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A HEURISTIC ALGORITHM FOR EQUIPMENT SCHEDULING AT AN AUTOMATED CONTAINER TERMINAL WITH MULTI-SIZE CONTAINERS

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Abstract:

With the increasing volume of shipping containers, container multimodal transport and port scheduling have attracted much attention. The allocation and dispatching of handling equipment to minimize completion time and energy consumption have always been a focus of research. This paper considers a scheduling problem at an automated land–maritime multimodal container terminal with multi-size containers, in which operating facilities and equipment such as quay cranes, vehicles, yard cranes, and external container trucks are involved. Moreover, the diversity of container sizes and the location of handshake areas in yards are concerned. A mixed integer programming model is established to schedule all operating facilities and equipment. To solve the mathematical model is a NP-hard problem, which is difficult to be solved by conventional methods. Then we propose a heuristic algorithm which merges multiple targets into one and designs an improved genetic algorithm based on the heuristic combination strategy in which 20-ft containers are paired-up to the same yard before allocation. After that, some experiments are designed to prove the effectiveness of the model and the algorithm. The effect of configurations on efficiency and energy consumption under different conditions is discussed, and the influences of different parameters and the proportion of 20-ft containers are also compared. Furthermore, the influence of locations of handshake area with different yard quantities are compared. To conclude, there is an optimal number of equipment to be allocated. If few equipment is used, the operation time will be prolonged; if too many, the energy consumption will be increased. When the yard operation is the bottleneck, the handover location should be in the centre, otherwise other locations might be feasible. When the proportion of 20-ft containers that can be combined is large, the method proposed in this paper has advantages over traditional methods. The proposed algorithm has made a breakthrough in improving efficiency and reducing energy consumption.

Keywords: *automated container terminal, integrated scheduling, multi-size containers, twin automated yard cranes, energy consumption*

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1. Introduction

With the development of globalization, the size and number of container ships are increasing year by year. Since the 21st century, China's container multimodal transport has entered a period of rapid development, especially the sea container volume and port throughput have increased significantly. With the continuous growth of international trade, coastal ports, as an important supplement to the international supply chain, are playing an increasingly significant role in integrated-transportation systems (Steenken et al., 2004). In the past decade, the cargo throughput of Chinese ports has steadily increased. The Statistics Bulletin on the Development of the Transportation Industry in 2019 released by the Ministry of Transport shows that all ports in China have completed 13.951 billion tons of cargo throughput and 261 million TEUs (Twenty-feet Equivalent Units) of container throughput, increases of 5.7% and 4.4% respectively over the previous year. In this context, port managers are constantly seeking to improve operations and gain cost efficiency.

Port production is a multi-type, multi-link joint operation affected by a complex external environment full of uncertain factors, as well as natural conditions and human factors. At the same time, ports are an important step of the logistics chain and key energy-consuming enterprises. With the national requirements tightened for energy conservation and emissions reduction, reduction of comprehensive energy consumption has become an urgent problem. In recent years, many container ports around the world have begun to consider the use of automation. Compared with traditional ports, automated terminals offer significant improvements in terms of safety, stability, reliability, equipment utilization, and operating costs. However, automated terminals started late in China, and new technology and equipment investment have made terminal operations even more complicated, rendering traditional management processes non-applicable. Therefore, in order to meet the increasing demand for container operations, energy savings, emissions reduction, automation, and other related needs, ports need to continuously improve their operation and management level while improving operational efficiency and reducing energy consumption.

At present, many automated terminals have relatively limited space resources. Although their infrastructure has been constantly constructed and improved, the contradiction between resource constraints and increasing container throughput is becoming increasingly prominent. The most direct and effective way to improve ports' operating capacity is to expand and add related operating equipment. However, none of these can be realized in a short time due to geographical factors and financial constraints. Therefore, under limited conditions, maximizing the use of existing resources through scientific and optimized management is a good way to improve the port-operation level. Many existing research focuses upon optimizing the allocation and dispatching of equipment with the unitary research objective of improving operating efficiency. However, the actual automated terminals' environment is very complicated, and various factors need to be considered. Therefore, the main contributions of this paper are as follows: 1) a research objective that considers both operating efficiency and energy consumption with multi-size containers; 2) the location of the best handshake areas for twin automated yard cranes; and 3) joint optimization of multiple operations and a novel chromosome generating strategy designed to improve the genetic algorithm for solutions.

The remainder of this paper is organized as follows. Section 2 reviews relevant literature. In Section 3, the integrated-scheduling problem with multi-size containers and twin automated yard cranes is described and formulated as a mixed-integer-programming (MIP) model. Section 4 describes the model's solution method, including the conversion of a multi-objective function into a single-objective one and the creation of an improved genetic algorithm based on combination rules. Numerical experiments are conducted in Section 5 to evaluate the effectiveness of the proposed solution methods, and different situations are discussed as well. In the end, conclusions and future research are given in Section 6.

2. Literature review

According to the problems studied in this paper, the relevant research literature can be grouped into three categories: joint-dispatching optimization of multiple processes and equipment; consideration of port-operation-dispatching strategy with uncertainty; and consideration of port-operation-dispatching methods taking energy consumption factors into account. In recent years, a number of studies have investigated joint-dispatching optimization of multiple processes and equipment(Jachimowski, 2017). Raa et al. (Raa et al., 2011), centering on berth allocation and wharf-crane dispatching, proposed an extended model that takes into account such realistic characteristics as maritime liens, priority berth location, and loading and unloading times. The solution to this model can guide planners relatively accurately. The results were verified with actual data. Salido et al. (Salido et al., 2012) believes that container stacking, berth allocation, and dock-crane allocation are three important and related issues for marine-container terminals. Therefore, a decision-making support system for managing these issues in a coordinated manner is proposed and a domain-oriented heuristic planner is developed in the system. Elwany et al. (Elwany et al., 2013) studied the problem of berth and dock-crane allocation under continuous berth conditions, using an effective initial prioritization and simulated annealing algorithm to search for the optimal solution. Tang et al. (Tang et al., 2014) studied the integrated scheduling of loading and unloading cranes and container trucks at terminals. Starting from a model for scheduling container trucks in operational lines, they built a mixed-integer programming model, with the goal of minimizing the duration of the total operations and solved the model by designing an improved particle-swarm-optimization algorithm. Blazewicz et al. (Blazewicz et al., 2011) studied the allocation of berths and dock cranes for incoming ships, and established a nonlinear model to solve the minimum amount of allocated equipment. Hu et al. (H. Hu et al., 2019) discussed the issue of joint vehicle dispatching and yard allocation in automated container terminals. Two types of vehicles, namely automatic-lifting vehicles (ALVs) and automatic guided vehicles (AGVs), were considered. Two mixed-integer linear-programming models were established for two types of vehicles with the objective of minimizing vehicle-operation costs. This is followed by the development of a three-stage decomposition method based on particle-swarm optimization for problem solving. These studies mostly focus on the cooperation and dispatching of equipment in the previous and subsequent processes for the purpose of finding a dispatching schedule that meets goals.

With the development of technology, automatic terminals have developed and more automatic equipment have been adopted into port production. For example, twin automated yard cranes which are unable to pass each other are often used in a storage yard. Gharehgozli et al. (Gharehgozli et al., 2017)studied the effect of a handshake area on the performance of twin automated stacking cranes (ASCs). Han et al. (Han et al., 2019) explored the scheduling of twin ASCs and the influences of the handshake areas location.

As mentioned earlier, relevant literature can also be found concerning the issue of current port operations affected by uncertain factors. Zhen et al. (Zhen et al., 2011) studied the berth allocation when ship-arrival or loading- and unloading-operation times are uncertain. Firstly, both the static and dynamic potential impacts are considered before formulating the berth plan. When the uncertainty occurred, the minimum-penalty cost could be used to adjust strategies, based on which a two-stage decision-making model under uncertain conditions is established. In addition, a metaheuristic method is proposed to solve large-scale problems, and the effectiveness of the method was verified by numerical experiments. Lu & Le (Lu & Le, 2014) considered the influence of uncertain factors upon dock dispatching, such as the truck speed in the storage yard, the speed of the storage-yard crane, and the lifting time of the crane, and proposed a comprehensive optimized dispatching model to minimize yard crane operation time on the basis of coordinating the dock crane and the storage yard truck. A particle-swarm-optimization algorithm is proposed to solve the model, and the results were evaluated. Golias et al. (Golias et al., 2014) considered the inherent uncertainty of the ship's arrival, loading, and unloading times to make the berth-dispatching problem closer to reality, and built a two-layer dual-objective-optimization model with the average and range of minimized total service time. The proposed scheme proved to provide a more robust berth-dispatching strategy under uncertainty. However, few studies have considered the influence of factors such as uncertain and multi-size containers.

Furthermore, energy consumption is receiving more and more attention from society, and research on energy-saving and emission-reduction methods at container ports is urgent. Du et al. (Du et al., 2011) studied berth allocation and proposed a mixed-integer

nonlinear-programming model considering fuel consumption by analyzing the power-function relationship between the fuel-consumption rate and the sailing speed. In order to balance the relationship between port-operating costs and fuel consumption, Hu et al. (Q.-M. Hu et al., 2014) proposed a new nonlinear multi-objective mixed-integer programming model considering ship fuel consumption and emissions in consideration of berths and shore-bridge allocation. They also overcame the difficulty of solving this nonlinear problem by transforming the model into a second-order mixed-integer cone-programming model. He et al. (He et al., 2015a) considered how to improve the service level of the container terminal and reduce energy consumption. In order to balance these two goals, they built a MIP model that integrated the quay crane (QC), internal truck, and yard crane (YC), and proposed a simulation-based optimization method that combined a genetic algorithm with a particle-swarm algorithm to find high-quality solutions of large-scale problems in a reasonable amount of time. For the berth-dispatching problem, Dulebenets et al. (Dulebenets et al., 2017) proposed a mixed-integer mathematical model with the goal of minimizing ship-service costs and carbon emissions from loading and unloading, and used a hybrid evolutionary algorithm that can be solved in an acceptable amount of calculation time for a decent berth plan. Tan et al. (Tan et al., 2021) studied the automated quay crane scheduling problem which the automated container terminal oriented, and discussed the trade-off between operation efficiency and energy consumption.
From these studies, we could see that there is a lack in research which considers uncertain and multi-size containers, and which takes into account the quantity of equipment and storage yards and joint-dispatching optimization of multiple processes along with twin ASCs and the location of handshake areas. In this paper, we aim to bridge the gap in the literature.

3. Problem formulation

3.1. Problem description

At present, many domestic and foreign automated ports adopt a vertical-shoreline layout. The cargo-handling equipment in the port, such as quay cranes, AGVs/ALVs, yard cranes, and external container trucks, not only affect the operation of the port, but are also the main contributors to energy consumption and carbon emissions in the port's land area. Therefore, by optimizing a series of core operations such as quay crane loading and unloading, AGVs/ALVs transportation, yard-bridge loading and unloading, and container-truck transportation, the land energy consumption and carbon emissions of the port can be reduced, and port-service efficiency can also be improved.
This article aims at improving service efficiency and reducing energy consumption by studying common loading operations in the scenario of Figure 1.
Figure 1 shows the layout of a container terminal. The external container trucks transport the containers that need to be loaded into the port, after which they arrive at the yard's transfer point. There are multiple yards in the port along the vertical shoreline with twin automated cranes in each yard (yard cranes use rail-mounted gantries, and transfer of containers is completed by cooperation between them with the handshake area; this kind of allocation helps to improve operational efficiency and is used by many ports, see in Figure 2). The landside yard crane closer to the external container truck takes care of the transfer of containers between that truck and the yard, and the seaside yard crane transfers containers between ALVs and the yard. After the ALVs' completion of the horizontal transport of containers between the yard and the quay crane, the quay crane loads containers onto the vessel. The operational process in this scenario is shown in Figure 3.
In this process, there is some diversity of container sizes carrying by the external container trucks. This paper considers the possibility of loading 20feet (20-ft) and 40feet (40-ft) containers; The type of crane is the same in all yards, and there are supporting brackets for ALV at the delivery site of the seaside yard and ALV. The quay crane is a double-dolly crane equipped with two transit platforms (TPs)，which can load one 40-ft container or two 20-ft containers at a time. While loading, the landside yard crane will drive empty to the external container-truck-delivery site, waiting for its next mission after stacking the last container in the yard. The seaside yard crane will drive empty to the next target position, waiting for the task to arrive and the target bracket to be idle after unloading the last container. ALVs can wait for the container to be delivered on the bracket or under the quay crane waiting for the quay crane to pick up the container; the dollies before and after the quay crane move to the target location after completing the previous container-transfer task. Therefore, this

paper not only considers joint-dispatching optimization of the quay crane, ALVs, and yard crane, but also makes reasonable allocation of yards for diversity in the arrival multi-size containers to improve service efficiency.

Throughout the entire process, the equipment in the port, namely the quay crane, ALVs, and yard crane, will consume energy and generate carbon emissions. In order to simplify the calculation, this paper considers that the energy consumption of the quay cranes, ALVs, and yard cranes is related to the use time (He et al., 2015a). The energy consumption of quay cranes and yard cranes is related to the running time. For ALVs, their energy consumption includes three parts: the running kilometers with containers, the running kilometers without containers and the waiting time.

To be as close to the actual situation as possible to ensure the validity of the research model in this paper, the following assumptions are made:

(1) In the entire process, only two sizes of containers, 20-ft and 40-ft, are considered. The service order of containers follows the principle of first-come-first-served and minimum energy consumption. In addition, emergency situations such as equipment failure are not considered, and time and energy loss during equipment transfer are not considered.

(2) The arrival time of external container trucks is known, and external container trucks are numbered in ascending order. Each external container truck can only be loaded with one container at a time, but the size of container is uncertain.

(3) Each storage yard can accommodate all incoming containers. Each yard is equipped with twin yard cranes, and each crane can only load/unload one container at a time. The parameters of the yard crane's operation are known.

(4) ALVs can load one 20-ft container or one 40-ft container or two 20-ft containers each time. The speeds of the ALVs with and without containers are known.

(5) QCs can load one 40-ft container or up to two 20-ft containers at a time. The parameters of the operation of the quay crane are known.

(6) Traffic congestion of ALVs on the path, as well as interference among QCs and YCs, is not considered here.

The parameter settings and mathematical models are explained as follows.

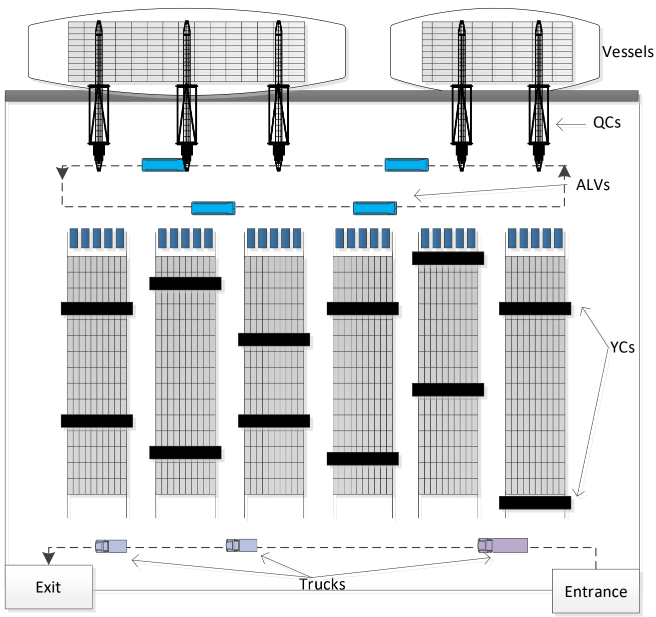

Fig. 1 Layout

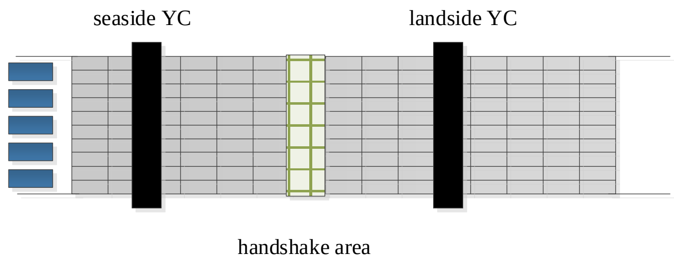

Fig. 2 layout of the yards, twin yard cranes and handshake area

Fig. 3 Loading operation process

3.2. Known parameters

Known parameters are:

I: the number of containers to be loaded, which is also the number of arriving external container trucks. $I \in \mathrm{N}+$;

i: the index of containers and external container trucks, $i \in \{1,2 \ldots I\}$;

k: the sequential number of containers operated by the equipment, $k \in \{1,2,3 \ldots\}$;

Size: randomly generated array of container-size identifiers loaded on the external container trucks;

N_Y: total number of available yards;

v_Y: Speed of YC moving along the yard (unit: m/s);

L_Y: the length of the yard (unit: m);

β: the proportion of the handshake area in the yard from the landside, $0 < \beta < 1$;

G: the number of ALV brackets arranged on the seaside side at each yard;

v_f: ALV's running speed at full load (unit: m/s);

v_e: ALV's running speed with no load (unit: m/s);

Q: the number of quay cranes;

Z: the number of transit platforms in each quay crane;

t_{qi}: the operating time required for the seaside dolly of the quay crane handling container i (unit: s);

t_{hi}: the operating time required for the landside dolly of the quay crane handling container i (unit: s);

W_{qc}: average energy consumption per hour when quay cranes are operating (unit: kwh/h);

W_{yc}: average energy consumption per hour when yard cranes are operating (unit: kwh/h);

W_{aw}: average energy consumption per hour when ALVs are waiting (unit: kwh/h);

W_{af}: average energy consumption per meter when ALVs are running with containers (unit: kwh/m);

W_{ae}: average energy consumption per meter when ALVs are running without containers (unit: kwh/m).

3.3. Decision variables

Decision variables are:

M: the number of ALVs;

N: the number of allocated yards;

x_{ink}^{r}: if the container task i is the kth operation of the landside yard crane n (Where r stands for the landside identification), the value is 1; otherwise, it is 0;

x_{ink}^{v}: if the container task i is the kth operation of the seaside yard crane n (Where v stands for the seaside identification), the value is 1; otherwise it is 0;

x_{ingk}: on the seaside side, if the container task i is the kth service task of the yard n bracket g, the value is 1; otherwise it is 0;

x_{imk}: if the container task i is the kth task of the ALV m, the value is 1; otherwise it is 0;

x_{iqk}: if the container task i is the kth task of the quay crane q, the value is 1; otherwise it is 0;

x_{iqzk}: if the container task i is the kth task of the transit platform z in the quay crane q, the value is 1; otherwise it is 0;

3.4. Auxiliary variables

Auxiliary variables are:

T_{si}: the time when container truck/container i arrives entrance;

T_{ai}: the time when the container truck/container i arrives at the delivery site of yards;

T_{bi}: the time when the container truck/container i accepts the loading and unloading service of the landside yard crane;

T_{li}: the time when the container truck i leaves the exit;
T_{di}: the time when container i is placed in the yard by the landside yard crane;
T_{fi}: the time when container i is loading by the seaside yard crane;
T_{pi}: the time when container i is placed on the ALV bracket by the seaside yard crane;
T_{mi}: the time when the ALV arrives the bracket to load container i;
T_{ri}: the time when container i is loading by the ALV;
T_{ui}: the time when container i is transported to the quay crane delivery site by ALV;
T_{hi}: the start time of the landside dolly of the quay crane serving container i;
$T_{\mathrm{z}i}$: the time when container i is placed on the transit platform;
T_{qi}: the start time of the seaside dolly of the quay crane serving container i;
$T_{\mathrm{e}i}$: the time when container i is loaded on board;
$C_{ii'}^{\mathrm{r}}$: the time required for the landside yard crane to move to the next-task delivery site after completing the previous one;
$C_{ii'}^{\mathrm{v}}$: the time required for the seaside yard crane to move to the next-task delivery site after completing the previous one;
S_{fi}: the travel distance of the ALV, after being loaded with the container i, at full load to the location of the target quay crane;
S_{ei}: the travel distance of the ALV, after completing delivery at the quay crane, with no-load to the position of the yard bracket where the target container i;
$C_{ii'}^{\mathrm{h}}$: the time required for the landside dolly of the quay crane to move to the next-task delivery site after completing the previous one;
$C_{ii'}^{\mathrm{q}}$: the time required for the seaside dolly of the quay crane to move to the next-task delivery site after completing the previous one.

3.5. Mathematical model

Based on the operational process and the optimization objective of this paper, the maximum completion time of a loaded container is used as a measure of the operating efficiency in the following equation:

$$\text{Min} \max(T_{\mathrm{e}i}) \tag{1}$$

Then, the total energy consumption consists of the energy used by quay cranes, ALVs, and yard cranes. These quantities can be obtained from the following three equations:

$$E_Q = \sum_q W_{\mathrm{qc}} \left(\max_{q,i}(T_{\mathrm{e}i}) - \min_{q,i}(T_{hi}) \right) \tag{2}$$

$$\begin{aligned} E_M = {} & \sum_I W_{\mathrm{aw}}[T_{hi} - T_{ui} + \max(T_{ri} - T_{mi}, 0)] \\ & + \sum_I (W_{\mathrm{af}} S_{\mathrm{fi}} + W_{\mathrm{ae}} S_{\mathrm{e}i}) \end{aligned} \tag{3}$$

$$\begin{aligned} E_N = {} & \sum_n W_{\mathrm{yc}} \Big(\max_{q,i}(T_{di}) - \min_{q,i}(T_{bi}) + \max_{q,i}(T_{pi}) \\ & - \min_{q,i}(T_{\mathrm{fi}}) \Big) \end{aligned} \tag{4}$$

In formulas (2), (3), and (4), i and i' indicate the numbers of two-container tasks that one quay crane, ALV, and yard crane have completed.
From this, a MIP model can be established. The objective function and corresponding constraints are as follows.
Objective functions and constraints:

$$\begin{cases} f_1 = \text{Min} \max(T_{\mathrm{e}i}) \\ f_2 = \text{Min } (E_Q + E_M + E_N) \end{cases}$$

subject to:

$$N \le N_{\mathrm{Y}} \tag{5}$$

$$T_{si} < T_{ai} \le T_{bi} < T_{li} \tag{6}$$

$$T_{bi} + \frac{\beta \cdot L_Y}{v_y} \le T_{di} \le T_{fi} \tag{7}$$

$$T_{fi} + \frac{(1-\beta) \cdot L_Y}{v_y} \le T_{pi} \tag{8}$$

$$T_{pi} \le T_{ri} \tag{9}$$

$$T_{ri} + \frac{S_{\mathrm{fi}}}{v_f} \le T_{ui} \le T_{hi} \tag{10}$$

$$T_{hi} + t_{\mathrm{hi}} \le T_{\mathrm{z}i} \le T_{qi} \tag{11}$$

$$T_{qi} + t_{\mathrm{qi}} \le T_{\mathrm{e}i} \tag{12}$$

$$T_{di} + C^{\mathrm{r}}_{ii'} \leq T_{bi'} \tag{13}$$

$$T_{pi} + C^{\mathrm{v}}_{ii'} \leq T_{fi'} \tag{14}$$

$$T_{hi} + \frac{S_{\mathrm{fi}'}}{v_e} \leq T_{ri'} \tag{15}$$

$$T_{\mathrm{z}i} + C^{\mathrm{h}}_{ii'} \leq T_{hi'} \tag{16}$$

$$T_{\mathrm{e}i} + C^{\mathrm{q}}_{ii'} \leq T_{qi'} \tag{17}$$

$$\begin{cases} \sum_n \sum_k x^{\mathrm{r}}_{ink} = 1, \forall i \in I \\ \sum_n \sum_k x^{\mathrm{v}}_{ink} = 1, \forall i \in I \\ \sum_n \sum_g \sum_k x_{ingk} = 1, \forall i \in I \\ \sum_m \sum_k x_{imk} = 1, \forall i \in \mathrm{I} \\ \sum_q \sum_k x_{iqk} = 1, \forall i \in I \\ \sum_q \sum_z \sum_k x_{iqzk} = 1, \forall i \in I \end{cases} \tag{18}$$

$$\begin{cases} \sum_i x^{\mathrm{r}}_{ink} \geq \sum_i x^{\mathrm{r}}_{in(k+1)}, \forall n \in N, i \in I \\ \sum_i x^{\mathrm{v}}_{ink} \geq \sum_i x^{\mathrm{v}}_{in(k+1)}, \forall n \in N, i \in I \\ \sum_i x_{ingk} \geq \sum_i x_{ing(k+1)}, \forall n \in N, \mathrm{g} \in \mathrm{G}, i \in I \\ \sum_i x_{imk} \geq \sum_i x_{im(k+1)}, \forall m \in M, i \in \mathrm{I} \\ \sum_i x_{iqk} \geq \sum_i x_{iq(k+1)}, \forall q \in Q, i \in I \\ \sum_i x_{iqzk} \geq \sum_i x_{iqz(k+1)}, \forall q \in Q, z \in Z, i \in I \end{cases} \tag{19}$$

$$x^{\mathrm{r}}_{ink}, x^{\mathrm{v}}_{ink}, x_{ingk}, x_{imk}, x_{iqk}, x_{iqzk} \in \{0,1\} \tag{20}$$

Constraint (5) indicates that the number of yards available for allocation does not exceed the total number of available yards; constraint sets (6-12) indicate that in the loading task, the start- and end-operation times of the container between various equipment conforms to the chronological order; constraint sets (13-17) indicate that, when the equipment has completed two-container tasks i and i' in succession, the time to start completing the next task i' is longer than or equal to the previous task-completion time plus travel time; constraint set (18) means all container tasks i can only be served once by each type of equipment; constraint set (19) means that all equipment performs operations in sequential order, and the order must be continuous; constraint set (20) means that all variables are binary ones.

4. Improved algorithm

Multi-objective planning and decision-making problems exist in many fields such as engineering practice, economic management, and scientific research. The research problem in this article falls into the category of multi-objective planning. Unlike the contradictions or conflicts between goals in general multi-objective problems, the two goals are not completely contradictory, because a shortened operating time can also reduce the energy consumption of the equipment. Therefore, the basic idea for solving the multi-objective-programming problem in this paper is to first transform it into a single-objective programming problem and then solve it. Common conversion methods include the weighted-combination method, the hierarchical-sequence method, the main-target method, and the comprehensive-evaluation method. Considering the characteristics of the model established above, this paper uses linear weighting to convert the two objective functions into one. The converted objective function is as follows:

$$\min f = \alpha f_1 + (1-\alpha) f_2 \tag{21}$$

where $\alpha, 1-\alpha \geq 0$ are the weight ratios of the two objective functions respectively.

After converting a multi-objective problem into a single-objective one, the model is an NP-hard problem theoretically, that is, the optimal solution to the problem is hard to be found with complex constraints in a limited time. At present, the optimization methods often used in the literature include mathematical programming (Ku & Beck, 2016), graph theory (Chen et al., 2013), heuristics (Homayouni et al., 2014), (Assadipour et al., 2014; Elaziz et al., 2019), and others. Among the common heuristic methods, genetic algorithms have been used in many studies to solve port-dispatching problems (Yang et al., 2018; J. Lin et al., 2020; Qiu et al., 2022). The genetic algorithm (GA) has the characteristics of global search, allowing the solution that it generates to usually be better than those obtained by other methods, and its search speed is faster, meaning that this algorithm is of good effectiveness. Therefore, this paper uses GA to solve the equipment allocation and joint equipment dispatching problems.

4.1. Chromosome representation

4.1.1. Traditional chromosomes

The coding method of the GA is simple, and genetic processes such as crossover and mutation are also relatively easy to implement. The algorithm has a wide search area and is widely used in solving scheduling problems.

According to the decision variables in this paper, we need to determine the order in which the containers are served and the equipment numbers that serve the containers when generating chromosomes; then we can obtain the container sequence served by the equipment. If the first-come-first-served principle is followed, the order of container numbers is the order in which they are served. Containers can be numbered in sequence according to the order of the container trucks' arrival. Because uncertain containers of uncertain size are considered in this paper, a matrix is needed to indicate the sizes of different containers. In this paper, 0 means a 40-ft container, 1 means a 20-ft container. According to the loading-operation process, the container yard to which each container is shipped, the bracket, the ALV number, quay-crane number, and transit-platform number are all needed to be determined. Therefore, the constructed chromosome is shown in Figure 4.

The chromosome indicates the transfer status of each container task between different loading and unloading equipment. For example, the No.1 truck carrying a 40-ft No.1 container stays at No.2 yard. The landside yard crane puts the container into the yard, and then the seaside yard crane transfers the container to the seaside bracket, followed by its transportation to the quay crane delivery site by the No.3 ALV, and then No.1 quay crane loads it to the vessel finally. Because each yard is equipped with twin yard cranes to accomplish the transfer operation, the yard number is also the numbers of the landside and seaside yard cranes, so the chromosomes can be simplified as shown in Figure 5.

After the chromosome is generated, the start and end times of each equipment serving the container can be calculated by combining the constraints in the mathematical model, and then the completion time of all containers can be calculated. The total energy consumption of the chromosome can be determined by the running time or moving distance of each machine. According to the structure description of the chromosome coding, the initial population can be generated randomly.

Container	1	2	3	4	5	6	7	8	9	10
Size identifier	1	0	1	0	1	1	1	1	0	0
Yard	2	1	3	3	4	4	2	3	1	4
landside YC	2	1	3	3	4	4	2	3	1	4
Seaside YC	2	1	3	3	4	4	2	3	1	4
Bracket	1	2	2	2	1	1	2	1	1	2
ALV	3	1	4	2	1	2	3	4	4	2
QC	1	1	2	2	3	3	3	3	1	2
TP	2	2	2	1	1	1	1	2	1	2

Fig. 4 General chromosome examples

Container	1	2	3	4	5	6	7	8	9	10
Size identifier	1	0	1	0	1	1	1	1	0	0
Yard	2	1	3	3	4	4	2	3	1	4
Bracket	1	2	2	2	1	1	2	1	1	2
ALV	3	1	4	2	1	2	3	4	4	2
QC	1	1	2	2	3	3	3	3	1	2
TP	2	2	2	1	1	1	1	2	1	2

Fig. 5. Simplified chromosome-coding examples

4.1.2. Heuristic chromosomes

In general, the chromosomes generated by the above method can meet requirements. However, in the scenario considered in this paper, ALVs and QCs can load and unload two 20-ft containers at a time, but in the general chromosome equipment only serve a single container (regardless of size) each time, which will cause a certain waste of resources. We can find ways to reduce the operating times of ALVs and QCs. For example, the seaside yard crane could place two 20-ft containers on the same bracket one after the other, that is, two 20-ft containers are combined to be loaded and unloaded by ALVs and QCs at a time. In theory, this strategy can shorten the number of operations of the ALVs and QCs to reduce energy consumption. The chromosome design needs to be improved in line with this strategy.

When considering the loading-operation process, given that the yard crane can only load and unload one container at a time, the pairing of two 20-ft containers can only be realized in the step when they are placed into the bracket by the seaside yard crane. That is, the previously arrived container is placed on the bracket but not initially transported by ALV, until next container is also placed on the same bracket. Hence, the original two ALV transports can be reduced to one, and the quay crane can also grab two 20-ft containers at a time, reducing one round-trip operation, so both energy consumption and operation time are shortened theoretically. After the yard numbers are randomly generated for all containers, the container combination rule can be obtained, as shown in Figure 6.

For 40-ft containers, there is no need for combination, and the identifier is 0. For 20-ft containers in the same yard, they can be paired in order. The previous identifier in each group is -1 and the next one is the previous container's number that needs to be combined; if the number of 20-ft containers in the yard is odd, the last unpaired 20-ft container will be transported by a single ALV. After the combination rule is determined, the bracket number is randomly assigned. For the container with a combination identifier of 0, the random generation of the bracket number is not affected; but for the container with a combination identifier of -1, the subsequent bracket number is not necessary for the time being; for the container with a combination identifier greater than 0, after being assigned randomly with a bracket number, the numbered containers in the combination identifier are also set to the same bracket number to achieve the combination of two 20-ft containers on the bracket. Then, for containers with non-negative combination identifiers, the ALV number, QC number, and TP number are still generated randomly; while containers with a combination identifier of -1 do not need to allocate these equipment numbers with corresponding positions are set to 0. These containers are shipped together with the latter combined container; therefore, there is no need to assign subsequent equipment numbers. Combining the above improvements, the resulting chromosome is shown in Figure 7.

Container	1	2	3	4	5	6	7	8	9	10
Size identifier	1	0	1	0	1	1	1	1	0	0
Yard	2	1	3	3	4	4	2	3	1	4
Combination rule	-1	0	-1	0	-1	5	1	3	0	0

Fig. 6. Generation of container combination rule identifier

Container	1	2	3	4	5	6	7	8	9	10
Size identifier	1	0	1	0	1	1	1	1	0	0
Yard	2	1	3	3	4	4	2	3	1	4
Combination rules	-1	0	-1	0	-1	5	1	3	0	0
Bracket	1	1	2	1	1	1	1	2	2	2
ALV	0	1	0	2	0	3	4	1	2	3
QC	0	1	0	2	0	3	1	2	3	1
TP	0	2	0	1	0	1	1	2	2	2

Fig. 7. Examples of improved chromosome coding

According to the improved strategy, the code for chromosome generation can be written as shown in Figure 8.

4.2. Objective function evaluation

The fitness can be used to evaluate the pros and cons of the equipment allocation and joint multi-equipment dispatching scheme. The greater the individual fitness value, the greater the probability that it will be selected. Because this paper is the minimum value of the objective function, the inverse value of the objective function is taken as the fitness function in the algorithm. The established fitness function is:

$$fit(y) = 1/f(y) \tag{22}$$

However, to calculate the fitness of a chromosome, we must first obtain the completion time of the operation corresponding to each chromosome, that is, the completion time of loading all the containers on the vessel, which needs to be achieved by chromosome decoding. Because chromosomes involve a variety of different equipment such as yards, brackets, ALVs, QCs, and their TPs, therefore according to the mathematical model established earlier, the constraints must be fully considered during decoding, so the decoding process can be obtained.

Procedure improved encoding scheme

Input: $I, Type, N, G, M, Q, Z$;
Output: the initial chromosomes Y
The size of each chromosome is set to $6 \cdot I$.
For each chromosome y
  For $i = 1$ to I
    Randomly generate a yard number from 1 to N to the container truck i.
  End
  Obtain the combination rule array $y(I+1{:}\,2I)$ based on $Type$ and the generated yard number array $y(1{:}\,I)$.
  For $i = 1$ to I
    If $y(I+i) \neq -1$
      Set $y(2I+i)$ by randomly generate a bracket number from 1 to G.
      If $y(I+i) > 0$
        Set $y\big(2I + y(I+i)\big) = y(2I+i)$.
      End
      Set $y(3I+i)$ by randomly generating an ALV number from 1 to M.
      Set $y(4I+i)$ by randomly generate a QC number from 1 to Q.
      Set $y(5I+i)$ by randomly generate a TP number from 1 to Z.
    End
  End
End

Fig. 8. Improved chromosome-generation code

4.3. Parent selection and genetic operators

After evaluating each chromosome with a fitness function, a mixed strategy of elite selection and roulette is used to select individuals in the population. In roulette selection, the probability of individuals being selected is determined according to the sum of individual and population fitness, which can be expressed by equation (23):

$$P_y = \frac{fit(y)}{\sum_1^Y fit(y)} \tag{22}$$

Individuals with high fitness values are more likely to be selected as parent individuals for overlapping mutation.

Elite selection is used to ensure that, when the GA is terminated, the result is that the most adaptive individuals appear in the past generations, and some of the most adaptive individuals in the current population are completely copied to the next generation's population.

After chromosome selection, genetic operations (C.-M. Lin & Gen, 2008), (Lee et al., 2012), (Frojan et al., 2015) are performed, including crossover and mutation operations. The crossover operation uses a two-point-crossover method, randomly selecting two different chromosomal individuals and swapping the two corresponding genes according to a certain crossover rate to achieve the purpose of genetic diversity. However, because the order of arrival of container trucks in this paper is determined externally, only different equipment numbers need to be set; and when the yard is allocated, changes in different yards allocated to various sizes of container will cause changes in the combination rules. Therefore, cross operations in this paper are only performed with three sub-chromosomes, namely, ALV number, QC number, and TP number allocation, as shown in Figure 9.

In addition, the GA also needs to perform mutation operations, that is, setting a mutation rate, randomly selecting an individual according to this mutation rate, and selecting a point or a section of the selected individuals to change the encoded value within the feasible range (i.e., mutation). Its main role is to ensure the diversity of the population in the algorithm and to avoid falling into a local optimal situation during the search for a feasible solution. This paper first performs mutation operation upon the sub-chromosomes of yard allocation. For any code in the sub-chromosomes, it is determined whether mutation is necessary by determining whether the randomly generated number is less than the mutation rate. However, after the yard allocation is changed, the combination rules will change accordingly, making it necessary to regenerate a combination-rule array. Then, the subsequent numbers of brackets, ALVs, QCs, and TPs need to be reallocated.

Parent1

ALV	0	1	0	2	0	3	4	1	2	3
QC	0	1	0	2	0	3	1	2	3	1
TP	0	2	0	1	0	1	1	2	2	2

Parent2

ALV	0	3	0	1	0	2	4	2	1	4
QC	0	2	0	2	0	1	1	1	3	3
TP	0	1	0	1	0	2	1	2	1	1

Offspring1

ALV	0	1	0	1	0	2	4	1	2	3
QC	0	1	0	2	0	1	1	2	3	1
TP	0	2	0	1	0	2	1	2	2	2

Offspring2

ALV	0	3	0	2	0	3	4	2	1	4
QC	0	2	0	2	0	3	1	1	3	3
TP	0	1	0	1	0	1	1	2	1	1

Fig. 9. The crossover operation

4.4. Stoppage rule

We use the maximum number of elapsed generations, which can be determined by experiments, as the GA's stoppage rule.

5. Computational experiments

Under the requirements of improving operational efficiency and reducing energy consumption, this paper considers different location of handshake areas and multi-size containers, and optimizes the equipment-dispatching scheme in the loading process. To verify the validity of the mathematical model and the GA proposed herein, we have performed numerical experiments.

All experiments are implemented in Matlab2016b and operated on a workstation with Intel Core TM i7–10710U@1.6-GHz processors and 16-GB RAM and a 64-bit operation system.

5.1. Parameters settings

The loading process of this paper involves the yards, YCs, ALVs and brackets, double-dolly QCs. The available quantity, operation, and energy consumption parameters (He et al., 2015b; Ai & Han, 2018) of the equipment are shown in Table 1. According to the standard QC allocation of general berths, the number of quay cranes is 3, and all can be used. The number of ALVs is variable, and different numbers such as 3-9 can be arranged. Moreover, the number of optional yards could be varied. In addition, assume that 40% of container trucks / containers are 20-ft containers. The weight coefficient α is set to 0.5, and the genetic-algorithm parameters are selected as follows: initial population 1000, selection operator 0.8, crossover operator 0.6, mutation operator 0.2, and generations 10.

Three scenarios with GA discussed in this article are: ① standard GA and no combination strategy, with any container size being operated by an ALV and a quay crane separately; ② improved GA and a combination strategy in which two 20-ft containers allocated to the same yard are paired up before being placed on the same bracket when operating the seaside YC, followed by the transportation of both containers by an ALV and their simultaneous loading onto the vessel by the QC; and ③ improved GA and a combination strategy in which 20-ft containers are paired-up to the same yard before allocation. Experiments are needed to compare different strategies.

According to the dispatching goals of the loading operation process, the experiments are designed as follows:

(1) Select a certain number of container trucks/containers I, and randomly generate the size-identifier array of containers loaded by external container trucks according to the 0-1 random allocation.
(2) Small sizes of containers were used for calculation with CPLEX and standard GA, and then compare the results and calculation time of two solutions.
(3) Given a handshake-area proportion and a container-size proportion, select a set of containers, yards and ALV configuration numbers, and draw solutions with the standard GA and improved GAs. Then, compare and discuss the completion time and energy consumption under three different scenarios.
(4) Change the weight coefficient α, and show the interaction between operation time and energy consumption.
(5) Change the number of yards and the location of handshake areas, and discuss the completion time and energy consumption in different cases.
(6) Change the proportion of 20-ft containers, and compare the differences in operating efficiency and energy consumption under the standard GA and improved GAs.

Table 1 Equipment parameters

Notation	Value	Notation	Value
Size	0,1 array	Z	2
v_y (m/ s)	1	t_{qi} (s)	60
v_f (m/s)	3	t_{hi} (s)	10
v_e (m/s)	6	W_{qc} (kwh/h)	150
N_Y	12	W_{yc} (kwh/h)	125
L_Y (m)	250	W_{aw} (kwh/h)	40
G	5	W_{af} (kwh/m)	0.0107
Q	3	W_{ae} (kwh/m)	0.008

5.2. Numerical experiments with small size instances

In order to validate the effectiveness of the model and GA algorithm proposed in this paper, some small sizes of instances are generated to compare the results of objective functions and computation time obtained by the standard GA and CPLEX.

As shown in Table 2, eight sets of data are set up to verify the effectiveness of the GA, in which the numbers of ALVs and yards go from 2 to 5. As can be seen from the table, the gap between the two methods is small (the maximum is 1.73%, the minimum is 0.08%). As the number of instances increases, the computation time of the GA is still within acceptable range, but the computation time of CPLEX increases exponentially (for the last set of data, the computation is out of memory if it is not limited in time, so it is obtained after setting up a limited time). Therefore, when the number of instances is large, CPLEX is difficult to obtain an exact solution in finite time, but the GA can make it.

As to the computing time, the computation time of CPLEX varies dramatically and grows exponentially as the instance size increases. In contrast, we can see that the computation time of GA is always very short in practice for small size instances.

Therefore, it is found that the proposed GA can obtain the optimal/near-optimal solutions of the joint equipment (QCs, ALVs and YCs) scheduling with reasonable computation times in the small size cases.

5.3. Numerical experiments with large size instances

With the increasing the number of instances, it is difficult for CPLEX to get the optimal solution within the limited time, so the GAs are adopted for solving large size problems by providing approximate solutions. With large size of instances, we perform the following experiments.

For the number of quay cranes and the maximum number of container yards have been determined, the sets of containers, allocated yards and ALVs are needed to be tested. Therefore, when the handshake area is in the center of yards, the proportion of 20-ft containers is 40%, and the coefficient α is 0.5, the experiment results are shown in Table 3 and Figure 10.

Table 3 shows the performances of three strategies with 30 different instances of equipment configuration. Figure 10 visualizes the data in Table 3. The horizontal axis in the figure shows the instance numbers, and the vertical axis is the completion time, energy consumption, and the weighted objective values.

For the three scenarios, the changes of completion time, energy consumption and weighted objective value brought by the changes of equipment number have the following characteristics.

For a constant number of allocated yards, as the number of ALVs increases, the completion time of the loading operation gradually decreases until it fluctuates within a very small range. In addition, as the number of ALVs increases, the energy consumption may first decrease, go down to a minimum and then go up. When the number of ALVs is fixed, the number of allocated yards becomes larger, reducing the completion time and increasing energy consumption. In general, more equipment allocated to each process is not necessarily better when energy consumption is considered. There is an optimal number of equipment configurations, which minimizes the operation time and the energy consumption. It indicates that more ALVs is not always better, and may lead to increased energy consumption.

Table 2. Results of small size instances

Number of containers	ALVs	Yards	standard GA		CPLEX		Gap (%)
			Weighted Objective Value	Time (s)	Weighted Objective Value	Time (s)	
10	2	2	867.1	5.67	863.5	0.83	0.42
10	3	3	719.8	7.13	719.2	269.7	0.08
10	4	4	587.6	10.3	586	581.2	0.27
10	5	5	513.1	9.44	506.4	2045.3	1.32
15	2	2	1342.8	6.23	1336.7	15.7	0.46
15	3	3	931.2	16.6	915.4	8022.1	1.73
20	2	2	1682.6	8.18	1677.6	1058.1	0.30
20	3	3	1273.5	9.61	1269.9	N/F	0.28

Gap = (Objective Value from the GA - Objective Value from CPLEX)*100/ Objective Value from CPLEX.

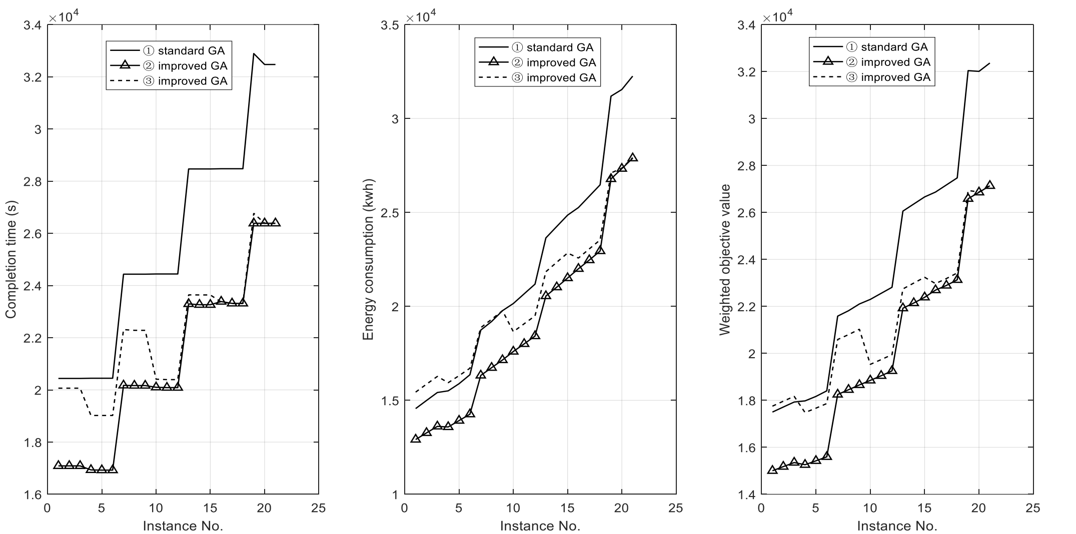

Fig. 10. Performances of different instances

Then, the results of three different scenarios are compared. As we can see, scenario ② and ③ with heuristic strategies show better operational efficiency, which may be due to the container-pairing behavior. From the perspective of decreasing energy consumption, the combination strategy in scenario ② are significantly better than other two scenarios. Although scenario ③ uses a combination strategy, in instances 1-9 the energy consumption is greater than if no strategy is used at all. It can be seen from the results that although the energy consumption of AGVs decreased, the energy consumption of YCs and QCs increased, so the overall energy consumption increased. The reason for this is that this kind of combination strategy causes some equipment to run longer.

Further analysis shows that the reduction in time and energy consumption mainly comes from ALVs and QCs. Without combination, multi-size containers are processed following the same steps, but the handing times for 20-ft containers can be halved after combination, leading to a reduction in both time and energy consumption. These theoretical studies on scheduling strategies have good practical significance for the energy consumption and cost control of automated terminals with multi-size containers.

From the above results, we found that scenario ② has obvious advantages, and also verifies the effectiveness of the GA with the combination strategy in chromosome generation to optimize the joint-dispatching scheme of handling equipment at automated terminals.

Table 3 Results of large size instances

No.	Containers	Yards	ALVs	① standard GA				② improved GA				③ improved GA			
				f_1 (s)	f_2 (kwh)	f	time (s)	f_1 (s)	f_2 (kwh)	f	time (s)	f_1 (s)	f_2 (kwh)	f	time (s)
1	500	8	4	20439	14561	17500	116.9	17088	12915	15001	111.8	20065	15438	17752	153.6
2	500	8	6	20439	14991	17715	116.6	17088	13267	15178	113.6	20065	15861	17963	117.2
3	500	8	8	20439	15417	17928	117	17088	13614	15351	112.1	20065	16273	18169	114.6
4	500	9	4	20447	15505	17976	121.1	16934	13582	15258	118.1	19019	15939	17479	117.9
5	500	9	6	20447	15886	18166	119.5	16926	13922	15424	118.2	19019	16314	17667	118.6
6	500	9	8	20447	16362	18404	119.9	16926	14262	15594	117.6	19019	16707	17863	123.1
7	600	9	4	24434	18737	21586	142.2	20174	16326	18250	138.5	22311	18869	20590	143.6
8	600	9	6	24434	19197	21816	143.6	20166	16736	18451	140.2	22283	19312	20798	143
9	600	9	8	24434	19772	22103	142.4	20166	17146	18656	139.3	22283	19773	21028	142.7
10	600	10	4	24442	20153	22297	149.2	20100	17598	18849	138.8	20410	18653	19531	143.7
11	600	10	6	24442	20670	22556	149.9	20087	18005	19046	139.6	20394	19075	19734	147
12	600	10	8	24442	21185	22814	145.9	20087	18421	19254	143.9	20394	19495	19945	146.8
13	700	10	4	28467	23645	26056	171.5	23295	20551	21923	164.8	23641	21845	22743	167.5
14	700	10	6	28467	24252	26359	170.2	23264	21023	22143	167.5	23639	22348	22993	172
15	700	10	8	28467	24856	26662	175	23264	21509	22387	165.5	23639	22841	23240	171.5
16	700	11	4	28475	25260	26868	179.4	23385	22003	22694	168.8	23368	22573	22970	175.7
17	700	11	6	28475	25866	27170	173.2	23316	22465	22890	170.7	23310	23060	23185	174
18	700	11	8	28475	26471	27473	174.5	23316	22949	23132	169.2	23310	23538	23424	173.9
19	800	12	4	32890	31189	32039	207.8	26385	26784	26584	195.1	26767	27101	26934	202.8
20	800	12	6	32470	31544	32007	205.2	26385	27332	26858	193	26385	27357	26871	202.5
21	800	12	8	32470	32256	32363	208.9	26385	27886	27135	192.9	26385	27918	27151	201.7

Note: f_1 indicates the completion time of the operation; f_2 indicates the energy consumption when the operation is completed; $f = \alpha f_1 + (1-\alpha) f_2, \alpha = 0.5$

Table 4 Comparisons with different weight coefficients

Containers	Yards	ALVs	$\alpha = 0$			$\alpha = 0.25$			$\alpha = 0.5$			$\alpha = 0.75$			$\alpha = 1$		
			f_1 (s)	f_2 (kwh)	f	f_1 (s)	f_2 (kwh)	f	f_1 (s)	f_2 (kwh)	f	f_1 (s)	f_2 (kwh)	f	f_1 (s)	f_2 (kwh)	f
300	6	8	13150	8683	8683	13150	8683	9799	13150	8683	10916	13150	8683	12033	13150	8683	13150
400	6	8	17345	11589	11589	17345	11589	13028	17345	11589	14467	17345	11589	15906	17345	11589	17345
500	9	8	16926	14262	14262	16926	14262	14928	16926	14262	15594	16926	14262	16260	16926	14262	16926
600	10	8	20087	18421	18421	20087	18421	18838	20087	18421	19254	20087	18421	19671	20087	18421	20087
700	11	8	23316	22949	22949	23316	22949	23041	23316	22949	23132	23316	22949	23224	23316	22949	23316
800	12	8	26385	27886	27886	26385	27886	27510	26385	27886	27135	26385	27886	26760	26385	27886	26385

Table 5 Comparisons with different locations of handshake area

β	0.1			0.3			0.5			0.7			0.9		
Yards	f_1 (s)	f_2 (kwh)	f	f_1 (s)	f_2 (kwh)	f	f_1 (s)	f_2 (kwh)	f	f_1 (s)	f_2 (kwh)	f	f_1 (s)	f_2 (kwh)	f
6	37866	18547	28206	29566	15433	22500	21516	13588	17552	29566	18316	23941	37866	23139	30502
8	28778	18079	23428	22578	15338	18958	17088	12915	15001	22338	17152	19745	28538	21612	25075
10	23121	18226	20674	18258	15732	16995	16935	14630	15782	18084	16505	17294	22944	20729	21836
12	19571	18733	19152	17183	16803	16993	16983	16665	16824	16857	16638	16748	19275	20093	19684
14	18185	19610	18898	17857	19009	18433	17726	18923	18325	17726	18912	18319	17802	19893	18848

5.4. Sensitivity analysis

5.4.1. The influence of different weights

In the previous experiments, we make two object functions with equal weights, but we also experiment with how the results change when the weights are different. As shown in Table 4, several sets of different container tasks and equipment configurations are selected, and the variation range of weight coefficient is set as α =[0,0.25,0.5,0.75,1]. The heuristic strategy in Scenario ② is selected to carry out initial chromosome generation, and then the results are shown in Table 4. It indicates that the values of completion time and energy consumption remained unchanged when the weights change, but the weighted fitness values change with the weights.

5.4.2. The influence of different handshake areas

For the storage yards with twin YCs, experiments were carried out in order to illustrate the influence of the location of handshake area. To simplify the experiments, it is assumed that the proportion of 20-ft containers is 40% and the weight coefficient α is 0.5. At the same time, the quantity of ALVs is 4 (which was also the optimal quantity configuration proved by the previous experiment), but the quantity of storage yards and the location of handshake area vary. The heuristic strategy in Scenario ② is selected for initial chromosome generation. The results are shown in Table 5 and Figure 11.

The following findings can be obtained from the results. When the number of yards is relatively small, the yard operation is the bottleneck in the whole loading process. At this time, the location of handshake area has a great impact on the operation efficiency and energy consumption, so it can be seen that the center of the yard is the optimal handshake location. When the number of yards is large, it will no longer be a bottleneck in the process. Therefore, the influence of the location of handshake area will be weakened, and the locations close to landside and seaside and the central location will get similar results. In a word, the location of handshake area is best set in the center of yards when the number of yards is small and the operation is a bottleneck; and many other locations can meet the requirements when the number of yards is large, then the location of handshake area can be diversified.

5.4.3. The influence of different container-size proportions

Comparison of three scenarios shows that the results of the proposed GA based on the combination rule have obvious advantages. In reality, the proportion of multi-size containers is not determined and may change. Therefore, this paper conducts further experiments to compare the results in objective values of the dispatching scheme calculated by the different strategies with different container proportions. In this case, the number of ALVs is 4, the number of allocated yards is 8, the weight coefficient α is 0.5 and the handshake area is in the center of yards. The results are shown in Table 6 and Figure 12.

Table 6 and Figure 12 show the comparisons with different container size proportions. For scenario ①, as the container size is randomly generated, the objective value stays the same. For scenario ②, when the proportion of 40-ft containers is reducing (namely, when the proportion is close to zero, it means more 20-ft containers can be combined), over time the weighted objective values gradually decrease, and the advantage becomes more significant. This also proves that the GA with the heuristic strategy in scenario ② is more suitable for optimizing scheduling in which more containers can be combined, and it has great advantages in situations requiring dispatching optimization with multi-size containers. For scenario ③, it can be seen from the figure that the objective value first decreases and then increases after reaching the minimum value. At some points, the results of this heuristic strategy are larger than those without heuristic strategies, so it is clear that this strategy is not suitable for this problem.

Therefore, the improved GA proposed in this paper is suitable for solving a type of terminal scheduling problems with multi-size containers. While heuristic strategies can improve the efficiency of algorithms, it is necessary to find the right strategy. At automated terminals, dispatchers should set up appropriate equipment configuration and strategies according to actual situations, and then carry out optimal scheduling solutions.

Table 6 Comparisons of different proportions of multi-size containers

40ft	20ft	Objective value								
		① standard GA			② improved GA			③ improved GA		
		f_1	f_2	f	f_1	f_2	f	f_1	f_2	f
0%	100%	20439	14561	17500	16156	12130	14143	31901	23177	27539
20%	80%	20439	14561	17500	16393	12417	14405	25749	19024	22386
40%	60%	20439	14561	17500	16427	12577	14502	22056	16524	19290
60%	40%	20439	14561	17500	16799	12856	14828	20646	15767	18206
80%	20%	20439	14561	17500	18689	13616	16152	18716	14407	16562

100%	0%	20439	14561	17500	20439	14561	17500	20439	14561	17500

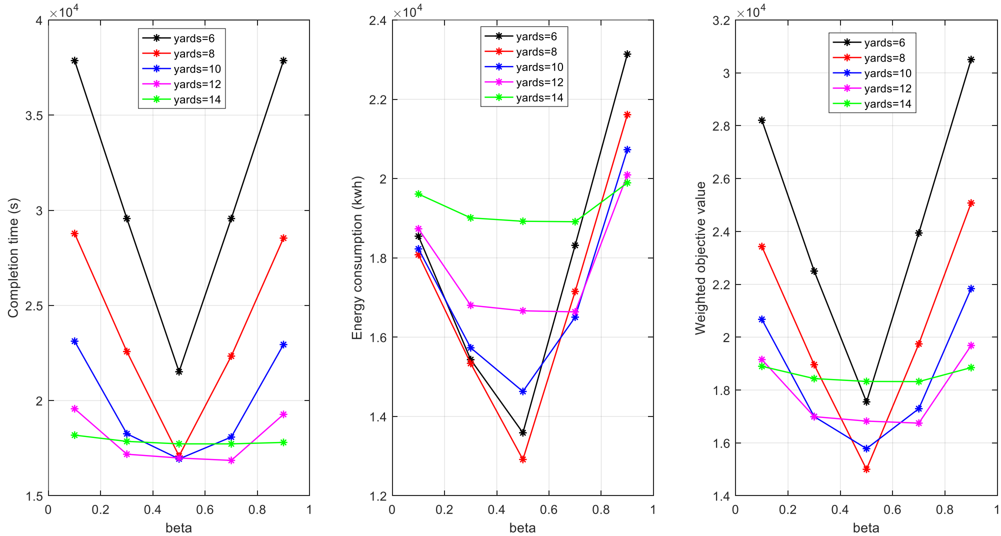

Fig. 11 Performances of different proportions of hanshake areas

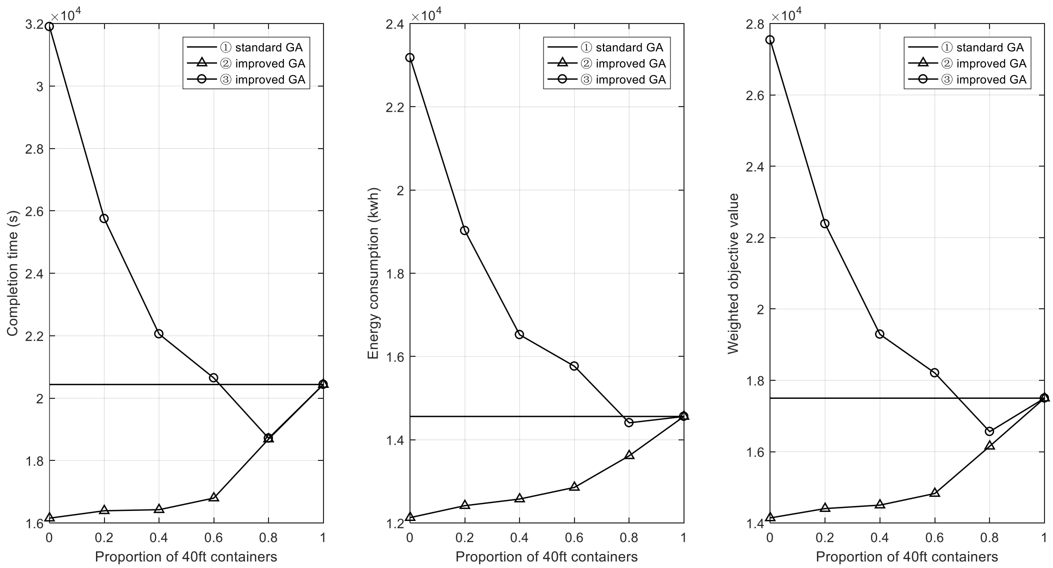

Fig. 2. Performances of different proportions of multi-size containers

6. Conclusions

This paper studies the integrated scheduling problem with multi-size containers in the loading process, establishes a mixed integer programming model to reduce the completion time and energy consumption, and proposes an improved GA with a heuristic chro-

mosome generation strategy. The combination strategies are proposed in the generation of chromosomes to improve the allocation of equipment. Then, we carry out several numerical experiments to verify the planning model and the improved GA. First, we compare the results under different scenarios with different equipment numbers, and find that the combination strategy adopted in this paper significantly reduces energy consumption and improves operational efficiency. We also find that there is an optimal number of equipment to be allocated. If few equipment is used, the operation time will be prolonged; if too many, the energy consumption will be increased. Second, we compare the influence of locations of handshake area with different yard quantities, and find that when the yard operation is the bottleneck, the handover location should be in the center, otherwise other locations might be feasible. Third, this paper compared the performance of the improved GA based on the combination strategy with different proportions of container sizes. It is found that when the proportion of 20-ft containers that can be combined is large, the method proposed in this paper has advantages over traditional methods, allowing it to effectively reduce energy consumption and improve operating efficiency.
Although the research in this paper addresses a gap in the literature, it has certain limitations. First, the research scenario in this paper is limited to the problem description and research assumptions in Section 3. Second, the number of quay cranes assigned to vessels is fixed. Third, we considered the diversity in container sizes. However, there are other uncertainties, such as the truck arrival time and the operation time of equipment. The above aspects are the directions of research that may be expanded in the future.

References

[1] Ai, L., Han, X., (2018). Coordinated scheduling of handling equipments at automated terminals considering energy consumption. *Journal of Shanghai Maritime University*, *39*(04), Article 04.

[2] Assadipour, G., Ke, G. Y., Verma, M., (2014). An analytical framework for integrated maritime terminal scheduling problems with time windows. *Expert Systems with Applications*, *41*(16), 7415–7424. DOI: 10.1016/j.eswa.2014.05.040.

[3] Blazewicz, J., Cheng, T. C. E., Machowiak, M., Oguz, C., (2011). Berth and quay crane allocation: A moldable task scheduling model. *Journal of the Operational Research Society*, *62*(7), 1189–1197. DOI: 10.1057/jors.2010.54.

[4] Chen, L., Langevin, A., Lu, Z., (2013). Integrated scheduling of crane handling and truck transportation in a maritime container terminal. *European Journal of Operational Research*, *225*(1), 142–152. DOI: 10.1016/j.ejor.2012.09.019.

[5] Du, Y., Chen, Q., Quan, X., Long, L., Fung, R. Y. K., (2011). Berth allocation considering fuel consumption and vessel emissions. *Transportation Research Part E: Logistics and Transportation Review*, *47*(6), 1021–1037. DOI: 10.1016/j.tre.2011.05.011.

[6] Dulebenets, M. A., Moses, R., Ozguven, E. E., Vanli, A., (2017). Minimizing Carbon Dioxide Emissions Due to Container Handling at Marine Container Terminals via Hybrid Evolutionary Algorithms. *IEEE Access*, *5*, 8131–8147. DOI: 10.1109/ACCESS.2017.2693030.

[7] Elaziz, M. A., Li, L., Jayasena, K. P. N., Xiong, S., (2019). Multiobjective big data optimization based on a hybrid salp swarm algorithm and differential evolution. *Applied Mathematical Modelling*. DOI: 10.1016/j.apm.2019.10.069.

[8] Elwany, M. H., Ali, I., Abouelseoud, Y., (2013). A heuristics-based solution to the continuous berth allocation and crane assignment problem. *Alexandria Engineering Journal*, *52*(4), 671–677. DOI: 10.1016/j.aej.2013.09.001.

[9] Frojan, P., Correcher, J. F., Alvarez-Valdes, R., Koulouris, G., Tamarit, J. M., (2015). The continuous Berth Allocation Problem in a container terminal with multiple quays. *Expert Systems with Applications*, *42*(21), 7356–7366. DOI: 10.1016/j.eswa.2015.05.018.

[10] Gharehgozli, A. H., Vernooij, F. G., Zaerpour, N., (2017). A simulation study of the performance of twin automated stacking cranes at a seaport container terminal. *European Journal of Operational Research*, *261*(1), Article 1. DOI: 10.1016/j.ejor.2017.01.037.

[11] Golias, M., Portal, I., Konur, D., Kaisar, E., Kolomvos, G., (2014). Robust berth scheduling at marine container terminals via hierarchical

optimization. *Computers Operations Research*, *41*, 412–422. DOI: 10.1016/j.cor.2013.07.018.
[12] Han, X., Wang, Q., Huang, J., (2019). Scheduling cooperative twin automated stacking cranes in automated container terminals. *Computers Industrial Engineering*, *128*, 553–558. DOI: 10.1016/j.cie.2018.12.039.
[13] He, J., Huang, Y., Yan, W., Wang, S., (2015a). Integrated internal truck, yard crane and quay crane scheduling in a container terminal considering energy consumption. *Expert Systems with Applications*, *42*(5), 2464–2487. DOI: 10.1016/j.eswa.2014.11.016.
[14] He, J., Huang, Y., Yan, W., Wang, S., (2015b). Integrated internal truck, yard crane and quay crane scheduling in a container terminal considering energy consumption. *Expert Systems with Applications*, *42*(5), Article 5. DOI: 10.1016/j.eswa.2014.11.016.
[15] Homayouni, S. M., Tang, S. H., Motlagh, O., (2014). A genetic algorithm for optimization of integrated scheduling of cranes, vehicles, and storage platforms at automated container terminals. *Journal of Computational and Applied Mathematics*, *270*, 545–556. DOI: 10.1016/j.cam.2013.11.021.
[16] Hu, H., Chen, X., Wang, T., Zhang, Y., (2019). A three-stage decomposition method for the joint vehicle dispatching and storage allocation problem in automated container terminals. *Computers Industrial Engineering*, *129*, 90–101. DOI: 10.1016/j.cie.2019.01.023.
[17] Hu, Q.-M., Hu, Z.-H., Du, Y., (2014). Berth and quay-crane allocation problem considering fuel consumption and emissions from vessels. *Computers Industrial Engineering*, *70*, 1–10. DOI: 10.1016/j.cie.2014.01.003.
[18] Jachimowski, R., (2017). Review of horizontal transport decision problems in the marine intermodal terminal. *Archives of Transport*, *44*(4), 35–45. DOI: 10.5604/01.3001.0010.6160.
[19] Ku, W.-Y., Beck, J. C., (2016). Mixed Integer Programming models for job shop scheduling: A computational analysis. *Computers Operations Research*, *73*, 165–173. DOI: 10.1016/j.cor.2016.04.006.
[20] Lee, K., Kim, B. S., Joo, C. M., (2012). Genetic algorithms for door-assigning and sequencing of trucks at distribution centers for the improvement of operational performance. *Expert Systems with Applications*, *39*(17), 12975–12983. DOI: 10.1016/j.eswa.2012.05.057.
[21] Lin, C.-M., Gen, M., (2008). Multi-criteria human resource allocation for solving multistage combinatorial optimization problems using multiobjective hybrid genetic algorithm. *Expert Systems with Applications*, *34*(4), 2480–2490. DOI: 10.1016/j.eswa.2007.04.016.
[22] Lin, J., Zhu, L., Gao, K., (2020). A genetic programming hyper-heuristic approach for the multi-skill resource constrained project scheduling problem. *Expert Systems with Applications*, *140*, 112915. DOI: 10.1016/j.eswa.2019.112915.
[23] Lu, Y., Le, M., (2014). The integrated optimization of container terminal scheduling with uncertain factors. *Computers Industrial Engineering*, *75*, 209–216. DOI: 10.1016/j.cie.2014.06.018.
[24] Qiu, J., Ren, W., Tang, M., Ma, P., Zhang, Y., (2022). Determination of Truck Maintenance Allocation Scheme Based on SA-GA. *Archives of Transport*, *62*(2), 59–71. DOI: 10.5604/01.3001.0015.9177.
[25] Raa, B., Dullaert, W., Schaeren, R. V., (2011). An enriched model for the integrated berth allocation and quay crane assignment problem. *Expert Systems with Applications*, *38*(11), 14136–14147. DOI: 10.1016/j.eswa.2011.04.224.
[26] Salido, M. A., Rodriguez-Molins, M., Barber, F., (2012). A decision support system for managing combinatorial problems in container terminals. *Knowledge-Based Systems*, *29*, 63–74. DOI: 10.1016/j.knosys.2011.06.021.
[27] Steenken, D., Voß, S., Stahlbock, R., (2004). Container terminal operation and operations research—A classification and literature review. *OR Spectrum*, *26*(1), Article 1. DOI: 10.1007/s00291-003-0157-z.
[28] Tan, C., Yan, W., Yue, J., (2021). Quay crane scheduling in automated container terminal for the trade-off between operation efficiency and energy consumption. *Advanced Engineering Informatics*, *48*, 101285. DOI: 10.1016/j.aei.2021.101285.
[29] Tang, L., Zhao, J., Liu, J., (2014). Modeling and solution of the joint quay crane and truck

scheduling problem. *European Journal of Operational Research*, *236*(3), 978–990. DOI: 10.1016/j.ejor.2013.08.050.

[30] Yang, Y., Zhong, M., Dessouky, Y., Postolache, O., (2018). An integrated scheduling method for AGV routing in automated container terminals. *Computers Industrial Engineering*, *126*, 482–493. DOI: 10.1016/j.cie.2018.10.007.

[31] Zhen, L., Lee, L. H., Chew, E. P., (2011). A decision model for berth allocation under uncertainty. *European Journal of Operational Research*, *212*(1), 54–68. DOI: 10.1016/j.ejor.2011.01.021.