Multiobjective Optimization of the Storage Location Allocation of a Retail E-commerce Picking Zone in a Picker-to-parts Warehouse

Yanchun Wan, Shudi Wang, Yujun Hu, Yanyang Xie

Abstract—**Storage location allocation has a great impact on the utilization of warehouse storage space, operation efficiency, cost and employee well-being. We establish a multiobjective model of storage location optimization of manual picking zones by adopting the principle of high delivery frequency priority, correlation principle and large-capacity priority principle. The intelligent genetic algorithm and particle swarm optimization (IGPSO) algorithm are used to solve the multiobjective model. By using the 3.6 million-order data of a retail e-commerce warehouse to optimize the storage location allocation, the results show that the maximum and average response time, the actual order picking time, the daily walking distance of the picker and other key indicators achieve good results. This research can be well applied to optimize the storage location allocation of similar retail e-commerce warehouses.**

Index Terms—**storage location allocation, multiobjective optimization, picker-to-parts warehouse, IGPSO algorithm, large volume priority**

I. Introduction

ONLINE shopping has become one of the mainstream consumption habits of Chinese residents. The COVID-19 pandemic in 2020 accelerated the digital transformation of physical industries. Data from the Ministry of Commerce showed that online retail sales of physical goods in China rose 12.0 percent, bucking the trend in 2021, and accounting for 24.5 percent of total retail sales of consumer goods.

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Yanchun Wan is an associate professor of Department of Electronic Commerce, South China University of Technology, Guangzhou 510006, China. (e-mail: tcycwan@scut.edu.cn).

Shudi Wang is a postgraduate student of Department of Electronic Commerce, South China University of Technology, Guangzhou 510006, China. (e-mail: 202121059432@mail.scut.edu.cn)

Yujun Hu is a researcher of Guangdong Planning Research & Design Academy of China Post Group, Guangzhou 510610, China. (e-mail: 13711588228@163.com).

Yanyang Xie is a postgraduate student of Department of Electronic Commerce, South China University of Technology, Guangzhou 510006, China. (e-mail: 13610048467@163.com)

The rapid development of retail e-commerce has increased customer expectations for the delivery time of purchased goods. The delivery time consists of the order picking time in the warehouse and the in-transit delivery time. Multiple studies confirm that order picking is one of the most time-consuming and cost-intensive warehousing activities [1],[2]. There are four methods to reduce the walking time or distance of order picking activity: first, determine the optimal picking route according to the order; second, plan the warehouse zoning; third, pick in batches; fourth, optimize the storage location. Storage location optimization refers to the correct assignment of certain products to the optimal position. Location setting is a necessary prerequisite for order picking, and the location of the product directly determines the picking distance, which directly affects the order response time. In addition, manual picking is still the mainstream method of picking. In the context of e-commerce sales with small batches, high frequency and diminishing order delivery time, research on storage location optimization not only helps improve picking efficiency and shorten order response time but also helps reduce the work intensity of pickers and operational costs.

The existing literatures on storage location optimization are mainly focused on one item in one storage location of mass storage area [3]-[5], while there are few literatures on the small picking areas, especially the problem of multiple items in one storage location, which is commonly used in practice. In this study, based on the principle of high delivery frequency priority, the principle of relevance and the principle of large volume priority, a multiobjective storage location optimization model of several items in one storage location in the picking area was established, and an intelligent optimization algorithm combining a genetic algorithm and a particle swarm optimization algorithm, the IGPSO algorithm, was creatively selected to solve this model. Furthermore, the manual KL e-commerce warehouse is taken as an example to carry out the calculation and optimization effect analysis, which can provide a reference for improving the storage location optimization of modern e-commerce warehouses.

The rest of this paper is structured as follows: In section II, we review the relevant literature on storage location optimization. In section III, we establish the storage location optimization model and design the IGPSO algorithm. In section IV, the model is analysed with examples. Finally, we summarize the prospects.

II. Literature Review

Storage location assignment affects almost all key indicators of a storage system, such as space utilization, [6]. Storage location optimization is a process of adjusting and reconfiguring the location of goods. It has been one of the hot topics in warehousing and logistics research in recent decades. Based on different objective requirements, scholars have carried out beneficial explorations on the problem of storage location optimization from multiple perspectives.

Maximizing space utilization is one of the main objectives of storage location optimization. For example, to solve the problem of maximizing space utilization under random storage, Quintaniua et al. [7] established a storage location optimization model to minimize the waste of storage space and verified that it can improve storage space utilization and shorten the time of picking. Alfathi [8] established an optimization model to maximize the utilization of shared storage space and verified the optimization effect of space use in steel coil warehouses.

Shortening the picking distance to improve the operation efficiency or order response speed is another important goal of storage location optimization. The principles of high delivery frequency priority and correlation are often used in this kind of storage location optimization research. High delivery frequency priority means that goods with high delivery frequency should be placed near the exit. For example, in the study of Otto et al. [9], goods with high delivery frequency were arranged in a compact fast picking area. Xie et al. [10] established storage space optimization with the minimum total weighted picking distance to solve the storage location assignment problem of the garment picking system. According to turnover-based policy, in the study of Wan and Liu [11], items with a higher turnover rate were stored in the storage locations closer to the pick-up and deposit (P&D) point. The correlation principle is to store goods with a high probability of being ordered at the same time nearby, which can improve the storage efficiency. For example, Pang et al. [3] optimized the assignment of goods by mining the correlation degree between different goods; after optimization, the operating efficiency was better than that of the near export storage strategy and the positioning storage strategy. According to the correlation of product demand intensity, Xu et al. [12] extended the traditional static storage location assignment problem to the multistage dynamic location optimization problem.

The storage location assignment of heavy-duty racks stored in large quantities affects the stability of the overall structure of the shelf. Therefore, shelf stability or structural safety is often used as an important goal of storage location optimization. For example, Yang et al. [13] established a biobjective optimization model based on in-out efficiency and shelf stability, and simulation experiments showed that this model can reduce the cost of loading, unloading and storage and reduce the operation time of in-out storage. Based on the lowest equivalent centre of gravity of the whole shelf and the highest operational efficiency, Jiao et al. [14] established a biobjective storage location optimization model and analysed the results with the experimental data of the automated warehouse.

In recent years, the environment and energy consumption have been gradually introduced into the study of storage location optimization. For example, Ene et al. [15] established a storage location optimization model that minimizes energy consumption and carried out an example analysis using the operation situation of a manual warehouse. Bortolini et al. [16] established a biobjective optimization model to minimize the operating time and energy consumption of the starer. Through the case of the beverage industry, it was found that compared with the model that only considered the minimization of operating time, the energy savings were 12.66%, and the time efficiency was reduced by only 2.52%.

Another delightful development is the introduction of warehouse employee well-being into the storage location optimization problem. Focusing only on picking performance will lead to a higher ergonomic risk to labour [9]. By introducing employee discomfort into storage location optimization, Larco et al. [4] established a biobjective storage location assignment model that minimizes the operation cycle and discomfort, and tested the optimization effect in two warehouses. In the layout optimization of U-shaped warehouses, Diefenbach et al. [17] considered two goals in storage location assignment. One goal was minimizing the total travel distance, and the other was minimizing the deviation of the ergonomic total pressure borne by employees. The optimized storage location assignment significantly reduced the picking walking distance and met the ergonomic pressure requirements at the same time.

In summary, scholars have made rich achievements in the study of storage location optimization, which effectively guides warehousing and logistics practice. Location optimization objects cover bulk storage areas and manual picking areas [8], [9], [14], [16], [17]. In specific modelling, scholars usually consider two or three storage location optimization objectives [3], [13], [14], [18]-[20]. In most studies, each location was assigned one item [3]-[5]. Few studies have considered placing more than one item in one storage location in a picker-to-parts warehouse. In addition, volume variables are often introduced into storage location assignment as capacity limits [20],[21], but how to effectively assign storage locations for different volumes of goods has not been systematically studied.

The main contributions of this paper are as follows: First, this study enriches the existing research of storage location assignment by introducing the problem of several items in one storage location assignment with a manual picking area as the background. Second, volume is an important factor affecting the storage location assignment in retail e-commerce, and this study innovatively introduces the volume priority principle into the storage location optimization problem. Finally, we use the IGPSO algorithm to solve the multiobjective optimization problem. IGPSO is an intelligent optimization algorithm mixed with a genetic algorithm and particle swarm optimization algorithm.

III. Model Establishment and Algorithm Design

A. Problem Description

This paper studies the location optimization problem in the case of the vertical layout of a picking area. The research area includes one main aisle (vertical aisle) and several auxiliary aisles (horizontal aisles), as shown in Fig. 1.

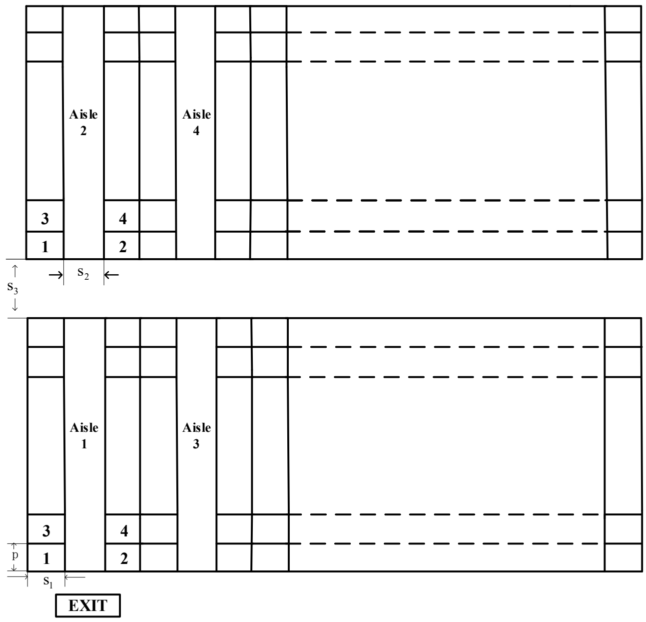

Fig. 1. Schematic diagram of the shelf layout of the picking area.

The aisle numbers for aisles distributed below are set as odd, and the aisle numbers for aisles distributed above are set as even in the Fig. 1. There are several columns of shelves on both sides of each aisle, of which the column number on the left is odd and the column number on the right is even. The shelf numbers from bottom to top are 1, 2…. Let x_i, y_i and z_i represent the aisle number, column number and layer number of the ith location, respectively; then, each location i has a corresponding location coordinate (x_i, y_i, z_i). Let a, b and c represent the number of aisles, columns and layers, respectively, and the value ranges of x_i, y_i and z_i are $1 \leq x_i \leq a$, $1 \leq y_i \leq b$, and $1 \leq z_i \leq c$.

According to the actual situation of the picking area of the case, the following modelling assumptions are put forward:

1) Each storage location must be allocated to at least one item of goods, and the volume of goods at each storage location must not exceed the capacity of one storage location.
2) To facilitate product management, the goods of each item can only be allocated to one storage location at a time.
3) One storage location can store more than one item of goods, but to facilitate management and reduce the error rate, one storage location can store only goods of three items at most.
4) Once there is a vacant space in the storage location, goods can be replenished to make effective use of the storage space.
5) The size of each storage location is the same, the thickness of the partition between shelves is ignored, and the width of each vertical aisle is the same.

B. Model Establishment

This part first sets the model parameters, takes the improvement of outbound operation efficiency as the main optimization direction, and adopts the priority principle of high delivery frequency, the principle of relevance and the principle of larger volume priority to establish a multiobjective model of storage location optimization.

Model parameters

The variables in the model are defined in Table I.

TABLE I
VARIABLES IN THE MODEL

Symbol	Description
$\boldsymbol{I}$	Location set
K	Item set
D_i	The distance between the ith location and the exit, which is the Manhattan distance
F_k	The frequency of the goods delivery of the kth item
t_{ki}	The decision variable, it is 1 if the kth item is assigned to the location i, otherwise it is 0
$d_{kk'}$	Location distance between the kth item and the k'th item
$c_{kk'}$	Correlation degree between the kth item and the k'th item
N_k	Order quantity containing the kth item in one cycle
$N_{kk'}$	Order quantity containing the kth item and the k'th item in one cycle
N	Order quantity in one cycle
$\boldsymbol{K}'$	Set of items except the kth item, $\boldsymbol{K}' = \left\{k' \mid k' \in \boldsymbol{K} \text{ and } k' \neq k\right\}$
V_k	Volume of the kth item
M	One storage location can accommodate the quantity of different item types at most
x_i、y_i、z_i	Represent the aisle number, column number and layer number of the ith location, respectively
x^k、y^k、z^k	Respectively represents the aisle number, column number and layer number of the location where the kth item is located
p	Width of a storage location
s_1	Depth of a storage location
h	Height of a storage location
s_2	Width of horizontal aisle
s_3	Width of vertical aisle
a、b、c	The number of horizontal aisles in the picking area, the number of columns in a aisle and the number of shelves

Optimization objectives based on the principle of high delivery frequency priority

The optimization model is established with the objective that the items with higher delivery frequency are stored in the location closer to the exit, that is, the objective function f_1 minimizes the sum of the product of the delivery frequency of all items and the distance from the location to the exit.

$$\min\ f_1 = \sum_{i \in \boldsymbol{I}} \sum_{k \in \boldsymbol{K}} D_i F_k t_{ki} \tag{1}$$

The goods of an item can only be allocated to one location, and each location can store goods of one item at least, but no more than M at most. Then, the relevant constraints t_{ki} can be obtained as follows:

$$t_{ki} \in \{0,1\} \tag{2}$$

$$\sum_{i \in \boldsymbol{I}} t_{ki} = 1, \boldsymbol{I} = \{1,2,3, \ldots, i\} \tag{3}$$

$$0 < \sum_{k \in \boldsymbol{K}} t_{ki} \leq M, \boldsymbol{K} = \{1,2,3, \ldots, k\} \tag{4}$$

The delivery frequency F_k is obtained by dividing the order quantity N_k containing the kth item in a cycle by the quantity of all orders N in this cycle as follows:

$$F_k = \frac{N_k}{N} \tag{5}$$

As shown in Fig. 2, the calculation formula of D_i is divided into the following four situations:

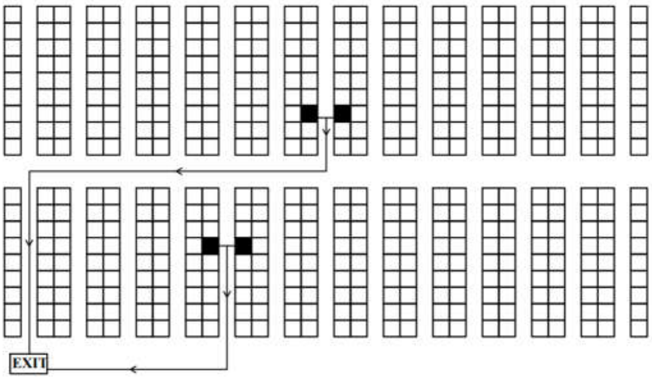

Fig. 2. Schematic diagram of the distance between storage location i and exit.

1) When the aisle is at the bottom of the distribution diagram and the storage location is on the left of the aisle, that is, when x_i and y_i are odd numbers, the distance between the storage location i and the exit is expressed as follows:

$$D_i = \frac{y_i + 1}{2} \bullet p + (x_i - 1)\left(s_1 + \frac{s_2}{2}\right) \tag{6}$$

2) When the aisle is at the bottom of the distribution diagram and the storage location is on the right of the aisle, that is, when x_i is an odd number, y_i is an even number, the distance between the storage location and the exit is expressed as follows:

$$D_i = \frac{y_i}{2} \bullet p + (x_i - 1)\left(s_1 + \frac{s_2}{2}\right) \tag{7}$$

3) When the aisle is on the top of the distribution diagram and the storage location is on the left of the aisle, that is, when x_i is an even number, y_i is an odd number, the distance between the storage location i and the exit is expressed as follows:

$$D_i = \frac{b + y_i + 1}{2} \bullet p + s_3 + (x_i - 1)\left(s_1 + \frac{s_2}{2}\right) \tag{8}$$

4) When the aisle is on the top of the distribution diagram and the storage location is on the right of the aisle, that is, when x_i and y_i are both even numbers, the distance between the storage location i and the exit is expressed as follows:

$$D_i = \frac{b + y_i}{2} \bullet p + s_3 + (x_i - 1)\left(s_1 + \frac{s_2}{2}\right) \tag{9}$$

In summary, the expression of D_i is expressed as follows:

$$D_i = \begin{cases} \frac{y_i + 1}{2} \bullet p + (x_i - 1)\left(s_1 + \frac{s_2}{2}\right), \\ x_i = 2n - 1 \text{ and } y_i = 2n - 1, n \in N^* \\ \frac{y_i}{2} \bullet p + (x_i - 1)\left(s_1 + \frac{s_2}{2}\right), \\ x_i = 2n - 1 \text{ and } y_i = 2n, n \in N^* \\ \frac{b + y_i + 1}{2} \bullet p + s_3 + (x_i - 1)\left(s_1 + \frac{s_2}{2}\right), \\ x_i = 2n \text{ and } y_i = 2n - 1, n \in N^* \\ \frac{b + y_i}{2} \bullet p + s_3 + (x_i - 1)\left(s_1 + \frac{s_2}{2}\right), \\ x_i = 2n \text{ and } y_i = 2n, n \in N^* \end{cases} \tag{10}$$

Optimization objectives based on the relevance principle

Goods with strong correlation should be stored in adjacent locations or even the same location, which can shorten picking distance. Based on this, an expression of the sum of the product of the location distance and the correlation degree of all items and other items can be established as follows:

$$\sum_{i \in \boldsymbol{I}} \sum_{k \in \boldsymbol{K}} t_{ki} \sum_{i \in \boldsymbol{I}} \sum_{k' \in \boldsymbol{K'}} d_{kk'} c_{kk'} t_{k'i} \tag{11}$$

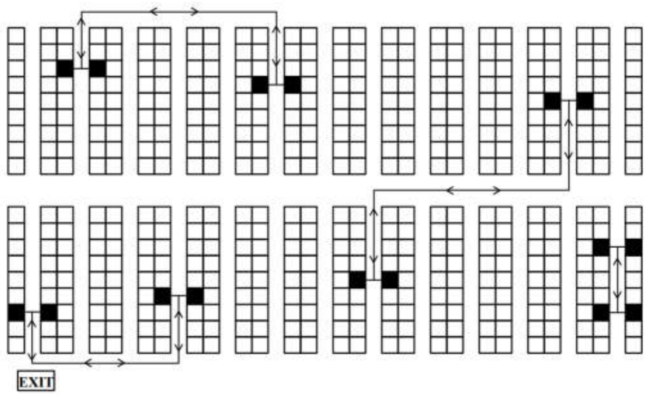

Fig. 3. Schematic diagram of the distance between the storage location of the kth item and the k'th item.

To facilitate the solution and make the order of magnitude difference between the objective functions small, we can obtain the objective function f_2 based on the correlation principle as follows:

$$\min\ f_2 = \sum_{i \in \boldsymbol{I}} \sum_{k \in \boldsymbol{K}} t_{ki} \frac{\sum_{i \in \boldsymbol{I}} \sum_{k' \in \boldsymbol{K'}} d_{kk'} c_{kk'} t_{k'i}}{\sum_{i \in \boldsymbol{I}} \sum_{k' \in \boldsymbol{K'}} t_{k'i}} \tag{12}$$

f_2 minimizes the sum of the location distance of each item and the location distance of other items allocated according to the correlation strength, and $c_{kk'}$ is the correlation degree between the kth item and the k'th item, which is determined by the order quantity N_k and the order quantity $N_{kk'}$. Therefore, $c_{kk'}$ is expressed as follows:

$$c_{kk'} = \frac{N_{kk'}}{N_k}, c_{kk'} \neq c_{k'k} \tag{13}$$

1) When the storage location of item k and item k' are in the same aisle, that is, when $x^k = x^{k'}$, three situations exist:
   a. When the locations of two items are on the same side of the aisle, that is, y^k and $y^{k'}$ are both odd or even numbers, $d_{kk'}$ is expressed as follows:

$$d_{kk'} = \frac{\left|y^{k'} - y^k\right|}{2} \bullet p \tag{14}$$

   b. When the location of item k is on the left side of the aisle and item k' is on the right side of the aisle, that is, when y^k is an odd number and $y^{k'}$ is an even number, $d_{kk'}$ is expressed as follows:

$$d_{kk'} = \frac{\left|y^{k'} - y^k - 1\right|}{2} \bullet p \tag{15}$$

   c. When the location of item k is on the right side of the aisle and item k' is on the left side of the aisle, that is, when y^k is an even number and $y^{k'}$ is an odd number, $d_{kk'}$ is expressed as follows:

$$d_{kk'} = \frac{\left|y^{k'} - y^k + 1\right|}{2} \bullet p \tag{16}$$

2) When the aisles of two items are both below or above the layout, that is, when x^k and $x^{k'}$ both are odd or even numbers, three cases exist:

a. When the storage locations of two items are on the left of the aisle, that is, when y^k and $y^{k'}$ are odd numbers, $d_{kk'}$ is expressed as follows:

$$d_{kk'} = \min\left(\frac{y^k + y^{k'} + 2}{2} \bullet p, bp - \frac{y^k + y^{k'} + 2}{2} \bullet p\right) + \frac{\left|x^k - x^{k'}\right|}{2}(s_1 + 2s_2) \tag{17}$$

b. When the storage locations of two items are on the right of the aisle, that is, when y^k and $y^{k'}$ are even numbers, $d_{kk'}$ is expressed as follows:

$$d_{kk'} = \min\left(\frac{y^k + y^{k'}}{2} \bullet p, bp - \frac{y^k + y^{k'}}{2} \bullet p\right) + \frac{\left|x^k - x^{k'}\right|}{2}(s_1 + 2s_2) \tag{18}$$

c. When the location of item k is on the left side of the aisle and item k' is on the right side of the aisle, that is, when one of the y^k and $y^{k'}$ is odd and the other is even, $d_{kk'}$ is expressed as follows:

$$d_{kk'} = \min\left(\frac{y^k + y^{k'} + 1}{2} \bullet p, bp - \frac{y^k + y^{k'} + 1}{2} \bullet p\right) + \frac{\left|x^k - x^{k'}\right|}{2}(s_1 + 2s_2) \tag{19}$$

3) When the storage locations of two items are located in the aisle, one of which is above and the other is below in the layout, that is, when one of the x^k and $x^{k'}$ is an odd number and the other is an even number, three cases exist.

We only discuss when the aisle of item k is below, and the aisle of item k' is above, that is, when x^k is an odd number, and $x^{k'}$ is an even number.

a. When the storage locations of two items are on the left or right of the aisle, that is, when y^k and $y^{k'}$ are both odd or even numbers, $d_{kk'}$ is expressed as follows:

$$d_{kk'} = \frac{b + y^{k'} - y^k}{2} \bullet p + s_3 + \frac{\left|x^{k'} - x^k - 1\right|}{2}(s_1 + 2s_2) \tag{20}$$

b. When the location of item k is on the left side of the aisle and the location of item k' is on the right side of the aisle, that is, when y^k is an odd number and $y^{k'}$ is an even number, $d_{kk'}$ is expressed as follows:

$$d_{kk'} = \frac{b + y^{k'} - y^k - 1}{2} \bullet p + s_3 + \frac{\left|x^{k'} - x^k - 1\right|}{2}(s_1 + 2s_2) \tag{21}$$

c. When the location of item k is on the right side of the aisle and the location of item k' is on the left side of the aisle, that is, when y^k is an even number and $y^{k'}$ is an odd number, $d_{kk'}$ is expressed as follows:

$$d_{kk'} = \frac{b + y^{k'} - y^k + 1}{2} \bullet p + s_3 + \frac{\left|x^{k'} - x^k - 1\right|}{2}(s_1 + 2s_2) \tag{22}$$

When the aisle of item k is above and the aisle of item k' is below, that is, when x^k is an even number and $x^{k'}$ is an odd number, k and k' will be exchanged according to the above formula. Because the distance between the location of the kth item and the k'th item is the same as the distance between the location of the k'th item and the kth item.$d_{kk'} = d_{k'k}$. To sum up:

$$d_{kk'} = \begin{cases} \frac{\left|y^{k'} - y^k\right|}{2} \bullet p, x^k = x^{k'} and\ y^k, y^{k'} = 2n-1 \\ or\ (x^k = x^{k'} and\ y^k, y^{k'} = 2n),\ n \in N^* \\ \frac{\left|y^{k'} - y^k - 1\right|}{2} \bullet p, x^k = x^{k'}, y^k = 2n-1, y^{k'} = 2n, n \in N^* \\ \frac{\left|y^{k'} - y^k + 1\right|}{2} \bullet p, x^k = x^{k'}, y^k = 2n, y^{k'} = 2n-1, n \in N^* \\ \min\left(\frac{y^k + y^{k'} + 2}{2} \bullet p, bp - \frac{y^k + y^{k'} + 2}{2} \bullet p\right) + \frac{\left|x^k - x^{k'}\right|}{2}(s_1 + 2s_2), \\ x^k, x^{k'} = 2n\ and\ y^k, y^{k'} = 2n-1\ or\ x^k, x^{k'}, y^k, y^{k'} = 2n-1, n \in N^* \\ \min\left(\frac{y^k + y^{k'}}{2} \bullet p, bp - \frac{y^k + y^{k'}}{2} \bullet p\right) + \frac{\left|x^k - x^{k'}\right|}{2}(s_1 + 2s_2), x^k, x^{k'} \\ = 2n-1\ and\ y^k, y^{k'} = 2n\ or\ x^k, x^{k'}, y^k, y^{k'} = 2n, n \in N^* \\ \min\left(\frac{y^k + y^{k'} + 1}{2} \bullet p, bp - \frac{y^k + y^{k'} + 1}{2} \bullet p\right) + \frac{\left|x^k - x^{k'}\right|}{2}(s_1 + 2s_2), \\ x^k, x^{k'}, y^k = 2n-1, y^{k'} = 2n\ or\ x^k, x^{k'}, y^{k'} = 2n, y^k = 2n-1, n \in N^* \\ \frac{b + y^{k'} - y^k}{2} \bullet p + s_3 + \frac{\left|x^{k'} - x^k - 1\right|}{2}(s_1 + 2s_2), x^k, x^{k'}, y^k = 2n-1, \\ y^{k'} = 2n\ or\ x^k, x^{k'}, y^{k'} = 2n, y^k = 2n-1, n \in N^* \\ \frac{b + y^{k'} - y^k - 1}{2} \bullet p + s_3 + \frac{\left|x^{k'} - x^k - 1\right|}{2}(s_1 + 2s_2), x^k, y^k = 2n-1 \\ and\ x^{k'}, y^{k'} = 2n, n \in N^* \\ \frac{b + y^{k'} - y^k + 1}{2} \bullet p + s_3 + \frac{\left|x^{k'} - x^k - 1\right|}{2}(s_1 + 2s_2), x^k, y^{k'} = 2n-1 \\ and\ x^{k'}, y^k = 2n, n \in N^* \\ \frac{b + y^k - y^{k'}}{2} \bullet p + s_3 + \frac{\left|x^k - x^{k'} - 1\right|}{2}(s_1 + 2s_2), x^k = 2n\ and\ x^{k'}, \\ y^k, y^{k'} = 2n-1\ or\ (x^k, y^k, y^{k'} = 2n\ and\ x^{k'} = 2n-1), n \in N^* \\ \frac{b + y^k - y^{k'} - 1}{2} \bullet p + s_3 + \frac{\left|x^k - x^{k'} - 1\right|}{2}(s_1 + 2s_2), x^k, y^k = 2n \\ and\ x^{k'}, y^{k'} = 2n-1, n \in N^* \\ \frac{b + y^k - y^{k'} + 1}{2} \bullet p + s_3 + \frac{\left|x^k - x^{k'} - 1\right|}{2}(s_1 + 2s_2), x^k, y^{k'} = 2n \\ and\ x^{k'}, y^k = 2n-1, n \in N^* \end{cases} \tag{23}$$

Optimization objectives based on the principle of larger volume priority

According to the foregoing, the number of items is greater than the number of storage locations in the picking area, every storage location can be arranged with 1~3 items, and only one storage location can be arranged for each item in a replenishment. On the one hand, more storage space should be arranged for goods with a large volume and high frequency of delivery in the storage location assignment to improve the quantity of each replenishment and reduce the replenishment times. On the other hand, the arrangement of more than one item in a single storage location will increase the probability of picking the wrong items, so items with a high frequency of delivery should be prioritized for storage location of only a single item.

Based on the above analysis, an optimization objective function is established to minimize the sum of the product of the volume of each item and frequency of delivery and the product of the quantity of items stored in the storage location, where V_k is the volume of item k:

$$\min\ f_3 = \sum_{k \in \boldsymbol{K}} \sum_{i \in \boldsymbol{I}} F_k V_k t_{ki} \sum_{k \in \boldsymbol{K}} t_{ki} \tag{24}$$

C. Algorithm Design

In recent years, using an improved or hybrid algorithm to solve problems has not been rare [22]-[26]. In this paper, the

IGPSO algorithm is used to solve the multiobjective storage location optimization model. IGPSO is an intelligent optimization algorithm combining a genetic algorithm (GA) and a particle swarm optimization (PSO) algorithm. A GA focuses on natural optimization search [14], a PSO algorithm focuses on comparison process search, so a GA has advantages in search solution, and a PSO algorithm has advantages in search time. The IGPSO algorithm introduces a genetic operator into the PSO algorithm, performs cross search, uses a genetic operator to iterate some particles, adjusts the inertia weight and mutation, and makes the particles evolve. When the particle population evolves to a certain extent, we mutate some particles. The method can not only avoid the algorithm falling into the local optimal solution but can also obtain high convergence accuracy, which will greatly increase the opportunity to obtain the optimal particles.

According to the above analysis, the IGPSO algorithm has the dual advantages of a genetic algorithm and a particle swarm optimization algorithm. It has better advantages than a single algorithm in search efficiency, solution accuracy and dealing with problems with different complexity. It can solve nonlinear and multiple extreme value problems in engineering and is suitable for the solution of the multiobjective storage location optimization model proposed in this paper.

The solution steps of the storage location optimization model based on the IGPSO algorithm are as follows:

Step 1: Initialize the relevant parameters in the algorithm, such as population size N, number of iterations j, crossover probability pc, selection probability, inertia weight w, self-learning factor c_1, group learning factor c_2, and particle fitness variance threshold C.

Step 2: Initialize the population, which is composed of N particles, set the storage location quantity limit and initial search interval, and initialize the particle position and flight speed.

Step 3: Calculate the fitness value of each particle $z_i = (z_{i1}, z_{i2}, \cdots z_{id})$ in the particle swarm, and record the historical optimal position $p_{bi} = (p_{bi1}, p_{bi2}, \cdots p_{bid})$ of particle i and the historical optimal position p_g of the whole particle swarm according to the fitness value.

Step 4: Judge whether the number of iterations j of particles is an even or odd number.

1) In odd generation, the PSO operator is used to update the velocity v_i^j and position z_i^j of particles as follows:

$$v_{id}^{j+1} = \omega \bullet v_{id}^{j} + c_1 r_1 (p_{bid} - z_{id}^{j}) + c_2 r_2 (p_{gd} - z_{gd}^{j}) \tag{25}$$

$$z_{id}^{j+1} = z_{id}^{j} + v_{id}^{j+1} \tag{26}$$

$$w(j) = w_{\min} + (w_{\max} - w_{\min}) e^{-k\left(\frac{j}{j_{\max}}\right)^2} \tag{27}$$

$$c_1 = c_{1s} + (c_{1e} - c_{1s}) \times \frac{j}{j_{\max}} \tag{28}$$

$$c_2 = c_{2s} + (c_{2e} - c_{2s}) \times \frac{j}{j_{\max}} \tag{29}$$

where w is the inertia weight, which is used to balance the global search and local search. c_1 is a self-learning factor, and c_2 is a group learning factor. r_1 and r_2 are random numbers between $(0,1)$, and these two parameters are used to maintain population diversity. c_{1s} and c_{2s} represent the iterative initial values of c_1 and c_2. c_{1e} and c_{2e} represent the iterative end values of c_1 and c_2.

2) In even generation, the velocity and position of particles are updated by the genetic operator:

Each particle is given a certain selection probability by the sequential selection method, and the better the particle is, the greater the selection probability. Then, the offspring are generated after the crossover between the parent generation selected based on a certain probability and the randomly selected parent generation. The offspring is represented by $child(z_i^j)$, and p represents the random number between $(0,1)$. In this way, it is convenient to obtain excellent particles and prevent premature entry into the local optimal solution. It is expressed as follows:

$$child(z_i^j) = p \times parent_1(z_i^j) + (1-p) \times parent_2(z_i^j) \tag{30}$$

$$child(v_i^j) = \frac{parent_1(v_i^j) + parent_2(v_i^j)}{\left|parent_1(v_i^j) + parent_2(v_i^j)\right|} \times \left|parent_1(v_i^j)\right| \tag{31}$$

Step 5: Analyse the aggregation degree of the particle swarm and calculate the fitness variance in the particle swarm. When the variance is less than the given threshold C, we use Gaussian variation measures to disperse the particles $z_i = p_b(i) \times (1 + 0.5\mu)$, and μ is a random vector obeying the $(0,1)$ normal distribution.

Step 6: Judge the fitness value of the new generation of particles, and update the historical optimal position p_{bi} of a single particle and the historical optimal position p_g of the whole particle swarm.

Step 7: Judge whether the number of iterations meets the requirements. If yes, continue to Step 8; otherwise, go to Step 4.

Step 8: Output the global optimal position p_g and optimal value of particle swarm optimization.

IV. Example Analysis of Storage Location Optimization

In this part, first, we set parameters, analyse the small sample algorithm effect and calculate large sample optimization result of the actual KL e-commerce warehouse. Then, we use the order data of a typical day and a peak promotion day of the KL e-commerce warehouse in 2019 to analyse the storage location optimization result.

A. Background and Parameter Determination

The KL e-commerce warehouse is responsible for the distribution of retail orders in southern China and mainly stores makeup and personal care. The picking area of the warehouse is a kind of vertical layout, as shown Fig. 1, consisting of a central main aisle and 26 picking aisles. Each picking aisle is flanked by 18 rows of shelves, all of which contain 4 layers, with a total of 1872 storage locations and 2683 SKUs (stock keeping units). At present, the average daily order quantity of the warehouse is more than 20,000. There are 6 picking posts, working in two shifts from 6:30 to 1:00 the next morning. The picking trolley is used to manually batch pick, and up to 12 orders are picked each time with the random order batch strategy. On peak sales days, the number of pickers will be increased to deal with the surge of orders. According to the actual situation of the KL e-commerce warehouse, the relevant parameters of the IGPSO algorithm are set as follows:

There are 2683 items in picking areas, so $k \in [1,2683], k \in \boldsymbol{N}^*$, and 1872 storage locations, so $i \in [1,1872], i \in \boldsymbol{N}^*$. The number of picking aisles a, the number of rack rows in each aisle b and the number of layers c are, respectively $a = 26$, $b = 18$, $c = 4$, and $1 \leq x_i, x^k \leq 26$, $1 \leq y_i, y^k \leq 18$, $1 \leq z_i, z^k \leq 4$. The upper limit of items stored in a location is 3, so $M = 3$.

p, s_1 and h represent the length, depth and height of a storage location, respectively. s_2 and s_3 represent the widths of the vertical aisle and horizontal aisle, respectively. The unit is set as metres (m). According to the actual situation, $p = 0.5$, $s_1 = 0.5$, $h = 0.5$, $s_2 = 1.2$ and $s_3 = 2.5$, and the walking speed of the picker is set to 1.2 m/s.

When calculating, we set population size $N = 50$, iteration number $j = 250$, crossover probability $pc = 0.8$, inertia weight $w = 0.8$, self-learning factor $c_1 = 0.5$, group learning factor $c_2 = 0.5$, fitness variance threshold $C = 10$, storage location parameter limitation $limit = [1, a \times b \times c]$, and initial search space $vlimit = [-100,100]$.

B. *The Multiobjective Weight Setting*

In this research, we adopt the weight coefficient method to solve the multiobjective optimization model of storage location assignment and introduce objective function conflict analysis to set the weight.

For the multiobjective optimization model, there is usually a certain conflict between different objectives; that is, improving one target value may worsen another target value. In this research, we use the RS (rough sets) method to analyse the conflict between the three objective functions of the optimization model [27]. We preprocessed the order data of the KL e-commerce warehouse picking area in the first half of 2019 and randomly selected 30 items for the objective function conflict analysis experiment. The target conflict matrix shown in Table II was obtained.

TABLE II
OBJECTIVE FUNCTION CONFLICT MATRIX

	$f_1(X_i)$	$f_2(X_i)$	$f_3(X_i)$
$f_1(X_i)$	-		
$f_2(X_i)$	0.25	-	
$f_3(X_i)$	1	0.875	-

As seen from Table Ⅱ, the conflict between f_1 and f_2 is small, so the weight should be similar or equal. The conflict between f_3 and f_1, f_2 is large, so the weight setting of f_3 should be different from f_1 and f_2. There is a large difference in the average daily outbound frequency of items in the picking area of e-commerce warehouses, and it conforms to the long tail effect. In this case, placing items with high outbound frequency near the exit is particularly important to improve the overall picking efficiency. Therefore, a high weight is given to f_1 in solving the multiobjective optimization of the KL e-commerce example.

According to the conflict analysis among objective functions and the status analysis of the e-commerce warehouse picking area, the weights of f_1, f_2 and f_3 are set to 3, 2.5, and 1, respectively. The multiobjective optimization function is converted into a single objective optimization function:

$$\min f = \min(f_1, f_2, f_3) = \min(3f_1 + 2.5f_2 + f_3) \tag{32}$$

C. *Small Sample Algorithm Effect Analysis*

Extracting 30 item samples from the KL e-commerce warehouse, we use the IGPSO algorithm, genetic algorithm and particle swarm optimization algorithm to solve the storage location optimization model and use MATLAB 2018A for programming. The convergence effect of these three algorithms in the solving process is shown in Fig. 4.

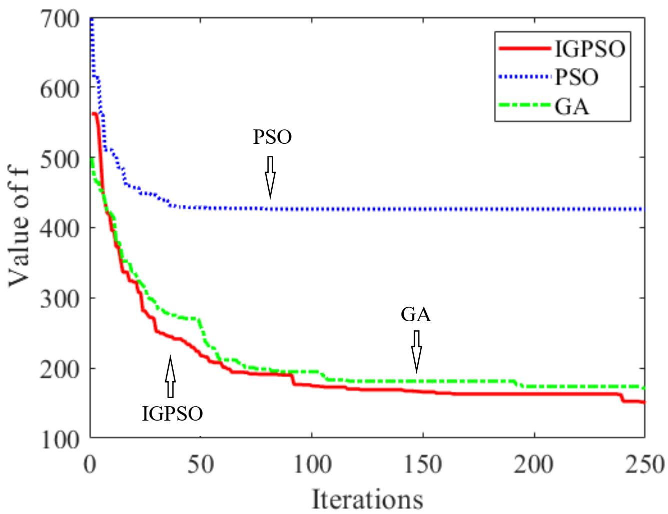

Fig. 4. Convergence effect of three algorithms and comparison of solution results.

As shown in Fig. 4, after 250 iterations, we use the IGPSO algorithm to find the optimal value. The PSO algorithm converges early, but the final convergence value is much larger than that of the GA and IGPSO algorithms. The GA starts to converge to the optimal value after approximately 195 generations, while the IGPSO algorithm converges to the optimal value after approximately 165 generations, and the obtained value is the best of the three algorithms.

D. *Large Sample Storage Location Optimization Calculation*

In this study, we collected data for more than 3.6 million orders from the KL e-commerce warehouse in the first half of 2019 as sample data and used the IGPSO algorithm validated by a small sample to solve the storage location optimization model. The solving process of the model is shown in Fig. 5. Fig. 5 shows that the algorithm converges to the optimal value in approximately 245 generations.

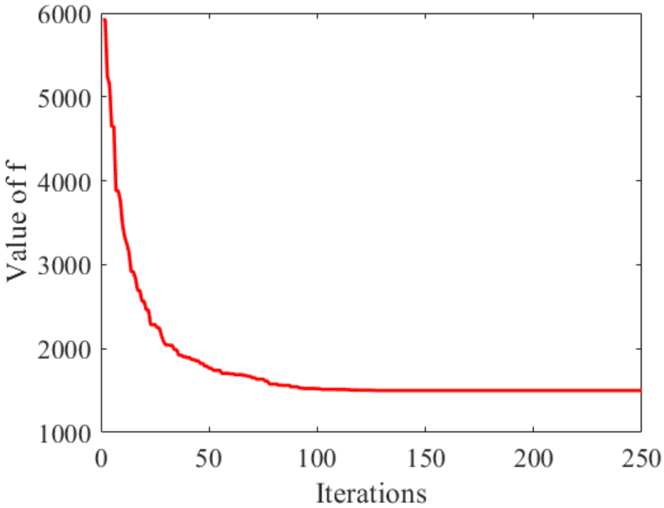

Fig. 5. Optimization process of the storage location solution result.

The optimal storage location-item allocation results are shown in Fig. 6, in which 1~3 items are allocated to one storage location. Further statistics show that among the 1872 storage locations, 1212 storage locations are allocated to only one item, 509 storage locations are allocated two items, and 151 storage locations are allocated to three items. All 2683 items are assigned to storage locations.

E. Storage Location Optimization Effect Analysis

We use the order data of a typical day and a peak promotion day of the KL e-commerce warehouse in 2019 to analyse the effect of location optimization. The order quantity of a typical day is 21,264, and it is added to 87,277 on a peak promotion day. The order quantity of a peak promotion day is 4.10 times the value of a typical day. There are obvious fluctuations between them, which is also one of the most obvious characteristics of e-commerce warehouses.

Optimization effect of typical day

It takes some time from the order arriving at the warehouse to the picking completion. The longest such time among them is called the maximum order response time, which is an important indicator affecting the customer service level. If the order is not responded to for a long time after arrival, the subsequent operation of the order will be greatly affected. Fig. 7 shows the storage location optimization effect on the maximum order response time on a typical day. Under the existing picking operation mode, the maximum order response time is 2.01 h before the location optimization and 1.93 h after the optimization, and the optimization rate is 3.98%. Another valuable finding is that the number of picking posts has a great influence on the maximum order response time. Before the storage location optimization, when the number of picking posts is reduced by 1 to 5, the maximum order response time is approximately doubled. At the same time, when the number of picking posts decreases to 4 or 3, the maximum order response time increases to 11.68 h or 23.42 h. However, when the number of picking posts increases from 6 to 9, the maximum order response time decreases from 2.01 h to 1.58 h, and the impact range is relatively small. Therefore, from this indicator, the existing arrangement of 6 picking posts is a relatively reasonable. After the storage location optimization, the effect of the number of picking posts on the maximum order response time is similar to that before the optimization. When the number of picking posts is between 3 and 9, the maximum order response time is reduced by 25.94% on average after the optimization, and the optimization effect is obvious.

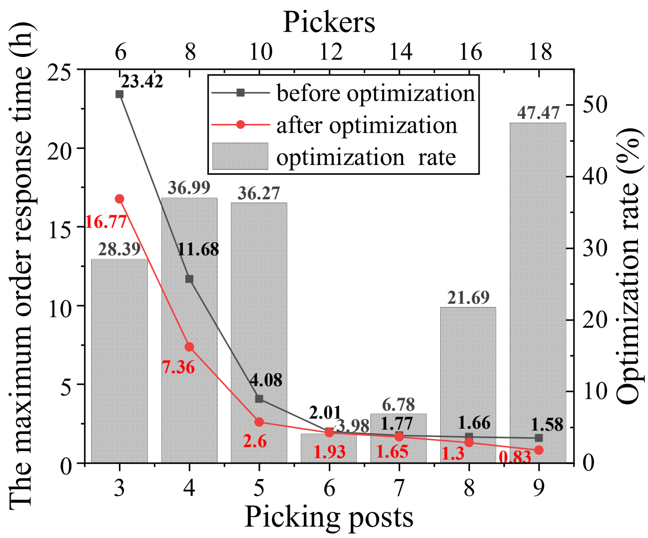

Fig. 7. Typical day storage location optimization effect on the maximum order response time.

The average order response time for a calculation period is the average time between when an order arrives at the warehouse and when it is picked. This indicator can well measure the overall efficiency level of the warehouse in order picking. Fig. 8 shows the storage location optimization effect on the average order response time on a typical day. According to the existing posts in the warehouse and the batch picking strategy, the average order response time is

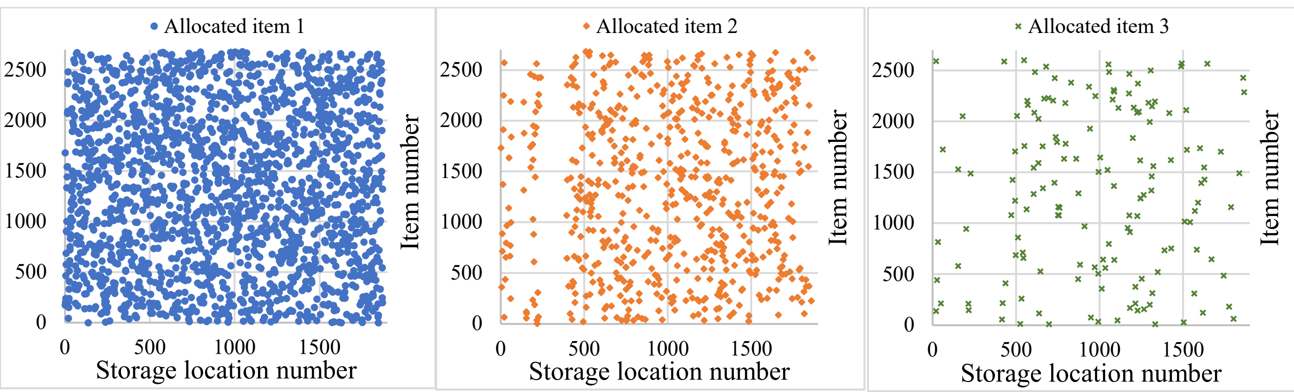

Fig. 6. Figure of storage location-items after optimization.

0.28 h, which is reduced to 0.24 h after the optimization, and the optimization rate is 14.29%. The number of picking posts has a great influence on the average order response time before and after the optimization. The lower the number of picking posts is, the greater the influence. When the number of posts is reduced from 6 to 5, the average response time before and after storage location optimization is increased to 0.90 h and 0.78 h, respectively. When the number of posts is reduced to 3, the average response time before and after storage location optimization is substantially increased to 6.20 h and 5.46 h, respectively. However, when the number of picking posts is increased to 9, the average response time before and after storage location optimization is reduced to 0.12 h and 0.10 h, respectively, which is a limited reduction. Therefore, from the perspective of the average order response time, the existing 6 posts are also a relatively reasonable arrangement. When the number of picking posts is between 3 and 9, the average order response time after the optimization is decreased by an average of 14.05% compared to that before the optimization.

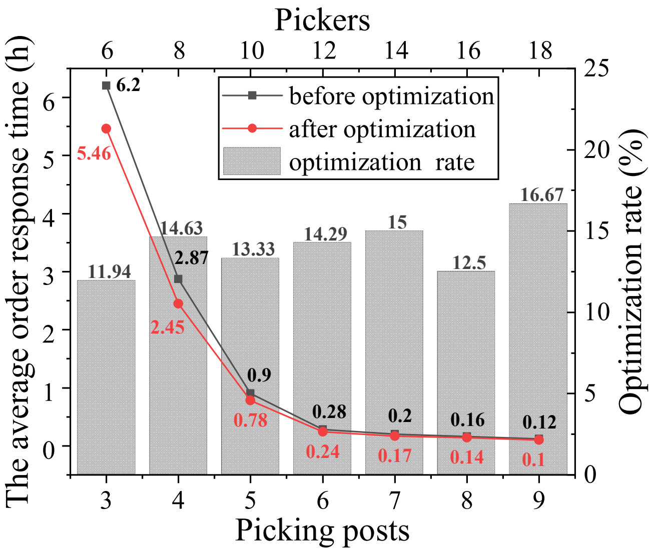

Fig. 8. Typical day storage location optimization effect on the average order response time.

The actual picking time is the average working time required by the two-shift staff to complete the picking of all orders arriving at the warehouse on a natural day. With the increasing labour costs and the study of ergonomics, the demand for pickers has become an increasingly important concern in warehouse operations. Many scholars have studied how to reduce the workload of pickers by improving warehousing operations, such as changing storage and picking methods [28],[29], optimizing layout and storage location assignment [30],[31].

Fig. 9 shows the storage location optimization effect on the actual picking time on a typical day. According to the existing picking posts in the warehouse and the batch picking strategy, before the storage location optimization, the actual working time of a single picking post under the two-shift system is 18.49 h. After the storage location optimization, the actual working time of a single picking post is reduced to 16.05 h, which is a reduction of 13.20%. It is conducive to improving picker well-being and job satisfaction. When the number of picking posts is between 3 and 9, the actual working time of a single picking post is reduced by 13.02% on average after storage location optimization, and the optimization effect is satisfactory.

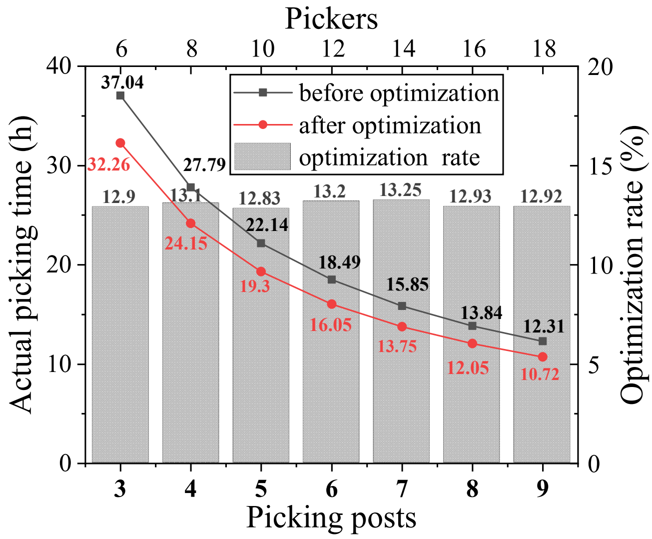

Fig. 9. Typical day storage location optimization effect on the actual picking time.

The picker's daily walking distance is the average walking distance of all pickers in the warehouse to complete the picking of all orders on a normal day. It is one of the important indicators reflecting the labour intensity of pickers. Fig. 10 shows the storage location optimization effect on the picker's daily walking distance on a typical day. According to the existing picking posts in the warehouse and the batch picking strategy, before and after the storage location optimization, the average daily walking distance of pickers is 17.86 km and 15.87 km, respectively, and the optimization rate is 11.13%. When the number of pickers varies from 6 to 18, the average daily walking distance of pickers is between 35.83 km and 11.94 km before the storage location optimization, and between 31.78 km and 10.57 km after the optimization, the average optimization rate is 11.22%.

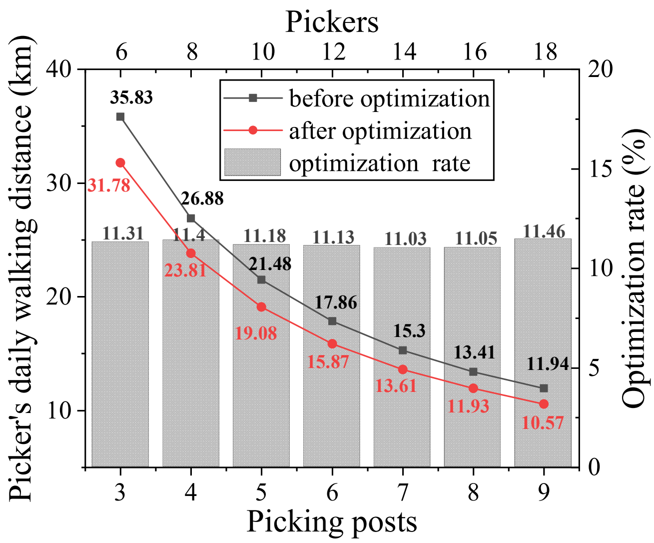

Fig. 10. Typical day storage location optimization effect on the picker's daily walking distance.

Optimization effect of peak day

The order quantity of peak days is significantly increased compared with that of typical days. With the frequent appearance of online shopping festivals, the increase in the number of peak days makes the research on peak days very meaningful. In a picker-to-parts warehouse, increasing the pickers is the main way to deal with peak demand. This part will compare the change in key picking indicators before and after optimization of the peak day, find the number of picking posts to make the key picking indicators achieve the same level of the typical day, and determine the influence of changing the number of picking posts on the picking indicators.

In Table III, from the perspective of the maximum order response time, to reach the target requirement of 2 h of typical days, 23 picking posts and 46 pickers should be configured before and after the storage location optimization. This number is 3.83 times that of typical days. If the maximum order response time is increased to less than 4 h, the number of picking posts before and after the storage location optimization is 21 and 20, respectively. If the maximum order response time is increased to less than 24 h, the number of picking posts before and after the storage location optimization is 11 and 10, respectively. Combined with the practice of the e-commerce retail enterprise, the number of picking posts can be chosen between 10 and 23 on peak days. Within this range, the maximum order response time after the storage location optimization is reduced by 8.62% on average compared with that before optimization.

TABLE III
SUMMARY TABLE OF PEAK DAY STORAGE LOCATION OPTIMIZATION EFFECT ON THE MAXIMUM ORDER RESPONSE TIME

Picking posts	Pickers	Before optimization	After optimization	Optimization rate (%)
6	12	51.79	48.62	6.12
7	14	41.82	41.2	1.48
8	16	35.89	34.88	2.81
9	18	29.79	28.7	3.66
10	**20**	**24.64**	**22.92**	**6.98**
11	**22**	**20.5**	**19.78**	**3.51**
12	24	18.95	18.63	1.69
13	26	14.83	14.59	1.62
14	28	15.24	13.08	14.17
15	30	12.55	12.03	4.14
16	32	11.28	10.82	4.08
17	34	9.06	8.62	4.86
18	36	6.84	6.23	8.92
19	38	5.78	5.34	7.61
20	**40**	**4.3**	**3.97**	**7.67**
21	**42**	**3.59**	**3.21**	**10.58**
22	44	2.75	2.36	14.18
23	46	1.99	1.38	30.65
24	48	1.45	1.21	16.55
25	50	1.18	0.97	17.8
Average				**8.46**

In Table IV, from the perspective of the average order response time, to meet the requirement of the typical daily average response time of 0.28 h, 25 picking posts and 50 pickers should be configured before and after the storage location optimization. The number of pickers is 4.17 times that of 12 pickers on a typical day, which is close to the growth rate of 4.10 times the order quantity. In practice, the average order response time of 1.0 h is still a good service level; in this situation, 20 picking posts are needed before and after the storage location optimization, and the average order response time after the storage location optimization is reduced by 5.43% compared with that before optimization. When the number of picking posts is decreased to 10, the average order response time before and after the optimization is 7.74 h and 7.35 h, respectively, and the optimization rate is 5.04%. When the number of picking posts varies between 10 and 23, the average order response time after the optimization is reduced by 4.80% on average compared with that before the optimization.

TABLE IV
SUMMARY TABLE OF PEAK DAY STORAGE LOCATION OPTIMIZATION EFFECT ON THE AVERAGE ORDER RESPONSE TIME

Picking posts	Pickers	Before optimization	After optimization	Optimization rate (%)
6	12	18.64	17.44	6.44
7	14	14	13.34	4.71
8	16	11.33	10.72	5.38
9	18	9.29	8.98	3.34
10	**20**	**7.74**	**7.35**	**5.04**
11	22	6.41	6.05	5.62
12	24	5.37	5.01	6.7
13	26	4.46	4.22	5.38
14	28	3.69	3.55	3.79
15	30	3.05	2.96	2.95
16	32	2.5	2.41	3.6
17	34	2	1.9	5
18	36	1.59	1.53	3.77
19	38	1.26	1.19	5.56
20	40	0.92	0.87	5.43
21	42	0.71	0.67	5.63
22	44	0.54	0.52	3.7
23	46	0.4	0.38	5
24	48	0.31	0.3	3.23
25	50	0.25	0.24	4
Average				**4.71**

In Table V, from the perspective of the actual picking time of orders, to reach the target requirement of 18.49 h actual picking time on typical days, 20 picking posts and 40 pickers should be configured before and after the storage location optimization. The number of pickers is 3.67 times that of 12 pickers on a typical day. In addition, optimization rate of the actual picking time on the peak day ranges from 2.38% to 3.36%, with an average optimization rate of 3.08%. It can be found that with the increase of picking posts between 7-24, optimization effect on the actual picking time has no significant change, which is about 3%. Combined with the practice of the e-commerce retail enterprise, before the peak day comes, warehouse managers can effectively shorten the actual order picking time by recruiting temporary pickers.

TABLE V
SUMMARY TABLE OF PEAK DAY STORAGE LOCATION OPTIMIZATION EFFECT ON THE ACTUAL PICKING TIME

Picking posts	Pickers	Before optimization	After optimization	Optimization rate (%)
6	12	62.27	60.51	2.83
7	14	53.41	51.78	3.05
8	16	46.77	45.29	3.16
9	18	41.52	40.23	3.11
10	20	37.05	36.17	2.38
11	22	33.78	32.85	2.75
12	24	30.93	30.08	2.75
13	26	28.63	27.69	3.28
14	28	26.57	25.68	3.35
15	30	24.73	23.94	3.19
16	32	23.18	22.39	3.41
17	34	21.77	21.04	3.35
18	36	20.48	19.85	3.08
19	38	19.39	18.79	3.09
20	**40**	**18.42**	**17.83**	**3.2**
21	42	17.55	16.96	3.36
22	44	16.72	16.16	3.35
23	46	15.98	15.45	3.32
24	48	15.26	14.79	3.08
25	50	14.53	14.18	2.41
Average				**3.08**

TABLE VI
SUMMARY TABLE OF PEAK DAY STORAGE LOCATION OPTIMIZATION EFFECT ON THE PICKER'S DAILY WALKING DISTANCE

Picking posts	Pickers	Before optimization	After optimization	Optimization rate (%)
6	12	72.39	68	6.07
7	14	61.98	58.28	5.97
8	16	54.21	51	5.93
9	18	48.14	45.34	5.82
10	20	43.47	40.8	6.13
11	22	39.46	37.09	5.99
12	24	36.15	34	5.94
13	26	33.42	31.38	6.09
14	28	31.03	29.15	6.07
15	30	28.95	27.2	6.04
16	32	27.18	25.5	6.19
17	34	25.53	24	6.01
18	36	24.14	22.67	6.12
19	38	22.92	21.47	6.31
20	40	21.78	20.4	6.33
21	42	20.97	19.43	7.36
22	44	20.01	18.55	7.33
23	46	19.11	17.74	7.16
24	48	18.34	17	7.34
25	50	17.35	16.32	5.92
Average				**6.3**

In Table VI, from the perspective of the picker's daily walking distance, under the existing picking strategy of warehouse, the average daily walking distance of pickers is 17.86 km on a typical day. Before and after the storage location optimization, 50 pickers and 44 pickers need to be configured, respectively, reflecting a 12% decrease after optimization. The increase in the picker's daily walking distance by approximately 20% is within the acceptable labour intensity range of pickers; that is, the daily walking distance is approximately 21.4 km. Before and after the storage location optimization, 42 and 38 pickers need to be allocated, respectively, reflecting a 9.5% decrease after optimization. When the number of picking posts varies from 10 to 23, the picker's average daily walking distance is between 43.47 km and 19.11 km before the storage location optimization and between 40.80 km and 17.74 km after the optimization, resulting in an average optimization rate of 6.30%.

Comparison of optimization effect between typical day and peak day

Based on the above results, we summarize the optimization rates of the four indicators on typical day and peak day. It can be seen from Table VII that the optimization rate of the maximum order response time on a typical day and peak day is 25.94% and 8.46% on average, respectively. Meanwhile, the optimization rate of the average order response time is 14.05% on a typical day and 4.71% on a typical day, respectively. The average optimization rates of the actual operation time of picking posts are 13.02% and 3.08%, respectively. The optimization rates of the picker's daily walking distance are 11.22% and 6.30%, respectively. The key indicators of the typical day and the peak day have achieved obvious optimization effects, and the effects of the typical day are better than those of the peak day. This is mainly because the data are half a year, most of which are regular sales days, and the characteristics, such as delivery frequency and correlation, are more closely matched with the conditions of the typical day, resulting in a relatively better optimization effect. In the future, we can try to collect more data on peak sale days for storage location optimization and make more in-depth discovery.

In horizontal comparison, the optimization rate of the maximum order response time is significantly higher than that of other indicators in the four indicators, whether it is a typical day or a peak day, so the model has the best optimization effect on the maximum order response time. This shows that the model in this paper can effectively shorten the maximum order response time, and well average the processing time of orders. Therefore, this research solves the actual problem that orders are not responded to for a long time.

TABLE VII
TABLE OF OPTIMIZATION RATE RESULTS OF FOUR INDICATORS ON TYPICAL DAY AND PEAK DAY (%)

	The maximum order response time	The average order response time	The actual picking time	The picker's daily walking distance
Typical day	25.94	14.05	13.02	11.22
Peak day	8.46	4.71	3.08	6.30

V. Conclusion Remarks

For manual picking zones in e-commerce, this paper establishes a multiobjective storage location optimization model to improve picking efficiency. Through the model construction and example analysis, we obtain the following conclusions.

First, based on the principle of high delivery frequency priority, the correlation principle and the principle of larger volume priority, we establish the multiobjective storage location optimization model. The principle of priority of large volumes is innovatively introduced to storage location optimization, and the problem of storing several items in one storage location is well solved. Furthermore, we scientifically determine the weight of the target combined with the multiobjective conflict method and use the IGPSO algorithm to solve the model. The analysis results of the small sample algorithm show that the IGPSO algorithm is better than the GA and PSO algorithms.

Second, we collected data for more than 3.6 million orders from the KL e-commerce warehouse in the first half of 2019 to optimize the large sample of storage location calculations and drew the optimized storage location assignment results. The results show that the maximum order response time, average response time, actual picking time and picker's daily walking distance on typical and peak days improve significantly from optimization, and the optimization improvement on a typical day is better than that on a peak day.

Third, combined with the existing random assignment strategy, this storage location optimization model can be easily applied to enterprise practice. For example, before the demand changes or peak days, the number of pickers can be scientifically determined in advance according to the forecast order information, the maximum order response time and other service indicators. Also, warehouse management personnel can adjust and optimize the storage location according to the results of storage location optimization, so as to better deal with the changes of orders.

The model proposed in this study effectively solves the storage location optimization problem and has good applicability to the picker-to-parts warehouse of similar e-commerce enterprises. In the future, the following areas can be further explored:

First, this paper is still limited to static storage location assignment, and the model can be extended to dynamic storage location optimization in the future. With the increasing fluctuation of orders, dynamic optimization can be continuously carried out in subsequent research. Dynamic cycle optimization of order data with shorter cycle (weekly, monthly) to better optimize the storage location so that the model can be better applied to the retail e-commerce practice of frequent increases in new items.

Second, there are more and more literatures that are not limited to the research and optimization of a certain process of warehousing operation, but focus on different combination optimization of storage location assignment, order batching, batch assignment and pickers routing to achieve higher warehousing operation efficiency. Scholars can establish a two-stage combination optimization model of storage location assignment and order picking to provide comprehensive solutions for the warehousing and logistics management of retail e-commerce.

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