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Research on Joint Order Picking and Delivery Scheduling of New Retail Enterprises

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ABSTRACT:*For new retail enterprises, how to arrange the order picking and deliverywill affect the order fulfillment time and delivery costs. This paper establishes a model of joint order picking and delivery scheduling and uses genetic algorithms to solve the problem. Joint scheduling enables enterprises to effectively reduce order fulfillment time within the range of acceptable distribution costs, thereby simultaneously reducing costs and increasing consumer satisfaction.*

KEY WORD*:New retail, Joint Order Picking and Delivery Scheduling, Genetic algorithm*

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I. INTRODUCTION

The new retail companies studied in this paper adopt a mode of deep integration of online and offline and modern logistics. The store in the main shopping scenario is also a logistics distribution center, that is, a "storage and store integration" model. After the store has gainedcustomers' trust, it will be able to realize the online sales of most FMCG products through mobile Internet and applications, thus realizing the two-way integration of online and offline traffic. The store has a wide variety of products, including not only fresh products such as meat, fruits, and aquatic products, but also other non-fresh products such as daily necessities to fully meet customers' daily needs. We take the pain points of traditional retail and e-commerce as well as the emergence of new retail as the research background, analyze the different order selection and distribution strategies of this type of new retail enterprises under different evaluation indicators, and explore the order fulfillment time and the problem of minimizing delivery costs.

We have observed that after the customer places an order in the APP, the order of the picking work, the arrangement of the pickers and packers, and the distribution strategy will all affect the time when the order finally reaches the customer, and then affect customer satisfaction. In addition, different delivery strategies will also generate different delivery costs, and there is a long-term relationship between delivery costs and order fulfillment time: when the order fulfillment time is optimal, the delivery cost will be high.When the delivery cost will be optimal, the order fulfillment time will be very long. Therefore, how to balance the relationship between the two to reduce distribution costs and improve customer satisfaction has become an urgent problem.

This paper uses order fulfillment time and delivery costs as evaluation indicators, and builds the model. Then we explore more effective algorithms for the model, combining the various stages in picking and distribution for research, while considering order fulfillment time and distribution costs. In order to achieve the purpose of improving customer satisfaction and reducing corporate distribution costs. Due to the large number of orders that companies process every day, the improvement of the performance of the algorithm can save more order fulfillment time and effectively reduce delivery costs for new retail companies with large orders. Reduced order fulfillment time can effectively improve consumer satisfaction, and lower delivery costs can increase corporate profits. Therefore, our research can provide decision support for relevant new retail companies, which has practical significance.

II. LITERATURE REVIEW

2.1 Order Picking

Order picking is the process of locating a series of specified commodities from their original storage location for the fulfillment of orders (Rouwenhorst & Reuter 2000), which is considered as a labor-intensive part and the highest cost in warehouse operations. The manual picking process is estimated to account for more than 55% of the total cost of warehouse operations (Riccardo 2012). There are many factors that should be considered in the optimization of the picking process, such as the size and layout structure of the warehouse (Pratik & Russell 2010)and other factors, and the planning of the picking path (Zhou & Guo 2014; Wang & Zhang 2016),order batch strategy (Wang & Zhang 2016; Wang & Zhou 2015; Wang & Zhang 2014), goods location design (Li & Wu 2015; Ning & Zhang 2014) and district-based picking (Zhou & Guo 2014), etc. But the number of multiple factors studied at once is very limited (Van & Ramaekers 2018).Many researchers focus on a specific topic for analysis and optimization (Bottani & Cecconi 2012). Henn and Schmid (2013)believe that the main problem of the batch picking system is to merge and convert orders, that is, order batches, and how to reorganize orders into batches is an effective method to improve order picking efficiency (Lenoble & Frein 2017).

2.2Orderdistribution

Orders in the distribution stage mainly involve vehicle routing planning and other issues during distribution. Vehicle routing problem (VRP) is a classic problem in academia. VRP is based on the needs of users scattered in various places and complying with relevant constraints to meet user needs as much as possible while achieving the goals of shortest transportation distance and minimum distribution cost. At present, many scholars have conducted related theoretical research.

Dantzig and Ramser (1959) first proposed the "truck scheduling problem", which simulated how homogeneous truck fleets can meet the oil demand of multiple gas stations from a central hub with minimum travel distance. Five years later, Clarke and Wright (1964)generalized the problem as a linear optimization problem common in the logistics and transportation fields. In the past few decades, the number of solutions introduced in the academic literature and the VRP problem variants have increased rapidly. The current VRP model is researched more on multi-models (Wang et al. 2019) or multi-target (Duan et al. 2019).The problem of current VRP modelis very different from the models proposed by Dantzig and Ramser (1959) and Clarke and Wright (1964), and the VRP-related commercial software is also emerging and used by many companies and departments (Drexl 2012; Janice & Randolph 2014).

Because VRP is NP-hard (Lenstra & Kan 1981), precise algorithms such as branch and bound method, cut-plane method, network flow algorithm, and dynamic programming method are only effective for small instances.But considering real life, the scale of the problem is generally large, and the heuristic algorithm is usually more suitable for practical applications. The so-called heuristic algorithm is an algorithm that solves the optimization problem with the help of the specific analysis or calculation experience of the problem. It can give a satisfactory solution to the problem quickly.Generallyit is a better feasible solution rather than an optimal solution. Since there are no polynomial algorithms for solving many combinatorial optimization problems, the research of heuristic algorithms has very practical significance. The classic heuristic algorithms are: active tabu search algorithm (Nanry & Barnes 2000), tabu embedded simulated annealing algorithm (Li & Lim 2003), block coding genetic algorithm (Pankratz 2005), hybrid algorithm of simulated annealing and large neighborhood search (Bent & Van 2004), constructed heuristic algorithm (Lu & Dessouky 2006), adaptive large neighborhood search algorithm (Ropke & Pisinger 2006), indirect local search algorithm with greedy decoding (Derigs & Döhmer 2008), hybrid ant colony algorithm (Fang& Ai 2019), etc.

2.3 Integrated Order Picking and Distribution

In the order picking and distribution process, the order of picking will affect the order fulfillment time and distribution costs, so combining research on order picking and distribution can make the total cost lower. Wang and Zhang (2016) summarized the joint scheduling problem of order picking and distribution into the production and distribution joint scheduling problem (IPDS). IPDS can be expressed using the five-parameter method as:$\alpha|\beta|\pi|\delta|\gamma$. Among them, α represents the production configuration set including single, parallel, flow and other production forms, β represents the order constraint set, π represents the distribution parameters, δ represents the number of customers, and γ represents the target to be optimized (Chen 2010).

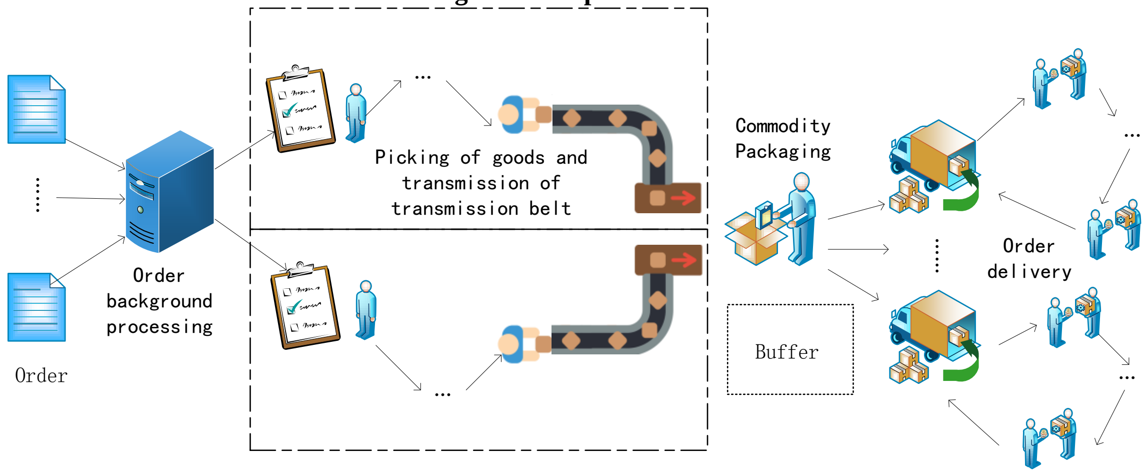
Li and Ma (2007) established an integer programming model for air transportation scheduling problems, and Zhong and Chen (2009) established a joint production and distribution scheduling model with delivery as the background. Low and Li (2013) and Low and Chang (2014) constructed a single-machine, multi-product, and multi-vehicle joint scheduling model considering delivery time windows, and Zhong (2015) constructed a model for machine scheduling and transportationcollaboration problem. Wang and Zhang (2016)built a joint order picking and distribution model under the B2C model.

And many scholars have researched and designed heuristic or intelligent optimization algorithms to solve the joint order picking and distribution scheduling problem. The more commonly used heuristic algorithms are: two-stage method (Hurter & Buer 1996), large-scale neighbors domain search algorithm (Farahani & Grunow 2012), polynomial time algorithm (Zhong & Chen 2009; Gao and Qi 2015), improved approximation algorithm (Zhong 2015), adaptive large-scale neighborhood search algorithm (Belo-Filho et al. 2015) and so on.

III. PROPOSED MODEL

This paper studies how to optimize the picking and delivery of online orders and offline orders for a new type of retail store-integrated retail enterprise. By observing the operation mode of a company in the new retail industry, we found that consumers obtain the store information within the distribution range through the mobile APP, enter the store online to select products and place orders, and the orders go through background processing, picking, conveyor belt transportation, packaging and finally delivered to consumers, as shown in Figure1.

Figure 1: Proposed Model



For convenience of expression, we will record the fresh products in the paper as type-A products and non-fresh products as type-B products, and make the following assumptions:

(1) The time of the background processing stage is related to the hardware processing capacity of the background processing system, and the processing time is very short compared with the time of merchandise picking, conveyor belt transportation, etc., so it is ignored.

(2) This paper considers the offline problem, that is, all the information about the order is known before the order is processed.

(3) There is no shortage of goods.

(4) The packing bags required by the picking personnel are sufficient, and there is no limit on the number.

(5) The transmission belt is available at any time during working hours and is in good condition without failure.

We divide the processing of these orders into four stages, of which the first three stages are the processing of orders within the storehouse (we consider the work of these three stages as the three-stage flowshop problems, and each order is regarded as a workpiece, and each workpiece is processed in each stage in sequence. The first stage represents the picking work of the picking staff; the second stage represents the transfer work of the conveyor belt; the third stage represents the packing work of the packing staff), The fourth stage is the distribution of orders.

Assume that there are n orders O_i to be processed, which can include a type-A sub-order O_i^A(representing a type-A product) and a type-B sub-order O_i^B (representing a type-B product). Next, what we mean by "order" and "workpiece" have the same meaning and are interchangeable. (Notice that in the first stage of picking and the second stage of conveyor belt conveying, it essentially processes the sub-workpieces of each workpiece.) According to the situation of the sub-workpieces, we divide the work pieces O_i into three classes:

Class I: Artifacts containing only type-A artifacts;

Class Ⅱ: Artifacts containing only type-B artifacts;

Class III: Artifacts containing two types of sub-artifacts.

(1) The first stage (picking work): there is a machine M_1^A (indicating that there is a picker) to process type-A sub-workpieces, and the processing time of the sub-workpiece O_i^A is p_{i1}^A; There is a machine M_1^B (indicating that there is a picker) to process the type-B sub-workpiece, and the processing time of the sub-workpiece O_i^B is p_{i1}^B. We noticed that: Class I workpieces only need to be processed on M_1^A, so: $p_{i1}^B = 0$, Class II workpieces only need to be processed onM_1^B, so: $p_{i1}^A = 0$.

(2) The second stage (conveyor belt transmission): there is a machine M_2^A (indicating a hook on the conveyor belt) to process the type-A sub-workpieces, the processing time of the sub-workpiece O_i^A is p_{i2}^A; there is a machine M_2^B (indicating a hook on the conveyor belt) to process the type-B sub-workpieces, the processing time of sub-workpiece O_i^B is p_{i2}^B. And we noticed that: Class I workpieces only need to be processed on M_2^A, so: $p_{i2}^B = 0$, Class II workpieces only need to be processed onM_2^B, so: $p_{i2}^A = 0$.

(3) The third stage (workpiece packaging stage): There is a machine (representing a packaging worker) to process the order, and the processing time of the workpiece O_i is p_{i3}.

(4) The fourth stage (distribution stage):

When the first three stages of processing are completed, the order is handed over to the distribution department. Since the transportation vehicle can deliver multiple orders at one time, the order is batched. The maximum number of orders in each batch is Q, that is, each batch of the delivery vehicle Up to Q orders can be loaded at the same time. There is no limit to the number of delivery vehicles. The transportation cost required for the vehicle to complete a distribution is D, and the vehicle returns to the distribution center after the distribution is completed.

We make the following declarations for the variables used inour model:

B is the order batch set, B={$B_1, B_2, \ldots, B_F$};

b_f is the order quantity in batch B_f,f=1,2, ..., F;

x_{if} is 0-1 variable, if $x_{if} = 1$ means order O_i is assigned to batch B_f;

y_i is 0-1 variable, if $y_i = 1$ means that order O_i contains type-A sub-workpiece;

z_i is 0-1 variable, if $z_i = 1$ means that order O_i contains type-B sub-workpiece;

s_{i1}^A is the start processing time of the type-A sub-workpiece in order O_i in the first stage;

c_{i1}^A is the processing completion time of the type-A sub-workpiece in order O_i in the first stage;

s_{i1}^B is the start processing time of the type-B sub-workpiece in order O_i in the first stage;

c_{i1}^B is the processing completion time of the type-B sub-workpiece in order O_i in the first stage;

s_{i2}^A is the start processing time of the type-A sub-workpiece in order O_i in the second stage;

c_{i2}^A is the processing completion time of the type-A sub-workpiece in order O_i in the second stage;

s_{i2}^B is the start processing time of the type-B sub-workpiece in order O_i in the second stage;

c_{i2}^B is the processing completion time of the type-B sub-workpiece in order O_i in the second stage;

s_{i3} is the start processing time of order O_i in the third stage;

c_{i3} is the processing completion time of order O_i in the third stage;

s_{i4} is the outbound time of order O_i;

s_f is the stat delivery time of batch B_f;

$$\min\left(\sum_{i=1}^{n} s_{i4} + F \times D\right) \tag{1}$$

s.t.

$$s_{i1}^A \geq 0, \forall O_i \in N \tag{2}$$
$$s_{i1}^B \geq 0, \forall O_i \in N \tag{3}$$
$$c_{i1}^A = (s_{i1}^A + p_{i1}^A) \times y_i, \forall O_i \in N \tag{4}$$
$$c_{i2}^A = (s_{i2}^A + p_{i2}^A) \times y_i, \forall O_i \in N \tag{5}$$
$$c_{i1}^A - s_{i2}^A \leq 0, \forall O_i \in N \tag{6}$$
$$c_{i1}^B - s_{i2}^B \leq 0, \forall O_i \in N \tag{7}$$
$$c_{i1}^B = (s_{i1}^B + p_{i1}^B) \times z_i, \forall O_i \in N \tag{8}$$
$$c_{i2}^B = (s_{i2}^B + p_{i2}^B) \times z_i, \forall O_i \in N \tag{9}$$
$$c_{i3} = s_{i3} + p_{i3}, \forall O_i \in N \tag{10}$$
$$max\{c_{i2}^A, c_{i2}^B\} - s_{i3} \leq 0, \forall O_i \in N \tag{11}$$
$$(s_{i1}^A - c_{j1}^A)(c_{i1}^A - s_{j1}^A) \geq 0, \forall i \neq j \tag{12}$$
$$(s_{i1}^B - c_{j1}^B)(c_{i1}^B - s_{j1}^B) \geq 0, \forall i \neq j \tag{13}$$
$$(s_{i2}^A - c_{j2}^A)(c_{i2}^A - s_{j2}^A) \geq 0, \forall i \neq j \tag{14}$$
$$(s_{i2}^B - c_{j2}^B)(c_{i2}^B - s_{j2}^B) \geq 0, \forall i \neq j \tag{15}$$
$$(s_{i3} - c_{j3})(c_{i3} - s_{j3}) \geq 0, \forall i \neq j \tag{16}$$
$$\sum_{f=1}^{F} x_{if} = 1, \forall O_i \in N \tag{17}$$
$$\sum_{O_i \in B_f} x_{if} \leq Q, \forall f = 1,2,\cdots,F \tag{18}$$
$$B_f = \{O_i | x_{if} = 1\} \tag{19}$$
$$\left\lceil \frac{n}{Q} \right\rceil \leq F \leq n \tag{20}$$
$$s_f = \max_{i=\{1,2,\cdots,n\}} \{c_{i3} \times x_{if}\}, f = 1,2,\cdots,F \tag{21}$$

$$s_{i4} = \max_{i=\{1,2,\cdots,n\}} \{s_f \times x_{if}\}, f = 1,2,\cdots,F \tag{22}$$

The objective function (1) represents the minimum sum of the total outbound time of the workpiece and the total distribution cost.Equations (2) to (3) indicate that the starting processing time of the type-A and type-B sub-workpieces is after zero.Equation (4) to (5) indicate the completion time of the type-A sub-workpiece in the first and second stages. Equations (6) to (7) indicate that the secondstage processing of type-A and type-B sub-workpieces must be processed after the first stage. Equations (8) to (9) represent the completion time of the type-B sub-workpiece in the first and second stages. Equation (10) represents the completion time of the workpiece in the third stage.Equation (11) indicates that both the type-A sub-workpiece and the type-B sub-workpiece in the workpiece must be processed before the third stage of processing can be performed. Equations(12) to (16) indicate that any machine can only process one workpiece or sub-workpiece at the same time. Equation (17) indicates that each order can only be assigned to one delivery batch. Equation (18) indicates that the capacity of any delivery batch cannot exceed the maximum capacity limit of the delivery vehicle. Equation (19) indicates the order setof batchB_f. Equation (20) represents the upper and lower bounds of the delivery batch. Equation (21) represents the delivery time of each batch is the time when the last order in the batch is processed, and equation (22) represents the order's outbound time is the time when the batch the order belongs is shipped out.

IV. ALGORITHM DESIGN AND NUMERICAL EXPERIMENT

4.1Genetic algorithm

Al-Anzi and Allahverdi (2013) proved that the two-stage assembly shop problem also has strong NP-hard characteristics in the case of only two parallel machines in the first stage. The problem studied in our model considers the three-stage assembly shop scheduling problem and the distribution cost is included in the scope of the study. Therefore, this problem is NP-hard. We use genetic algorithms to solve the problem. For the convenience of description, the relevant details of the genetic algorithm are first introduced below:

4.1.1 Encoding and decoding

A chromosome represents the order in which each order is processed on each machine, and each gene on the chromosome represents an order.

4.1.2 Genetic operator

The genetic operators used in this paper are: selection, crossover, and mutation. The parent individuals are selected from the initial population, and then the offspring individuals are generated by the crossover and mutation operators.

(1) Selection

This paper uses the roulette selection method to select the parent individuals from the parent population.

(2) Crossover

In this paper, the chromosome crossover operation is performed using a partially matched crossover method. First, randomly select two crossover points, and then exchange the gene fragments between the two crossover points. Replace to complete the crossover operation. Since the new chromosomes after the exchange contain duplicate gene values, we replace the duplicate genes by the mapping relationship of the parental alleles.

(3) Mutation

After the crossover operation is completed, we need to randomly select two loci in order to exchange the genes of the corresponding loci of each progeny individually. This process needs to be performed (for the number of orders and the probability of mutation).

4.1.3 Iteration termination conditions

The genetic algorithms in this paper are set as follows: When the number of iterations is 500, the iteration is terminated.

Thenwe design the algorithm. First of all, we designed an algorithm CA-Wfor arranging the processing sequence of the order processing stage and the batch operation of orders after processing. The algorithm CA-Wis now described as follows:

Step1 : For the sequence of workpieces$\{O_1, O_{2,\dots,}O_n\}$, the processing order of the type-A sub-artifacts of each artifact O_i^A $(\mathrm{i} = 1,2, \dots, n)$ in the sequence in the first and second stages is $\{O_1^A, O_2^A, \dots, O_n^A\}$, and the processing order of the type-B sub-artifacts of each artifactO_i^B $(\mathrm{i} = 1,2, \dots, n)$ in the sequence in the first and second stages is $\{O_1^B, O_2^B, \dots, O_n^B\}$. The assembly process sequence of each workpiece in the third stage is$\{O_1, O_{2,\dots,}O_n\}$.

Step2: After the third stage of assembly is completed, the orders $\{O_1, O_{2,...,}O_n\}$are allocated to the batchesB_f(f=1,2, ..., F) in accordance with the batch-by-batch method. Each batch can accommodate up to Qorders.

Subsequently, we designed a genetic algorithm WF-GAto solve the problem of our model. Now the algorithm WF-GAis described as follows:

Step1: Determine the population sizeP, crossover probabilityc, mutation probabilitym, and termination conditions of the algorithm iteration, and then initialize the population (randomly generate P individuals).

Step2: Call the algorithm separately for each individual in the population to calculate the fitness value of all individuals for the fitness function.

Step3: Based on the fitness values of all individuals, a selection operator is used to select a pair of parent individuals.

Step4: Use the crossover and mutation operators on the selected pair of parent individuals to generate offspring individuals.

Step5: The newly generated offspring individuals are added to the population by replacing the parent individuals, so as to complete the population update. Then repeatedly repeat Step3and Step4until the termination condition is met, then stop iteration, and output the processing order of the optimal individual and the calculated according to the order.

4.2 Numerical Experiment

All programming in this paper is based on C++, the compiler version is Mingw32-gcc-c++ 6.3.0.1, the development environment is JetBrains CLion 2019.2.5 x64, the computer operating system for numerical experiments is Windows10, the processor is Intel i5-3230M, the memory size is 8G, and the memory type is DDR3L.

4.2.1 Generate an instance

In order to verify the effectiveness of the algorithm WF-GA to solve the model, after fully considering the assumptions and the actual situation in the model, we randomly generated 3 sets of 60 instances for the experiment according to the parameters in Table1, each instance contains 50 workpieces, we set the transportation cost per batch to 10 and the upper limit of the transportation vehicle capacity to 8. In each instance, the processing time of the workpiece in each stage is set to follow a uniform distribution of a certain interval. The data interval of 60 groups of instances following the uniform distribution is shown in Table 1: Column “A1” represents the normally distributed interval that the type-A sub-workpiece processing time in the first stage, column “A2” represents the normally distributed interval that the type-A sub-workpiece processing time in the second stage.Column “B1” represents the normally distributed interval that the type-B sub-workpiece processing time in the first stage, column “B2” represents the normally distributed interval that the type-B sub-workpiece processing time in the second stage. Andcolumn “Batch” represents the normally distributed interval that the workpiece processing time in the third stage.

Table1: Data range of processing time for each of the 60 examples

Group	Example	A1	A2	B1	B2	Batch
X	1-20	[5,10]	[2,3]	[3,9]	[1,2]	[2,8]
Y	21-40	[0,10]	[0,3]	[0,9]	[0,2]	[0,8]
Z	41-60	[1,100]	[1,100]	[1,100]	[1,100]	[1,100]

4.2.2 Parameter selection

In the genetic algorithm, different parameters will have different effects on the results. Therefore, we set 7 different parameter combinations (population size, cross probabilityand mutation probability) for each group of instances to find better parameters. Because of the relatively large scales of each of the three groups, in order to achieve better results, set Pto 50, 100, 150, and maintain the same scale in each iteration. The crossover probability is generally set to be large, so it is set to 0.7, 0.8, and 0.9. The mutation probability is generally set between 0.05-0.1, but considering the problem is NP-hard, set it to 0.1, 0.2, 0.3 to expand the search space, and set the number of iterations to 500.

Set 7 groups of parameters: (50,0.7,0.1), (100,0.7,0.1), (150,0.7,0.1), (150,0.8,0.1),(150,0.9,0.1), (150,0.8,0.2), (150,0.8,0.3). Five experiments were performed for each group of examples to average the results to search for the best parameters suitable for each group of experiments. We conducted 2100 experiments. Finally, the results of the three groups under different parameters are shown in Table2:

Table2: Parameter selection

Group	50,0.7,0.1	100,0.7,0.1	150,0.7,0.1	150,0.8,0.1	150,0.9,0.1	150,0.8,0.2	150,0.8,0.3
X	9891.24	9866.6	9841.42	9837.34	9848.64	9845.04	9837.48
Y	6134.18	6084.36	6075.3	6059.6	6062.1	6069.39	6077.38
Z	73479.63	72640.24	71986.36	71949.42	72148.32	71971.14	72019.94

The parameter selection process is as follows:

Firstly, we set the values of c and m to 0.7 and 0.1; then set the values ofP to 50, 100, and 150. The experimental results show that the results are optimal when P=150, so wesetPto 150.

Then, based on the setting in the first step, we set the value of m to 0.1 and observe the change of the result with the change of c. The experimental results showed that the results were optimal when c=0.8, so we set the value of c to 0.8.

Finally, based on the previous two steps, we set the values of m to 0.1, 0.2, and 0.3. The experimental results of the parameters show that the results were optimal when m=0.1, so we set the value of m to 0.1.

In summary, the parameters of all genetic algorithms in this paper are set to (150, 0.8, 0.1).

4.2.3 Numerical experiments

We run each instance 5 times in accordance with the algorithm WF-GA, record the value and run time of each run separately, calculate the arithmetic average of the output value of 5 runs of each instance, as the output value of the instance；calculate the arithmetic average of the output time of 5 runs of each instance as the running time of this instance.

4.3 Analysis of experimental results

4.3.1 Algorithm robustness test

In order to evaluate the robustness of the algorithm WF-GA, we ran each instance 5 times and performed a total of 300 experiments to evaluate the span between the optimal solution (denoted as S_B) and the average (denotedas S_A) in the three groups. This span is called relative deviation (denoted as RD), and it is calculated as $R_D=(S_A-S_B)/S_A*100\%$.

It can be seen from Table3 that after each group of instances is run 5 times, the span between $S_A$and $S_B$is small, the average RD of group X is only 0.73%, the average RD of group Z is 1.75%. The average of three groups is less than 4%, indicating that the relative deviation of each group of instances is small, which proves that the algorithm is robust in the scenario represented by the three groups of instances.

4.3.2Comparison algorithm

Next, in order to verify the effectiveness of the algorithm WF-GA, we designed a comparison algorithm CA. The algorithm arranges processing and distribution according to the order of order arrival. It is widely used in daily operations due to its simple for operation. Therefore, it is practical significance to use the algorithm CA as a comparison algorithm. First of all, briefly describe the algorithm CA:

Step1: Arrange all the workpieces in the order in which they arrived at the order processing system (that is, the order in which the orders were generated).

Step2: Apply the algorithm CA-W and calculate to get $\sum_{i=1}^{n} s_{i4} + F \times D$.

4.3.3Algorithm validity check

Table3 show the experimental results of the three groups. The column “WF-GA” is the average of 20 instances of each groupaccording to the algorithm WF-GA; the column “Time” is the average running time(ms) of each instance running 5 times according to the algorithm WF-GA. The column “CA” is the average of 20 instances of each group according to the algorithm CA.

Table3: Experimental results and analysis

Group	WF-GA	Time	CA	Reduced value compared to CA	Improvement ratio compared with CA (%)
X	9835.78	306.97	11228.50	1392.72	12.37
Y	6059.60	302.70	8280.40	2220.80	26.73
Z	71949.42	291.04	94010.70	22061.28	23.40

From Table3, we can see that the results of the algorithm WF-GA are better than the results calculated by the algorithm CA. For group X, the average improvement ratio compared to the algorithm CA is 12.37%, for group Y, the average improvement ratio compared to the algorithm CA is 26.73%,and for group Z, the average improvement ratio compared to the algorithm CA is 23.40%, which indicates that the algorithm WF-GA has excellent performance for the processing group instances.

V. CONCLUSION

In this paper, we researched from the perspective of a new type of retail company that selected the third-party logistics “integrated warehouse and store”, and took the total order delivery time and total distribution cost as the evaluation index. First, we established a model based on the characteristics of the problem. In the model, we assume that the distribution cost of each batch of the order is a constant. For a newly established enterprise, due to its limited operating capital and labor costs, this rough calculation of distribution costs can be used. Next, we designed a genetic algorithm for the model, and also generated three groups of 60 examples that simulated different scenarios. After selecting the parameters of the genetic algorithm, a numerical experiment was performed, and the robustness of the algorithm WF-GA was analyzed based on the experimental results. Then, a comparison algorithm is designed based on the "first come, first processed" idea. By comparing the results of the numerical experiments of the two algorithms, we find that the algorithm WF-GA performs better than the algorithm CA in the three scenarios simulated by the experiment.

The results of the numerical experiments in this paper can provide decision support in picking and distribution for new retail companies that choose the "integrated warehouse and store" of third-party logistics. The first-come-first-served method is convenient to operate, but compared with the algorithm we designed to combine order picking and distribution, using the first-come-first-processing method will make the sum of the total outbound order time and the total distribution cost higher.The increasing of the total distribution cost will reduce the profit of the enterprise, and a higher total delivery time will reduce customer satisfaction.

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