TOBACCO STORAGE PATH PLANNING BASED ON ADAPTIVE LARGE NEIGHBORHOOD SEARCH ALGORITHM

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The traditional manual picking method in tobacco warehouses can no longer meet the diverse order needs of customers. In response to the low efficiency and high cost of traditional manual picking, this paper proposes a path picking problem for multiple parking lots and vehicles. To solve this problem, an Adaptive Large Neighborhood Search (ALNS) algorithm is proposed, and a K-Means clustering algorithm is designed to cluster the picking points to improve the initial solution quality. Compared with traditional genetic algorithm, simulated annealing and Tabu search, ALNS algorithm has better results.

Keywords: Tobacco warehouse, Vehicle path, Logistics delivery, Adaptive Large Neighborhood Search, K-means clustering algorithm

1. Introduction

In recent years, with the continuous development of the tobacco industry, consumer demand has shown a trend of diversification and personalization, which has raised the requirements for picking goods in tobacco warehousing centers. According to relevant statistics, material picking accounts for 40% of warehouse operations, and the use of manpower related to picking reaches more than 50% [1][2]. Because of the airtight requirements of tobacco warehouse, it is important to reduce the frequency of inbound and outbound, shorten the path picking distance and time for tobacco warehouse picking.

Vehicle path planning is a typical NP hard problem[3], which is mainly solved by precise algorithm and heuristic algorithm. The traditional precise algorithm uses a mathematical model to obtain the optimal solution of the target value through calculation. Such algorithms include dynamic programming, branch and bound methods[4][5]. However, with the expansion of the scale of the problem, its calculation time will increase exponentially and it is not easy to converge, so it can only be used in small-scale VRP problems[6]. In order to make up for this

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situation, more and more scholars devote their energy to the research of heuristic algorithms. Such algorithms include genetic algorithm [7], ant colony algorithm[8][9], simulated annealing algorithm [10][11] and so on, which can find the optimal solution in the constrained region in a short time.

Goods picking is an important work in the warehouse, and the efficiency of picking directly affects the operating efficiency of enterprises. In this regard, academia has done a lot of research on path planning. Chen effectively reduced warehouse congestion based on indoor information sharing technology for possible congestion problems in warehouse picking [12]. Xue aims to minimize the total picking time. He proposed a picking-order method of analyzing first and then combing, which is more effective [13]. Liu built three path picking models for Citroen's warehouse layout. Through numerical experiments, it was found that the mixed and S-line picking paths were significantly better than the return path strategy [14]. Yu took the shortest path and the least number of turns of AGV in the warehouse as the optimization goal. better rules for ant information interaction are established and a model based on parallel sorting ant colony algorithm is built, which improved the AGV trolley picking efficiency [15]. Tan proposed to build a hybrid algorithm combining ant colony algorithm as one stage and multiple genetic algorithms as two stages for the last mile delivery problem[16].

In addition, scholars continue to expand from the basic problems of path planning to more scenarios, including time windows [17][18],pickup and distribution [19][20], collaborative distribution [21][22], etc. For different problems, scholars have also proposed different solutions. Considering the actual situation, Chen abandoned the hard time window and proposed a method to find the first K shortest paths for soft time piercing [17]. Chang first uses adaptive spatiotemporal neural network to predict the location of potential customers, and then allocates taxi orders based on track sharing graph, effectively balancing the supply and demand relationship [19]. Zhao used K-Means algorithm to preliminarily cluster customers, and then used variable neighborhood search to optimize the joint distribution of riders and UAVs. The results show that this method is more efficient than the traditional single rider distribution [21].

It can be seen that the problem of path picking has become a topic of great research significance. However, the traditional warehouse path optimization problem often has only one entrance and exit, that is, the picker starts from one location and needs to return to the starting point after picking. However, for large warehouses, vehicles are often scattered everywhere and need to be delivered to the processing place after picking. Therefore, based on the problem description and model assumptions, this paper constructs a mathematical model to solve the problem for large-scale tobacco warehouse, designs an adaptive large neighborhood search algorithm through an adaptive framework and classical operators, solves the desensitized actual order data, and compares it with traditional genetic algorithms to prove the effectiveness of this algorithm. This research is helpful to improve the picking efficiency of the warehouse, get rid of the traditional "person to person" picking mode, and promote the development of tobacco enterprises to "goods to person" robot automatic picking.

2. Problem definition and mathematical modeling

2.1. Problem definition

In a tobacco warehouse, there are A depots, where several trucks are stored. When receiving the picking task, the vehicles start from different depots, pick at the storage location, and then distribute the raw materials to the cigarette processing place. The picking quantity of the operator at each picking point is q_j, q^{max} is the maximum carrying capacity of each picking truck. The operator picks according to the picking sequence until the vehicle cannot load the materials at the next location. It is the collection of storage locations in the warehouse.

2.2. Model Assumptions

1) The vehicle capacity is not less than the maximum capacity of the demand node.

2) Vehicles depart from multiple depots.

3) There are several vehicles in each parking lot, that is, the number of each parking lot meets the actual demand.

4) Uniform vehicle type.

2.3. Mathematical model

To solve the above problem, the following model is established considering the minimization of picking path.

$$G=min\sum_{h\in H}\sum_{r\in R}X_{ij}^{r}Y_{r}^{h}d_{ij}^{r} \tag{1}$$

$$\text{s.t.} \qquad \sum_{\mathrm{r\in R}}\sum_{\mathrm{i\in N}}\mathrm{X_{ij}^{r}}=1,\mathrm{j}\in\mathrm{C} \tag{2}$$

$$\sum_{r\in h}Y_{r}^{h}=1 \tag{3}$$

$$\sum_{i\in N}\sum_{j\in C}X_{ij}^{r}\times q_j\le q^{max} \tag{4}$$

$$X_{ij}^{r}\in\{0,1\},\forall i,j\in N,\forall r\in R \tag{5}$$

$$Y_{r}^{h}\in\{0,1\},\forall r\in R,\forall h\in H \tag{6}$$

In the above model, Equation (1) is the objective function, finding the minimum sum of distances; Equation (2) ensure that each picking point is accessed and only once; Equation (3) ensure that each section of the itinerary is managed by only one person; Equation (4) ensure that the weight of the picked goods does not exceed the maximum carrying capacity of the carrier. Where d_{ij} is the distance from i to j, $Y_r^{\hbar}$ judges whether the journey r is the responsibility of the operator $\hbar$, if yes, it is 1, otherwise it is 0, and X_{ij}^{r} judges whether the travel r is from j to i. If yes, it is 1, otherwise it is 0.

3. Algorithm design metaheuristic

The adaptive large neighborhood search algorithm (ALNS) is a high-quality metaheuristic algorithm. Its core is to update the neighborhood through the destruction and repair mechanism to find a better solution in the neighborhood. At the same time, the adaptive algorithm can dynamically select the damage and repair operators and seek better operators according to rules to obtain better results.

In this paper, firstly, according to the number of collection points, the picking points are classified by K-Means clustering analysis to generate high-quality initial solutions. Then, the initial solutions are deconstructed by destruction, repair and insertion operators. A better neighborhood is selected by adaptive algorithm, and the objective optimization value is obtained after multiple iterations. The specific algorithm steps include:

Step 1: According to their coordinates, use K-Means algorithm to cluster picking points. According to the location of the parking lot, assign nearby picking points to the picking range of the parking lot.

Step 2: Add the clustered picking points to the journey in turn to form an initial solution.

Step 3: Select a group of damage and repair operators by roulette wheel gambling to generate a new solution S^*. The higher the score, the higher the probability of the operator being selected.

Step 4: The ALNS algorithm sets inner and outer loops, while the outer loop adopts Metropolis acceptance criteria to avoid falling into local optima. The initial temperature is 0.2 times the current solution, the temperature cooling rate is 0.9, and the operator score is reset every ten times. The operator weight is updated every ten times in the inner loop.Adopt the Metropolis acceptance criteria, that is, first compare the new solution S^* with the current solution S. If the new solution S^* is better than the current solution S, update the current solution S, and further compare it with the optimal solution S_{best}. If the new solution S^* is better than the optimal solution S_{best}, update the optimal solution S_{best}, and vice versa. When the new solution S^* is greater than the current solution S, but its difference is less than the initial T value, the solution is also accepted to avoid falling into the local optimum, and the T value gradually decreases at a certain rate.

Step 5: There will be three scenarios for operator scores based on the above steps.Adjust the operator score and update the corresponding weight according to the update of the solution.

Step 6: Repeat Step 3~5 above until the number of cycles is reached to obtain the final optimal solution S_{best}.

Fig. 1shows the flow of the adaptive large neighborhood search algorithm.

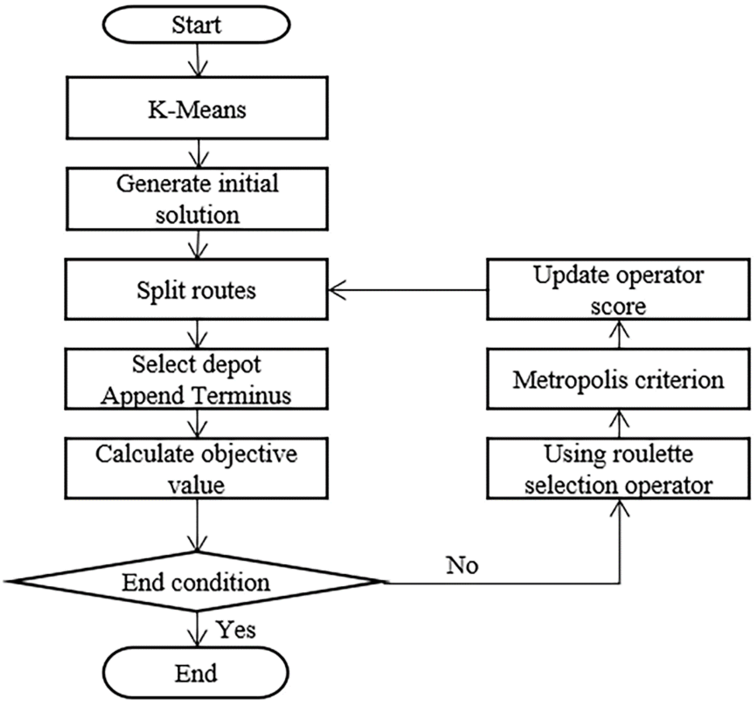

Fig. 1. Flow chart of adaptive large neighborhood search algorithm

3.3.1. Initial solution generation

The K-Means algorithm is used to cluster the picking points into three categories and add the ingredients to the empty journey according to the following principles: (1) The ingredients have not been selected; (2) The remaining load of the current journey can be loaded with the ingredients; (3) If the ingredients cannot be added to the existing journey, start to recreate a journey.

3.3.2. Destruction operator

In this paper, we design two destruction operators, Random Destroy and Worst Destroy.

1) Random Destroy: within the set upper and lower limits of random damage, a segment of travel is randomly deleted from the original travel with the probability of discrete uniform distribution.

2) Worst Destroy: The worst damage operator calculates the target value after removing each material, and successively deletes the location points that increase the path distance to the maximum, so as to continuously optimize the target value. The specific calculation is to calculate the distance reduction $\Delta(i)$ after removing node i, $\Delta(i) = f(s) - f(s_{-i})$. $f(s)$ is the distance when passing node i

and $f(s_{-i})$ is the distance after taking point i. Sort all $\Delta(i)$ and delete the node i corresponding to the maximum value$\Delta(i)$.

3.3.3. Repair operator

This paper sets Random Repair, Greedy Repair and Regret Repair to insert the deleted node into the original solution according to different rules.

1)Random Repair: In the list of deleted nodes, select nodes in turn and place them at random locations to form a new path.

2) Greedy Repair: For the removed node, consider placing it in the original path in isolation to find the location that minimizes the incremental path. The specific calculation is to calculate the increased distance$\Delta(i)$ after adding node i, $\Delta(i) = f(s) - f(s_{+i})$. $f(s)$ is the distance when passing node i and $f(s_{+i})$ is the distance after adding point i.

3) Regret Repair: Greedy Repair operator places nodes that are far away behind, and these nodes have less selectivity in the later stage. The proactive nature of the Regret Repair operator makes up for this defect. The Regret Repair operator calculates the increments $i_1, i_2, i_3, i_4, \cdots\cdots$of q nodes to be removed and inserted into each position on the path. The increments are sorted from small to large. Then, it calculates $\Delta = (i_2 - i_1) + (i_3 - i_1) + (i_4 - i_1) + \cdots$, and the largest node Δ is firstly inserted into the position with the smallest increment.

3.3.4. Adaptive search

The core of ALNS algorithm is to find an operator with better performance in history retrieval through adaptive search, improve the operation efficiency of the algorithm through operator selection, and obtain a better solution. The specific performance is as follows:

1) Define the weight of the damage operator as w_i^d, and define the weight of the repair operator as w_i^r.

2) Update operator score: select the corresponding operator through roulette. The rules for operator score change are as follows:

① If the target value of the new solution is less than the optimal solution, update the optimal solution:

$$\xi_i = \xi_i + \alpha_1 \tag{7}$$

② If the target value of the new solution is smaller than the current solution but larger than the optimal solution:

$$\xi_i = \xi_i + \alpha_2 \tag{8}$$

③ If the target value of the new solution is greater than the current solution but less than the T value, the new solution is also accepted:

$$\xi_i = \xi_i + \alpha_3 \tag{9}$$

3) Update operator weight: update operator weight after each algorithm, λ is used to control the influence of operator-on-operator weight during solution search, $\lambda \in (0,1)$. Among them, 0 represents that the historical performance of the

operator has no effect on the operator weight, while 1 represents that the operator weight remains unchanged. The operator weight only depends on the performance of the current search process. The operator's current score is ξ_i. The parameters N^d and N^r respectively represent the number of neighborhood breaking and neighborhood repairing operators.

$$w_i^d = \lambda w_i^d + (1-\lambda)\xi_i^d / \sum_{i=1}^{N^d} \xi_i^d \tag{10}$$

$$w_i^r = \lambda w_i^r + (1-\lambda)\xi_i^r / \sum_{i=1}^{N^r} \xi_i^r \tag{11}$$

4) Repeat 2-3 steps: the probability of each damage and repair operator being selected is:

$$p_i^d = w_i^d / \sum_{j=1}^{N^d} w_j^d \tag{12}$$

$$p_i^r = w_i^r / \sum_{j=1}^{N^r} w_j^r \tag{13}$$

4. Computational Experiments

The experimental environment for this article is Intel Core i7-7700HQ CPU@2.80GHz The processor speed is 2808MHz, and the above process is solved using Python 3.10.This paper randomly selects the actual order data of a tobacco company warehouse in 2021 for 8 days as the experimental data, and the data is desensitized. The number of picking points is 48, 49, 60, 64, 92, 108, 123, 173 in turn, and there are 3 parking lots. The cigarette processing place is located in the middle of the parking lot, so that vehicles can return to the parking lot after distribution of materials. The vehicle type is a light truck with a load capacity of 10 tons. Other specific parameters are shown in Table 1.

Table 1

Relevant parameter settings

Iterations	K-Means	100
	Internal circulation of ALNS	10
	External circulation of ALNS	10
Operators	Upper limit of random damage	0.4
	Lower limit of random failure	0.1
	Worst damage upper limit	20
	Lower limit of worst failure	5
	Operator reward score α_1	30
	Operator reward score α_2	20
	Operator reward score α_3	10
Parking lot	Number	3

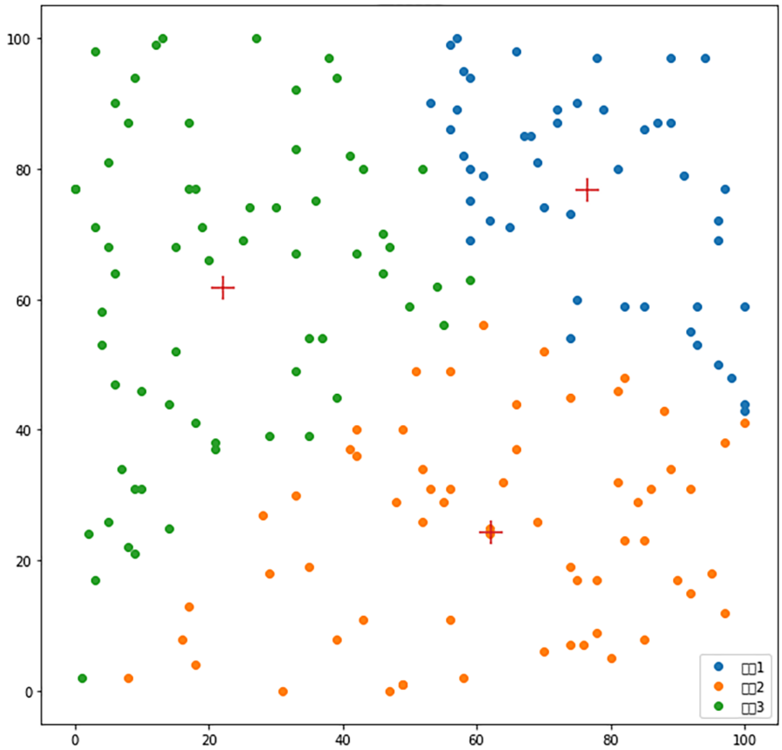

Fig. 2.K-Means algorithm clustering results

Taking the calculation example with 173 picking points as an example, the clustering results and path selection obtained by K-Means algorithm and ALNS algorithm are shown in the Fig. 2 and Fig. 3. It can be seen that the clustering analysis results of the final path selection of trucks starting from different collection points are relatively similar to those of the initial solution generation process, proving that the quality of the initial solution obtained through the K-Means algorithm is higher and has a significant effect on the generation of the optimal solution.

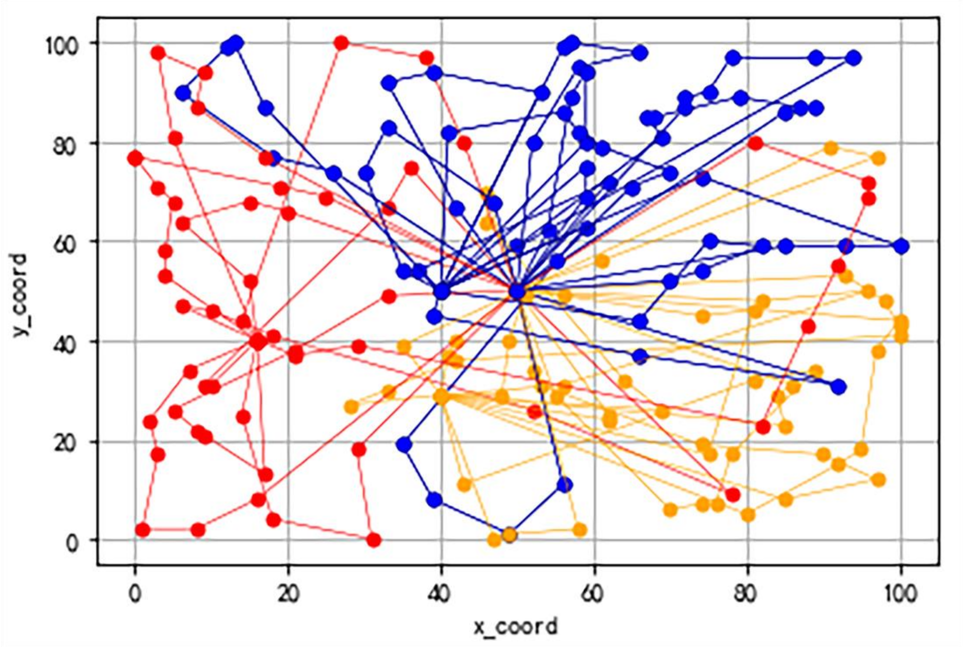

Fig. 3. ALNS Algorithm Path Selection Results

In terms of solution results, this paper compares with the traditional tabu search algorithm (TS), genetic algorithm (GA) and simulated annealing algorithm (SA) and obtains the following table when the number of iterations is 100. The error is the difference between the average distance and the optimal distance.

It can be seen from Table 2 that the ALNS algorithm works better when the sample size is large.

Table 2

Comparison of ALNS algorithm with other algorithms

Number	Number of picking points	ALNS Average distance	ALNS Optimal distance	Error（%）	TS	GA	SA
1	48	710	681	4.04	1952	1427	1737
2	49	1183	1143	3.40	2257	1908	2119
3	60	1247	1166	6.51	2426	2013	2141
4	64	1562	1517	2.88	2849	2114	2851
5	92	2164	2081	3.84	3926	3811	3520
6	108	2558	2536	0.84	4145	4395	4201
7	123	2524	2468	2.23	4863	4775	4602
8	173	3790	3690	2.63	8111	7668	6912

The error is between 3.40 and 6.51% when the sample size is below 60 picking points, while the error is only about 3% when the sample size is above 60. When comparing with other algorithms, it can be seen that ALNS algorithm is significantly superior to the other three algorithms in the same iteration number, and the overall algorithm quality is nearly twice as high as TS, about 80% higher than GA, and 90% higher than SA. From the scale of the example, when the number of picking points is less than 92, the solution quality is ALNS>GA>SA>TS. When the number of picking points reaches 92, ALNS>SA>GA>TS. It can be seen that compared with the traditional heuristic algorithm, the ALNS solution quality used in this paper is better and the effect is better.

Fig. 4 shows that ALNS algorithm has better convergence than other algorithms. In the solution of the same example, ALNS optimizes the target value to the global optimum after about 20 iterations.

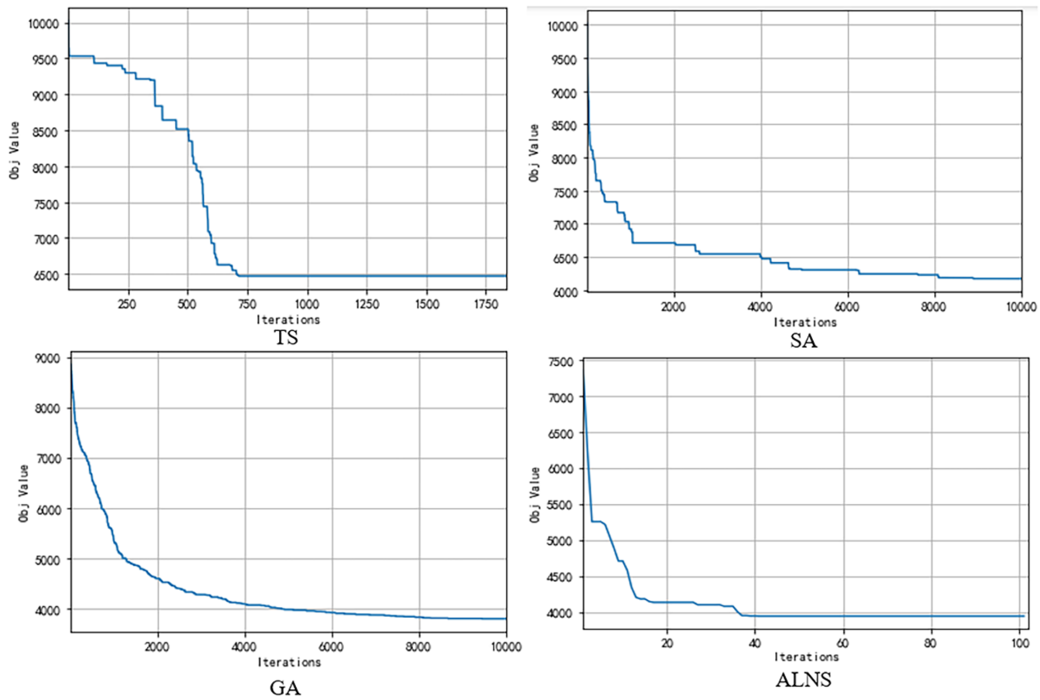

Fig. 4. Comparison of convergence curves between ALNS algorithm and other algorithms

Although TS converges quickly, it is easy to fall into the local optimum, and the quality of the optimized value is poor. Compared with SA, the convergence curve of GA is smoother, representing that the GA algorithm is more robust.

5. Conclusions

With the increasing variety of tobacco raw materials, the traditional goods picking mode has lower efficiency and higher cost. This paper proposes an adaptive large neighborhood search algorithm for the "arrival of people" picking mode used in traditional tobacco warehouses. The algorithm uses K-Means clustering to generate the initial solution, and then uses damage and repair operators to gradually generate the optimal solution under the adaptive framework, and sets the selection probability for each neighborhood, updates the selection probability according to the solution generation situation, and uses the Metropolis criterion to avoid falling into local optimization, thus effectively improving the quality of the final solution. Establish the shortest path objective function, take three different parking lots as the starting point of the journey, take a cigarette processing place as the end point of the journey, conduct simulation calculation through 8 groups of actual data after desensitization, and compare with the classical genetic algorithm, tabu search and simulated annealing experiments, finally prove that ALNS algorithm can effectively shorten the path.

This paper considers the characteristics of different starting and ending points of the picking path, which is more consistent with the actual picking and distribution situation. However, due to the fact that in the actual order picking and selection, there are centralized order bursts, real-time changes and other situations, it is hoped that more scholars will pay attention to the path planning problem of dynamic real-time changes.

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