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Research Article

Integrated Optimization of Mixed Cargo Packing and Cargo Location Assignment in Automated Storage and Retrieval Systems

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To improve the delivery efficiency of automated storage and retrieval system, the problem of the integrated optimization of mixed cargo packing and cargo location assignment is addressed. An integrated optimization model of mixed cargo packing and location assignments with the shortest time for the stacker in a certain historical period is established and is transformed into a conditional packing problem. An improved hybrid genetic algorithm based on a group coding method is designed to solve the problem. When the initial population is generated, a new heuristic algorithm is designed to improve the convergence speed of the genetic algorithm considering the correlation and frequency of the goods outbound. A heuristic algorithm for a two-dimensional rectangular-packing problem is designed to determine whether a variety of goods can be mixed in packing. Taking actual data from an automated storage and retrieval system for an aviation food company as an example, the established model and design algorithm are verified and the influence of changes in the outbound delivery orders on the optimization result is analyzed. The results show that compared to the method of separate storage of goods based on cube-per-order index rules and a phased optimization method of mixed storage of goods, an integrated optimization method of mixed cargo packing and location assignment can improve the outbound delivery efficiency of the stacking machine by 11.43–25.98% and 1.73–5.51%, respectively, and reduce the cargo location used by 50–55% and 0–10%, respectively. The stronger the correlation of the goods leaving a warehouse, the greater the potential of the design method in this paper to improve the efficiency of the stacker.

1. Introduction

In recent years, with the rapid development of e-commerce, intelligent manufacturing, air transportation, and other fields, higher requirements have been proposed for the input–output efficiencies of warehouses and logistics. Automated storage and retrieval systems (AS/RSs) are widely used in various industries for storage. Cargo packing and storage location assignments are essential links in the operation of an AS/RS. When a container stores only one type of goods (known as "separate cargo packing"), the cargo packing is optimized mainly to increase the loading rate of the container and reduce the number of used containers, without much impact on the outbound efficiency of AS/RS. In practical applications, an outbound delivery order often contains a variety of goods. If goods that are often in the same outbound delivery order are mixed and stored in the same container, it can greatly improve the outbound efficiency of the AS/RS. In logistics storage, the probability that two different items are required by the same order is defined as the outbound correlation. Separate cargo packing and cargo location assignment are not strong and can be optimized separately. Mixed packing and cargo location assignment are strongly correlated, which has a great impact on the efficiency of AS/RS. Therefore, the integrated optimization of mixed cargo packing and cargo location assignment must be studied.

The bin-packing problem (BPP) is an overall layout scheme for optimizing the loading of small items into large

Table 1: Sample outbound goods delivery data.

Period	Outbound goods delivery times					
	1	2	3	1 and 2 in the same order	1 and 3 in the same order	2 and 3 in the same order
1	80	60	20	5	10	0
2	100	95	10	8	10	0

containers. BPP achieves certain optimization goals under certain constraints. In 1831, Gauss first raised the issue of packing problems, which he called layout problems [1]. The BPP can be divided into one-dimensional, two-dimensional, and three-dimensional cases based on the dimensions of the loaded goods and containers. In AS/RS, to facilitate access, when the goods are mixed and packed, they cannot be stacked. Therefore, whether a variety of goods can be mixed and loaded into the feed bin depends on whether the bottom surface of multiple goods can be loaded into the bottom of the feed bin, which is a two-dimensional packing problem. The two-dimensional packing problem, as a typical combinatorial optimization problem, has inspired many studies, which have focused on mathematical models or algorithms. Cui [2] proposed a branch and bound algorithm to solve the identical item-packing problem. Polyakovskiy et al. [3] proposed a guided search of the delivery date for the two-dimensional packing problem with hybrid feasibility constraints. Lodi et al. [4] proposed a partial-enumeration algorithm for the two-dimensional packing problem with truncation constraints. He et al. [5] used the tree-search method to iterate and optimize the algorithm results and proposed the best-of-fit algorithm for solving the two-dimensional packing problem. Wei et al. [6] proposed the least-wasted-first algorithm to solve rectangular-packing problem. Shang et al. [7] proposed a heuristic optimal residual-space algorithm based on the idea of making the placement of small rectangles tighter and the remaining space smoother; the three stages were space division, placement-position selection, and optimal solution searching. Thomas and Chaudhari [7] proposed a hyper-heuristic algorithm based on a genetic algorithm to solve the two-dimensional packing problem. In the existing research on two-dimensional packing problems, the vast majority of optimization targets are minimizing the quantity of bins used and the main optimization goal of maxed cargo packing in AS/RS is to achieve the highest outbound efficiency. Gao [8] used a clustering method to store a variety of drug combinations in one bin. The shuttle could select a variety of drugs from one bin, thereby improving picking efficiency. Gao only studied the mixed packing problem of drug varieties but did not consider the limitation of the quantity of drugs in stock.

The optimization problem of cargo location assignment for AS/RS has received a significant amount of attention, and many scholars have conducted optimization studies on cargo location assignment primarily from the viewpoints of cargo turnover efficiency, correlation of outbound cargo deliveries, shelf stability, multi-carrier AS/RS, multiport AS/RS, and dynamic cargo location assignment. Heskett [9] proposed the cube-per-order index (COI) rule. COI refers to the required cargo location storage space divided by the frequency of outbound deliveries of a cargo in unit time. The greater the COI of a good, the closer the good should be stored to the exit. Lee et al. [10] assumed that an order generally contains more than two types of goods and that these goods were generally stored in different locations. They designed a new heuristic method that is superior to the COI rule. Sadiq et al. [11] studied the dynamic assignment rule of cargo locations in warehouses and proposed a heuristic algorithm for the reassignment of the cargo location based on material categories, therefore reducing the reassignment time of the cargo location and the picking time of outbound goods deliveries. Song et al. [12] studied multiport access-type AS/RS and conducted comprehensive analyses and studies of cargo location assignments and instruction sequence ordering. Yang et al. [13] explored the integrated optimization problem of location assignment and sequencing in multishuttle automated storage/retrieval systems under the modified 2n-command-cycle pattern. The storage and retrieval (S/R) location assignment and S/R-request-sequencing decisions are jointly considered. An integer quadratic-programming model is formulated to describe this integrated optimization problem. Recently, the main research trend for AS/RS is integrated optimization of the cargo location assignment and instruction sequence. However, there has been no research on the integrated optimization of mixed cargo packing and cargo location assignment.

In AS/RS, cargo packing and cargo location assignment are two interrelated work phases. Therefore, the optimization of the two phases must be integrated to improve the warehouse-outbound efficiency. In this study, the relation between the two phases is considered and the constraint upon the size and quantity of the bottom surface of each cargo is considered during mixed cargo packing. Based on data for outbound delivery orders in a certain historical period, an integrated optimization model of mixed cargo packing and cargo location assignment with the goal of minimizing the outbound delivery time of stackers is established. In addition, a hybrid genetic algorithm is designed to solve the model and the validities of the model and algorithm are verified using the example data.

2. Problem Description

The simple example below illustrates the integrated optimization of mixed cargo packing and location assignment.

The AS/RS studied herein is assumed to be a type of roadway stacked. The stacker has only one vehicle, and each location can only store one cargo container.

Assuming that there are goods of Types 1, 2, and 3, the outbound goods data in a certain period is shown in Table 1.

Table 2: Comparison of times for outbound cargo delivery under different storage strategies.

Strategy	Storage location			Outbound delivery times of the stacker		Time for outbound delivery (s)		
	1	2	3	Period 1	Period 2	Period 1	Period 2	total
1	A	B	C	160	205	13300	16975	30275
2	A	B	A	150	195	12300	16075	28375
3	A	A	B	155	197	12500	15810	28310

The outbound operations are sorted out of the warehouse in small batches, the replenishment is timely, and there is no shortage of goods. Any two of the three types of goods can be mixed into one container; however, all three types of goods cannot be simultaneously loaded into one container. The stacker only performs the outbound job. The standby position of the stacker is at the entrance. The time that stacker performs one outbound operation consists of the running time from the entrance to the pick-up position, the pick-up time, the running time from the pick-up position to the entrance, and the delivery time.

Suppose that there are three cargo locations, i.e., A, B, and C, and the stacking machine achieves outbound delivery for these cargo locations in 80 s, 85 s, and 90 s, respectively. Three types of cargo packing and location assignment strategies are as follows. (1) The goods are packed separately, and those with high outbound delivery frequency are located near the warehouse exit. (2) The goods are mixed. Cargo packing and location assignment are optimized separately. Goods with high delivery correlation are stored together, and those with high delivery frequency are located near the warehouse exit. (3) The goods are mixed and integrated optimization of cargo packing and location assignment are performed to minimize the total operating time of two time periods. Under these different storage strategies, the outbound cargo delivery times are shown in Table 2.

Table 2 shows that, under strategy 1 in Period 1, the number of outbound operations of the stacker is given by the outbound-goods-1 delivery times + the outbound-goods-2 delivery times + the outbound-goods-3 delivery times, namely $80 + 60 + 20 = 160$ (times). The time of delivery is the outbound-goods-1 delivery times × the outbound delivery time to location A + the outbound-goods-2 delivery times × the outbound delivery time to the location B + the outbound-goods-3 delivery times × the outbound delivery time to the location C, which is $80 \times 80 + 60 \times 85 + 20 \times 90 = 13300$ (s). The data for Period 2 can be similarly obtained.

Under Strategy 2, since goods 1 and 3 are simultaneously stored at Location A, the number of outbound operations of the stacker in Period 1 is the outbound-goods-1 delivery times + the outbound-goods-2 delivery times+ the outbound-goods-3 delivery times - the number of times that goods 1 and 3 are shipped out at the same time, namely, $80 + 60 + 20 - 10 = 150$ (times). The time of delivery is the outbound-goods-1 delivery times × the outbound delivery time to the location A + the outbound-goods-2 delivery times × the outbound delivery time to the location B + the outbound-goods-3 delivery times × the outbound delivery time to the location A - the number of times that goods 1 and 3 are shipped out at the same time × the outbound delivery time to the location A, namely:

$80 \times 80 + 60 \times 85 + 20 \times 90 - 10 \times 80 = 12300$ (s). The data for Period 2 can be similarly obtained.

Under Strategy 3, the numbers of outbound operations of the stacker and the working time are obtained by referring to the calculation method under Strategy 2.

Analyzing Table 2, in Periods 1 and 2, the stacker operates for the longest time under Strategy 1. In Period 1, the stacker operates for the shortest time under Strategy 2, while in Period 2 the stacker operates for the shortest time under Strategy 3. Under Strategy 3, the total working time of the two periods is the shortest.

The above example indicates that mixed packing can significantly shorten the stacker's working time for outbound deliveries. Therefore, a phased optimization of the mixed cargo packing and location assignment does not necessarily lead to an optimal storage solution and an integrated optimization of the mixed cargo packing and location assignment matters.

3. Assumptions and Modeling

3.1. Assumptions. To simplify the model, the following reasonable assumptions for the system were put forward:

(1) The AS/RS consists of multiple lanes, each of which is relatively independent with separate stackers and inbound and outbound accesses;

(2) Each cargo location can store a variety of goods;

(3) The smallest packaging unit for each cargo inventory is a rectangular parallelepiped;

(4) When the cargo is packed, the bottom surface of the cargo is orthogonal to the bottom surface of the container and the height direction of the cargo is consistent with that of the container;

(5) When the goods are mixed and packed, the same types of goods are stored in a centralized manner;

(6) The bottom of the container is considered to be a two-dimensional coordinate system, with the long side as the x-axis and the wide side as the y-axis;

(7) The number of each variety of goods during each inbound delivery is less than the maximum storage capacity of this variety of goods in one location;

(8) Goods are replenished in a timely manner, with no shortage of goods at the time of outbound delivery;

(9) The specification of each cargo location is the same;

(10) The entrance and exit for the cargo delivery are on the first floor of the 0th column of the lane; and

(11) The correlation and frequency of outbound cargo delivery are relatively uniform over a certain period.

3.2. Definitions of Symbols. The symbols in the model are defined as follows.

n refers to the number of varieties of goods in the warehouse.

m refers to the number of vacant locations for cargo warehousing. Even if $m \leq n$, goods for inbound delivery can be stored in the warehouse.

p refers to the number of outbound delivery orders during a certain period in a record.

N_i refers to the maximum stock quantity of the smallest package unit in stock of the cargo $i(i = 1, 2, ..., n)$.

V_i refers to the volume of the smallest package unit in stock of the cargo $i(i = 1, 2, ..., n)$.

W_i refers to the weight of the smallest package unit in stock of the cargo $i(i = 1, 2, ..., n)$.

l_i refers to the length of the smallest package unit in stock of the cargo $i(i = 1, 2, ..., n)$.

w_i refers to the width of the smallest package unit in stock of the cargo $i(i = 1, 2, ..., n)$.

h_i refers to the height of the smallest package unit in stock of the cargo $i(i = 1, 2, ..., n)$.

L refers to the length of container.

W^B refers to the width of container.

H refers to the height of container.

N_i^B refers to the quantity stored at the bottom of the container of the smallest package unit of the cargo $i(i = 1, 2, ..., n)$, $N_i^B = \lceil N_i / \lfloor H/h_i \rfloor \rceil$.

x_{qj1} refers to the x-axis coordinate of the lower left corner of cargo $q(q = 1, 2, ..., N_i^B)$ in the position $j(j = 1, 2, ..., m)$.

y_{qj1} refers to the y-axis coordinate of the lower left corner of cargo $q(q = 1, 2, ..., N_i^B)$ in the position $j(j = 1, 2, ..., m)$.

x_{qj2} refers to the x-axis coordinate of the upper right corner of cargo $q(q = 1, 2, ..., N_i^B)$ in the position $j(j = 1, 2, ..., m)$.

y_{qj2} refers to the x-axis coordinate of the upper right corner of cargo $q(q = 1, 2, ..., N_i^B)$ in the position $j(j = 1, 2, ..., m)$.

$V_{\max}$ refers to the maximum storage volume for a single location.

$W_{\max}$ refers to the maximum storage weight for a single location.

t_j refers to the total working time of the stacker to collect (or unload) goods once at a location $j(j = 1, 2, ..., m)$.

t_{Hj} refers to the horizontal working time of the stacker at a location $j(j = 1, 2, ..., m)$.

t_{Vj} refers to the vertical running time of the stacker at a location $j(j = 1, 2, ..., m)$.

t_F refers to the total time taken by the stacker fork to collect (or unload) the goods.

T_k refers to the operating time of the stacker for the k$^{\text{th}}$ outbound delivery order, with $k(k = 1, 2, ..., p)$.

T refers to the total working time of the stacker for all p outbound delivery orders at a certain time in the record.

u_{ik} refers to the state variable. $u_{ik} = 1$ indicates that the cargo $i(i = 1, 2, ..., n)$ is listed on the outbound delivery order $k(k = 1, 2, ..., p)$, while $u_{ik} = 0$ indicates that the cargo $i(i = 1, 2, ..., n)$ is not listed on the outbound delivery order $k(k = 1, 2, ..., p)$.

z_{ij} is the decision variable. $z_{ij} = 1$ indicates that the cargo $i(i = 1, 2, ..., n)$ is stored at the location $j(j = 1, 2, ..., m)$, while $z_{ij} = 0$ indicates that the cargo i is not stored at the location j. If $\sum_{i=1}^{n} z_{ij} > 1$, a variety of goods are mixed into container in the location j.

3.3. Modeling. The optimization goal of the system is to reduce the total working time of the stacker for all p outbound delivery orders in a certain period to the shortest possible time by optimizing the mixed cargo packing and the cargo location assignment schemes. When the time taken by the stacker for each outbound delivery order is calculated, the working time is calculated only once if the order involves goods at the same location. The working time T_k of the stacker for the order $k(k = 1, 2, \cdots, p)$ is

$$T_k = \sum_{j=1}^{m} \left\lceil \frac{\sum_{i=1}^{n} u_{ik} z_{ij}}{n} \right\rceil \cdot t_j. \tag{1}$$

In (1), if there are multiple goods in order k stored in the location j, then $\sum_{i=1}^{n} u_{ik} z_{ij} > 1$, $\lceil \sum_{i=1}^{n} u_{ik} z_{ij} / n \rceil = 1$. The total working time t_j of the stacker for a one-time goods collection (or unloading) at the location $j(j = 1, 2, \cdots, m)$ is

$$t_j = 2t_F + 2 \max \left\{ t_{Hj}, t_{Vj} \right\}. \tag{2}$$

The total working time of the stacker for all p outbound delivery orders is

$$T = \sum_{k=1}^{p} T_k. \tag{3}$$

Equations (1), (2), and (3) are combined to obtain the system optimization objective function as follows:

$$\begin{aligned} \min T = \sum_{k=1}^{p} \Bigg(\sum_{j=1}^{m} \left\lceil \frac{\sum_{i=1}^{n} u_{ik} z_{ij}}{n} \right\rceil \\ \times \left(2t_F + 2 \max \left\{ t_{Hj}, t_{Vj} \right\} \right) \Bigg). \end{aligned} \tag{4}$$

The constraint conditions are

$$\sum_{j=1}^{m} z_{ij} = 1, \quad \forall i \tag{5}$$

$$\sum_{i=1}^{n} u_{ik} \geq 1, \quad \forall k \tag{6}$$

$$\sum_{i=1}^{n} N_i V_i z_{ij} \leq V_{\max}, \quad \forall j \tag{7}$$

$$\sum_{i=1}^{n} N_i W_i z_{ij} \leq W_{\max}, \quad \forall j \tag{8}$$

$$\sum_{i=1}^{n} l_i \times w_i \times N_i^B \times z_{ij} \le L \times W \tag{9}$$

$$\begin{aligned} &0 \le x_{qj1} < L, \\ &0 \le y_{qj1} < W, \\ &0 < x_{qj2} \le L, \\ &0 < y_{qj2} \le W, \\ &\forall q,\ \forall j \end{aligned} \tag{10}$$

Equation (5) indicates that one type of cargo is stored at only one cargo location. Equation (6) demonstrates that an outbound delivery order contains one or more types of goods. Equation (7) shows that the total volume of all goods stored at a cargo location $j(j = 1, 2, \cdots, m)$ cannot be larger than the maximum storage volume of that location. Equation (8) indicates that the total weight of all goods stored at a cargo location $j(j = 1, 2, \cdots, m)$ cannot be heavier than the maximum storage weight for that cargo location. Equation (9) indicates that the sum of the bottom area of all the goods stored in the location $j(j = 1, 2, \cdots, m)$ is smaller than the bottom area of the container. Equation (10) indicates that the bottom of all goods stored in the location $j(j = 1, 2, \cdots, m)$ is within the container.

4. Algorithms to Solve the Model

Currently, the algorithms most commonly used to solve the BPP are heuristic algorithms and genetic algorithms [2–8, 14]. A heuristic algorithm can only obtain an approximate solution of the problem, while a genetic algorithm has a strong global search ability and can obtain a better solution. When a genetic algorithm is used to solve the packing problem, its coding can be expressed via three methods: (1) an expression based on the bin, (2) an expression based on the item, and (3) an expression based on the population [15]. Falkenauer [16] proposed a population-based expression of the packing problem that consists of two parts. Part 1 is the encoding of the bin, and Part 2 indicates which item is stored in which bin. Zhang et al. [17] used the population-based expression method to encode and design a hybrid genetic algorithm to improve the solution of the packing problem. Even though a genetic algorithm has a strong global search ability and can obtain a better solution, its main problem currently is that its convergence speed to the global optimal solution is slow and its timeliness is poor. To solve the packing problem using a genetic algorithm, Zhang et al. [18] designed an improved genetic algorithm to generate the initial population by adding a descending optimal adaptation algorithm. Using this optimal individual preservation strategy, the evaluation criterion of the adaptation is converted, which improves the solving speed of the genetic algorithm and the probability of finding the optimal solution.

This paper focuses on the problem of the integrated optimization of mixed cargo packing and cargo location assignment; accordingly, a hybrid genetic algorithm based on population expression coding and an embedded heuristic algorithm is designed to solve the optimization model established in the previous section.

4.1. Similarity Coefficient Calculation. When generating the initial population, the two strongly correlated cargoes that satisfy the weight, volume, bottom area, and bottom-surface-assembly constraints are first loaded into the same container to improve the convergence speed of the algorithm. The correlation between the two goods is measured using the similarity factor. A previous study [8] presented a detailed analysis of the calculation of the similarity coefficient. In this study, the Rogers–Tanimoto similarity coefficient [8] is used to measure the correlation between the two goods. This coefficient is calculated as shown in

$$RTSC_{ii'} = \frac{a+d}{a+2(b+c)+d} \tag{11}$$

i, i' refers to two different goods for which the similarity coefficients need to be calculated;

a refers to the number of orders for goods i and i' at the same time.

b refers to the number of orders for only goods i.

c refers to the number of orders for only goods i'.

d refers to the number of orders for neither goods i nor i'.

4.2. Design of the Bottom-Surface-Assembly Algorithm. Equations (7), (8), and (10) can be used to determine whether the weight, volume, and bottom area constraints are satisfied when judging the multiple goods-mixed packing. The bottom-assembly constraint needs to be analyzed and calculated according to the two-dimensional rectangular-packing problem, which is described as follows. Let $A = \{a_r \mid r = 1, 2, \ldots, R)$ be a set of small rectangles of different specifications, where N_r is the number of each small rectangle, l_r is the length, and w_r is the width. We determine whether all small rectangles in A can be loaded into a large rectangle b of length L and width W. All similar small rectangles must be placed in a concentrated manner. If the area occupied by the same type of small rectangles is not rectangular, then fill it with blanks to form a new rectangle c_r of length l_r^C and width w_r^C, with $l_r^c \le L, w_r^c \le W$. Let $C = (c_r \mid r = 1, 2, \ldots, R)$ to avoid inconvenient picking caused by the mixing of different goods. All small rectangles are placed orthogonally, and the same types of small rectangles are placed in the same direction. According to the characteristics of mixed cargo packing in AS/RS in combination with the best-residual-space algorithm (BRSA) [14], a bottom-surface-assembly algorithm (BSAA) is designed herein. The algorithm is described as follows.

Step 1. N_r small rectangles of the same size a_r are spliced into a new rectangle c_r of length l_r^C and width w_r^C. The insufficient portion is filled with blanks. Splicing along W direction of b according to priority, there are two splicing methods in Figures 1(a) and 1(b). In Figure 1(a), $l_r^C = \lfloor W/w_r \rfloor \times w_r$ and

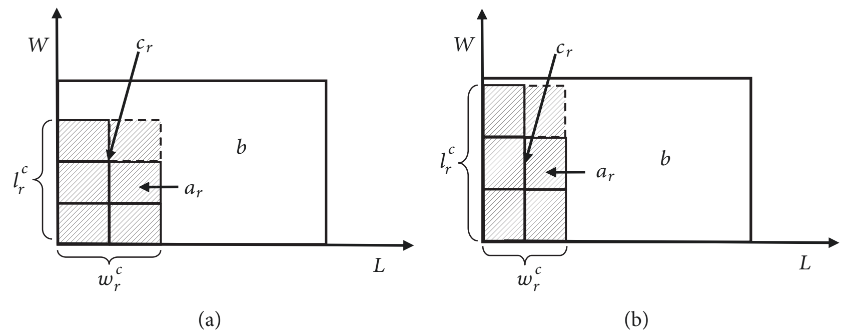


Figure 1: Same-sized rectangle-assembly diagram.

$w_r^C = \lceil N_i^B / \lfloor W/w_r \rfloor \rceil \times l_r$. In Figure 1(b), $l_r^C = \lfloor W/l_r \rfloor \times l_r$ and $w_r^C = \lceil N_i^B / \lfloor W/l_r \rfloor \rceil \times w_r$. Choose l_r^C for the larger scheme to reduce waste in the W direction. $C = \{c_r \mid r = 1, 2, \ldots, R\}$ is the set of the new rectangles c_r.

Step 2. According to the optimal residual-space algorithm [14], all small rectangles in the set C can presumably be loaded into a large rectangle b, and the judgment result is output.

4.3. Hybrid Genetic Algorithm Design

4.3.1. Chromosome Coding Design. The chromosome structure based on the population coding method is as follows: the position of the gene represents the location, and the value of the gene represents all the items stored at the location. The length of the chromosome is the number of positions available in the warehouse. Assuming there are 10 goods to be put into storage, the possible chromosomes are, for example, {(1, 2, 3), (4, 5), (6, 7, 8), (9, 10)} and {(1, 3, 6), (2, 4, 5), (7, 8, 9, 10)}. The latter chromosome indicates that goods Nos. 1, 3, and 6 are stored in the first location and goods Nos. 2, 4, and 5 are stored in the second location and goods Nos. 7, 8, 9, and 10 are stored in the third location. This coded representation allows the gene to represent both the goods and the location. The principle of this representation is that, in the packing problem, the genetic operator only operates on the population part of the chromosome and the item part only indicates which goods compose a group.

4.3.2. Initial Population Generation. Of the heuristic algorithms used to solve the BPP, the first-fit decreasing (FFD) algorithm and the best-fit decreasing (BFD) algorithm are two excellent off-line algorithms. To enhance the search ability of the genetic algorithm and to try to find the solution closest to the optimal solution of the packing problem, the FFD or BFD algorithm can be used to generate the dominant individuals [18] when initializing the population.

When initializing the population, this paper draws on the FFD and BFD algorithms and designs the following heuristic algorithm.

Step 1. Establish a collection ITEM of goods to be inbound and sorted according to the COI rule.

Step 2. Establish a collection LOCATION of cargo locations to be assigned and sorted according to the distance to the exit from near to far.

Step 3. Establish a collection CITEM of cargo locations that are already assigned, select the goods i with the minimum COI in the collection ITEM, assign the cargo location j nearest to the exit in the collection LOCATION, store the goods i that have already been assigned to cargo location j in the collection CITEM, and delete the goods i and the cargo locations j that have already been assigned from the collections ITEM and LOCATION, respectively.

Step 4. Select the goods i' with the largest similarity coefficient in the collection ITEM and the assigned cargo locations that have already assigned, whose inbound weight and volume are smaller than the remaining capacity of the assigned cargo locations. If i' exists, switch to Step 5. If i' does not exist and ITEM is not empty, switch to Step 3 and select the goods stored at the next cargo location $j + 1$. If ITEM is empty, then CITEM is the first individual in the initial population and switch to Step 6.

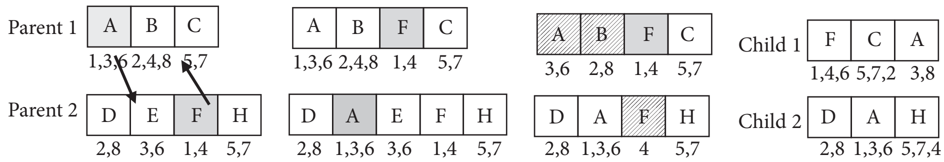
Step 5. Call the BSAA algorithm designed in Section 4.2 to determine whether the goods can be stored in the cargo location. If it can be deposited, the goods will be stored in the cargo location and removed from the collection ITEM. If it cannot be deposited, switch to Step 3 and select the goods to be deposited in the next location $j + 1$.

Step 6. Randomly select two cargo locations, exchange the stored goods, and generate a new individual.

Step 7. Repeat Step 6 until all individuals in the initial population are generated.

In terms of the population size, more is better in theory. However, considering the calculation cost, the population size is sufficient if satisfactory results can be obtained. In general, the population size is between 10 and 100.

4.3.3. Fitness Calculation and Population Selection. Roulette selection, sorting, scale conversion, and competitive selection are common methods used in genetic algorithms. The most



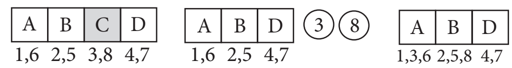
(a) Select cross section

(b) Insert cross section

(c) Eliminate repeated goods and empty cargo locations

(d) Reassign the remaining goods to the location of the duplicate goods

Figure 2: The crossover process.



(a) Select mutation position

(b) Remove mutated cargo location

(c) Reinsert the removed goods

Figure 3: The variation process.

well-known and most commonly used method is roulette selection. When making a roulette selection, the goal is generally to maximize the fitness function and, therefore, the objective function can be transformed as follows:

$$f = \frac{1}{\min T} = \frac{1}{\sum_{k=1}^{p}\left(\sum_{j=1}^{m}\left\lceil \frac{\sum_{i=1}^{n} u_{ik} z_{ij}}{n} \right\rceil \times \left(2t_F + 2 \times \max\left\{t_H, t_V\right\}\right)\right)}. \tag{12}$$

This paper implements an elite retention strategy when using the roulette selection method. The idea of this strategy is to directly copy the best individuals (called the elite individuals) that have appeared in the evolution process of the population to the next generation without pairing and crossing; the advantage is that the optimal individual will not be lost or destroyed via selection, crossing, and mutation. The elite retention strategy plays an important role in improving the global convergence ability of the improved standard genetic algorithm.

4.3.4. Crossover Operator. The crossover process is shown in Figure 2.

The crossover process is described as follows.

Step 1. Select two parents, and randomly select a crossover position in each parent.

Step 2. Select the crossover position in the first parent, and insert it before the crossover position of the second parent to generate offspring.

Step 3. Remove all repetitive goods from the generated offspring.

Step 4. Remove the cargo locations where repetitive goods are located. Call the BSAA algorithm designed in Section 4.2 to determine whether the remaining cargo can be placed in other cargo locations. If they can be placed inside, then assign the goods to the other cargo locations according to the BFD heuristic algorithm. If not, assign the goods to new cargo locations.

Step 5. Change the role of the two parents, and reapply Steps 2–4 to generate the second offspring.

4.3.5. Mutation Operator. The variation process is shown in Figure 3.

The mutation process is described as follows.

Step 1. Randomly select a mutation location.

Step 2. Remove the cargo location after this location.

Step 3. Call the BSAA algorithm to determine whether the goods in the removed cargo location can be placed at other location. If they can be placed, assign the goods to another cargo location according to the BFD heuristic method. If not, assign the cargo to a new cargo location.

5. Case Analysis

5.1. Case Data

5.1.1. Description of the Example Data. To verify the correctness of the integrated optimization model of mixed cargo packing and cargo location assignment of the AS/RS and the effectiveness of the optimization algorithm established in this paper, the inbound and outbound delivery data in the AS/RS of an aviation food company were selected as an example. Orders to this aviation food company during the peak season number more than 90,000 per day. In addition, there are nearly 700 categories of ingredients and raw materials; therefore, inbound and outbound deliveries are very frequent. The company's AS/RS consists of three roadways, six rows of shelves, and three stackers. The shelf size is 10 floors with 47 columns. The length, width, and height of the container are 1.2, 1, and 0.8 m, respectively. The maximum load of the container is 800 kg. The outbound delivery data for this AS/RS in the first half of 2018 are shown in Table 3.

According to the data in Table 3, there are 80 categories of high-frequency picked outbound goods with outbound deliveries every day, accounting for 14.9% of the total number of categories of high-frequency picked outbound goods. In addition, the number of high-frequency picking outbound operation instructions accounts for 50.57% of the total picking outbound instructions, indicating that the optimization of the cargo location assignment of the high-frequency picked outbound goods has a significant effect on improving the outbound efficiency of the entire system. According to similarity coefficient calculation method used for outbound cargo deliveries described in Section 3.1, the pairwise correlation coefficient of the 80 categories of high-frequency picked outbound goods can be calculated; this reveals that there is a strong outbound correlation. The outbound correlation data of some of the high-frequency picked outbound goods are shown in Table 4.

Using an analysis of the above data, the 80 categories of goods with high outbound frequency, less than one whole pallet of every outbound quantity, and strong outbound correlation were selected for testing, which conforms to the requirements of the optimization algorithm for the cargo location assignment based on mixed packing.

5.1.2. Estimation of the Quantity of Inbound Goods. The picking and replenishing method of the warehouse is assumed to be "wave-picking and entire- replenishment." The replenishment period of 80 categories of high-frequency outbound goods is 1 day. The single inbound quantity was determined according to the historical single-day maximum outbound quantity and the stock safety limitations of the 80 categories of high-frequency picked outbound goods. The inbound data for the 80 categories of high-frequency picked outbound goods were calculated according to a statistical analysis of the historical data. Some of these data are shown in Table 5.

5.1.3. Assumptions for Inbound Cargo Locations. To improve the outbound efficiency and reliability of the AS/RS, the goods are evenly assigned to each roadway. By analyzing the operating efficiency of the AS/RS during a certain period of time, the operation time of each stacker can be calculated. If the operation time of each stacker is relatively balanced and the overall operation time is smaller, this indicates that the operating efficiency of the system is high. When verifying the model and algorithm, without loss of generality, it can be assumed that the inbound goods are assigned to only one roadway and then divided equally. According to the actual situation in the integrated optimization management of the system, the 80 cargo locations closest to the exit are selected as the inbound cargo locations. Because there is mixed packing in these 80 categories of inbound goods, the actual number of used cargo locations is less than 80. After determining the mixed storage of the 80 categories of high-frequency outbound goods, the remaining cargo locations are arranged to store other goods.

5.2. Case Calculation Results and Analysis

5.2.1. Test Environment and Algorithm Parameter Settings. MATLAB R2014 was used for the programming, and the test was conducted on a WIN 64-bit operating system in a 4GB RAM and Intel Core(TM) i5-6500 (3.2 GHz) environment.

The parameters of the genetic algorithm are set as follows. The population size is set according to the categories of test goods, namely, 30, 50, 80, and 100, respectively, and the categories of corresponding test goods are 20, 40, 60, and 80, respectively. The crossover probability is set to 0.92. The mutation probability is set to 0.15. The number of iterations is set according to the size of the population; for 70, 100, 150, and 180 iterations, the corresponding population sizes are 30, 50, 80, and 100, respectively.

5.2.2. Basic Performance Test and Algorithm Comparison. The checking calculation was performed on the integrated optimization algorithm of mixed cargo packing and cargo location assignment (hereafter referred to as the "integrated optimization algorithm"), the cluster-based phased optimization method of mixed storage of goods and cargo location assignment in [8] (hereafter referred to as the "phased optimization algorithm"), and the separate storage of goods and cargo location assignment algorithm based on COI rules (hereafter referred to as the "COI rule optimization algorithm"). The checking calculation is divided into two cases. Case 1: The number of types of goods tested is the same, and the correlation coefficients of the goods differ. The 80 categories of goods selected in Section 5.1 were divided into four groups from high to low correlation coefficient, i.e., from 1 to 20, from 21 to 40, from 41 to 60, and from 61 to 80. Case 2: The number of types of goods tested and the correlation coefficients of goods both differ. The 80 categories of goods selected in Section 5.1 were divided into four groups from high to low correlation coefficient, i.e., from 1 to 20, from 1 to 40, from 1 to 60, and from 1 to 80. When using the method proposed in [8], considering the minimum stock of each category of good, each cargo location can store up to two categories of goods. After the two cases were run 20 times respectively, the average optimization comparison results obtained are shown in Tables 6 and 7, respectively.

A comparison and analysis of the optimized data of Tables 6 and 7 reveals the following:

(1) In terms of the improvement of the stacker operation, the efficiency of the phased optimization algorithm is 16.22% and 19.74% greater than that of the COI rule optimization algorithm, respectively; the efficiency of the integrated optimization algorithm is 18.88% and 22.82% greater than that of the COI rule optimization algorithm, respectively; and the efficiency of the integrated optimization algorithm is 3.37% and 4.01% greater than that of the phased optimization algorithm, respectively.

(2) In terms of the number of used cargo locations, the phased optimization algorithm uses half the number of

Table 3: Outbound delivery data for an aviation food company's AS/RS in the first half of 2018.

Total number of outbound delivery orders	Categories of outbound goods	Categories of picked outbound goods	Categories of high-frequency picked outbound goods with outbound delivery every day	Number of outbound delivery orders containing high-frequency picked outbound goods	Proportion of the total number of categories in the picked outbound goods	Proportion of the categories of high-frequency picked outbound goods in the picked outbound goods	Number of outbound operation instructions	Number of picking outbound operation instructions	Number of high-frequency picking outbound operation instructions	The ratio of picking operation instructions to all instructions	Proportion of the number of high-frequency picking operation instructions in the picking outbound instructions
5628	686	537	80	2621	78.28%	14.9%	41999	17713	8958	42.21%	50.57%

Table 4: Outbound correlation data of some high-frequency picked outbound goods.

Product 1	Product 2	Number of outbound delivery orders containing product 1	Number of outbound delivery orders containing product 2	Number of outbound delivery orders containing both products	Number of outbound delivery orders containing neither of the two products	Correlation coefficient of the outbound delivery for these two types of goods
Bagged Biluochun	Bagged Pu'er tea	164	163	150	2144	0.023989689
Taiting champagne sparkling wine	Chateau de Bensse dry red wine 2013	150	169	136	2138	0.026839339
Aluminum lunch box with a white cover	138 aluminum lunch box	157	133	120	2151	0.036618646
Basket bag 03 (thin)	Blue disposable rubber gloves 02	158	181	136	2118	0.025717514
Wong Lo Kat throat lozenge	A-grade oolong	202	180	131	2070	0.027127063
Yili 6.95 grams of two-compartment ground coffee	Gold coffee	129	161	100	2131	0.041498347
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locations as the COI rule optimization algorithm; the integrated optimization algorithm uses 50–55% fewer locations than the COI rule optimization algorithm; and the integrated optimization algorithm uses 0–10% fewer locations than the phased optimization algorithm.

(3) The stronger the similarity of the outbound goods, the better the improvement effect of the integrated optimization algorithm and the phased optimization algorithm. At the same time, for a stronger similarity of the outbound goods, the integrated optimization algorithm performed better than the phased optimization algorithm.

(4) The number of used cargo locations after the optimization of the algorithm can achieve dynamic optimization according to the inbound quantity, specifications, and stock of the goods.

(5) The algorithm in this paper can be solved using an intelligent algorithm, avoiding the direct calculation of the outbound cargo correlation and greatly improving the calculation efficiency. When the quantity of inbound goods is large, the computational efficiency advantage of the integrated optimization algorithm is more obvious than that of the phased optimization algorithm.

5.2.3. Optimized Analysis of the Operation Time of the Stackers in a Single Outbound Order. The operation time of the stackers for a single outbound stacker is an important indicator of the operation efficiency of the AS/RS. When improving the outbound delivery efficiency of the AS/RS, it is necessary to consider the improvement in the outbound delivery time for each outbound delivery order and to try to ensure that most of the outbound delivery times of the outbound delivery orders can be reduced. The phenomenon where the improvement effect of the outbound delivery times for some outbound delivery orders is very satisfactory while the improvement effect of other outbound delivery orders is not should be avoided. For the stacker operation time for a single outbound delivery order containing high-frequency outbound goods, the integrated optimization algorithm and the phased optimization algorithm are used for a statistical analysis, as shown in Table 8.

Table 8 illustrates that the optimization effect of the integrated optimization algorithm is superior to that of the COI rule optimization algorithm in terms of the optimization of the stacker operation time in a single outbound delivery order containing high-frequency outbound goods.

5.2.4. Analysis of the Impact of Changes in the Outbound Delivery Orders on the Optimization Results. The proposed cargo location assignment optimization algorithm based on mixed cargo packing is designed to perform mixed cargo packing and cargo location assignment with the help of historical outbound delivery order data according to the

Table 5: Inbound data of outbound goods picked at partial high-frequency.

Representative number for the product name	Product name	Specification	Unit	Minimum package unit size (length × width × height) (mm)	Historical maximum outbound quantity in a single day	Stock safety limit	Maximum number of storage units at a single cargo location	Single maximum number of inbound units acquired via estimation
1	Bagged Biluochun	25 g × 100	Tin	485 × 210 × 385	1100	220	2000	1320
2	Taiting champagne sparkling wine	375 ml × 12	Bottle	295 × 245 ×255	180	30	576	210
3	Aluminum lunch box with a white cover	1 × 2000	Bin	495 × 395 × 285	2	1	4	3
4	Basket bag 03(thin)	1 × 1000	Bin	585 × 330 × 370	6	2	10	8
5	Wong Lo Kat throat lozenge	1 × 200 × 10 packs	Bottle	300 × 300 × 300	18000	3000	54000	21000
6	Yili 6.95 grams of two-compartment ground coffee	1 × 216	Pack	295 × 295 × 180	864	170	7560	1034
……	……	……	……		……	……	……	……

outbound correlation and frequency, which is a predictive cargo location assignment. This algorithm has stringent requirements for the stability of the outbound correlation and frequency. If the fluctuations are large, the optimization effect of this method is obviously reduced and the outbound efficiency may also be significantly reduced. Therefore, when using this method, the historical data should be analyzed for a certain period, such as one month, to predict the future outbound delivery of goods and to optimize the mixed cargo packing and the cargo location assignment. This problem is analyzed and explained using the data in Section 4.1. The data consist of the historical outbound data for May 2018, and the outbound data in June are assumed to be future outbound data. The total number of outbound orders in June is 46, and 20 categories of high-frequency outbound goods were selected for the comparative analysis. The comparison data are shown in Table 9.

Table 9 shows that the optimization results of the mixed cargo packing and the location assignment calculated according to the historical data are not optimal for the actual outbound delivery data. Compared to the actual data, the stacker operation time in the forecasting data increases by approximately 6.2%. In practical applications, taking into account the cost of adjusting the cargo locations and increasing the replenishment times, a balance should be set for adjusting the cargo location assignment. When the loss resulting from the operation time increasing due to the predicted cargo location assignment is larger than the cost of adjusting the cargo location and increasing the replenishment times, the cargo location should be reassigned.

5.2.5. Analysis of the Algorithm Convergence. Multiple operation results of the algorithm show that the program can converge after a limited number of iterations and obtain optimized results. The algorithm convergence curve is shown in Figure 4 for different categories and population sizes of goods.

Figure 4 indicates that, with the increase in the category number and the population size of the goods, the convergence speed of the algorithm decreases; however, it can still converge after a relatively small number of iterations.

6. Conclusions

Based on an analysis of mixed cargo packing and cargo location assignment in an AS/RS, this paper established an integrated optimization model of mixed cargo packing and cargo location assignment with the goal of minimizing the stacker operation time based on historical outbound delivery order data. This was transformed into a packing problem with constraints, and the group coding method was used to perform chromosome coding with a genetic algorithm. When the initial population was generated, the correlation and frequency of outbound deliveries were considered and the FFD and BFD heuristic algorithms were used to design a new algorithm, which improved the convergence speed

Table 6: Comparison of the outbound optimization data for high-frequency outbound goods. (The number of types of goods tested is the same, and the correlation coefficient of the goods is different.)

Categories of goods	Serial number of the tested goods	Average pairwise correlation coefficient of the goods	Number of outbound delivery orders containing the test goods	Operation time of stackers (s)			Number of used cargo locations (unit)			Operation time of the algorithm (s)			Improvement effect of the algorithm (percentage improvement of the stacker operation efficiency)		
				COI rule optimization algorithm	Phased optimization algorithm	Integrated optimization algorithm	COI rule optimization algorithm	Phased optimization algorithm	Integrated optimization algorithm	COI rule optimization algorithm	Phased optimization algorithm	Integrated optimization algorithm	Phased optimization algorithm relative to COI rule optimization algorithm	Integrated optimization algorithm relative to COI rule optimization algorithm	Integrated optimization algorithm relative to phased optimization algorithm
20	1~20	0.03148	1136	217254	169680	160816	20	10	9	103	218	156	21.90	25.98%	5.51%
20	21~40	0.01923	1228	220638	178517	171687	20	10	9	115	231	164	19.09%	22.19%	3.98%
20	41~60	0.01026	1092	210352	180877	176841	20	10	9	98	205	148	14.01%	15.93%	2.28%
20	61~80	0.00687	956	202496	182451	179355	20	10	10	90	192	139	9.90%	11.43%	1.73%

Table 7: Comparison of the outbound optimization data for high-frequency outbound goods. (The number of types of goods tested is different, and the correlation coefficient of goods is also different.)

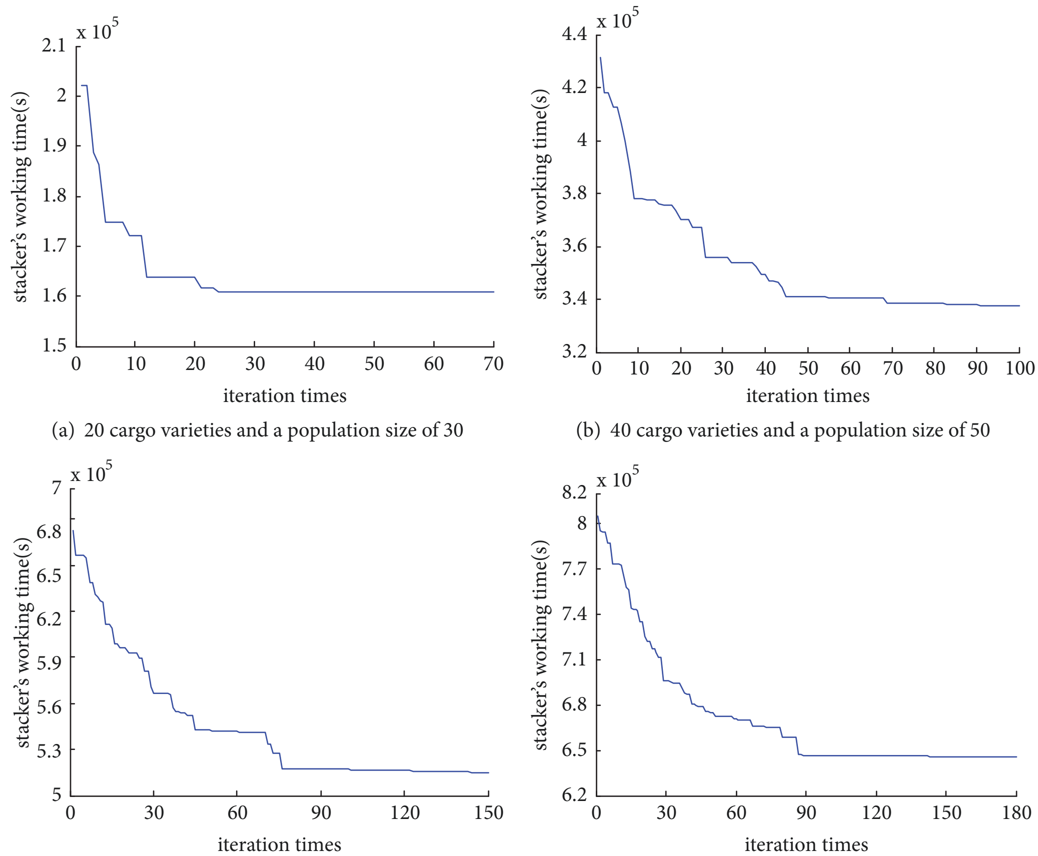
Categories of goods	Serial number of the tested goods	Average pairwise correlation coefficient of the goods	Number of outbound delivery orders containing the test goods	Operation time of stackers (s)			Number of used cargo locations (unit)			Operation time of the algorithm (s)			Improvement effect of the algorithm (percentage improvement of the stacker operation efficiency)		
				COI rule optimization algorithm	Phased optimization algorithm	Integrated optimization algorithm	COI rule optimization algorithm	Phased optimization algorithm	Integrated optimization algorithm	COI rule optimization algorithm	Phased optimization algorithm	Integrated optimization algorithm	Phased optimization algorithm relative to COI rule optimization algorithm	Integrated optimization algorithm relative to COI rule optimization algorithm	Integrated optimization algorithm relative to phased optimization algorithm
20	1~20	0.03148	1136	217254	169680	160816	20	10	9	103	218	156	21.90	25.98%	5.51%
40	1~40	0.02684	1713	441837	351957	337742	40	20	20	126	458	182	20.34	23.56%	4.21%
60	1~60	0.01826	2151	665580	538170	514776	60	30	29	141	937	225	19.14	21.65%	3.20%
80	1~80	0.01097	2621	807771	665802	645635	80	40	38	167	2124	274	17.58	20.07%	3.12%

Table 8: Comparison of the operation time optimization for a single outbound stacker with high-frequency outbound goods.

Month	Total number of outbound delivery orders containing high-frequency outbound goods	Improvement effect of the phased optimization algorithm relative to the COI rule optimization algorithm						Improvement effect of the integrated optimization algorithm relative to the COI rule optimization algorithm					
		The stacker operation time is reduced by more than 80%		The stacker operation time is reduced by more than 50%		The stacker operation time is increased		The stacker operation time is reduced by more than 80%		The stacker operation time is reduced by more than 50%		The stacker operation time is increased	
		Number of outbound delivery orders	Proportion	Number of outbound delivery orders	Proportion	Number of outbound delivery orders	Proportion	Number of outbound delivery orders	Proportion	Number of outbound delivery orders	Proportion	Number of outbound delivery orders	Proportion
1	514	13	2.53%	332	64.59%	49	9.53%	52	10.12%	368	71.60%	44	8.56%
2	382	5	1.31%	201	52.62%	31	8.12%	33	8.64%	262	68.59%	32	8.38%
3	430	7	1.63%	232	53.95%	43	10.00%	39	9.07%	289	67.21%	36	8.37%
4	419	8	1.91%	224	53.46%	46	10.98%	43	10.26%	280	66.83%	37	8.83%
5	407	7	1.72%	223	54.79%	44	10.81%	36	8.85%	278	68.30%	32	7.86%
6	469	9	1.92%	256	54.58%	51	10.87%	45	9.59%	332	70.79%	42	8.96%
Total	2621	49	1.87%	1468	56.01%	264	10.07%	248	9.46%	1809	69.02%	223	8.51%

Table 9: Analysis of the impact of order changes on the optimization results.

Cargo location assignment based on outbound orders and the month	Mixed cargo packing and cargo location assignment results: simplified code of the cargo location (simplified code of goods)	Stacker operation time for outbound orders in June (s)
5	1(1,8), 2(2,11), 3(3,13,16), 4(4,6,15), 5(9,19), 6(7,20), 7(5,10), 8(12,18), 9(14,17)	54185
6	1(1,11), 2(2,8), 3(3,13,16), 4(4,6,15), 5(9,19), 6(7,20), 7(12,18), 8(5,10), 9(14,17)	51023



(a) 20 cargo varieties and a population size of 30

(b) 40 cargo varieties and a population size of 50

(c) 60 cargo varieties and a population size of 80

(d) 80 cargo varieties and a population size of 100

Figure 4: Algorithm convergence curves.

of the genetic algorithm. A heuristic algorithm for two-dimensional rectangular-packing problem is designed to determine whether a variety of goods can be mixed packing. Taking the actual data from an AS/RS of an aviation food company as an example, the established model and design algorithm were verified and the influence of changes in the outbound delivery orders on the optimization result was analyzed. The results showed that compared to the phased optimization algorithm of mixed storage and cargo location assignment based on clusters and the separate cargo location allocation algorithm based on COI rules, the integrated optimization method of mixed cargo packing and location allocation could improve the outbound delivery efficiency of the stacking machines. The stronger the correlation of the outbound delivery cargo, the greater the potential of the proposed algorithm to improve the efficiency of the stacker. Changes in the outbound delivery orders had a large influence on the proposed algorithm. The proposed algorithm is suitable for an AS/RS with relatively stable outbound deliveries.

This paper does not include a quantitative computational analysis of time losses during outbound delivery by stackers caused by order changes; this calls for further research.

Data Availability

The data in this paper, mainly including the outbound orders in a certain period of time, are sourced from an enterprise automated storage and retrieval system project completed by the author and stored in the SQL Server database and are available upon request. You can contact the author via E-mail: 317165496@qq.com.

Conflicts of Interest

The authors declare no conflicts of interest.

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References

[1] M. P. Kennedy and L. O. Chua, "Unifying the tank and hopfield linear programming circuit and the canonical nonlinear programming circuit of chua and lin," *IEEE Transactions on Circuits and Systems II: Express Briefs*, vol. 34, no. 2, pp. 210–214, 1987.

[2] Y. Cui, "Simplest optimal cutting patterns for equal rectangles," *Operations Research Letters*, vol. 34, no. 6, pp. 630–638, 2006.

[3] S. Polyakovskiy and R. M'Hallah, "A hybrid feasibility constraints-guided search to the two-dimensional bin packing problem with due dates," *European Journal of Operational Research*, vol. 266, no. 3, pp. 819–839, 2017.

[4] A. Lodi, M. Monaci, and E. Pietrobuoni, "Partial enumeration algorithms for two-dimensional bin packing problem with guillotine constraints," *Discrete Applied Mathematics: The Journal of Combinatorial Algorithms, Informatics and Computational Sciences*, vol. 217, no. part 1, pp. 40–47, 2017.

[5] K. He, W. Huang, and Y. Jin, "An efficient deterministic heuristic for two-dimensional rectangular packing," *Computers & Operations Research*, vol. 39, no. 7, pp. 1355–1363, 2012.

[6] L. Wei, D. Zhang, and Q. Chen, "A least wasted first heuristic algorithm for the rectangular packing problem," *Computers & Operations Research*, vol. 36, no. 5, pp. 1608–1614, 2009.

[7] J. Thomas and N. S. Chaudhari, "Design of efficient packing system using genetic algorithm based on hyper heuristic approach," *Advances in Engineering Software*, vol. 73, pp. 45–52, 2014.

[8] Y. Gao, *A Study of Packing Strategy of Mini-load Automated Storage and Picking System in Medical Logistics Distribution Center*, Shangdong University, Ji'nan, China, 2016.

[9] J. Heskett, "Cube-per-order-a key to warehouse stock location," *Transportation and Distribution Management*, vol. 2, pp. 27–31, 1963.

[10] M.-K. Lee, "A storage assignment policy in a man-on-board automated storage/retrieval system," *International Journal of Production Research*, vol. 30, no. 10, pp. 2281–2292, 1992.

[11] M. Sadiq, T. L. Landers, and G. Don Taylor, "An assignment algorithm for dynamic picking systems," *IIE Transactions*, vol. 28, no. 8, pp. 607–616, 1996.

[12] Y. B. Song, Z. Y. Jiang, and B. Z. Sun, "Integrated optimization of operations in multiple-I/O points automated storage and retrieval system," *Journal of Central South University (Science and Technology)*, vol. 47, no. 06, pp. 1930–1939, 2016.

[13] P. Yang, Y. Peng, B. Ye, and L. Miao, "Integrated optimization of location assignment and sequencing in multi-shuttle automated storage and retrieval systems under modified 2n-command cycle pattern," *Engineering Optimization*, vol. 49, no. 9, pp. 1604–1620, 2017.

[14] Z. Y. Shang, J. N. Gu, W. Ding, and etal., "Heuristical gorithmfor 2D rectangle packing problem," *Computer Integrated Manufacturing Systems*, vol. 24, no. 03, pp. 583–590, 2018.

[15] G. N. Xuan and R. W. Cheng, *Genetic Algorithm and Engineering Optimization*, Tsinghua University Press, Beijing, China, 2004.

[16] E. Falkenauer, "A new representation and operators for genetic algorithms applied to grouping problems," *Evolutionary Computation*, vol. 2, no. 2, pp. 123–144, 1994.

[17] D. B. Zhang, G. Q. Liu, J. Wang et al., "Genetic algorithm based on group coding for bin-packing problem," *Computer Engineering and Design*, vol. 29, no. 12, pp. 3154–3156, 2008.

[18] Y. J. Zhang, Y. Liu, and S. J. Xie, "An improved genetic algorithm for Bin-packing problem," in *Control Engineering of China*, vol. 23, pp. 327–331, 03 edition, 2016.