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Improved Genetic Algorithm in Multi-objective Cargo Logistics Loading and Distribution

Zhilin He
Chengdu Agriculture college, Economic trade department, Chengdu, Sichuan, 611130, China
E-mail: zhilinhe3@163.com

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To solve the problem of material distribution path planning in a production workshop, this paper proposes research on multi-objective cargo logistics loading and distribution based on an improved genetic algorithm. This paper improves the genetic algorithm to solve the problem (P), that is, the evolution model based on the genetic algorithm draws lessons from the coding mode of the genetic algorithm, and uses the row insertion method to obtain the initial population. The improved genetic algorithm is better than the traditional genetic algorithm. The rapid development of railway transportation towards high speed, high density, and heavy load has led to even higher requirements for the safety of railway signal equipment. The safety of railway signal equipment is an important part of ensuring railway traffic safety, thus, it is very necessary to study a system that can diagnose the fault of railway signal equipment according to the actual situation. This article utilizes the genetic algorithm of artificial intelligence for investigating the loading and distribution of logistics in transportation. It is demonstrated that genetic algorithm integration is an effective method to improve the performance of logistic distribution model. The convergence speed of the improved genetic algorithm is fast, and it shows a stable upward trend with the increase of the number of iterations.

Povzetek: Predlagan je izboljšan genetski algoritem za učinkovito logistično natovarjanje in distribucijo, kar izboljšuje uspešnost in hitrost logistične distribucije.

1 Introduction

With the rapid development of science and technology and the acceleration of the process of global economic integration, the logistics activities in the daily business activities of enterprises play a more and more important role in the global economic development, and their impact on all aspects of global economic activities is becoming more and more obvious [1]. Especially with the development of e-commerce websites, logistics has gradually become an important competitive field for enterprises [2]. Logistics distribution refers to integrated and systematic management that coordinates with the daily business activities of enterprises such as production, procurement, supply, and sales, and integrates the corresponding logistics activities such as distribution, handling, loading and unloading, storage, transportation, packaging, and information transmission. Its purpose is to provide customers with the best service at the lowest possible cost, to improve the overall economic benefits of the enterprise and enhance the overall competitive level of the enterprise [3].

At present, in China's logistics industry, important decision-making problems such as distribution center location, transportation route, inventory control and cargo assembly scheme are still in the state of semi manual decision-making, and the technical support of the whole logistics activities lags behind the global average level [4]. Like the vast majority of different businesses, sharing is a major problem for logistics factories now, from Uber-style ways to deal with last-mile conveyance, to more operations specialist organizations and organizations at big business level, cooperation is re-imagined in the entire SLN (sharing logistics network). By and large, various capabilities in SLN can be shared, from request assortment, pressing, arranging, to ship, stockpiling and conveyance, qualified conventional suppliers are allowed to go along with it and import their own accessible operations assets into asset pool for summon, and the coordinated suppliers perform brought together asset evening out to fulfil irregular strategies needs from different clients. Contrasted and the ordinary frameworks independently set-up, SLN with enormous clients prompts further developing individual asset productivity, defending by and large asset work, reducing transport expense, and saving conveyance time.

For instance, asset evening out in SLN can further develop responsibility by changing the rundown of operations task start times and re-establishing the priority connection among undertakings intra-stage, and furthermore can keep up with the power in asset productivity considering benefit assignment and administration criticism between stage. One might say that multi-stage asset evening out among customary suppliers is particularly essential to asset the board in SLN, which is the obvious elements of Industry 3.5. Multi-stage asset evening out issue in sharing planned operations network is a multi-objective improvement issue, which is firmly non-deterministic polynomial hard in open circle climate.

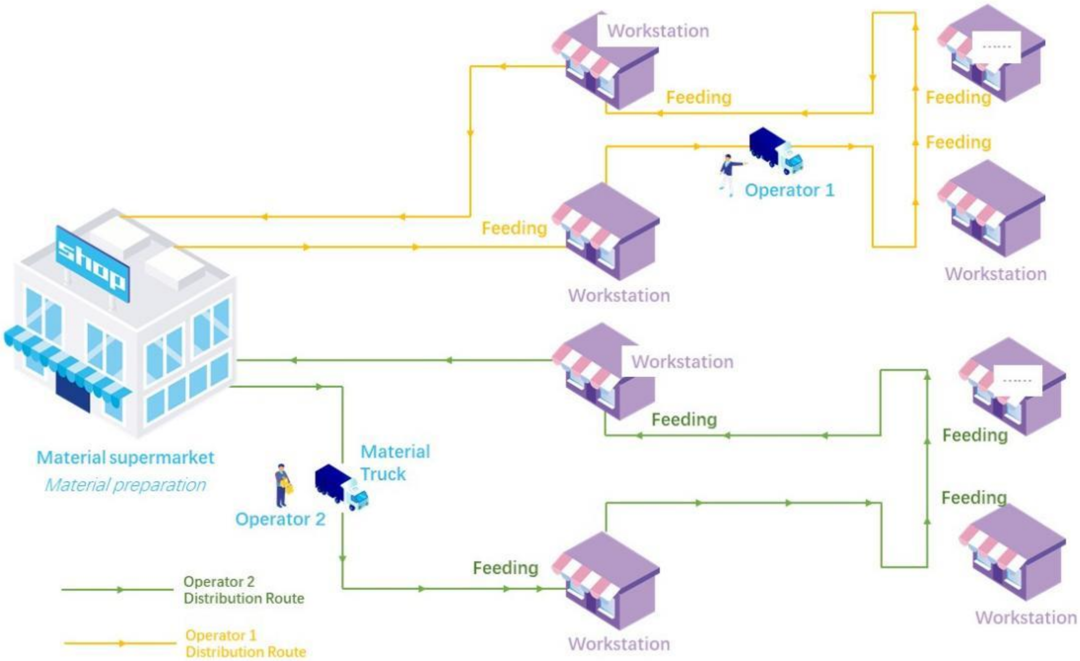

Figure 1: Material distribution process

Especially in the e-commerce environment with huge transaction volumes and extremely fast transaction speed, the contradiction between information flow and logistics has seriously affected the service quality of enterprises. Therefore, through the research on the optimization of distribution path, we can clarify the work details of each link of logistics distribution in enterprise business activities, and further improve the relevant technical system, to improve the overall intelligent level of the logistics industry. It is assumed that each operator's initial position is in the material supermarket. When the operator completes all batching tasks, he returns to the material supermarket. Dispatch the minimum number of operators to load the material truck according to the assigned task and send it to each workstation in turn until all materials are delivered and returned to the material supermarket. The material distribution process is shown in Figure 1 [5].

The rest of this article is organized as: Section 2 presents the related works in various domains. Section 3 consists of multi-objective mathematical model and its solution using genetic algorithm. Results and analysis are discussed in section 4 followed by concluding remarks in section 5.

2 Related work

Aiming at this research problem, Yun and Li changed the constraints in the distribution path and analyzed the impact of each index on the path [6]. Feng *et al.* proposed an optimization model aiming at the shortest distribution path and the least distribution times [7]. Sheng *et al.* used a hybrid particle swarm optimization algorithm to solve the material distribution model aiming at material transportation cost, transportation time, and line inventory [8]. Abbasi *et al.* proposed a material distribution method focusing on stations, and established a material flow path optimization model with the optimization objective of minimizing the total distribution time [9]. Wang *et al.* mainly establish models for VRP problems in two processes of auxiliary materials and replenishment and use a genetic algorithm to solve them with the goal of path optimization [10]. Saric *et al.* studied the just-in-time distribution of materials under the condition of limited distribution vehicles and solved it with an improved genetic algorithm and three-stage heuristic algorithm [11]. Mazhari *et al.* expounded on the problems existing in the material distribution process of the automobile assembly line and put forward the material distribution path optimization model with a time window with the goal of the shortest distribution distance [12]. Zan *et al.* proposed an optimization model to minimize distribution cost and solved the model by using dynamic programming and simulated annealing genetic algorithm [13]. Minaei *et al.* proposed an M- VRPTW research model based on the VRPTW problem [14]. Grisales *et al.* proposed a VRPTW mathematical model with time window constraints based on multi-supply points and place dependence and further summarized the research progress of VRPTW [15]. Based on the current research, this paper proposes the research of multi-objective cargo logistics loading and distribution based on an improved genetic algorithm.

A technique which considers wavelet frames for micropolar fluid flow is used for high mass transfer [16]. The vibration over the sandwich plates of laminated skew is studied through finite element [17]. The numerical simulation based on space time fractional equation are evaluated [18]. The proposed work can further be extended by using integration approaches of Artificial Intelligence and Machine learning as studied from several studies [19-21]. This paper improves the genetic algorithm to solve the problem (P), that is, the evolution model based on the genetic algorithm draws lessons from the coding mode of the genetic algorithm, and uses the row insertion method to obtain the initial population. In the crossover operation, the narrow gene similarity is used to distinguish the chromosome similarity, and the double variation rate is added to the mutation operation in the evolution process. MATLAB is used to realize the algorithm, and compared with the traditional genetic algorithm to verify the feasibility and effectiveness of the proposed model and algorithm.

3 Mathematical model establishment

This section includes the description of model establishment including variables and providing solution based on genetic algorithm.

3.1 Decision variables

$$x_{ijk} = \begin{cases} 1, \text{Moving tool from station I to station J;} \\ 0, \text{Otherwise;} \end{cases} \quad (1)$$

$$y_{ik} = \begin{cases} 1, \text{Station I is serviced by handling tool K;} \\ 0, \text{Otherwise;} \end{cases} \quad (2)$$

3.2 Multi-objective mathematical model

According to the problems, the following mathematical models are constructed:

A. Optimization objectives

Minimize total distance traveled:

$$d = \min \sum_{k=1}^{K} \sum_{i=0}^{N} \sum_{j=0}^{N} d_{ij} x_{ijk} \quad (3)$$

Minimize vehicle usage:

$$v = \min \sum_{i=0}^{N} \sum_{k=1}^{K} x_{0jk} \quad (4)$$

Average satisfaction of the largest chemical industry:

$$u = \max \frac{1}{N} \sum_{i=1}^{N} u_i(t_i) \quad (5)$$

Maximize vehicle capacity:

$$l = \max \frac{\sum_{i=1}^{N} q_i}{KQ} \quad (6)$$

B. Constraints

$$ET_i \le t_i \le LT_i, i \in \{1,2,...,N\} \quad (7)$$

$$\sum_{i=1}^{N} q_{iQ} y_{ik} \le Q, k \in \{1,2,...,K\} \quad (8)$$

$$\sum_{k=1}^{K} y_{ik} = 1, i \in \{1,2,...,N\} \quad (9)$$

$$\sum_{I=0}^{N} x_{ijk} = y_{jk}, k \in \{1,2,...,K\} \quad (10)$$

$$\sum_{j=0}^{N} x_{ijk} = y_{jk}, k \in \{1,2,...,K\} \quad (11)$$

$$\sum_{i=0}^{N} x_{i0k} = 1, k \in \{1,2,...,K\} \quad (12)$$

$$\sum_{j=0}^{N} x_{0ik} = 1, k \in \{1,2,...,K\} \quad (13)$$

$$\sum_{i=1}^{R} \sum_{j=1}^{R} x_{ijk} \le |R| - 1, R \in \{1,2,...,n\} \quad (14)$$

Where n is the number of jobs; K is the number of distribution tools; Q is the carrying capacity; Q_i is the demand of station i; D_{ij} is the distance from stations i and j; D is the service time at station i; T_{ij} is the travel time from station i to station j; W_i is the waiting time at station i; t_i is the time to start service station i. Equation (3) ~ equation (6) represents the objective function, which is the driving distance of distribution tools, number of used tools, station satisfaction, and carrying rate in turn; Equation (7) means that the service shall not be started outside the time window; Equation (8) represents the carrying capacity constraint; Equation (9) indicates that each station has and only has one distribution tool service; Equations (10) to (11) represent the relationship between two variables x_{ijk} and y_{ik}; Equations (12) to (13) indicate that the distribution tools leave the warehouse and finally drive back to the warehouse; Equation (14) is a branch elimination constraint [22].

3.3 Solving the model with an improved genetic algorithm

The material distribution path planning problem in the production workshop is an NP problem. At present, many heuristic algorithms have their defects in solving multi-objective and multi-constraint optimization problems, such as slow convergence, premature convergence, unbalanced global optimization ability, and local search ability. Therefore, this paper improves the genetic algorithm to solve the problem (P), that is, based on the evolution model of the genetic algorithm, draws lessons from the coding mode of the genetic algorithm, and uses the row insertion method to obtain the initial population. In the crossover operation, the narrow gene similarity is used to distinguish the similarity of chromosomes, and the double mutation rate is added to the mutation operation in the evolution process [23].

3.4 Construct chromosomes to produce the initial population

The quality of initial population generation determines the starting point of algorithm search. The high-quality population can accelerate the convergence of the algorithm and improve the solution efficiency [24]. When there is no feasible insertion position in the current distribution tool path, a new distribution tool is opened, and this paper improves it on this basis, as described in step 4.

Definition 1: The optimal insertion position is in the set of feasible insertion positions of the current path, and the initial feasible population generation steps are as follows:

Step 1: Randomly arrange N stations to obtain the station sequence set $X = \{x_1, x_2, \dots, x_N\}$, then assign it to the vehicle from left to right, and finally initialize the distribution path number Car_Code=0;

Step 2: Set car_Code = Car_Code + 1, the newly opened delivery tool, and its path number is Car_Code, arrange the leftmost station in the current x to the new path, and delete the station from X;

Step 3: Judge whether X is empty. If yes, go to step 5; Otherwise, go to step 4.

Step 4: Take the leftmost station in the current set X and judge whether there is a feasible insertion position in the current distribution tool path. If it exists, insert it into the best insertion position of the current distribution tool path, and turn to step 3; If it does not exist, judge whether it exists from small to large according to the path number of the distribution tool. If it exists, insert it into the best insertion position of the path, and turn to step 3, otherwise turn to step 2.

Step 5: Calculate the best start service time of the generated feasible chromosome to maximize the average station satisfaction of the chromosome. *Step 6:* Repeat steps 2 to 5, and stop when the number of feasible chromosomes reaches the specified number. Among them, the feasible insertion location and the best service start time are determined as follows:

i. Determination of feasible insertion position

If the feasible distribution path of an established distribution tool is B and the start service time at the station x_i is t_{xi}, the maximum delay time for the distribution tool to arrive at the station is:

$$\max\_pone(x_i) = \begin{cases} LT_{xi} - t_{xi} + W_{xi}, i = p \\ \min\begin{Bmatrix} LT_{xi} - t_{xi} + W_{xi}, \\ \max\_pone(x_{i+1}) \end{Bmatrix}, 1 \le i \le p-1 \end{cases} \tag{15}$$

If a station x_s is inserted after the i^{th} station in the feasible path, the path is still feasible, then condition 1 capacity constraints:

$$\sum_{i=1}^{p} q_{xi} + q_s \le Q \tag{16}$$

Condition 2-time constraints, the time when the delivery tool reaches the station s shall not be later than the lower limit of the time window of the station, that is, when $t_{xi} + T_{xi} + T_{xi,s} \le LT_s$ and $i = 0$, $t_{xi} = T_{xi} = 0$, $T_{x1,s} = T_{0,s}$. When $i \le P - 1$ the delivery tool must meet the following requirements when arriving at the station X_{i+1}:

$$\begin{aligned} &\max\{t_{xi} + T_{xi} + T_{xi,s}, ET_s\} + T_s + T_{s,xi+1} \le \\ &t_{xi+1} + \max\_pone(x_{i+1}) - W_{xi+1} \end{aligned} \tag{17}$$

ii. Determination of the best service start time

In the feasible path obtained by the above operation, the comprehensive satisfaction of the station is not the best. Based on the research on the determination method of the best start service time, this paper adjusts the time from the last station of the distribution tool path, omits the determination of the non-push able part, and improves the calculation of the maximum deferrable amount.

The calculation steps of the best service start time are as follows:

Step 1: Assume that the distribution path of a distribution tool is $(x_1, x_2, \dots, x_p)$.

Step 2: Divide the delivery tool path into several segments $(x_i, x_{i+1}, x_{i+2}, \dots, x_j)$, meet condition $W_{xi+1} = W_{xi+2} = \cdots = W_{xj} = 0$, when $i \ne 1$, $W_{xi} \ne 0; W_{xj} < p, W_{xj+1} \ne 0$.

Step 3: Take the last segment of the distribution path and set it as $(x_1, x_2, \dots, x_m)$, Adjust the service start time of the station $x_m, x_{m-1}, \dots, x_2, x_1$ in sequence; Under the condition of meeting the time constraint, the maximum delay to station $x_s (s = 1, 2, \dots, m)$ is $t_0 = \max\{t' | \sum_{n=s}^{m} u_{xn}'(t_{xn} + t') \ge 0\}$.

Step 4: Take the previous segment of the adjusted segment in the current distribution tool path and adjust it according to the method in step 3; If the segment forms a new segment with the latter segment in the current distribution tool path, readjust the newly formed segment; Otherwise, go to step 5.

Step 5: Continue to repeat step 4 until the service start time of all stations in the distribution tool path is determined.

3.5 Fitness function

The fitness of each individual is calculated according to the optimization target value and weight parameter. The solving function is as follows:

$$f(h_k) = \alpha_1 \frac{d_k}{d_{\max}} + \alpha_2 \frac{v_k}{v_{\max}} + \alpha_3 \left(1 - \frac{u_k}{u_{\max}}\right) + \alpha_4 \left(1 - \frac{l_k}{l_{\max}}\right)$$
$$\sum_{i=1}^{4} \alpha_i = 1, a_i \geq 0, i = 1,2,3,4 \tag{18}$$

Where, h_k represents chromosome K; d_k, v_k, u_k, l_k represent the driving distance of chromosome h, the total number of distribution tools used, the average satisfaction of stations, and the carrying rate of distribution tools; $d_{max}, v_{max}, u_{max}, l_{max}$ represents the maximum travel distance, the maximum number of distribution tools used, the maximum average satisfaction of stations, and the maximum carrying rate of chromosomes in the current population; $\alpha_i (i = 1, 2, 3, 4)$ is the weight coefficient [25].

4 Results and analysis

This section illustrates the result and analysis of proposed system using genetic algorithm. The distance between stations is measured along with the driving schedule which is presented in this section.

In material distribution in the production workshop, there are 9 stations and a warehouse, and the carrying capacity of the distribution tool is 12 units. The service time, reservation time, and demand of each station are shown in Table 1, and the driving time and distance between each station are shown in Tables 2 and 3; Improve the basic parameters of the genetic algorithm and take the population size pop_Size = 100, number of iterations Max_Gen = 200, selection probability $P_x = 0.8$, crossover probability $P_c = 0.8$, double mutation probability Local_Pm = 0.1 and Global_Pm=0.2.

Table 1: Information about each station

Station number	1	2	3	4	5	6	7	8	9
Service time/min	3.1	5.1	7.8	5.2	4.2	6.9	7.6	6.2	5.5
Reservation time / min	33,37,39	5.7.4.10	26,27,30	18,20,22	15,18,21	31,34,36	9,11,12	22,25,27	29,33,35
Demand/ unit	3.8	5.2	2.7	2.8	4.4	4.8	5.7	2.7	4.7

Table 2: Distance between stations and Driving Schedule (stations 1-4)

Station number		Driving time/min				
		Warehouse 0	Station 1	Station 2	Station 3	Station 4
	0	0	10	5	9	11
Driving distance/m	1	23.43	0	6	5	7
	2	27.12	24.10	0	9	7
	3	12.29	16.54	15	0	6
	4	26.49	36.59	18.49	21.07	0
	5	11.59	33.31	30.21	20	21.56
	6	7.11	29.30	32.42	18. 65	28.69
	7	7.79	26.79	34.39	19.51	33.49
	8	21.89	25.31	43.59	28.89	47.79
	9	20.11	7.89	29.79	18.35	39.80

According to the above algorithm, Matlab simulation is used to calculate under different weight settings. The results are shown in Table 4.

It can be seen from Table 4 that the setting of optimization target weight parameters has a great impact on the experimental results [26]. d. L is closely related to v, that is, d increases with the increase of v, and l decreases with the increase of 0; u is opposite to d, v and l, that is, the increase of u is at the cost of the increase of d and v and the decrease of L [21].

Table 3: Distance between stations and Driving Schedule (stations 5-9)

Station number		Driving time/min				
		Station 5	Station 6	Station 7	Station 8	Station 9
	0	5	11	7	10	10
	1	8	6	8	11	10
	2	9	12	7	11	11
	3	6	11	6	6	9
Driving distance/m	4	8	6	11	9	10
	5	0	9	10	12	9
	6	9.59	0	10	10	9
	7	14.69	6.15	0	5	6
	8	31.39	22.39	17.19	10	10
	9	31.69	25.79	21.89	17.51	0

Table 4: Simulation results

Weight setting				**Experimental result**			
$\boldsymbol{\alpha_1}$	$\boldsymbol{\alpha_2}$	$\boldsymbol{\alpha_3}$	$\boldsymbol{\alpha_4}$	d	v	u	l
0.7	0.1	0.1	0.1	209.31	5	0.849	0.621
0.1	0.7	0.1	0.1	227.53	4	0.679	0.767
0.1	0.1	0.7	0.1	243.31	6	0.951	0.521
0.1	0.1	0.1	0.7	231.21	4	0.761	0.776

It can be seen from Table 4 that the setting of optimization target weight parameters has a great impact on the experimental results [20]. d. L is closely related to v, that is, d increases with the increase of v, and l decreases with the increase of 0; u is opposite to d, v and l, that is, the increase of u is at the cost of the increase of d and v and the decrease of L [27].

To prove the effectiveness of the improved genetic algorithm proposed in this paper, the improved genetic algorithm takes the weights $\alpha_1 = 1$, $\alpha_2 = 1$ and $\alpha_3 = 1$ respectively, which is compared with the corresponding single objective solution of the traditional genetic algorithm ($\alpha_4 = 1$ is not analyzed here because l is inversely proportional to v). The traditional genetic algorithm is used to calculate this example. The initial population size is 100, the selection probability and crossover probability are 0.8, and the mutation probability is 0.1 [28].

As shown in Figure 2, when $\alpha_1 = 1$, the improved genetic algorithm shows a stable downward trend after 30 generations and converges to 55 generations [29]. However, the convergence speed of the traditional genetic algorithm is very slow in the middle and late stages, and it does not begin to converge until generation 126. As shown in Figure 3, when $\alpha_2 = 1$, the improved genetic algorithm has no fluctuation. From the whole image, the two have a downward trend, that is, the connecting line between the starting point and the convergence point. The slope of the improved genetic algorithm is significantly greater than that of the traditional genetic algorithm [30].

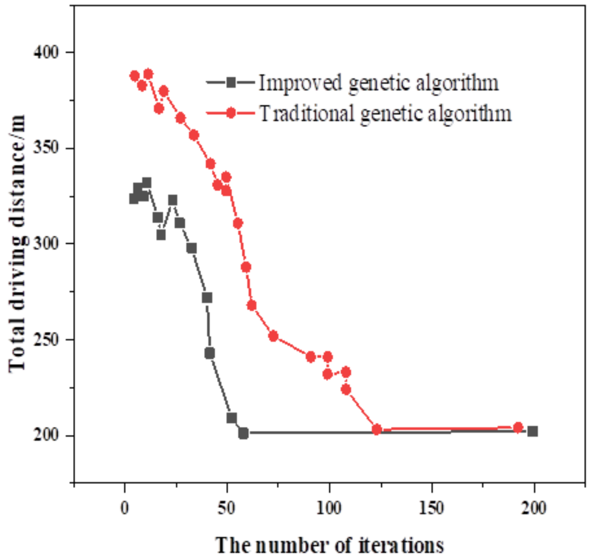

Figure 2: Comparison of travel distance convergence of distribution tools.

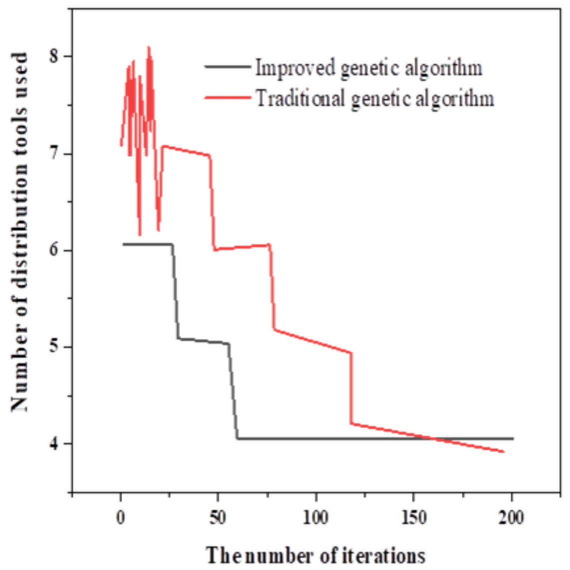

Figure 3: Convergence comparison of usage number of distribution tools.

As shown in Figure 4, when $\alpha_3 = 1$, the convergence speed of the improved genetic algorithm is also fast, showing a stable upward trend with the increase in the number of iterations [31]. To sum up, from the convergence diagrams in Figures 2, 3, and 4, it is obvious that the improved genetic algorithm is superior to the traditional genetic algorithm [32].

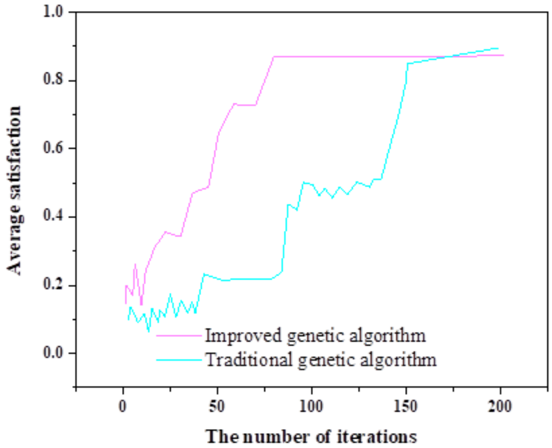

Figure 4: Convergence comparison of station average satisfaction.

In the crossover operation, the narrow gene similarity is used to distinguish the chromosome similarity, and the double variation rate is added to the mutation operation in the evolution process. The basic parameters of the genetic algorithm are improved and the population size pop is taken_ size = 100, number of iterations Max_ gen = 200, the selection probability $P_x = 0.8$, crossover probability $P_c = 0.8$, double mutation probability Local_ Pm = 0.1 and Global_ Pm=0.2. Matlab simulation is used to calculate under different weight settings. When $\alpha_1 = 1$, the improved genetic algorithm shows a stable downward trend after 30 generations and converges to 55 generations; However, the convergence speed of the traditional genetic algorithm is very slow in the middle and late stages, and it does not begin to converge until generation 126. When $\alpha_2 = 1$, the improved genetic algorithm has no fluctuation. From the whole image, we can see the downward trend between the two, that is, the connection between the starting point and the convergence point. The slope of the improved genetic algorithm is significantly greater than that of the traditional genetic algorithm. When $\alpha_3 = 1$, the convergence speed of the improved genetic algorithm is fast, and it shows a stable upward trend with the increase in the number of iterations.

5 Conclusions

In this paper, based on the research of multi-objective cargo logistics loading and distribution based on an improved genetic algorithm, a multi-objective mathematical programming model under the condition of fuzzy station reservation time is constructed, and an improved genetic algorithm is proposed to solve the model. In the algorithm design, the feasible insertion method is used to generate the initial population to speed up the convergence speed. The concept of narrow gene similarity is proposed to avoid the cross operation of individuals with high similarity. At the same time, the double mutation mechanism is added to the mutation process to control the search range and convergence speed of the global solution space. Finally, the algorithm is implemented by MATLAB and compared with the traditional genetic algorithm to verify the feasibility and effectiveness of the proposed model and algorithm. The next research will consider the dynamic changes in workstation material requirements. In future work this research, delicate time window should to be thought of as because of the impediment of difficult time window in this paper, which can recognize the distinction among calculations. Moreover, the double effect of vulnerability from resource supply and client request is one more worry in proposed system.

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