Biobjective Optimization for Online Order Batching and Batch Assignment with Multiple Pickers in Retail E-commerce Warehouses

Yanchun Wan, Shudi Wang and Yujun Hu

Abstract—**Online order picking has become one of the key issues for ensuring the service level of modern retail e-commerce. This paper studies the online order batching and batch assignment problem (OOBBAP) with multiple pickers of picker-to-parts warehouses. First, we establish a biobjective optimization model that minimises the total picking time and order response time. Then, an online order batching algorithm embedded with the sequencing algorithm and optimal path algorithm is designed to solve the model. Finally, we use retail e-commerce from China with data on 87,277 orders of an online shopping festival to examine the optimization results of the model. The optimization results of the key indicators are satisfactory. The optimization rates of the maximum order response time, average order response time, total picking time, average picking time of picking posts, picker total walking distance and average walking distance are between 7.45% and 30.20%. The model demonstrates an excellent ability to solve the OOBBAP in multiple picker warehouses, which can provide a reference solution for similar picking problems in picker-to-parts retail e-commerce warehouses.**

Index Terms—**online order batching, batch assignment, variable neighbourhood search, picker-to-parts warehouses.**

I. INTRODUCTION

IN recent years, with the rapid development and wide application of the mobile internet, retail e-commerce has risen rapidly. With its features of convenient browsing, complete categories and fast distribution, online shopping has become one of the mainstream consumption channels in many countries. The COVID-19 epidemic has also promoted the development of retail e-commerce further. For example, China's online retail sales increased by 14.8% year-overyear to 9.8 trillion RMB, reaching 24.9% of retail sales in 2020 (Ministry of Commerce of the People's Republic of China 2021).

A fast and reliable order lead time has a crucial influence on purchasing decisions [1]. To shorten customer order completion time, the warehouse needs to respond to orders quickly and shorten the warehousing operation time, which is largely determined by the picking time. Picking refers to the process of removing the goods from the storage locations, such as removing items from stacks or shelves, to the designated location according to the product items and quantity specified by the customer's order. The picking process concentrates 60% of warehouse operating time [2] and 50-75% of operating costs [3]. Therefore, picking system optimization is a hot topic in high-frequency and multi-Item e-commerce warehouses.

For strategic purposes, warehouses are divided into manual and automated warehouses. Correspondingly, there are two main types of picking systems: parts-to-picker systems and picker-to-parts systems, which are widely used in practice [4]. For automatic warehouses, some studies focus on the design of automatic order fulfillment systems [5]. However, in China, manual warehouses still account for the majority, so research on manual warehouses is of great importance. In operation, research on order picking focuses on order batching, batch assignment and picker routing [6],[7]. Order batching refers to collecting multiple orders into a batch for picking. The purpose of order batching is to shorten the picker's average walking distance and working time and then improve picking efficiency as a result [8].

Order batching is divided into offline and online order batching according to whether orders are known accurately before batching. Most of the existing order batching studies focus on offline batching [9]-[11]. However, before the order arrives at the retail e-commerce warehouse, the order placing time, item and quantity are all unknown. Retail e-commerce warehouses need to respond to order requirements quickly, which is becoming increasingly shorter in practice. Therefore, integrated research on online order batching and picking operations is a research trend [12].

To meet the demands of numerous unpredictable orders in modern retail e-commerce companies, especially on promotion days, this research conducts a systematic study on OOBBAP in picker-to-parts warehouses. Furthermore, we

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consider both internal operation efficiency and external service requirements, which help to make more comprehensive decisions on picking operations. Finally, we design algorithms suitable for solving the model under the condition of large samples.

The rest of the paper is organised as follows. In Section II, we review research advancements on picking operations. In Section III, we describe constructing a biobjective optimization model to solve OOBBAP with multiple pickers. In Section IV, we discuss designing an algorithm considering the time window strategy, order batching strategy, and batch assignment strategy to calculate the optimization decision. In Section V, we use the order data of a real retail e-commerce warehouse to verify the optimization results. Finally, we summarise the research and propose some future research directions.

II. Literature Review

Picking operations study decision-making of the batching method, picking sequence, travel route, batch assignment, etc., to minimise travel distance or picking time. From the scope of the study, picking operations include single order batching research or integrating one or more picking processes, such as order batching and batch assignment, order batching, and routing optimization. Order batching research is generally divided into online (dynamic) batching and offline (static) batching. In the offline state, the order information is known in advance, and the research determines which batch the order is divided into. In contrast, the order information is updated dynamically in online batching. Offline order batching is still the mainstream of the field, and online order batching and picking integration will be the trend in the future [12].

Offline order batching and related problems have been studied widely. In recent years, offline order batching research has been continuously improved on traditional heuristic algorithms. Hong and Kim [10] proposed an order batching model with the S-shape routing method, and a large-scale heuristic algorithm was used to obtain the near optimal solution. Many scholars study the combinatorial problem of order batching and picker routing. Valle et al. [13] studied it by introducing effective inequalities to establish models and then used heuristic algorithms to solve them with large order samples. Li et al. [14] used the similarity coefficient and further optimised it with ant colony optimization combined with local search to achieve optimization. Ardjmand et al. [11] compared three algorithms, including the list-based simulated annealing (LBSA) algorithm, the genetic algorithm (GA), and the GA-LBSA algorithm, to solve the batching and routing optimization model. Experiments showed that the LBSA algorithm can obtain a better solution for the small-scale order batching problem, but the GA and GA-LBSA algorithms are better at improving the calculation speed. The variable neighbourhood search (VNS) algorithm shows its own advantages in solving the maximum minimisation problem, and it has been adopted by many scholars in picking operation optimization. For example, Menéndez et al. [15] proposed several optimization algorithms based on the VNS in picking batching optimization and proved that the two-stage VNS algorithm is better than the existing optimal algorithm. In joint research on storage location optimization and order batching, Xiang et al. [16] proposed a heuristic algorithm for order batching. The algorithm takes maximising order correlation or minimising order alienation as the initialisation goal, and they improved it by using the VNS algorithm. Silva et al. [17] comprehensively considered the storage and order batching problems in four special cases and proposed a general VNS algorithm, which is effective for small samples.

Offline order picking assumes that all order information is known in advance, but it is not suitable for a real situation. In the retail e-commerce environment, numerous unpredictable orders fluctuate and need to be responded to in time. Some scholars have studied online order picking optimization problems under different time window strategies, batching strategies and order sizes. Early studies of online order batching were mainly about the problem with one picker. For example, Chew and Tang [18] modelled the order picking system as a queuing system where customers need to combine services, derived the expected function of total picking time, and discussed the impact of batch size and results on delivery tardiness. Based on the queuing theory, Le-Duc and Koster [19] built a model with minimising picking time and performed random order experiments to obtain the optimal batch size. In practice, an online order picking system is operated by multiple pickers simultaneously. Therefore, it is critical to consider order batching and order assignment simultaneously. Gil-Borrás et al. [20] simulated an online order picking system with two pickers and proved that it is better by using a variable neighbourhood search algorithm rather than a seed algorithm for order batching optimization. Chen et al. [21] proposed a Green-area algorithm for online order batching. Once a new order arrives, the system allocates the picking task according to the green area of each picker's upcoming picking area and updates the picker's route in real-time. Gil-Borrás et al. [22] proposed a combination method of a heuristic hybrid algorithm and VNS to solve online order batching and assignment with multiple pickers. For the frequently arrived B2B e-commerce order problem, Leung et al. [23] proposed an integrated online order batching approach under a fixed and variable time window batching strategy. To minimise the total tardiness, Lin et al. [9] studied the joint order batching and picker Manhattan routing problem using a particle swarm optimization algorithm. To minimise the turnover time, Zhang et al. [24] designed online batching algorithms with multiple pickers based on the fixed time window strategy. Scholz et al. [25] proposed a method considering order batching, batch assignment, sequencing, and picker routing problems and simultaneously used the corresponding mathematical model to solve small instances and proposed a variable neighbourhood descent algorithm to solve large samples.

Whether it was online or offline order batching and order assignment, most scholars generally carried out single-objective optimization research. In offline order batching studies, the minimisation of the travelled distance is a common optimization goal [9]-[11]. Minimisation of costs has gradually become a new research direction. For example, Attari [26] used minimisation of the trans-shipment cost as the objective function to establish a model. Silva [17] used the minimisation of total routing cost as an optimization goal. The time factor is more important in online order batching and batch assignment research, so this kind of research mainly focuses on the optimization of time, such as minimising the total completion time [24],[27] and minimising the maximum completion time of customer orders [28],[29]. In recent years, scholars have begun to establish biobjective or multiobjective models to solve online order batching and assignment problems. For example, Gil-Borrás et al. [30] established a biobjective optimization model that minimises the maximum order completion time and minimises the order turnover time in an order batch study. Gil-Borrás et al. [22] established an optimization model of three objectives, which optimise the batch picking time, completion time, and workload balance.

At present, with the rapid development of retail e-commerce, the number of orders increases exponentially, especially at "online shopping festivals." The order quantity of retail of e-commerce exceeds 10,000, but the number of samples used in most papers is much smaller. Cergibozan and Tasan [12] summarised 40 papers related to order batching and found that only one paper’s sample size was more than 10,000.

The study of online order batching and integration assignment and routing is a trend in picking systems. In research on picking operations, the total picking time of all orders mainly reflects the internal picking efficiency, and the order response time is an important aspect of the customer service level. Whether offline or online, most scholars have only considered one aspect. This paper reviews the online order batching and batch assignment problem (OOBBAP) with multiple pickers in an innovative method, which integrates optimization of external customer response time and internal operation efficiency.

III. Model Building

In this section, we describe the research problem first, and then a biobjective model on OOBBAP with multiple pickers is established.

A. Problem Description

We build the model based on the F warehouse of the K e-commerce platform, a full-category self-retail e-commerce platform in China. The F warehouse is a cosmetic and health care warehouse of this platform responsible for order distribution in Guangdong, Guangxi, Jiangxi, and Hainan provinces. At present, the warehouse has a total of 2,683 SKU items, with an average daily order volume of more than 20,000.

Some light shelves are arranged in the picking zone of the F warehouse. The layout diagram of the picking zone is shown in Figure 1. It is a double zone picking area composed of three parallel horizontal channels and thirteen longitudinal channels, with a total of four layers. Each longitudinal channel has two columns of shelves on the left and right, and each column has 18 rows, with a total of 1872 storage locations. The width, depth, and height of each space are 0.5 metres, the width of the longitudinal channel is 1.2 metres, and that of the horizontal channel is 2.5 metres. There is only one entrance in the picking zone, which is in front of the leftmost passageway.

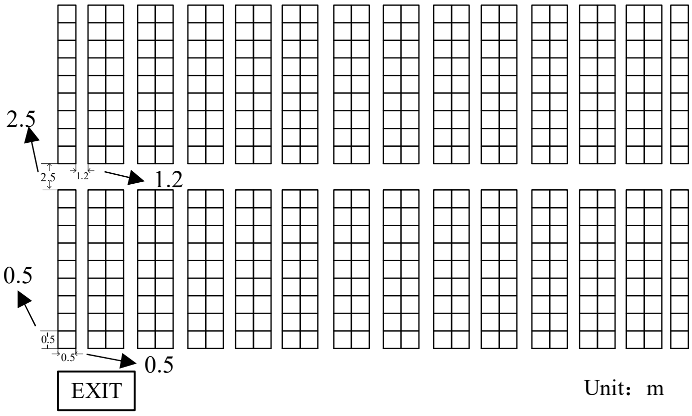

Fig. 1. Layout diagram of the picking zone of the F warehouse

The flow chart of online order batching and batch assignment is shown in Figure 2. In the F warehouse, the orders of the warehouse arrive online. After the orders arrive, they must go through three processes: order batching, batch assignment, and picking execution. Specifically, after arriving, the orders are first combined through certain rules and divided into different batches for picking. After the batches are decided, different batches are assigned to the pickers, and the pickers then go to the corresponding picking area to carry out the picking work.

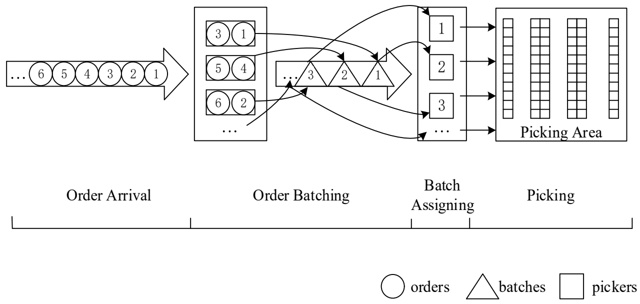

Fig. 2. Flowchart of online order batching and batch assignment

To highlight the main problems, this paper proposes the following assumptions for the model.

1) All order information is unknown until it arrives at the warehouse.
2) Each order contains at least one item and is only allowed to assign a batch.
3) Each batch contains the same number of orders.
4) Multiple order picker posts are set up to carry out the picking operations simultaneously. Each batch can only be assigned to one picker, and each picker can only pick one order at the same time. Each picker can only start picking a new batch after finishing the previous one.
5) All pickers walk at the same speed and spend the same amount of time picking up an item, regardless of the number of items needed to be picked.
6) There is sufficient inventory in the storage location, and the shortage of inventory is not considered.
7) Pickers use an optimal strategy to schedule the picking routes.

B. Model Building

To create the model, the following notations are used.

TABLE I
PARAMETERS AND VARIABLES

Symbol	Parameter description
I	order set, I = {1,2,3, ..., i}
J	batch set, J = {1,2,3, ..., j}
J'	set of all order batches before the jth batch, $J' \in \{j' \mid j' = j-1, j \in J\}$
P	set of pickers working at the same time, P = {1,2,3, ..., p}
C	the capacity of an order batch
v	the walking speed of the picker
t_{pick}	the unit time for a picker to pick up a kind of item
T_i^{arrive}	the arrival time of the order i at the warehouse
T_i^{finish}	the picking completion time of order i
T_j^{start}	the picking start time of batch j
T_j^{finish}	the picking completion time of batch j
T_j^{ready}	the time when the batch j was formed
k_j	the number of different kinds of items in batch j
s_j	total walking distance of batch j
x_{ij}	1 if order i is assigned to batch j, otherwise 0
y_{jp}	1 if batch j is assigned to picker p, otherwise 0
t_j^{rest}	the rest time of the picker before picking batch j, that is, the time between the picker completing the previous batch to batch j picking
$t_j^{service}$	the time required for picking of batch j
$t_i^{response}$	the response time of order i, that is, the time between its arrival to completion picking

We consider two objectives, that is, improving picking efficiency and order response speed. The first objective function is established as follows:

$$\min\left[\max_{p\in P}\sum_{j\in J} y_{jp}(t_j^{rest}+t_j^{service})\right] \tag{1}$$

Objective function (1) is for completing order picking in less time. In a multiple picker warehouse, the total service time of picking depends on when the last picker completes all his picking tasks. The total service time of the picker's picking time consists of the sum of the time required for picking all batches assigned to the picker and the rest time the picker obtains before they start picking the next batch. Let represent the decision variable of whether batch j is assigned to picker p.

The second objective function is established as follows:

$$\min\left[\max_{i\in I}(t_i^{response})\right] \tag{2}$$

Objection function (2) means that to improve the order response speed, the longest order response time should be minimised. To better focus on order batching, this paper defines the order response time as the time between the order's arrival at the warehouse and its completion.

The constraints (3)-(9) of the model are as follows:

$$s.t. \quad \sum_{i\in I} x_{ij} = C, \sum_{j\in J} x_{ij} = 1, \sum_{p\in P} y_{jp} = 1 \tag{3}$$

$$T_i^{arrive} \le \max(x_{ij}T_j^{ready}) \le \max(x_{ij}T_j^{start}) < \max(x_{ij}T_j^{finish}) \tag{4}$$

$$t_i^{response} = T_i^{finish} - T_i^{arrive} \tag{5}$$

$$T_i^{finish} = \max(x_{ij}T_j^{finish}) \tag{6}$$

$$T_j^{finish} = T_j^{start} + t_j^{service} \tag{7}$$

$$T_j^{start} = t_j^{rest} + \min_{p\in P}\sum_{j'\in J'} y_{j'p}(t_{j'}^{rest} + t_{j'}^{service}) + T_1^{arrive} \tag{8}$$

$$T_j^{ready} \geq \max(T_i^{arrive} x_{ij}) \tag{9}$$

$$T_j^{rest} = \begin{cases} 0, & T_j^{ready} < \min_{p\in P} \sum_{j'\in J'} y_{j'p}(t_{j'}^{rest} + t_{j'}^{service}) + T_1^{arrive} \\ T_j^{ready} - \min_{p\in P} \sum_{j'\in J'} y_{j'p}(t_{j'}^{rest} + t_{j'}^{service}) - T_1^{arrive}, & T_j^{ready} \geq \min_{p\in P} \sum_{j'\in J'} y_{j'p}(t_{j'}^{rest} + t_{j'}^{service}) + T_1^{arrive} \end{cases} \tag{10}$$

Objective function (3) means that every order can only be assigned to one batch, and the upper limit of the order quantity of an order batch cannot exceed C. An order batch can only be assigned to one picker in each work shift. Function (4) indicates that the time when batch j is formed cannot be earlier than the arrival time of the last order of this batch. The picking start time of batch j cannot be earlier than the time when it is formed and should be earlier than the picking completion time of batch j. Function (5) indicates that the order response time defined in this paper is the time between the order arriving at the warehouse and picking completion. Function (6) indicates that the picking completion time of each order is the picking completion time of its assignment batch, and (7) indicates that the picking completion time of each assignment batch is equal to the picking start time of the batch plus the picking service time required for the batch. Objective function (8) indicates that each order batch will be assigned to the picker who has completed all his previous picking tasks first. The picking start time of this batch is equal to the picking completion time of its last picking task plus the rest time (if it has) before picking this batch. Function (9) indicates that the time of completion of each order batch cannot be earlier than the arrival time of the latest order arriving at the warehouse in that batch.

If the picker post has not completed the previous picking task after a new order batch is assigned, there is no rest time before the next batch picking starts; otherwise, there is a rest time before the next batch picking starts, and the rest time is the time difference between the time when the next batch assigned is formed and the time when all previous picking tasks of this picker post are completed. Based on this, we establish constraint (10).

The time required for picking batch j is equal to the item picking time plus the total walking time of picking batch j:

$$t_j^{service} = t_j^{pick} + t_j^{travel} \tag{11}$$

The item picking time of batch j is equal to the number of types of items contained in batch j multiplied by the unit item picking time, and the range of k_j varies according to the actual order data:

$$t_j^{pick} = k_j t_{pick} \tag{12}$$

The walking time required for picking each order batch is the total walking distance required for picking it divided by the walking speed of the picker:

$$t_j^{travel} = \frac{S_j}{V} \tag{13}$$

IV. Algorithm Design

In the real e-commerce environment, the order information is not known in advance, and many orders arrive at the warehouse continuously, so the warehouse cannot wait until all orders arrive to calculate and batch them uniformly. Therefore, it is necessary to design an effective online algorithm to solve online order batching. The problems that need to be solved in this online algorithm are as follows:

1) When to start batching, that is, the time window strategy of batching.
2) How to batch, that is, the offline batch strategy of which type of picking batch the order is divided into in each time window.
3) Which picker is assigned to the divided order batches, that is, the assignment strategy of the order batches.

A. Time Window Strategy

The time window strategy of online order batching is usually divided into a fixed time window batch strategy and a variable time window batch strategy. If a fixed time window is used, there is a large difference between the peak and trough periods of the same length of the time window, which will cause an imbalance in the distribution of the workload. In the peak time, many orders will be generated in a time window, resulting in great picking pressure. If the variable time window is used in the trough period, it will need to wait for a longer time to reach a fixed batch. Some pickers will be idle, and the order response speed will be slower.

To make full use of the resources, when a picker returns to the idle state, if the order quantity in the time window does not reach the capacity of an order batch, it continues to wait for new orders to arrive at the warehouse until the orders reach the quantity required for a picking batch or the picking operation is directly carried out when the last customer order arrives at the warehouse.

Therefore, this paper sets up two decision points to divide the time window:

1) The last customer order arrives at the warehouse.
2) There is at least one idle picker in the warehouse, and unbatched orders reach the number of at least one order batch.

Whenever a decision point appears, at the end of the time window $[T_n^{begin}, T_n^{end}]$ where this decision point is located, the system batches all orders arriving within that time window. The end of one time window T_n^{end} is also the beginning of the next time window T_{n+1}^{begin} until a new decision point appears.

B. Order Batching Strategy

The batches of orders placed in each time window are equivalent to the batches of orders in the offline environment. Most offline batch studies are usually based on the goal of optimal overall efficiency or cost, and then the order batch problem is resolved by establishing an objective function with the least picking distance or picking time. Since each order batch is allocated to different pickers, the balance of the individual workload is not considered from the point of view of the overall cost, so it is easy to have a "bucket effect." That is, the operator who finally completes the picking task is the "short board," which determines the picking time of the whole operation. To minimise the picking time of each picker, the goal of minimising the maximum picking time can be used instead of the goal of minimising the total time, which can balance the workload among individuals, reduce the maximum picking time and improve the efficiency of the whole picking operation.

In this way, we can set up a function with the goal of minimising the completion time of the maximum order batch in the offline batch environment of each time window, and $\min[\max_{j\in J}\{T_j^{service}\}]$ assists in solving orders in batches under each time window. If there are orders with less than one order batch after completion in batches according to the principle, these orders will merge to the next time window for batching. To ensure the orders' response time, all orders can only be delayed in batches by one time window at most.

C. Batch Assignment Strategy

Most commonly used assignment strategies are first come first served (FCFS) and workload balance rules. To minimise the total picking time, the pickers who finish the picking work the earliest should be allowed to take on a longer picking task without considering the rest time of the pickers. At the same time, to ensure the response time of the order, the order batches arriving in the earlier time window should be picked first, and the order batches in the next time window can be picked only after the order batches in the previous time window are completed. The specific assignment strategy steps are as follows:

Step 1: All order batches that have been completed and not yet allocated in time window $[T_n^{begin}, T_n^{end}]$ are collected in set B_n, sorted in order from largest to smallest according to the picking time required for each order batch, and then the last batch number j in the previous time window $[T_{n-1}^{begin}, T_{n-1}^{end}]$ continues to be numbered sequentially.

Step 2: Compare the time $T_p^{complete}$ when each picker completes all assigned order batches; then assign the order batch to the picker with the shortest completion time $T_p^{complete}$ according to the sequence number j in B_n. Next, update the completion time $T_p^{complete}$ after the picker is assigned a new task. Remove the assigned order batches b_j from the unassigned order batch set B_n and continue Step 2 until $B_n = \phi$.

D. The Online Algorithm

According to the previous analysis, the overall idea of the online order batching algorithm designed in this paper is shown in Figure 3.

E. Algorithm Accuracy Test

In this section, a small-scale calculation experiment is carried out to verify the accuracy of the algorithm, and the genetic algorithm (GA) and the online order batching algorithm proposed in this chapter are used to solve the biobjective online order batching model proposed in Section III.

At a beauty products warehouse of a Chinese e-commerce platform, 2,247 orders that arrived between 0:00 and 1:00 on a sales day in 2019 were selected as samples, which were tested by 10 groups of different items randomly generated by MATLAB, and the parameters were set according to the actual situation of the warehouse. The specific parameters and test results are shown in Table II and Table III, respectively.

TABLE II
PARAMETERS AND VALUES

Parameters	Values
Number of pickers at the same time, p	6
Capacity of an order batch, C	12
Picking time for each item in front of the storage location, t_{pick}	5s
The walking speed of the picker, v	1 m/s

The genetic algorithm has good applicability to the order picking problem. Many studies use GA to solve the problem and have achieved good results [31]-[37]. Therefore, we use GA as the comparison algorithm in this study (Appendix). As seen in Table III, through the comparison of several groups of experiments, the maximum difference between the value obtained by the online algorithm and the traditional genetic algorithm is 1.61%, and the gap is controlled within 5%. The accuracy of the algorithm is good and can be used in larger-scale calculations. Compared with the traditional heuristic algorithm in which offline order batching must know the arrival time of the order in advance, the online order batching algorithm in this paper can solve the online order batching problem with high precision. At the same time, the online order batching algorithm comprehensively solves the problem of real-time order batching and task assignment.

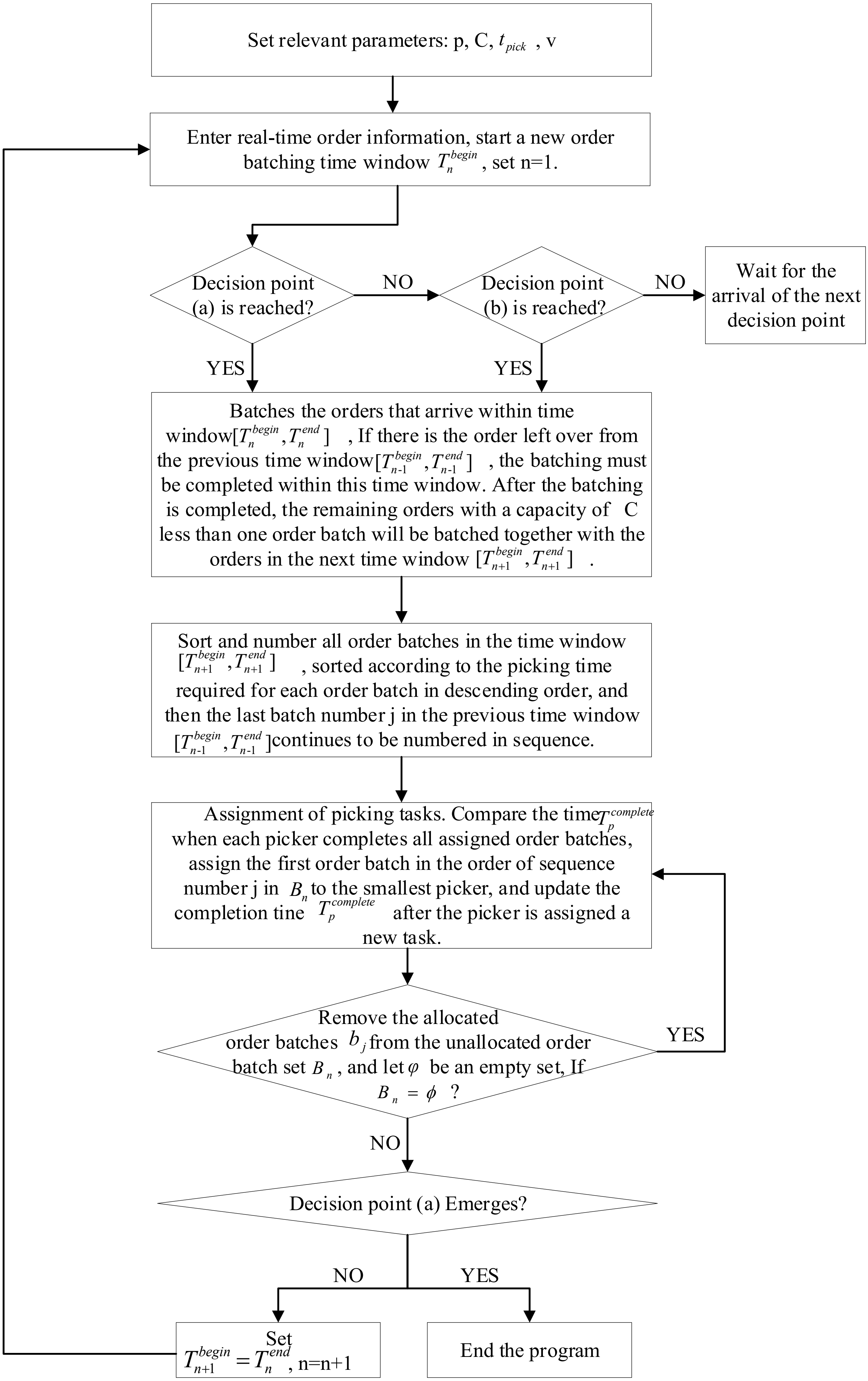

Fig. 3. Flow chart of the online order batching algorithm

TABLE III
COMPARISON OF THE OPTIMIZATION RESULTS OF THE GENETIC ALGORITHM AND ONLINE ALGORITHM

Serial number	Genetic Algorithm: Total picking time (h)	Genetic Algorithm: Maximum order response time (s)	Online batch method in this paper: Total picking time (h)	Online batch method in this paper: Maximum order response time (s)
1	1.1842	471.2	1.1867 (+0.21%)	463.6 (-1.61%)
2	1.2256	476.5	1.2431 (+1.43%)	468.9 (-1.59%)
3	1.2076	473.7	1.2253 (+1.47%)	466.5 (-1.52%)
4	1.2367	477.8	1.2398 (+0.25%)	467.8(-2.09%)
5	1.2456	479.5	1.2589 (+1.07%)	478.9(-0.13%)
6	1.2642	482.1	1.2787 (+1.15%)	480.6 (-0.31%)
7	1.2562	476.5	1.2631 (+0.55%)	475.6 (-0.19%)
8	1.2543	475.7	1.2539 (-0.03%)	476.7 (+0.21%)
9	1.2254	472.8	1.2338 (+0.69%)	471.6(-0.25%)
10	1.2375	478.6	1.2504 (+1.04%)	478 (-0.13%)

V. CASE ANALYSIS

In this section, we conduct a case analysis by using actual data from a picking zone of a Chinese e-commerce warehouse.

A. *Picking Operation of The Warehouse*

Traditionally, in daily picking operations, the F warehouse was divided into three shifts for 24 hours, and 6 pickers were arranged for each shift, that is, there were 6 picking posts. The picker used the pick-while-sort mode for batch picking. In the picking process, pickers randomly selected orders in the unprocessed order queue to form order picking batches, with a maximum of 12 orders per picking batch. This manual picking method was not divided into batches according to the correlation of goods to reduce the picking distance and time, nor was it conducive to shortening the maximum response time of the order. In addition, it was often inaccurate to determine the increased number of sellers based on the experience of managers during online shopping festivals, which lengthened the order response time or wasted picking human resources. According to the field investigation of the F warehouse, the specific parameters of the selected picking zone are shown in Table IV.

TABLE IV
PARAMETERS OF THE PICKING ZONE

Parameters	Values
Quantity of items in stock	2683
Quantity of storage location	1872
Longitudinal aisle	13
Longitudinal aisle width	1.2 m
Horizontal aisle	3
Horizontal aisle width	2.5 m
Number of rows of shelves	18
Number of layers of shelves	4
The length, width, and depth of a storage location	0.5 m
The picker's walking speed v	1.2 m/s
Picking time for each item in front of the storage location t_{pick}	5s
Order batch for one operation of picking trolley	12

B. *Result Analysis*

We obtained the data of all 87,277 orders received by the F warehouse on an online shopping festival on the K e-commerce platform in 2019. The random online batch method and online batch optimization method proposed in this research are used to perform comparison experiments. Six indices of three dimensions, order response time, picking time and picking distance, are compared in the following section.

Comparative analysis of the order response time

This section uses the maximum response time and average response time to compare the effect of the order response time before and after optimization. The maximum response time of an order is the longest time from arrival to completion of picking among all orders arriving at the warehouse in a day. The average response time for an order is the average time each order takes from arriving at the warehouse to completing the picking in a day. Figure 4 and Figure 5 show the order response time calculation results of the random order batching method and the online batch optimization method proposed in this paper.

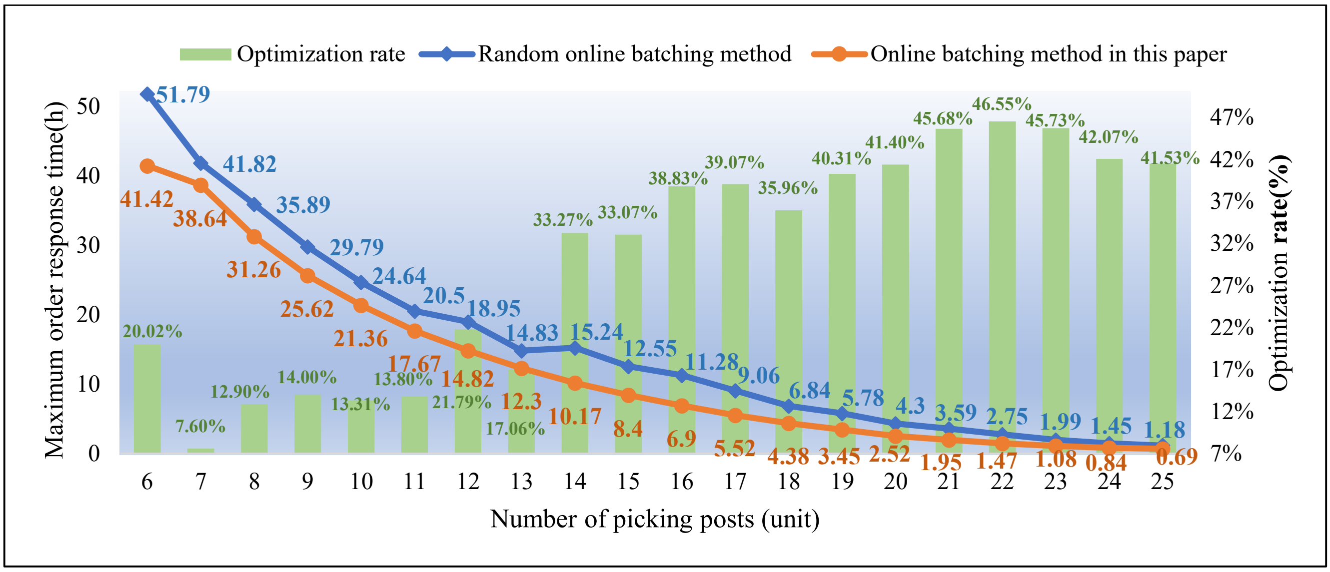

Fig. 4. Comparison of maximum order response time results

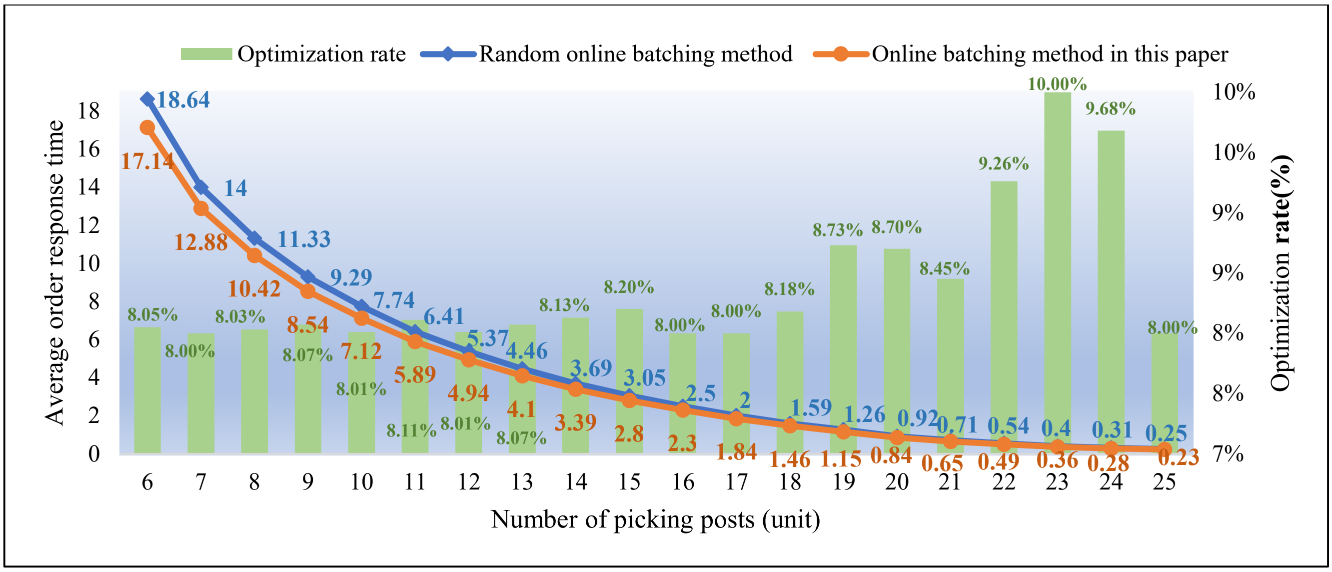

Fig. 5. Comparison of average order response time results

It can be concluded from Figure 4 and Figure 5 that regardless of how many posts are selected, the maximum response time and average response time obtained by the optimal batching method are better than those obtained by the random batch method. When the number of picking posts is changed between 6 and 25, after using this online batch algorithm, the average optimization rates of the maximum response time and average response time of orders are 30.20% and 8.38%, respectively, with an outstanding optimization effect. This is mainly because the time window strategy of the optimised batch algorithm proposed in this paper stipulates that the order picking operation of the next time window can be carried out only when the order picking operation of the previous time window is completed, which can greatly reduce the order response time.

By using this online order batch model, the number of picking posts and employees can be determined accurately according to the order quantity, and it saves manpower compared with the random batching algorithm. In the current situation, the maximum response time for orders of online shopping festivals is 4 hours. At this time, 21 and 19 picking posts need to be set by using online random batching and this research's algorithm, respectively. The average response times of the order are 0.71 h and 1.15 h, respectively, both of which are less than 2 hours. If the maximum response time of the future order is reduced to 2 hours, 23 and 21 picking posts need to be set by using online random batching and this research's algorithm. The average response times of the corresponding orders are 0.40 h and 0.65 h, respectively, both of which are less than 40 min. Under the two levels of service commitment, the online batching algorithm proposed in this paper can reduce 2 posts, accounting for 9.52% and 8.70% of the number of posts before optimization, which can effectively reduce labour costs.

Comparative Analysis of the order picking time

In this section, the total picking time and the average picking time are used to compare the optimization effect of the picking time. The total picking time is the total time from the arrival of the first order on the same day to the completion of all order picking in the day, including the staff's rest time when the order has not yet arrived. The average picking time of the order is the average working time spent picking all picking posts in the day, which excludes the rest time during the operation when the order has not yet arrived. Table V and Table VI show the comparison of the total order picking time and the average picking time obtained by the random batching method and the online batching method of this paper when the number of picked posts is between 6 and 25.

TABLE V
COMPARISON OF TOTAL ORDER PICKING TIME RESULTS

Number of picking posts (unit)	Number of pickers in a day (person)	Total order picking time		
		Random online batching method (h)	Online batching method in this paper (h)	Optimization rate
6	18	63.89	58.64	8.22%
7	21	54.84	50.53	7.86%
8	24	48.89	45.05	7.85%
9	27	44.28	39.84	10.03%
10	30	40.68	36.60	10.03%
11	33	37.69	33.91	10.03%
12	36	35.24	31.70	10.05%
13	39	33.03	28.40	14.02%
14	42	31.41	27.01	14.01%
15	45	29.89	25.70	14.02%
16	48	28.59	24.58	14.03%
17	51	27.44	24.49	10.75%
18	54	26.44	24.43	7.60%
19	57	25.61	24.42	4.65%
20	60	24.82	**24.41**	**1.65%**
21	63	24.69	**24.40**	**1.17%**
22	66	24.65	**24.39**	**1.05%**
23	69	24.59	**24.39**	**0.81%**
24	72	24.57	**24.39**	**0.73%**
25	75	24.50	**24.39**	**0.45%**
Average				**7.45%**

TABLE VI
COMPARISON OF AVERAGE ORDER PICKING TIME RESULTS

Number of picking posts (unit)	Number of pickers in a day (person)	Average order picking time		
		Random online batching method (h)	Online batching method in this paper (h)	Optimization rate
6	18	62.27	56.66	9.01%
7	21	53.41	48.60	9.01%
8	24	46.77	42.56	9.00%
9	27	41.52	37.79	8.98%
10	30	37.05	33.71	9.01%
11	33	33.78	30.74	9.00%
12	36	30.93	28.15	8.99%
13	39	28.63	26.05	9.01%
14	42	26.57	24.18	9.00%
15	45	24.73	22.51	8.98%
16	48	23.18	21.09	9.02%
17	51	21.77	19.81	9.00%
18	54	20.48	18.64	8.98%
19	57	19.39	17.65	8.97%
20	60	18.42	16.76	9.01%
21	63	17.55	15.97	9.00%
22	66	16.72	15.21	9.03%
23	69	15.98	14.54	9.01%
24	72	15.26	13.88	9.04%
25	75	14.53	13.23	8.95%
Average				**9.00%**

It can be seen in Table V and Table VI that regardless of how many posts are selected, the results of the total picking time and the average picking time obtained by the optimal batch method in this paper are better than those obtained by the random batch method. When the number of picked posts is 6-25, the average optimization rate of the optimised batching algorithm is 7.45% compared with the random batching algorithm. When the number of picking posts increases to more than 20, the optimization rate of the total picking time obtained by the optimization batching method proposed in this paper decreases sharply. This is because regardless of how the number of picking posts changes, it takes more than 24 hours to complete the order picking on a natural day, and there is no more range for optimization. It can also be seen in Table VI that the average picking time decreases with the increase of picking posts under the two algorithms. The optimization rate of the optimization batching algorithm in this paper is between 8.95% and 9.04%.

Comparative Analysis of walking distance

In this section, the pickers' total walking distance and the average walking distance are used to compare the batching optimization effect of online orders. In this paper, the total walking distance of the picker is defined as the sum of the walking distance of all the order picking work arriving at the warehouse in the day, and the average walking distance is the average walking distance of all pickers who complete the order picking of the warehouse on the same day. Figure 6 and Table VII show the comparison of the optimization results of the random order batching method and the online batching method proposed in this paper.

It can be concluded from Figure 6 that regardless of how many posts are selected, the walking distance obtained by the optimised batching method in this paper is better than that obtained by the random batching method, and the optimization rate is between 8.13% and 12.08%. The change in the number of selected posts has no substantial effect on the total walking distance of the pickers.

Table VII shows that with the increase in the number of picking posts and pickers, the average walking distance of pickers decreases gradually. When there are only 6 picking posts, the average walking distances before and after optimization are 48.26 km and 42.58 km, respectively, far exceeding a picker's average daily workload. According to the service target of a maximum response time of 4 hours, 21 and 19 picking posts need to be set before and after optimization, respectively. Correspondingly, the average daily walking distances of pickers before and after optimization are 13.98 km and 13.52 km, respectively. The total number of pickers is reduced by 6 by using the optimised batching method in this paper, but the picker's working load is slightly reduced, which shows that the optimization model in this paper can save labour costs.

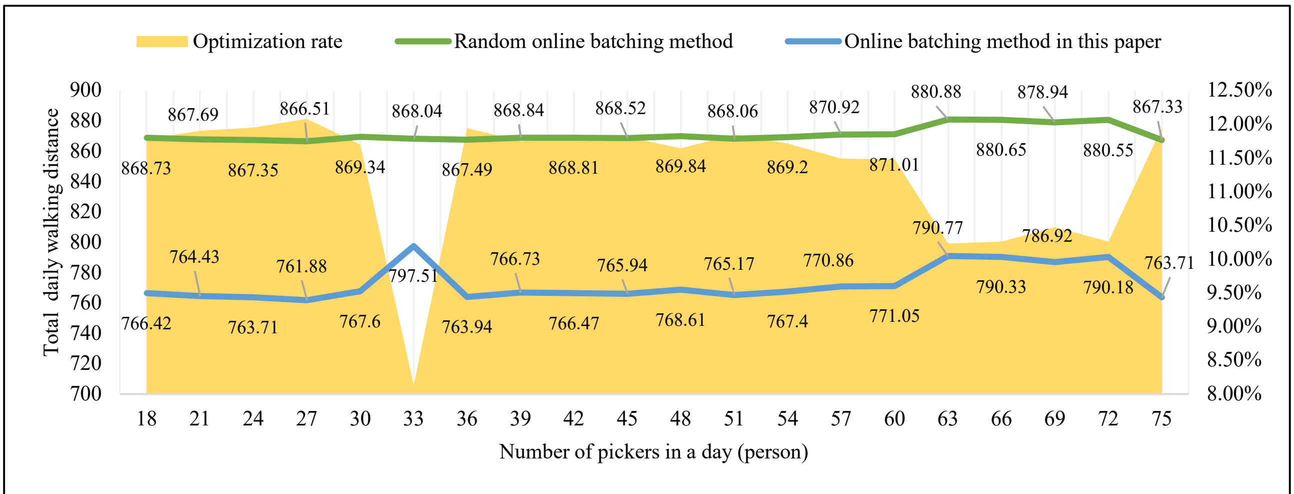

Fig. 6. Comparison of total daily walking distance results

TABLE VII
COMPARISON OF AVERAGE DAILY WALKING DISTANCE RESULTS

Number of picking posts (unit)	Number of pickers in a day (person)	Average daily walking distance of pickers		
		Random online batching method (h)	Online batching method in this paper (h)	Optimization rate
6	**18**	**48.26**	**42.58**	**11.78%**
7	21	41.32	36.40	11.90%
8	24	36.14	31.82	11.95%
9	27	32.09	28.22	12.08%
10	30	28.98	25.59	11.70%
11	33	26.30	24.17	8.13%
12	36	24.10	21.22	11.94%
13	39	22.28	19.66	11.75%
14	42	20.69	18.25	11.78%
15	45	19.30	17.02	11.81%
16	48	18.12	16.01	11.64%
17	51	17.02	15.00	11.85%
18	54	16.10	14.21	11.71%
19	**57**	**15.28**	**13.52**	**11.49%**
20	60	14.52	12.85	11.48%
21	**63**	**13.98**	**12.55**	**10.23%**
22	66	13.34	11.97	10.26%
23	69	12.74	11.40	10.47%
24	72	12.23	10.97	10.26%
25	75	11.56	10.18	11.95%
Average				**11.31%**

Further, we compare and analyse the optimization effects of the three kinds of indicators. Table VIII shows the average optimization rate of six indicators. It can be seen that the average optimization rate of the maximum order response time is much higher than other indicators. This shows that the model and algorithm designed in this paper can effectively reduce the maximum order response time and make the response time of each order tend to balance. This has a good application effect for picking warehouses that often have orders that have not been processed for a long time. In addition, the model and algorithm designed in this paper also have a good effect on reducing picker's walking distance. This can reduce the work intensity of the picker, thus improving the satisfaction and work efficiency of the picker.

TABLE VIII
AVERAGE OPTIMIZATION RATE RESULTS OF SIX INDICATORS (%)

Indicator		Average optimization rate
Order response time	Maximum order response time	30.20%
	Average order response time	8.38%
Order picking time	Total order picking time	7.45%
	Average order picking time	9.00%
Walking distance	Pickers' total walking distance	11.31%
	Average daily walking distance of pickers	11.31%

VI. CONCLUSION

This paper reviews online order batching and batch assignment integration problems at the warehouse operation level and selects the most widely used picker-to-part system as the research object. The main contributions of the study are as follows:

1) The optimization model in this paper considers both the internal operation efficiency and the external customer service level by establishing a biobjective optimization model. The model takes minimising the maximum order picking time as the internal operation efficiency objective and minimising the maximum customer order response time as the external customer service objective. This makes the model more suitable for operations and management practices in retail e-commerce warehouses.
2) Aiming at solving the biobjective optimization model, in this paper, we discuss designing a superior algorithm considering the time window strategy, order batching strategy and batch assignment strategy, and the optimal routing algorithm is embedded in it. The algorithm synthetically solves the three problems of picking operations, including order batching, batch assignment and routing optimization. Compared with the traditional heuristic algorithm, the algorithm in this paper has good accuracy and high applicability to large samples.
3) This paper uses the real order data of an online shopping festival in 2019 to compare optimization results. In terms of the external customer service level, with the same number of pickers, the optimization results of the case show that the maximum order response time and average order response time are reduced by an average of 30.20% and 8.38%, respectively. In terms of internal operational efficiency, the total order picking time is reduced by an average of 7.45%. The pickers' labour intensity is reduced, that is, the pickers' average walking distance per day is reduced by an average of 11.31%. In addition, to meet the service requirement of the maximum order response time of 4 h, the optimization method of this paper can reduce 2 picking posts, with a total of 6 pickers, accounting for 9.52% of the original 63 pickers, which can save on the picking cost of the picker-to-part warehouse.

The number of customers is difficult to accurately predict in advance in e-commerce warehouses, and orders fluctuate and require timely responses, all of which can be effectively solved by the online order batching and assignment optimization model proposed in this paper. It has a certain degree of advancement and applicability and can provide a reference for similar e-commerce warehouses to comprehensively solve the practical problems of order picking. This article can be further explored in the following aspects:

1) The overall picking process can be comprehensively considered in the future. Online order batching can be introduced into warehouse operation decision-making issues such as warehouse layout and storage location allocation.
2) With the increase in pickers at the same time, channel congestion may become an important factor affecting picking operations. Therefore, we can try to introduce

aisle congestion into online order batching optimization research to increase the scope of use of the model.

3) The application of automated picking warehouse is increasing gradually. In the future, we can study automated picking warehouse. Compared with manual picking warehouse, the change of goal and constraints of automatic picking is the focus of model construction. In terms of research methods, automatic picking can be studied through clustering analysis, data mining and other in-depth learning methods. How to control the work of automation equipment is one of the aspects of research conclusions.

APPENDIX

Order batching

Step 1: Initialise settings. Set population size N=100, iterations number d=250, crossover probability pc=0.8, mutation probability pm=0.1. Set problem constraints. Number I order from 1 to I. Let the fitness function $f=\dfrac{1}{5\cdot\max_{j\in J}\left(t_j^{service}\right)+\max_{j\in j}\left(t_j^{it}\right)}$; t_j^{it} is the arrival time difference between the order with the earliest arrival time and the latest arrival time in the jth order batch.

Step 2: Coding. Using the method of real number coding, if the order quantity is I, the chromosome is a random arrangement of positive integers within I. Batching is performed in order of arrangement. If the order quantity of each batch is C, then on a chromosome, starting from the first gene of the individual, each C gene is the batching result of a batch. Randomly generate 100 individuals as the initial population P (0).

Step 3: Individual evaluation. Calculate the fitness of each individual in P(d).

Step 4: Selecting operation. The elite selection strategy is adopted to select the individual with the greatest fitness, and it is directly copied to the next generation without crossover and mutation operations.

Step 5: Crossover. A random number r in the [0,1) interval is generated for each individual. If r<pc, the individual needs to perform crossover. It can be seen from the coding method that the order adjustment of genes within each individual can change the order batching result, and the value of each gene cannot be repeated and cannot be omitted. Based on this, we use a mapping-based crossover. First, two-point crossover is adopted, and two entry points are randomly selected on the individual's gene string. The gene part between the two entry points is reserved. The reserved part and the reserved part of the individual with which the paired crossover is performed form a mapping relationship. After the crossover operation, the gene values at both ends of the individual who are the same as the reserved part in the middle are replaced with the gene values that form a mapping relationship with the reserved part of the individual.

Step 6: Mutation operation. Generate a random number r in the [0,1) interval for each individual. If r<pm, the individual needs to perform the mutation operation. Perform random exchange mutation on one-tenth of the genes that will be randomly selected by the individuals who will use the mutation operation.

Step 7: Iteration. After the population P(d) is selected, crossed and mutated, the next generation population P(d+1) is obtained.

Step 8: Termination condition. If d=250 and the fitness function converges, the individual with the largest fitness in this generation is used as the optimal solution. The batch results are output, and the calculation is terminated.

Order assignment

Step 1: Initialise settings. Set population size N=100, iterations number d=250, crossover probability pc=0.8, mutation probability pm=0.1, fitness function $f=\dfrac{1}{\max_{p\in P}\sum_{j\in J}y_{jp}\left(t_j^{service}\right)}$. Set problem constraints. Number J batch from 1 to J. Number P pickers from 1 to P.

Step 2: Coding. Using the method of real number coding, each order batch is regarded as a gene of the chromosome, the sequence number of the picker assigned to the order batch is the value of the gene, and 100 individuals are randomly generated as the initial population P(0).

Step 3: Individual evaluation. Calculate the fitness of each individual in P(d).

Step 4: Selecting operation. The elite selection strategy is adopted to select the individual with the greatest fitness, and it is directly copied to the next generation without crossover and mutation operations.

Step 5: Crossover. Generate a random number r in the [0,1) interval for each individual. If r<pc, the individual needs to perform a single-point crossover operation; that is, a crossover point is randomly selected for the individual who needs to perform a crossover operation. The right side of the intersection is swapped with the corresponding part of the individual it is paired with.

Step 6: Mutation operation. Generate a random number r in the [0,1) interval for each individual. If r<pm, the individual needs to perform the mutation operation. One-tenth of the genes of the individuals who use the mutation operation are randomly selected to mutate, and the mutated gene values are in the [1, P] interval.

Step 7: Iteration. After the population P(d) is selected, crossed and mutated, the next generation population P(d+1) is obtained.

Step 8: Termination condition. If d=250 and the fitness function converges, the individual with the largest fitness in this generation is used as the optimal solution. The assignment results are output, and the calculation is terminated.

Picking sequence

Step 1: Initialise settings. Set population size N=50, iterations number d=250, crossover probability pc=0.8, mutation probability pm=0.1, fitness function $f=\dfrac{1}{\max_{i\in I}\left(t_i^{response}\right)}$. Set problem constraints.

Step 2: Coding. Each order batch assigned by the picker is regarded as a gene of the chromosome. Randomly generate 50 individuals in different orders as the initial population P (0).

Step 3: Individual evaluation. Calculate the fitness of each individual in P(d).

Step 4: Selecting operation. The elite selection strategy is adopted to select the individual with the greatest fitness, and it is directly copied to the next generation without crossover and mutation operations.

Step 5: Crossover. A random number r in the [0,1) interval is generated for each individual. If r<pc, the individual needs to perform crossover. The genes' order adjustment within each individual can change the order batch picking sequence, and each gene value cannot be repeated and cannot be omitted. Based on this, we use a mapping-based crossover. First, two-point crossover is adopted, and two entry points are randomly selected on the individual's gene string. The gene part between the two entry points is reserved. The reserved part and the reserved part of the individual with which the paired crossover is performed form a mapping relationship. After the crossover operation, the gene values at both ends of the individual are the same as the reserved part in the middle and replaced with the gene values that form a mapping relationship with the reserved part of the individual.

Step 6: Mutation operation. Generate a random number r in the [0,1) interval for each individual. If r<pm, the individual needs to perform the mutation operation. Perform random exchange mutation on one-tenth of the genes that will be randomly selected by the individuals who will use the mutation operation.

Step 7: Iteration. After the population P(d) is selected, crossed and mutated, the next generation population P(d+1) is obtained.

Step 8: Termination condition. If d=250 and the fitness function converges, the individual with the largest fitness in this generation is used as the optimal solution. The assignment results are output, and the calculation is terminated.

REFERENCES

[1] Kübler P, Glock CH, and Bauernhansl T, "A new iterative method for solving the joint dynamic storage location assignment, order batching and picker routing problem in manual picker-to-parts warehouses," *Computers and Industrial Engineering*, vol. 147, 2020.

[2] Drury J, *Towards More Efficient Order Picking*. IMM Monograph No. 1, The Institute of Materials Management: Cranfield,1988.

[3] Frazelle E, *World-Class Warehousing and Material Handling*. second ed, McGraw-Hill: New York, 2006.

[4] Marchet G, Melacini M and Perotti S, "Investigating order picking system adoption: a case-study-based approach," *International Journal of Logistics-Research and Applications*, vol. 18, no. 1, pp. 82-98, 2015.

[5] Lucia Cassettari, Fabio Curro, Marco Mosca, Roberto Mosca, Roberto Revetria, Stefano Saccaro, and Gabriele Galli, "A 4.0 automated warehouse storage and picking system for order fulfillment," *Lecture Notes in Engineering and Computer Science: Proceedings of The World Congress on Engineering 2021*, 7-9 July, 2021, London, U.K., pp317-327.

[6] Van Gils T, Caris A, Ramaekers K and Braekers K, "Formulating and solving the integrated batching, routing, and picker scheduling problem in a real-life spare parts warehouse," *European Journal of Operational Research*, vol. 277, no. 3, pp. 814-830, 2019.

[7] Yanchun Wan, and Yong Liu, "Integrating optimized fishbone warehouse layout, storage location assignment and picker routing," *IAENG International Journal of Computer Science*, vol. 49, no.3, pp957-974, 2022.

[8] Shah B and Khanzode V, "A comprehensive review of warehouse operational issues," *International Journal of Logistics Management*, vol. 26, no. 3, pp. 346-378, 2017.

[9] Lin CC, Kang JR, Hou CC and Cheng CY, "Joint order batching and picker Manhattan routing problem," *Computers and Industrial Engineering*, vol. 95, pp. 164–174, 2016.

[10] Hong S and Kim Y, "A route-selecting order batching model with the S-shape routes in a parallel-aisle order picking system," *European Journal of Operational Research*, vol. 257, no. 1, pp. 185–196, 2017.

[11] Ardjmand E, Bajgiran O S and Youssef E, "Using list-based simulated annealing and genetic algorithm for order batching and picker routing in put wall based picking systems," *Applied Soft Computing*, vol. 75, pp. 106-119, 2019.

[12] Cergibozan C and Tasan AS, "Order batching operations: an overview of classification, solution techniques, and future research," *Journal of Intelligent Manufacturing*, vol. 30, no. 1, pp. 335-349, 2019.

[13] Valle CA, Beasley JE and da Cunha AS, "Optimally solving the joint order batching and picker routing problem," *European Journal of Operational Research*, vol. 262, no. 3, pp. 817–834, 2017.

[14] Li JB, Huang RH and Dai JB, "Joint optimization of order batching and picker routing in the online retailer's warehouse in China," *International Journal of Production Research*, vol. 55, no. 2, pp. 447–461, 2016.

[15] Menéndez B, Pardo EG, Alonso-Ayuso A, Molina E and Duarte A, "Variable Neighborhood Search strategies for the Order Batching Problem," *Computers & Operations Research*, vol. 78, pp. 500–512, 2017.

[16] Xiang X, Liu C and Miao L, "Storage assignment and order batching problem in Kiva mobile fulfilment system," *Engineering Optimization*, vol. 50, no. 11, pp. 1941-1962, 2018.

[17] Silva A, Coelho LC, Darvish M and Renaud J, "Integrating storage location and order picking problems in warehouse planning," *Transportation Research Part E: Logistics and Transportation Review*, vol. 140, 2020.

[18] Chew EP and Tang LC, "Travel time analysis for general item location assignment in a rectangular warehouse," *European Journal of Operational Research*, vol. 112, no. 3, pp. 582–597, 1999.

[19] Le-Duc T and de Koster RMBM, "Travel time estimation and order batching in a 2-block warehouse," *European Journal of Operational Research*, vol. 176, no. 1, pp. 374-388, 2007.

[20] Gil-Borras, S., Pardo, E.G., Alonso-Ayuso, A. and Duarte, A., "Basic VNS for a variant of the online order batching problem," in *Variable Neighborhood Search. 7th International Conference, ICVNS 2019,* Rabat, Morocco, 2019, pp.17-36.

[21] Chen F, Wei Y and Wang H, "A heuristic based batching and assigning method for online customer orders," *Flexible Services and Manufacturing Journal*, vol. 30, no. 4, pp. 640-685, 2017.

[22] Gil-Borras, S, Pardo, EG, Alonso-Ayuso, A and Duarte, A, "A heuristic approach for the online order batching problem with multiple pickers," *Computers and Industrial Engineering*, vol. 160, 2021.

[23] Leung KH, Lee CKM and Choy KL, "An integrated online pick-to-sort order batching approach for managing frequent arrivals of B2B e-commerce orders under both fixed and variable time-window batching," *Advanced Engineering Informatics*, vol. 45, 2020.

[24] Zhang J, Wang X, Chan FTS and Ruan JH, "Online order batching and sequencing problem with multiple pickers: A hybrid rule-based algorithm," *Applied Mathematical Modelling*, vol. 45, pp. 271–284, 2017.

[25] Scholz A, Schubert D and Wäscher G, "Order picking with multiple pickers and due dates – Simultaneous solution of Order Batching, Batch Assignment and Sequencing, and Picker Routing Problems,"

[26] *European Journal of Operational Research*, vol. 263, no. 2, pp. 461–478, 2017.

[27] Attari, MYN, Torkayesh, AE, Malmir, B and Jami, EN, "Robust possibilistic programming for joint order batching and picker routing problem in warehouse management," *International Journal of Production Research*, vol. 59, no. 14, pp. 4434-4452, 2020.

[28] Chen TL, Cheng CY, Chen YY and Chan LK, "An efficient hybrid algorithm for integrated order batching, sequencing and routing problem," *International Journal of Production Economics*, vol. 159, pp. 158–167, 2015.

[29] Henn S, "Algorithms for on-line order batching in an order picking warehouse," *Computers & Operations Research*, vol. 39, no. 11, pp. 2549–2563, 2012.

[30] Xu X, Liu T, Li K and Dong W, "Evaluating order throughput time with variable time window batching," *International Journal of Production Research*, vol. 52, no. 8, pp. 2232–2242, 2014.

[31] Gil-Borras, S, Pardo, EG, Alonso-Ayuso, A and Duarte, A, "GRASP with variable neighborhood descent for the online order batching problem," *Journal of Global Optimization*, vol. 78, no. 2, pp. 295–325, 2020.

[32] Hsu, C.-M., Chen, K.-Y., Chen and M.-C., "Batching orders in warehouses by minimizing travel distance with genetic algorithms," *Computers in Industry*, vol. 56, no. 2, pp. 169–178, 2005.

[33] Tsai, C.-Y., Liou, J. J. H. and Huang, T.-M., "Using a multiple-GA method to solve the batch picking problem: Considering travel distance

and order due time," *International Journal of Production Research*, vol. 46, no. 22, pp. 6533–6555, 2008.

[34] Azadnia, A. H., Taheri, S., Ghadimi, P., Mat Saman, M. Z. and Wong, K. Y, "Order batching in warehouses by minimizing total tardiness: A hybrid approach of weighted association rule mining and genetic algorithms," *Scientific World Journal*, 2013.

[35] Chirici, L. and Wang, K.-S., "Tackling the storage problem through genetic algorithms," *Advances in Manufacturing*, vol. 2, no. 3, pp. 203–211, 2014.

[36] Olateju Samuel Olaniyi, Adebayo Kayode James, Abdullahi Adinoyi Ibrahim, and Aderibigbe Felix Makanjuola, "On the application of a modified genetic algorithm for solving vehicle routing problems with time windows and split delivery," *IAENG International Journal of Applied Mathematics*, vol. 52, no.1, pp101-109, 2022.

[37] Minghui Zhao, Yongpeng Zhao, Changxi Ma, and Xu Wu, "Robust Optimization of Mixed-Load School Bus Route Based on Multi-Objective Genetic Algorithm," *Engineering Letters*, vol. 30, no.4, pp1543-1550, 2022.