387	Mar.9 16:00
vessel 19	4#	1702	Mar.10 23:00
vessel 20	5#	345	Mar.2 9:00
vessel 21	5#	414	Mar.4 21:00
vessel 22	5#	1392	Mar.6 17:00
vessel 23	5#	404	Mar.8 18:00
vessel 24	6#	613	Mar.2 13:00
vessel 25	6#	1552	Mar.5 5:00
vessel 26	6#	200	Mar.6 23:00
vessel 27	6#	448	Mar.9 2:00
vessel 28	7#	148	Mar.3 2:00
vessel 29	7#	259	Mar.5 9:00
vessel 30	7#	149	Mar.7 4:00

Table 5
The input data of instances.

Group	Vessels NO.	Inbound containers	N^a	N^b
Group 1	28	148	50	20
	29	259	50	20
	30	149	50	20
	10	256	50	20
Group 2	8	888	50	20
	16	904	50	20
	13	675	50	20
	1	858	50	20
Group 3	25	1552	50	20
	2	1600	50	20
	17	1505	50	20
	19	1702	50	20

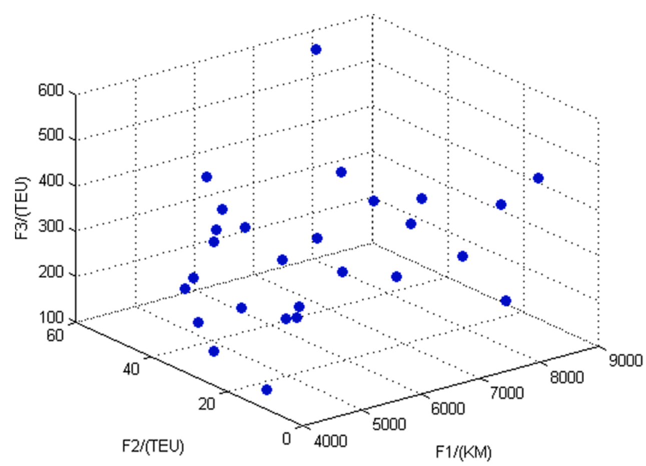


Fig. 7. Distribution of Pareto solution under NSGA-II.

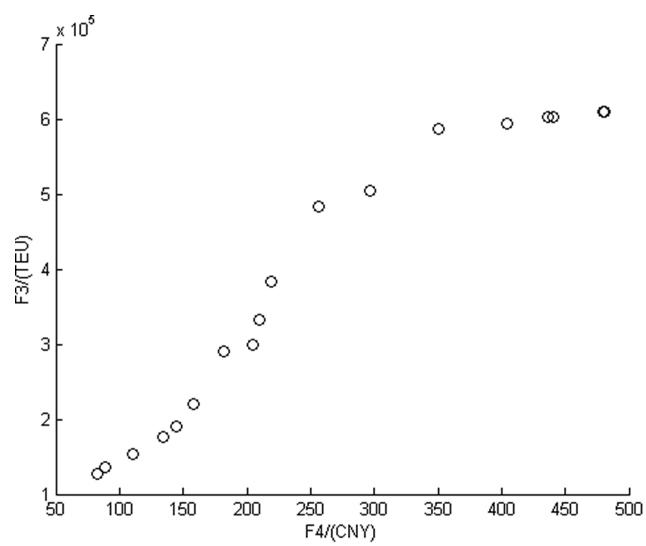


Fig. 8. Distribution of Pareto solution under optimization model.

Table 6 shows the performance of NSGA-II regarding the objective function and the results of the optimization model obtained by the GAMS software. In the preliminary analysis of the optimization model, it is found that the calculation time is generally more than 2 h. We restrict the optimization model to run 1 h (3600 s) of time limit per each instance. The reason why we set this time limit is that it is in practice the terminal planner uses about 1 h of the day to make this decision.

A total of ten replications for each instance are conducted to

Table 6
Comparison between NSGA-II solutions and optimization results.

Instance ID	Inbound containers(TEU)	Optimization Model					NSGA-II					GAP(%)
		Time (s)	$F3_{opt}$ (TEU)				Time (s)	$F3_{NSGA}$-II (TEU)				
			Max	Min	Mean	Standard deviation		Max	Min	Mean	Standard deviation	
1	238	1378.26	78	78	78	0	68.82	80	75	77	0.87	1.28
2	412	1862.73	123	123	123	0	83.71	123	120	121	1.12	1.63
3	537	2018.19	158	158	158	0	101.37	162	149	154	1.05	2.53
4	725	2417.36	244	244	244	0	113.65	245	227	232	0.96	4.92
5	865	2569.21	312	312	312	0	132.80	320	293	305	1.67	2.24
6	1123	2789.27	437	437	437	0	151.79	451	412	420	3.15	3.89
7	1248	3812.75	490	490	490	0	175.34	462	439	448	2.71	8.57
8	1461	3350.93	512	512	512	0	237.26	494	460	477	4.22	6.84
9	1697	>3600.00	634	535	583	3.96	289.17	568	526	539	5.05	7.55
10	1842	>3600.00	697	589	614	4.17	370.43	592	545	561	4.78	8.63
Average	–	2644.30				0.81	172.43				2.56	4.81

calculate the average performance of the NSGA-II and the exact method of optimization model. To investigate the randomness of NSGA-II in contrast with the performance of the exact method of optimization model, the max, average, min of the objective value and standard deviation are be calculated. To compare the performance of both solutions approaches, we use the widely used data of CPU time. Besides, the average of the number of shared storage space of the dry port is computed as GAP = ((Mean_$F3_{opt}$- Mean_$F3_{NSGA}$-II)/Mean_$F3_{opt}$) * 100% is used to measure the specific performance of these two approaches, where Mean_$F3_{opt}$ and Mean_$F3_{NSGA}$-II denote the optimization and the NSGA-II, respectively.

It can be seen from the effectiveness, GAMS failed to obtain the objective value for the instances with more than or equal to 1697 TEU, given a 3600-s computational limit. Obviously, NSGA-II is a better approach to handle large scale problems. Concurrently, the standard deviation reveals the randomness of the two approaches in ten replications. It can be observed that the exact solution can be obtained by the optimization model with less than or equal to 1461 TEU, while the experimental results have deviation with the number of inbound containers more than or equal to 1697 TEU. Meanwhile, the average standard deviation of NSGA-II is 2.56, which is higher than the average standard deviation 0.81 calculated by GAMS. It can be seen that the GAP between NSGA-II and the optimization model is not large, and the average GAP is equal to 4.81%. In the 10 instances, although the solution obtained by optimization model is slightly better than NSGA-II, the overall CPU time of NSGA-II is relatively short. The experimental results present that the two approaches have their own advantages. The optimization model method is adopted in small-scale computational experiments, and NSGA-II is used in large-scale experiments.

In order to further investigate the effectiveness of NSGA-II in large-scale instances, we compared it with the multi-objective particle swarm optimization (MOPSO). A total of ten replications for the experimental instance with 1842 TEU inbound containers were conducted to calculate F3 and F4 respectively. Table 7 displays the comparison of results among the NSGA-II and MOPSO. It can be observed that the average performance of NSGA-II is better than MOPSO with respect to F3, and to F4. With respect to CPU time, MOPSO shows higher search speed and a lower standard deviation. Considering the overall performance, the effectiveness of NSGA-II is better than that of MOPSO.

Table 7
Comparison between NSGA-II and MOPSO.

	NSGA-II			MOPSO		
	F3 (TEU)	F4(CNY)	Time (s)	F3 (TEU)	F4(CNY)	Time (s)
Best	556	892,364	190.45	592	729,123	312.15
Worst	413	1,436,289	267.38	545	1,186,508	465.74
Average	482	1,102,583	234.91	561	984,726	370.43
Standard deviation	7.21	5.47	2.43	4.28	2.95	5.19

6.3. Comparisons and performance analysis with random stacking strategy

This subsection demonstrates the performance of the proposed yard sharing strategy with random stacking strategy. Based on the arrival of inbound containers, the random stacking strategy searches the unfilled container block as the designated stacking location. If the stacking location is not the same order and consignor, the container cannot be stacked in that location.

Several experiments are conducted to explore the contribution of yard sharing strategy compared with random stacking strategy. To evaluate the performance of different stacking strategy on objectives of the shared storage space of the DP and the cost combined with container transportation and imbalance of containers, we select eight instances with different scales and consider the storage of single vessel import containers.

The performance of the two strategies in three aspects and the GAPs of three objectives are demonstrated in Table 8. The computations were repeated in ten runtimes to obtain the results. It is observed from the results that the yard sharing strategy is better than the random stacking strategy in terms of increasing the shared storage space of the DP and decreasing the cost combined with container transportation and imbalance of containers, which are represented by F3 and F4 respectively in Table 8. Specifically, compared with random stacking strategy, F3 increased by an average of 14.63% under yard sharing. So that F4 decreased by an average of 21.28% and Obj increased by at least 12.50%. These results certify the effectiveness of yard sharing strategy.

6.4. Comparisons between shared yard and not shared

In an effort to uncover the performance of yard sharing strategy between CT and DP, the inbound containers that is unloaded from vessels are directly stacked at the CT without considering yard sharing strategy is proposed and simulated. 10 instances that are generated for different number of inbound containers are used to substantiate the performance of the strategy in five aspects: (1) F1 - the total travel distance for assignment; (2) F2 - imbalance of two yard in a period; (3) F3 - shared storage space of the DP; (4) average storage rate in CT; (5) average storage rate in DP.

To achieve the objective of F1, F2 and F3, Table 8 displays the results of solving 10 instances with and without yard sharing strategy. Each approach was repeated ten times for each instance. The inbound containers unloaded from each vessel have to be stacked in blocks of CT without yard sharing strategy. Hence, it is foreseeable that the total travel distance for assignment under the consideration of yard sharing strategy among all instances are higher than that without yard sharing,

Table 8
Performance of the comparation between two stacking strategy.

NO.	Inbound container (TEU)	Yard sharing strategy			Random stacking strategy			GAP (%)		
		F3 (TEU)	F4 (CNY)	Obj	F3 (TEU)	F4 (CNY)	Obj	F3	F4	Obj
1	1177	421	602,124	0.72	356	795,623	0.64	18.26	24.32	12.50
2	888	352	516,283	0.84	290	620,835	0.53	21.38	16.84	58.49
3	503	182	291,493	0.69	163	327,284	0.58	11.66	10.94	18.97
4	440	144	175,372	0.82	119	336,485	0.61	21.01	47.88	34.43
5	558	205	296,538	0.81	184	368,241	0.58	11.41	19.47	39.66
6	259	89	135,852	0.78	82	153,742	0.62	8.54	11.64	25.81
7	1332	462	604,967	0.73	409	825,341	0.53	12.96	26.70	37.74
8	256	85	130,751	0.83	76	149,364	0.62	11.84	12.46	33.87

which can be obtained from the GAP of F1 in Table 9. As for F2, due to the low utilization rate of DP blocks in the beginning period, imbalance in number of containers in a period among blocks of CT and DP without yard sharing strategy is more than that under yard sharing (shown in Fig. 9). Due to the contribution of shared storage space made by DP yard under the strategy of yard sharing, the average storage rate in CT has decreased from 76.25% to 61.84%, which eases the busy operation of CT. At the same time, the average storage rate in DP rises from 25.72% to 45.69%, which increases the utilization rate of the yard resources. Therefore, the yard sharing strategy balances the overall container operation volume of the CT and the DP.

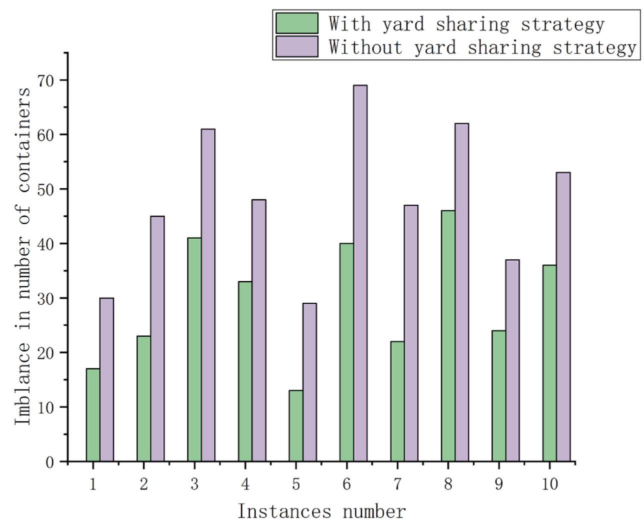


Fig. 9. Comparison of imbalance for different instances.

6.5. *Comparisons among different distance*

The distance between CT and DP unlocks the critical bottleneck of the performance of storage space assignment considering yard sharing, and influences the number of inbound containers to be stacked in the CT and DP. Meanwhile, the travel distance of container trucks between block b in DP and the berth location of vessel v in mathematical model will be affected by the length of transport passage directly, i.e., the distance between CT and DP.

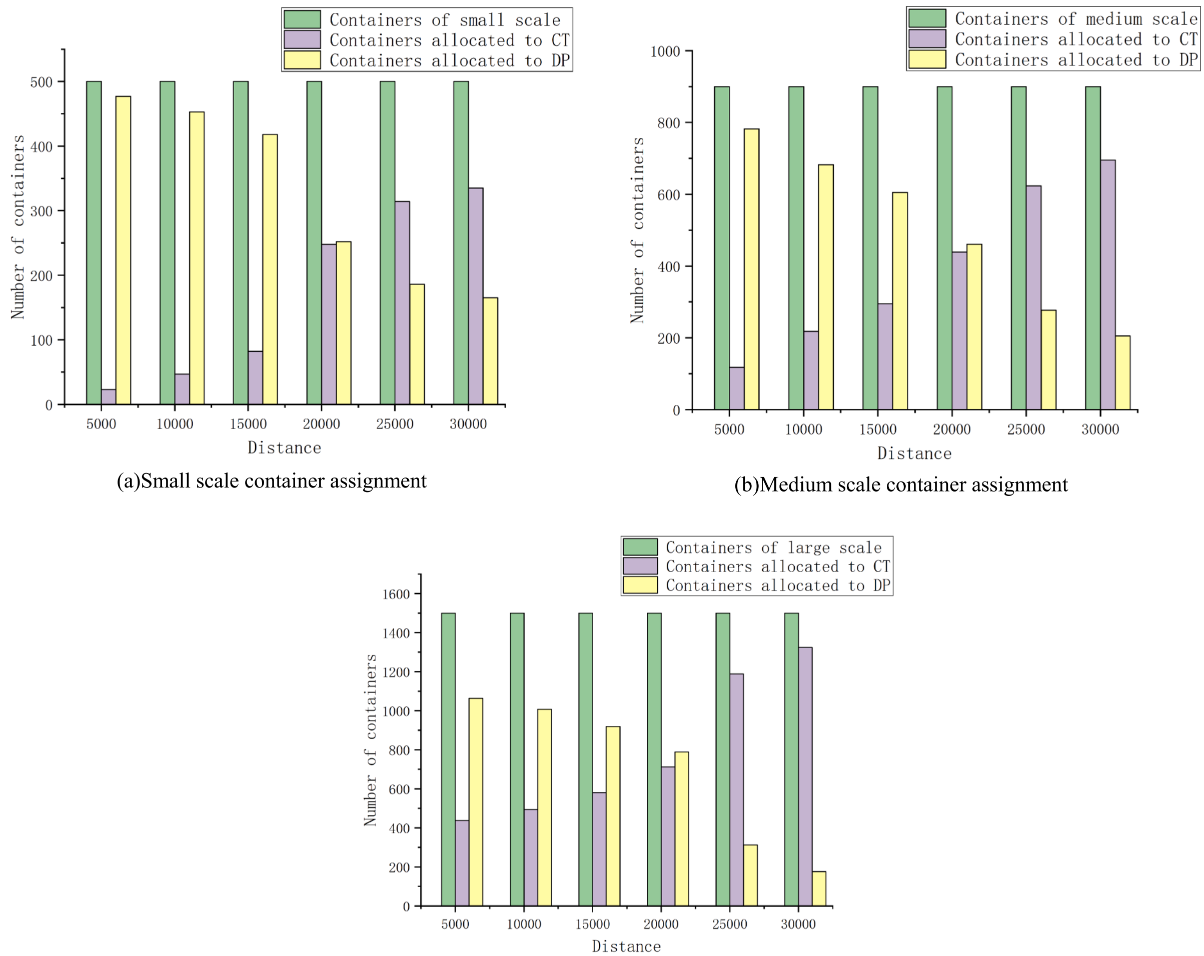
The number of allocated inbound containers is distinctly showed in Fig. 10. It is possible to observe that, in terms of the different scales inbound containers from single vessel, the trend of overall assignment of the number of inbound containers is that with the increase of distance, the number of containers stacked in DP gradually decreases while the number of containers stacked in CT increases. Interestingly, if the DP is very close to the CT approximately 5 km, most inbound containers will be transported and stacked in DP, especially in small scale (shown in Fig. 10(a)). However, the proportion of containers allocated to DP is lower than that of medium-sized and small-scale when the number of inbound containers is 1500TEU on a large scale at the distance of 5 km. The cause for this phenomenon that can be the available shared storage space of inbound containers of a single vessel can be stacked in DP. When the distance is 20 km, about half of the containers will be stacked to DP. Subsequently, with the increase of distance, the growth rate of containers stacked in DP slows down. Especially, when the distance exceeds 25 km, most containers are stacked in CT. At this time, distance has become the main reason for restricting container assignment. The reason behind this is because the increase in distance leads to increased travel time and freight costs of DP.

6.6. *The influence of considering imbalance*

Another concern stated here is the imbalance of number of containers among different blocks. Fig. 11 illustrates the performance that is demonstrated by the imbalance in number of containers over the 24 periods tested within a day. Obviously, the performance that considers the work load balance of blocks in the objective function is better than that without considering. The average imbalance of the number of containers among all blocks is 28.31, while another situation reaches 53.25. Thus, considering workload balance in blocks is beneficial for

Table 9
Comparisons between yard sharing or not.

NO.	With yard sharing strategy					Without yard sharing strategy					GAP (%)	
	F1 (km)	F2 (TEU)	F3 (TEU)	Average storage rate in CT (%)	Average storage rate in DP (%)	F1 (km)	F2 (TEU)	F3 (TEU)	Average storage rate in CT (%)	Average storage rate in DP (%)	F1	F2
1	4231	17	113	61.84	45.69	3314	30	0	76.25	25.72	27.67	43.33
2	5302	23	222			3869	45	0			37.04	48.89
3	7029	41	187			5270	61	0			33.38	32.79
4	4397	33	136			3271	48	0			34.42	31.25
5	8656	13	410			5713	29	0			51.51	55.17
6	4670	40	159			3733	69	0			25.10	42.03
7	5347	22	205			3935	47	0			35.88	53.19
8	5204	46	417			3406	62	0			52.79	25.81
9	5818	24	354			4309	37	0			35.02	35.14
10	8972	36	178			5699	53	0			57.43	32.08



(a)Small scale container assignment

(b)Medium scale container assignment

(c)Large scale container assignment

Fig. 10. Container assignment of different scales at different distances.

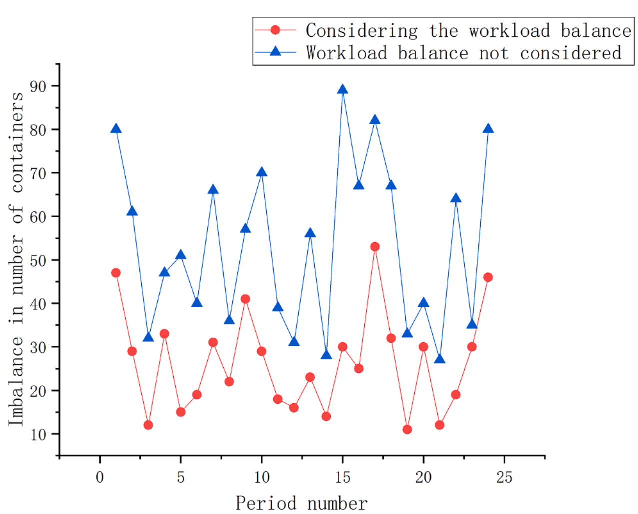


Fig. 11. Imbalance of the number of containers.

reducing imbalance in number of containers. Based on the analyses above, it is easy to draw conclusion that considering workload balance in blocks adjusts the storage space assignment effectively.

6.7. *Sensitivity analysis*

In this subsection, sensitivity analysis is conducted to investigate the effectiveness of the proposed model in two aspects. First, the α selected as a parameter for θ will affect the result directly; Second, the feasible distance between CT and DP will influence the inbound containers assignment. Table 10 reports solutions of F1, F2 and F3 with the different value of α for θ in three groups, in which the dataset is taken from Table 5. The parameter α be set as -1, $-1/2$, 0, 1/2, 1, and θ from

Table 10
Investigation of the parameter α of θ.

α	θ	Objective	Group1	Group2	Group3
-1	0	F1(km)	40,162	81,323	13,230
		F2(TEU)	31	53	76
		F3(TEU)	356	517	792
$-\frac{1}{2}$	$\frac{1}{8}\pi$	F1(km)	38,263	77,184	12,332
		F2(TEU)	27	47	65
		F3(TEU)	318	456	727
0	$\frac{1}{4}\pi$	F1(km)	35,501	71,596	17,827
		F2(TEU)	21	39	59
		F3(TEU)	289	402	653
$\frac{1}{2}$	$\frac{3}{8}\pi$	F1(km)	33,729	67,062	99,774
		F2(TEU)	15	32	53
		F3(TEU)	241	341	578
1	$\frac{1}{2}\pi$	F1(km)	31,135	60,392	85,531
		F2(TEU)	10	26	49
		F3(TEU)	153	293	512

0 to π for suiting container operation scale. In general, with the increase of θ, more inbound containers are transported to stack in DP to improve yard sharing rate with longer total travel distance for assignment and less imbalance in number of containers. On the contrary, the smaller θ is, the less inbound containers stacking in DP under the consideration of yard sharing strategy is.

8 instances with different distances are used to test the sensitivity of the feasible distance between CT and DP. A total of ten replications for each instance were conducted to calculate the average performance of the sensitivity. As shown in Table 11, the value of the cost combined with container transportation and imbalance of containers of different cases is illustrated. Fig. 12 elucidates the trend of an increase in the value of distances and some other reasonable parameter intuitively. Apparently, regardless of the number of containers, there is a whole growth in cost with the distance from 5 km to 30 km because transportation cost is the main part. The cost growth slows down in the 20–30 km stage, and there is no obvious increase like that in the 5–15 km stage. It is interesting that the cost will be decreases when the scale of CT yard expands, e.g. set-1 and set-3, but it will be increased when the scale of DP yard expands, e.g. set-5 and set-6. The reasons behind this are obvious, that is because the shortage of storage space in CT and the surplus of storage yard resources in DP, the containers are tend to be transported to DP for storage.

6.8. Discussion on the computational results

The conclusions are restricted to the setting of the test instances. Firstly, we compared the optimization model with NSGA-II, and the results showed that the optimization model was effective. Next, we mainly carried out the experimental demonstration from four aspects, comparisons and performance analysis with random stacking strategy, comparisons between shared yard and not shared, comparisons among different distance, the influence of considering imbalance were reported. Include specifically: i) comparing with random stacking strategy, F3 and Obj increased while F4 decreased; ii) with the contribution of shared storage space made by DP yard under the strategy of yard sharing, the average storage rate in CT decreased while that in DP rose; iii) with the increase of distance, the number of containers stacked in DP gradually decreased while the number of containers stacked in CT increased; iv) the performance that considered the work load balance of blocks in the objective function was better than that without considering.

In general, the proposed optimization model considered yard sharing strategy and imbalance of containers outperforms traditional storage mode to achieve better solution quality. It is possible that CT operator and DP operator can achieve mutual benefits and win–win results through cooperation. It is observed from the computational results that the yard sharing strategy is better than the random stacking strategy in terms of increasing the shared storage space of DP and decreasing the cost combined with container transportation and imbalance of containers. Concurrently, the yard sharing strategy to balance the overall container operation volume of CT and DP is to ease the busy operation of CT and increase the utilization rate of DP yard resources. Furthermore, it is noteworthy that the distance between CT and DP is an important factor to be considered. Therefore, we can conclude that the yard sharing strategy with the consideration of workload balance in blocks for CT and DP can adjust the storage space assignment effectively.

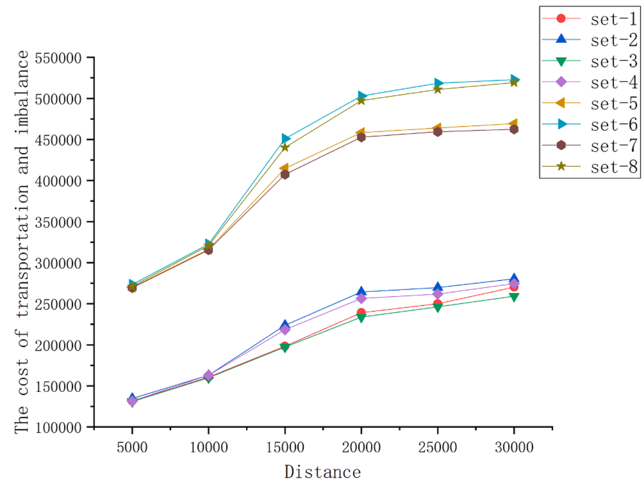


Fig. 12. Computational results of various distance between CT and DP.

7. Conclusion

Facing the shortage of storage space of container terminal yard, our paper investigates this actual problem through following approaches. A yard sharing strategy that uses the surplus storage space of dry port to ease container congestion is proposed to help terminal operator makes decision for container storage space assignment between container terminal and dry port. In addition, a multiple-objective mixed integer programming model that considers yard sharing strategy with the objectives of minimizing total travel distance, minimizing imbalance in number of containers, maximizing shared storage space of the dry port is formulated to obtain optimal solution. A meta-heuristics algorithm as NSGA-II with elitist strategy is used to solve the problem. Numerical experiments are conducted to validate the proposed method and elucidate the problem of yard sharing strategy. The following results can be obtained: (1) compared with random stacking strategy, F3 is increased by an average of 14.63% under yard sharing, and at the same time, F4 is decreased by an average of 21.28% and Obj increased by at least 12.50%; (2) compared with traditional strategy, yard sharing strategy balances the overall container operation volume of the CT and the DP; (3) the overall trend of inbound container assignment is: the number of containers allocated to DP decreases gradually, while the number of containers allocated to CT increases with the increase of the distance between the two terminals; (4) considering workload balance in blocks shows the effectiveness of the storage space assignment by decrease imbalance in number of containers. Finally, sensitivity analysis is conducted in aspects of, weight coefficient and feasible distance, which verifies the effectiveness of proposed method.

Table 11
Sensitivity analysis of the distance between CT and DP.

NO.	Inbound container (TEU)	N^a	N^b	Distance (km)					
				5	10	15	20	25	30
Set-1	500	30	10	131,534	160,785	198,352	239,173	250,032	270,283
Set-2	500	30	20	134,742	162,848	223,847	264,375	269,781	280,474
Set-3	500	50	10	130,853	159,823	197,426	233,846	246,284	259,342
Set-4	500	50	20	131,627	163,052	218,364	256,389	261,838	274,627
Set-5	1000	30	10	270,127	316,373	414,927	458,264	463,920	469,251
Set-6	1000	30	20	273,514	322,756	451,024	502,846	518,364	522,865
Set-7	1000	50	10	269,348	315,404	407,323	452,724	459,303	462,427
Set-8	1000	50	20	271,125	320,822	440,236	497,262	510,863	519,374

However, the study has its own limitations in the current model. Further directions need to be considered to expand the scope of research: (1) the storage assignment with the inbound containers and outbound containers mixed up in one block should be considered; (2) container operation considering time window should be studied; (3) an algorithm can solve large-scale instances and is fast in calculation.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. The number of containers in block a at the beginning of the planning horizon

block a	na	block a	na	block a	na	block a	na	block a	na
1	783	11	949	21	723	31	753	41	844
2	736	12	736	22	951	32	805	42	832
3	754	13	917	23	864	33	782	43	779
4	732	14	763	24	956	34	853	44	843
5	793	15	809	25	783	35	930	45	736
6	727	16	793	26	921	36	778	46	867
7	923	17	753	27	790	37	948	47	848
8	901	18	773	28	946	38	759	48	882
9	810	19	808	29	774	39	904	49	879
10	793	20	940	30	780	40	763	50	902

Appendix B. The number of containers in block b at the beginning of the planning horizon

block b	nb	block b	nb	block b	nb	block b	nb
1	136	6	154	11	147	16	109
2	89	7	106	12	168	17	85
3	93	8	150	13	151	18	158
4	112	9	118	14	182	19	136
5	167	10	98	15	104	20	172

References

[1] L. Chen, Z.Q. Lu, The storage location assignment problem for outbound containers in a maritime terminal, Int. J. Prod. Econ. 135 (2012) 73–80.
[2] J.F. Cordeau, G. Laporte, L. Moccia, G. Sorrentino, Optimizing yard assignment in an automotive transshipment terminal, Eur. J. Oper. Res. 215 (2011) 149–160.
[3] F.T. Chang, G.H. Zhou, W. Cheng, C. Zhang, C.I. Tian, A service-oriented multi-player maintenance grouping strategy for complex multi-component system based on game theory, Adv. Eng. Inf. 42 (2019) 1–13.
[4] R. Dekker, P. Voogd, E. van Asperen, Advanced methods for container stacking, OR Spectrum 28 (2006) 563–586.
[5] K. Deb, A. Pratap, S. Agarwal, T. Meyarivan, A fast and elitist multi-objective genetic algorithm: NSGA-II, IEEE Trans. Evol. Comput. 6 (2) (2002) 182–197.
[6] M.A. Darfoun, M.E. El-Hawary, Multi-objective optimization approach for optimal distributed generation sizing and placement, Electr. Power Compon. Syst. 43 (7) (2015) 828–836.
[7] F. Facchini, S. Digiesi, G. Mossa, Optimal dry port configuration for container terminals: A non-linear model for sustainable decision making, Int. J. Prod. Econ. 219 (2020) 164–178.
[8] S. Favuzza, M.G. Ippolito, E. Riva Sanseverino, Crowded comparison operators for constraints handling in NSGA-II for optimal design of the compensation system in electrical distribution networks, Adv. Eng. Inf. 20 (2) (2006) 201–211.
[9] J.L. He, C.M. Tan, Y.T. Zhang, Yard crane scheduling problem in a container terminal considering risk caused by uncertainty, Adv. Eng. Inf. 39 (2019) 14–24.
[10] J.L. He, C.M. Tan, W. Yan, W. Huang, M. Liu, H. Yu, Two-stage stochastic programming model for generating container yard template under uncertainty and traffic congestion, Adv. Eng. Inf. 43 (2020), 101032.
[11] X.J. Jiang, L.H. Lee, E.P. Chew, Y.B. Han, K.C. Tan, A container yard storage strategy for improving land utilization and operation efficiency in a transshipment hub port, Eur. J. Oper. Res. 221 (2012) 64–73.
[12] X.J. Jiang, J.G. Jin, A branch-and-price method for integrated yard crane deployment and container allocation in transshipment yards, Transp. Res. Part B 98 (2017) 62–75.
[13] X.F. Jin, K.T. Park, K.H. Kim, Storage space sharing among container handling companies, Transp. Res. Part E 127 (2019) 111–131.
[14] K.H. Kim, K.T. Park, A note on a dynamic space-allocation method for outbound containers, Eur. J. Oper. Res. 148 (2003) 92–101.
[15] A. Konak, D.W. Coit, A.E. Smith, Multi-objective optimization using genetic algorithms: A tutorial, Reliab. Eng. Syst. Saf. 9 (2006) 992–1007.
[16] B.L. Lin, S.Q. Liu, R.X. Lin, J.X. Wang, M. Sun, X.D. Wang, C. Liu, J.P.X.J. Wu, The location-allocation model for multi-classification-yard location problem, Transp. Res. Part E 122 (2019) 283–308.
[17] L. Li, R.R. Negenborn, B.D. Schutter, Intermodal freight transport planning – A receding horizon control approach, Transp. Res. Part C 60 (2015) 77–95.
[18] D. Liu, H.L. Yang, Joint slot allocation and dynamic pricing of container sea-rail multimodal transportation, J. Traffic Transp. Eng. (English Edition) 2 (3) (2015) 198–208.
[19] M. López-Ibáñez, J. Dubois-Lacoste, L.P. Cáceres, M. Birattari, T. Stützle, The irace package: Iterated racing for automatic algorithm configuration, Oper. Res. Perspect. 3 (2016) 43–58.
[20] B. Niu, T. Xie, L.J. Tan, Y. Bi, Z.X. Wang, Swarm intelligence algorithms for yard truck scheduling and storage allocation problems, Neurocomputing 188 (2016) 284–293.
[21] K.K.H. Ng, C.K.M. Lee, F.T.S. Chan, Y.Q. Lv, Review on meta-heuristics approaches for airside operation research, Appl. Soft Comput. 66 (2018) 104–133.
[22] K.K.H. Ng, C.K.M. Lee, F.T.S. Chan, Y.C. Qin, Robust aircraft sequencing and scheduling problem with arrival/departure delay using the min-max regret approach, Transp. Res. Part E 106 (2017) 115–136.
[23] S. Nagaballi, V.S. Kale, Pareto optimality and game theory approach for optimal deployment of DG in radial distribution system to improve techno-economic benefits, Appl. Soft Comput. 92 (2020), 106234.
[24] T.D. Nguyen, T.H. Tran, N.D. Hoang, Prediction of interface yield stress and plastic viscosity of fresh concrete using a hybrid machine learning approach, Adv. Eng. Inf. 44 (2020), 101057.
[25] A.R. Rahimi-Vahed, M. Rabbani, R. Tavakkoli-Moghaddam, S.A. Torabi, F. Jolai, A multi-objective scatter search for a mixed-model assembly line sequencing problem, Adv. Eng. Inf. 21 (1) (2006) 85–99.
[26] N. Srinivas, K. Deb, Multiobjective optimization using nondominated sorting in Genetic Algorithms, Evol. Comput. 2 (3) (1995) 221–248.
[27] C. Tan, J.L. He, Y. Wang, Storage yard management based on flexible yard template in container terminal, Adv. Eng. Inf. 34 (2017) 101–113.
[28] C. Tan, J.L. He, H. Yu, Mathematical modeling of yard template regeneration for multiple container terminals, Adv. Eng. Inf. 40 (2019) 58–68.
[29] Y. Tao, C.Y. Lee, Joint planning of berth and yard allocation in transshipment terminals using multi-cluster stacking strategy, Transp. Res. Part E 83 (2015) 34–50.
[30] M. Teleb-Ibrahimi, B. De Castilho, C.F. Daganzo, Storage space vs. handling work in container terminals, Transp. Res. B 12 (1) (1993) 13–32.

[31] M. Taleb-Ibrahimi, Modeling and Analysis of Container Storage in Ports, PhD Thesis, University of California at Berkeley, 1989.
[32] M. Wiercx, M.V. Kalmthout, B. Wiegmans, Inland waterway terminal yard configuration contributing to sustainability: Modeling yard operations, Res. Transp. Econ. 73 (2019) 4–16.
[33] X. Xiang, C.C. Liu, L.X. Miao, Reactive strategy for discrete berth allocation and quay crane assignment problems under uncertainty, Comput. Ind. Eng. 126 (2018) 196–216.
[34] Y. Xie, D.P. Song, Optimal planning for container prestaging, discharging, and loading processes at seaport rail terminals with uncertainty, Transp. Res. Part E Logistics Transp. Rev. 119 (2018) 88–109.
[35] B.C. Yan, X.N. Zhu, D.H. Lee, J.G. Jin, L. Wang, Transshipment operations optimization of sea-rail intermodal container in seaport rail terminals, Comput. Ind. Eng. 141 (2020), 106296.
[36] M.Z. Yu, X.T. Qi, Storage space allocation models for inbound containers in an automatic container terminal, Eur. J. Oper. Res. 226 (2013) 32–45.
[37] L. Zhen, C. Xu, K. Wang, Y. Ding, Multi-period yard template planning in container terminals, Transp. Res. Part B 93 (2016) 700–719.
[38] L. Zhen, E.P. Chew, L.H. Lee, An integrated model for berth template and yard template planning in transshipment hubs, Transp. Sci. 45 (4) (2011) 483–504.
[39] C.H. Zhou, W.C. Wang, H.B. Li, Container reshuffling considered space allocation problem in container terminals, Transp. Res. Part E 136 (2020), 101869.