Research on Intelligent Warehouse Order Splitting Problem Based on Adaptive Genetic Algorithm

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Abstract. With the rapid development of e-commerce, the order processing speed and efficiency of intelligent warehouses have become key factors for enterprise competitiveness. This article roughly divides the orders in intelligent warehouses into two categories. In response to the problem of manual sorting stations being idle in order sorting, an order splitting strategy based on adaptive genetic algorithm is studied, with the optimization goal of minimizing the total order completion time. The order splitting problem in intelligent warehousing systems is studied. The algorithm introduces crossover and mutation operators with adaptive transformation probabilities, and combines the taboo table in the taboo search algorithm to optimize and adjust the iterated population. Finally, the effectiveness of the proposed method is verified through simulation experiments.

Keywords: intelligent warehouse; Order batching; Order splitting; Adaptive Genetic Algorithm

1 INTRODUCTION

In recent years, with the rapid development of the construction industry, it has become a pillar industry of China's national economy. Simultaneously, construction enterprises are also expanding and developing rapidly. As market competition intensifies, saving costs and maximizing profits have become the primary considerations for every construction enterprise. As one of the traditional three objectives of project management, project cost management directly affects the level and outcome of engineering project management, and also significantly impacts economic benefits.[8] Therefore, strengthening cost management is an important goal that cannot be ignored by every enterprise. Regarding cost management, scholars at home and abroad have proposed theories such as full-life cycle, full-process, and comprehensive project management, as well as all-staff, all-process, and all-round cost management. These methods have become the main methods of project cost management in China and many other countries around the world. Bi Xing proposed a cost performance evaluation analysis method based on summarizing project cost conclusions. Mao Hongtao and others revealed the mechanism of organizational environment on the cost management of engineering projects and its significance to enterprise cost management. Ji Li et al. studied the cost budget mechanism to test the impact of government inter-

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vention on project costs. Qi Jiantao started with the project cost management issues that are prone to arise throughout the construction process of engineering projects and proposed specific solutions. Wang Yankui et al. explored cost control in real estate development projects based on BIM technology. Most domestic and foreign scholars study the influencing factors and management issues of cost management, with less under the practical application requirements of intelligent warehouses, studies the order sorting problem of two types of mixed sorting orders and some orders that can be split, and proposes an improved adaptive genetic algorithm to solve the problem.

2 PROBLEM DESCRIPTION AND SORTING STRATEGY

Smart warehouse orders are generally divided into two types. One is online orders, which contain a variety of products but require a small quantity of each product. The second type of orders mainly comes from bulk purchases in offline stores. These types of orders have a small variety of products but a large quantity, and are referred to as manual orders. The number of online orders accounts for over 81.4% of the actual total warehouse orders, while the number of manual orders is much smaller than the actual proportion of online orders [6-7]. The intelligent warehouse order picking mainly consists of three parts: order batching, sorting of batches after batching, and the final product removal location selection. As shown in Figure 1, it is a flowchart of the AVSS system.

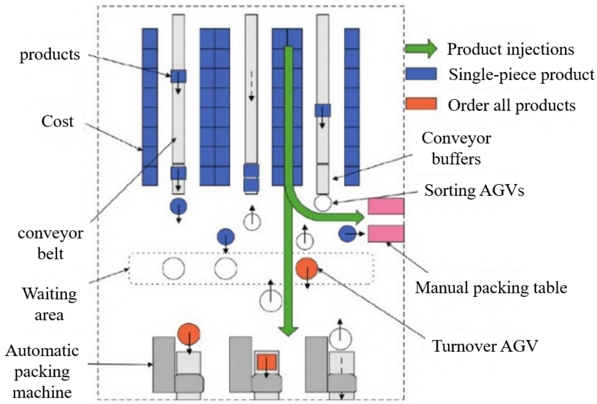

Fig. 1. AVSS system layout diagram and product flow

Due to the characteristics of two types of orders, when these two orders ap-pear in the same batch, a larger quantity of goods are required for manual orders. Therefore, more sorting AGVs are needed to go to the manual mobile phone station for packaging. This will result in a large number of sorting AGV queues blocking the entrance of the manual collection station, affecting the overall sorting efficiency [8]. If there are only online orders in a batch of orders, the manual collection station will not be utilized, resulting in idle situations and unnecessary resource waste. In order to solve the series of problems that arise in manual collection stations mentioned above, this article proposes the concept of order splitting. Split manual orders into individual sub orders and divide them into different order batches to solve the problem of manual collection station congestion caused by a large number of manual orders in the same batch [9-10]. At the same time, fully utilize the manual collection stations in each batch.

3 MATHEMATICAL MODELS AND ADAPTIVE GENETIC ALGORITHM

3.1 Problem Assumptions and Variables

In the complex operation of the AVSS system, once the sorting scheme is determined, the entire process needs to be strictly carried out in the predetermined order. This process includes three main stages: product removal, product sorting, and order packaging. These steps rely on a series of advanced equipment to ensure that each task can be efficiently and accurately completed. In order to better understand this process and simplify the analysis of the problem, this article proposes the following assumptions:

(1) There are goods in the warehouse that can meet all order requirements;

(2) All orders are known before sorting, and each batch has the same number of orders;

(3) After the manual order is split, each sub order has a unified quantity specification;

(4) The handover operation time of all devices is consistent;

(5) Not considering the cancellation of orders and the addition of new orders;

(6) If the remaining equipment can meet the needs of the next batch of orders, the sorting of the next batch of orders will start immediately;

(1) model parameter

I Represents a collection of warehouse orders, $i \in \mathrm{I}=\{1,2,\cdots,m\}$; I^R Represents the set of manual orders after splitting; I_g^{R} The set of sub orders after splitting the manual order g, $I_g^{\mathrm{R}} \subset I^R,\ \mathrm{g} \in \{1,2,\cdots,G\}$; I^W Represents a collection of online orders, $I^W \cup I^R = I, I^W \cap I^R = \varnothing$; b represents the packaging time of each manual order item; a represents the number of manual collection stations; $(i,j) \in U$ The quantity of the j item in order i is J_i; U represents the set of all order items; $l \in L = \{1,2,\cdots,p\}$ Indicates the order batch; C_l Indicates the number of manual sub orders split in a batch l; k Indicates the down shelf storage location;

(2) Decision variables

x_{ijk} It is a 0-1 variable. If the product (i,j) is removed from the storage k location, it is 1; otherwise, it is 0; v_{il} It is a 0-1 variable. If the order i is assigned to a batch l, it is 1; otherwise, it is 0; $y_{l'l}$ It is a 0-1 variable. If the batch l' precedes the batch l, it is 1; otherwise, it is 0.

3.2 Model Establishment

(1) The moment when online order i starts packaging.

$$T_{si}^{\ A} = \max\left\{T_{iz}^{\ Z} + d_v, T_{si'}^{\ E}\right\} \tag{1}$$

$T_{si'}^{\ E}$ The packaging time of the previous order i' was completed; $T_{iz}^{\ Z}$ Order i sorting completion time; d_v Run time.

The time when online order i completes packaging:

$$T_{si}^{\ E} = T_{si}^{\ A} + p_i \tag{2}$$

p_i Indicates the time required for packaging machine packaging order i.

(2) Manual order packaging

① When the last item (m',n') of manual order g is sorted, order g begins packaging. The packaging completion time for the order is:

$$T_g^{\ E} = T_{m'n'f}^{\ \ E} + b\sum_{i=1}^{n} J_i \tag{3}$$

$T_{m'n'f}^{\ \ E}$ The last item (m',n') sorting completion time of manual order g; $b\sum_{i=1}^{n} J_i$ the total packaging time of manual order g.

This article constructs a mathematical model with the optimization objective of minimizing the total order completion time when manual orders can be split, as follows:

$$\min\max\left\{\begin{array}{l}\max\left\{T_{si}^{\ E} \middle| i \in I^W\right\} \\ \max\left\{T_g^{\ E} \middle| g \in \{1,\cdots,G\}\right\}\end{array}\right. \tag{4}$$

$$s.t.\sum_{k=1}^{q} x_{ijk} = \sum_{k \in K_{ij}} x_{ijk} = 1, \forall (i,j) \in U \tag{5}$$

$$\sum_{i=1}^{E}\sum_{j=1}^{J_i} x_{ijk} \le 1, \forall k \in K \tag{6}$$

$$\sum_{l=1}^{p} v_{il} = 1, \forall i \in I \tag{7}$$

$$C_l \le a, \forall l \in L \tag{8}$$

$$T_l^A \ge v_{il'} y_{l'l} T_{si}^{\ A}, \forall l \in L \tag{9}$$

Equation (4) represents the objective function of the minimum completion time of the total order, which is to select the larger value from the maximum time when the last manual order and the last online order packaging are completed, and then select the minimum time from it to be the minimum time when the total order is completed; Equation (5) is a constraint that ensures that each item can only be removed from one corresponding storage location; Equation (6) is a constraint that ensures the removal of one item from each storage location; Equation (7) is a constraint to ensure that orders are not repeatedly divided into different batches; Equation (8) is a constraint to ensure that the number of manual sub orders included in each batch does not exceed the number of manual collection stations; Equation (9) is a constraint that ensures that the order meets the sorting conditions for the first time, and the sorting start time should be after the packaging of the previous batch of orders.

4 IMPROVE ADAPTIVE GENETIC ALGORITHM

4.1 Problem Encoding and Fitness Function

The fitness function can determine the evolutionary direction of the population in genetic algorithms. In this paper, the goal is to minimize the total completion time of orders. the fitness function uses the reciprocal of the total completion time. The larger the value of the fitness function of the current solution, the smaller the total completion time, and the better the solution.

$$f = \frac{1}{\min\max\left\{\begin{array}{l}\max\left\{T_{hi}{}^{E} \middle| i \in I^{W}\right\} \\ \max\left\{T_{g}{}^{E} \middle| g \in \{1,\cdots,G\}\right\}\end{array}\right.} \tag{10}$$

This article designs double layered chromosomes and describes them using real number encoding, as shown in Figure 2. The value of the chromosome in the first layer represents the batch in which the corresponding order is placed, while the value in the second layer represents the order in which the corresponding batch is removed from the shelves. For example, in Figure 2, the I_1 order is distributed in the 7th batch of L_7, the 7th batch of L_7 is the 4th batch to be taken off the shelves, the I_2 order is distributed in the 8th batch of L_8, the 8th batch of L_8 is the 7th batch to be taken off the shelves.

	I_1	I_2	I_3	I_4	I_5	I_6	I_7	I_8
Order batches	7	8	4	6	3	5	1	2
Batch sorting	1	3	2	5	6	8	4	7
	L_1	L_2	L_3	L_4	L_5	L_6	L_7	L_8

Fig. 2. Coding

4.2 Algorithm Process Design

Based on the advantages and disadvantages of genetic algorithm, this paper proposes an improved adaptive genetic algorithm (IAGA) combined with taboo search algorithm, which introduces adaptive transformation probability into the genetic algorithm.

Step 1: Set algorithm parameters, including maximum number of iterations, population size, and cross mutation probability, etc;

Step 2: Generate the initial population and initialize the individuals in the random population according to the encoding method in section 3.1. Generate initial population;

Step 3: Fitness calculation, calculate the fitness f of each individual;

Step 4: Perform genetic operations on individuals based on roulette wheel selection and elite solution preservation, and update the population based on adaptive transformation probability crossover and mutation operators;

Step 5: Merge the new population and then perform a taboo search local operation loop on it;

Step 6: If the maximum number of iterations is reached, terminate the algorithm to output the optimal solution. Otherwise, proceed to Step 3.

4.3 Adaptive Mutation Probability

Traditional genetic algorithms typically use fixed probability values in mutation operations, which may lead to poor performance in certain problems. To address this issue, this article introduces adaptive mutation probability into the algorithm. By dynamically adjusting the probabilities of crossover and mutation, the algorithm can avoid slow convergence and falling into local optima due to inappropriate probability settings. Therefore, in order to better adapt to the characteristics of the problem, improve the performance and efficiency of the algorithm, while retaining diversity in the population, this paper adopts the Tanh function to adaptively control the mutation probability P_b, as shown in equation (11); Equation (12) represents the expected value of fitness.

$$P_b = \begin{cases} P_{b\min} + \dfrac{\exp\left[2B\dfrac{f_b - u_f}{f_{\max} - u_f}\right] - 1}{\exp\left[2B\dfrac{f_b - u_f}{f_{\max} - u_f}\right] + 1} & f_b \geq u_f \\ P_{b\max} & f_b \angle u_f \end{cases} \tag{11}$$

$$u_f = \frac{f_{\max} - f_{\min}}{2} \tag{12}$$

$P_{b\min}$, $P_{b\max}$ represents the minimum and maximum probability of variation; B is the curve smoothing parameter for hyperbolic tangent, with a value of 9.903748 in this article: $f_{\max}$、$f_{\min}$ representing the maximum and minimum fitness values, respectively; u_f Indicates the expected fitness value; f_b Represents the fitness of the individual to be mutated. By introducing fitness related concepts in the Tanh function, it can be achieved that ① individuals with poor fitness will also have higher transformation probabilities, improving the overall level of solutions; ② When individuals do not reach the expected fitness level in the early stages, it can also ensure the evolution of the population and avoid the phenomenon of population stagnation in the early stages of evolution.

4.4 Cross Operator

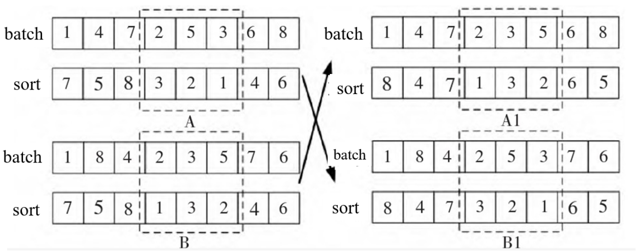

Fig. 3. Schematic Diagram of Cross Operation

To avoid the occurrence of a large number of infeasible solutions in crossover, which may result in the loss of better individuals, this paper adopts a new crossover method to perform crossover operations on double chromosomes. Firstly, two chromosomes are randomly selected as parents, and a segment of genes is randomly selected on the parents. If the number values of the two segments of genes are equal, pairwise exchange is carried out. If they are different, a new segment of genes is selected.

5 NUMERICAL EXPERIMENTAL ANALYSIS

To verify the effectiveness of the algorithm proposed in this article, a comparison is made between the IAGA algorithm and the IAGA algorithm. The running results of the IAGA algorithm under split and non split orders are discussed, and the optimization effect of the IAGA algorithm is compared and analyzed with the traditional genetic algorithm GA. The population size is set to 100, the minimum and maximum crossover probabilities of the Tanh function are 0.07 and 0.8, the minimum and maximum mutation probabilities are 0.02 and 0.1, the maximum number of iterations is 200, and the maximum number of local searches per generation is 25. The cross mutation probabilities of the GA algorithm in the comparative experiment are 0.8 and 0.1, respectively. The population size of the fruit fly algorithm SFOA is set to 10, the sub population size is 7, the knowledge base update rate is 0.1, and the number of elite fruit flies is 2; The population size of the grey wolf algorithm GWO is set to 80.

5.1 Numerical Examples and Parameters

The equipment parameters involved in the AVSS system operation process are shown in Table 1. To better match the actual situation, real data is used for the equipment parameters, which are sourced from a certain e-commerce warehouse. And design 5 examples, with the parameters shown in Table 1. Set the product quantity limit for manual orders, which should not exceed 4000 and not be less than 150. Set the equal quantity of orders in each batch to 25 and conduct experimental analysis on the 5 examples.

Table 1. Example parameter

Example	Order quantity	Total product quantity	Number of manual orders	Quantity of manual order products
1	500	6000	2	678
2	800	8000	4	1176
3	1000	10000	6	1725
4	1000	11000	8	2133
5	1000	11000	10	3074

5.2 Model Validation

Conduct comparative experiments on the effectiveness of order splitting strategies based on different data in Table 2. Table 3 shows the comparison results of the IAGA algorithm under manual order splitting and non splitting conditions. The comparison indicator cpm in the last column is equal to the total completion time of the comparison algorithm Qa IAGA algorithm/the total completion time of the comparison algorithm. From the final data, it can be seen that the split algorithm can significantly reduce the total completion time of orders, which is 11.31%~29.46% lower than the non split algorithm. The running time of the algorithm after splitting is also relatively reduced.

Table 2. The comparison result of manual order splitting and non-splitting

Example	IAGA (not disassembled)		IAGA (disassembled)		Cpm/%
	Qa	Ti	Qa	Ti	
1	1.334	3.86	0.941	2.30	29.46
2	1.450	4.40	1.286	3.07	11.31
3	2.153	7.12	1.777	3.94	17.46
4	2.640	11.98	1.899	5.96	28.07
5	3.612	18.47	2.730	8.61	24.42

The split IAGA algorithm was compared and analyzed with other algorithms, and the results are shown in Table 3. In the 5 examples, the running time of IAGA algorithm is slightly longer than other algorithms, and the total completion time of orders is also the shortest, which is 16.05%~26.44% less than traditional genetic algorithm GA, 1.75%~5.34% less than fruit fly algorithm SFOA, and 8.91%~26.73% less than GWO. The test results show that as the order size increases and the number of manual orders increases, the algorithm's solving time and the total completion time of orders also increase. It can be seen that manual orders have a significant impact on the completion time, which is also the key to controlling the completion time The improved IAGA algorithm has a longer running time in terms of solving time, but the efficiency of obtaining the optimal solution significantly increases. Moreover, as the scale and quantity increase, the optimal solution obtained by IAGA is significantly better than other algorithms. It can be seen that the algorithm and splitting strategy proposed in this article perform excellently in the process of finding the optimal solution.

Table 3. Algorithm comparison

Ex-	GA		SFOA		GOW		IAGA		Cpm1	Cpm2	Cpm3
ample	Qa	Ti	Qa	Ti	Qa	Ti	Qa	Ti	/%	/%	/%
1	1.121	2.34	0.971	2.55	1.397	3.46	0.941	4.30	16.05	1.75	6.71
2	1.587	3.19	1.293	3.76	1.476	5.46	1.286	6.07	18.50	2.19	8.91
3	1.832	4.25	1.599	5.03	2.099	7.14	1.577	9.94	13.91	0.94	13.26
4	2.453	8.26	2.010	6.58	2.741	10.95	1.899	13.96	26.44	5.34	25.17
5	2.713	11.31	2.612	9.01	3.574	12.53	2.031	15.61	20.28	2.78	26.73

6 CONCLUSION

This article proposes a new intelligent warehouse order batching strategy based on adaptive genetic algorithm, which is used to solve the problems of actual sorting AGV blockage and idle manual sorting stations when two types of orders are mixed sorted in the warehouse. A mathematical model for order sorting problem was established with the optimization objective of minimizing the total order completion time. Adaptive genetic algorithm was used for optimization and adjustment. Finally, the effectiveness of order splitting was verified through comparative experiments. There are still certain shortcomings in the research of this article. In the actual operation process of AGV, obstacles and insufficient power on the road can lead to errors and deviations in the running path of AGV cars. The article only uses the ratio of Manhattan distance and speed between the starting point and the ending point to replace the running time, which is significantly different from the actual situation. At the same time, the status of product orders is also not fixed in practice, and uncertainties such as additional orders, order cancellations, equipment failures, etc. were not considered in the article. Future research should try to reproduce the problems in the warehouse sorting process as much as possible, and can also explore the batch sorting problem of warehouse orders in depth based on these uncertainty scenarios.

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