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Applied research on site selection for urban logistics distribution center based on fruit fly optimization algorithm

Yuan Xion[1]

Abstract. Through the optimization algorithm of fruit flies, there is a local optimum solution for the location of logistics distribution center, and it is prone to fall into the local minimum. In order to achieve reasonable allocation of the site of logistics distribution center, an improved optimization algorithm for Drosophila melanogaster is proposed in this paper, and function optimization problem and site selection of logistics distribution center are chosen as the objects of study. Function optimization problem verifies that improved fruit fly optimization algorithm exhibits faster convergence rate and higher convergence precision, so it can be applied in other research fields. A mathematical model for site selection of logistics distribution center is established according to the coordinates of logistics distribution centers in 31 cities and their demand for goods and materials. Besides, improved fruit fly optimization algorithm is applied for optimization solution to achieve the optimal allocation of distribution path and save cost. The simulation result indicates that the algorithm has the advantages of fast convergence rate and high precision.

Key words. Fruit fly optimization algorithm, logistics distribution center, chaotic system, logistic system, demand quantity.

1. Introduction

As e-commerce grows rapidly, logistics industry as an emerging industry is developing at a fast speed. The site selection method of logistics distribution center as a middle link connecting customers sand suppliers decides logistics distribution mode and distribution distance and influences work efficiency and economic benefit of logistics system. The study on site selection of logistics distribution center has important practical significance and theoretical value. Therefore, distribution center site selection model and optimization method in logistics network layout attract extensive attention of domestic and overseas research scholars.

[1]Nanchang University, Nanchang, 330031, China

Revelle and Swain [1] proposed slack linear programming algorithm for site selection problem in 1970. In 1978, for large-scale logistics site selection problem, Erlekotter [2] put forward both way slope algorithm and local search algorithm. The empirical study shows this method has good effect and high efficiency. In 1988, Kazuyoshi Hidaka [3] applied greedy heuristic algorithm and balloon search heuristic algorithm successively to solve large-scale facility site selection problem. In 1999, Yamada took minimum transportation cost and minimum CO_2 emission as the objective function[4] to select the site of logistics distribution center. Although traffic distribution was considered, this model could only handle small-scale site selection problem. In 2001, Wang Zhanquan and Yang Dongyuan [5] applied global search optimization technique, established site selection model based on genetic algorithm, compared and analyzed it with traditional mixed integer programming solution. With regard to logistics center site selection for perishable products, Jiang Dali and Du Wen [6] combined global search capacity of genetic algorithm and local search capacity of ALA method to put forward a mathematical model for logistics center site selection based on AGA integer programming in 2003. The result indicates that this algorithm can greatly increase the probability of acquiring the optimal distribution path and the optimal site. In 2006, Wu Bing, Luo Ronggui and Peng Weihua [7] came up with logistics center site selection optimization model based on genetic algorithm of priority coding. The result indicates that this method can effectively reduce the difficulty in solving site selection problem. In 2008, Zhao Dongling, Yu Longzhen and Chen Changju [8] established 0–1 integer programming model for logistics center site selection and proposed an improved single-point PMX intersection method to solve large-scale logistics distribution optimization problem by combining the thought of genetic variation. The result shows the improved algorithm has good effect, and is superior to improved single-point intersection method in terms of convergence rate and optimal solution.

2. Improved fruit fly optimization algorithm

2.1. Fruit fly optimization algorithm

Fruit fly optimization algorithm (FOA) is a new evolutionary computation method which was proposed by Pan [9] in 2011. At present, it is widely applied in function optimization, SVM parameter optimization, knapsack problem and optimization of neural network weight and threshold value, etc. Although this algorithm has such advantages as few control parameters, fast convergence rate and high convergence precision, it has local optimum problem and thus may be easily caught in local minimum. This paper combines ergodicity, regularity and randomness advantages of logistic chaotic system and proposes fruit fly optimization algorithm based on logistic chaotic system to overcome local optimum problem of FOA.

Step 1: Set fruit fly population size *popsize* and maximum iteration times of FOA; initialize fruit fly population position at random; the initialization results are expressed as X_begin and Y_begin, respectively.

Step 2: Calculate random optimizing direction and distance of fruit fly individuals according to (1) and (2):

$$x_i = X\_begin + Value \times rand()\,, \tag{1}$$

$$y_i = Y\_begin + Value \times rand()\,. \tag{2}$$

In (1) and (2), $Value$ represents search distance of fruit fly, while x_i andy_i represent the position of fruit fly individuals in the next moment.

Step 3: Estimate the distance d_i between fruit fly individuals and the original point according to formula (3); then apply formula (4) to figure out smell concentration s_i of fruit fly individuals:

$$d_i = \sqrt{x_i^2 + y_i^2}\,, \tag{3}$$

$$s_i = \frac{1}{d_i}\,. \tag{4}$$

Step 4: Substitute smell concentration s_i into formula (5)—smell concentration decision function—and calculate smell concentration of fruit fly individuals at current position

$$Smell_i = Function(s_i) \tag{5}$$

Step 5: Find out the best smell concentration and the best position of fruit fly individuals. The best smell concentration is expressed as $Smell_{\mathrm{b}}$, and the best position is expressed as x_{b} and y_{b}.

Step 6: Reserve and record the best position and the best smell concentration of fruit fly. The best smell concentration $Smellbest = Smell_{\mathrm{b}}$; the initial position of fruit fly $Y\_begin = y_{\mathrm{b}}$, $X\_begin = x_{\mathrm{b}}$; besides, fruit fly population searches towards the best position.

Step 7: Iterate for optimizing and repeat iteration steps 2–5 and judge whether the smell concentration is better than that in the last iteration. If it is better, execute Step 6.

2.2. Logistic chaotic system

Chaos phenomenon extensively exists in nonlinear system. It is an aperiodic motion form. Since the sequence generated by chaotic system has good randomness, ergodicity and regularity, chaotic sequence is widely applied in signal processing, nonlinear control, image encryption and other relevant fields.

The expression of logistic chaotic system is shown in Formula (6) [11, 12]

$$x(n+1) = ux(n)(1 - x(n)),\ x(n) \in [0,\, 1]\,. \tag{6}$$

In formula (6), n is iteration number, u represents chaos control parameter (when $u = 4$, logistic system is in the chaotic state. A transformation calculation formula of chaos variable of Cx_i is shown in formula (7)

$$Cx(n+1)_i = 4Cx(n)_i(1 - Cx(n)_i),\ i = 1, 2, ..., N\,. \tag{7}$$

In Formula (7), $Cx(n)_i$ represents the value of the ith chaos variableCx_i of chaotic mapping after the nth chaos variable. When $Cx_i \in [0,\ 1]$ and $Cx_i \notin \{0.25, 0.50, 0.75\}$, the system is in the chaotic state. The optimization parameter $x_i \in [a_i,\ b_i]$ in Formula (7) can be transformed through mutual mapping of formulae (8), (9) and chaos parameter $Cx_i \in [0,\ 1]$.

$$Cx_i = (x_i - a_i)/(b_i - a_i)\,, \tag{8}$$

$$x'_i = a_i + Cx_i(b_i - a_i)\,. \tag{9}$$

In formula (9), x'_i represents the value that the ith chaos variableCx_i after chaotic mapping is transformed to conventional variable.

2.3. Improved FOA

Logistic chaos theory is introduced in FOA to improve it. The main process of improved FOA is as follows:

Step 1: Set fruit fly population size *popsize* and maximum iteration times $Iteration$ of FOA; initialize fruit fly population position at random between 0 and 1, and express it as vector z_i.

Step 2: Map the $z_i$component to chaos parameter $Cz(n)_i$, $Cz(n)_i = [0,\ 1]$ according to formula (8).

Step 3: Conduct chaotic mapping for chaos parameter $Cz(n)_i$ according to formula (7).

Step 4: Carry out mapping transformation for each component according to formula (9), and the mapping is conventional variable z'_i in $[a_i,\ b_i]$; calculate fitness $f(z'_i)$, choose the minimum $f(z'_i)$ in the population and record the minimum $f(z'_i)$, $fit(gen) = f(z'_i)$.

Step 5: Optimize and iterate; repeat the steps 2–4.

Step 6: If the stop condition is met (iteration times is greater than the maximum iteration time $Iteration$), select the minimum fit and make $Smellbest = \min(fit(gen))$. At this moment, record smell concentration S_g of minimum $f(z'_i)$.

Step 7: To make sure the initial value to be gained is within the small interval of optimal parameter in the initial iteration, if the parameter is greater than 0, $B \in [0,\ 1]$. Through repeated verification, $B = 0.25$ is chosen in this paper. Apply $S_i = S_g + 2B \times rand() - B$ to generate tiny disturbance population near the selected smell concentration S_g. Meanwhile, apply S_i to assess $f(S_i)$. Choose $f(S_i)$ with the smallest fitness in the population and make $Bestsmell = \min(f(S_i))$. If $Bestsmell < Smellbest$, $Smellbest = Bestsmell$ and make $S_g = S_i$.

Step 8: Carry out secondary iteration and optimization; update smell concentration S_i and repeat Step 7.

Step 9: If the stop condition is met (iteration times is greater than the maximum iteration time *Iteration*), output *Smellbest*, $P = S_g$.

2.4. Mathematical model for logistics distribution center site selection

To achieve the optimal selection of urban logistics distribution center, the following hypotheses are accepted [13]: goods capacity of logistics distribution center can satisfy the demand for goods at each demand point, and total goods amount at the logistics distribution center is decided by goods demand of distribution demand point; one distribution center only supplies a demand point; the transportation expenses from the logistics distribution center to the factory are not taken into account.

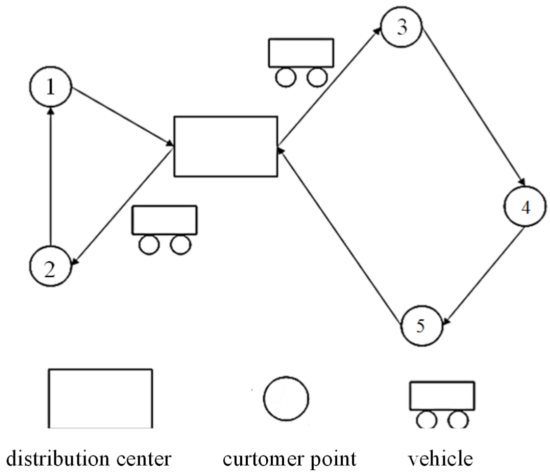

Fig. 1. Distribution diagram

Based on the above hypotheses, the mathematical model for logistics distribution center site selection can be established. The distribution diagram is shown in Fig. 1. The mathematical model is a site selection and distribution model. Under the condition of meeting upper limit of distance, it is necessary to find out the distribution center from n demand points and distribute goods to each demand point. The objective function is the minimum sum of product between the demand and distance from each distribution center to the demand point. The objective function is:

$$\min F = \sum_{i \in N} \sum_{j \in M_i} w_i d_{ij} Z_{ij} \,. \tag{10}$$

The constraint conditions are

$$\sum_{j \in M_i} Z_{ij} = 1, \; i \in N \,, \tag{11}$$

$$Z_{ij} \leq h_j,\ i \in N,\ j \in M_i\,, \tag{12}$$

$$\sum_{j \in M_i} h_j = p\,, \tag{13}$$

$$Z_{ij},\, h_j \in \{0,\, 1\},\ i \in N,\ j \in M_i\,, \tag{14}$$

$$d_{ij} \leq s\,. \tag{15}$$

In the above constraints, $N = \{1, 2, ..., n\}$ is the serial number set of all demand points, M_i represents the set of alternative distribution centers whose distances from the demand point i are less than s, $i \in N$, $M_i \subseteq N$, and w_i represent the demand quantity of demand points, d_{ij} refers to the distance from the demand point i to the nearest distribution center j, and Z_{ij} represents 0–1 variable and service demand distribution relation of users and logistics center. When $Z_{ij} = 1$, the demand quantity of demand point j is supplied by distribution center j, or else $Z_{ij} = 0$. Symbol h_j represents 0–1 variable. When $h_j = 1$, the demand point j is chosen as the distribution center. Symbol s represents the upper limit of distance from the demand point served by the newly-built distribution center.

Formula (11) guarantees that each demand point can be served by only one distribution center. Formula (12) guarantees the demand quantity of demand point can only be set to point supply of distribution center. In other words, there will be no customer where there is no distribution center. Formula (13) specifies that the number of selected distribution centers is p. Formula (15) guarantees that the demand point is within the scope that the distribution center can reach.

3. Analysis and discussion

3.1. Optimization of logistics distribution center site selection using IFOA algorithm

The steps of optimizing logistics distribution center site selection with IFOA algorithm are as follows. The flow chart is shown in Fig. 2.

Step 1: Set population size *popsize* and maximum iteration times *Iteration* of IFOA algorithm.

Step 2: Calculate fitness function value of fruit fly individuals according to formula (10) and search the position and optimal value of fruit fly individuals and global optimal individual.

Step 3: Update speed and position of fruit fly population.

Step 4: Figure out fitness and update position and speed.

Step 5: If $gen > Iteration$, save the optimal solution, otherwise $gen = gen + 1$, and turn to Step 3.

Step 6: The best position and the best distribution path of corresponding logistics distribution center according to the optimal position.

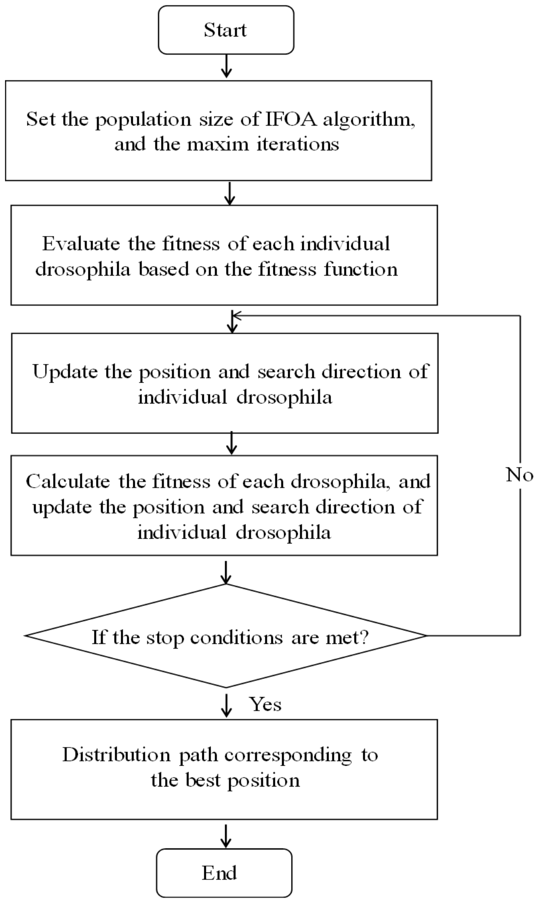

Fig. 2. Flow chart of optimizing logistics distribution center site selection with IFOA algorithm

3.2. Experimental simulation

To verify the effect and superiority of IFOA, set fruit fly population size $sizepop = 20$ and the maximum interaction times $Iteration = 100$. The optimization result is shown in Figs. 3–6 for four different standards.

1) $Rastrigin$ function

$$\min f(x_1, x_2) = 20 + x_1^2 + x_2^2 - 10(\cos(2\pi x_1) + \cos(2\pi x_2)),\ x_1, x_2 \in [5, 5]\,.$$

2) $Schaffer$ function

$$\min f(x, y) = 0.5 + \frac{\sin^2\sqrt{x^2+y^2} - 0.5}{(1+0.001(x^2+y^2)^2)^2},\ x, y \in [-10, 10]\,.$$

3) $F4$ function

$$\min f(x_1, x_2) = 100(x_1^2 - x_2^2) + (1 - 2x_1 + x_1^2),\ x1, x2 \in [-1, 1]\,.$$

4) $Sphere$ function

$$\min f(x) = \sum_{i=1}^{n} x_i^2,\ |x_i| \le 15,\ n = 10\,.$$

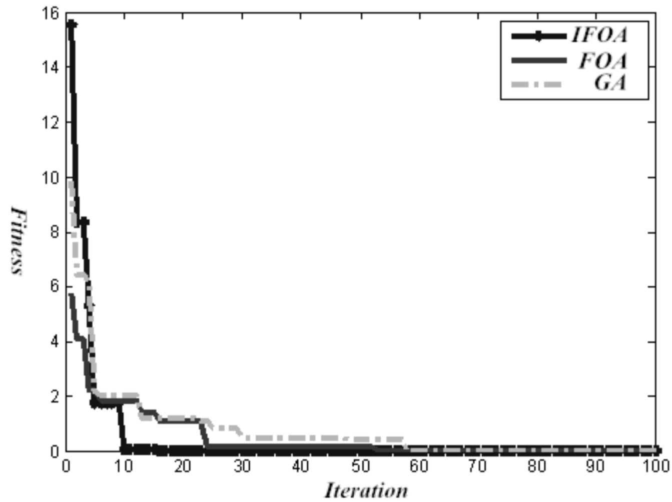

Fig. 3. Convergence graph of $Rastrigin$ function

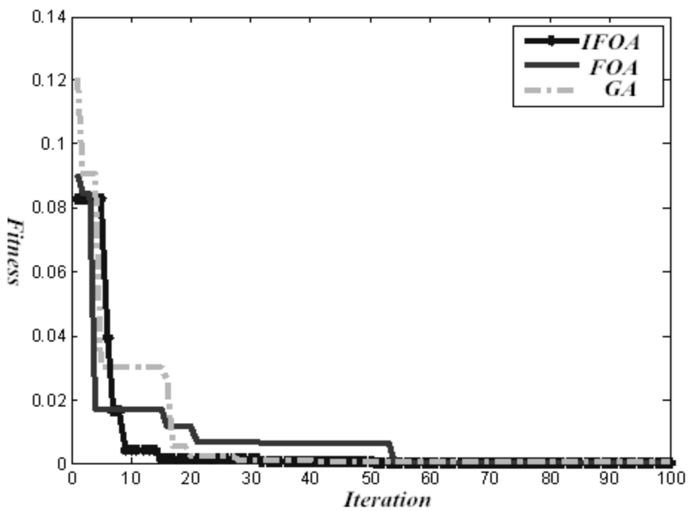

Fig. 4. Convergence graph of $Schaffer$ function

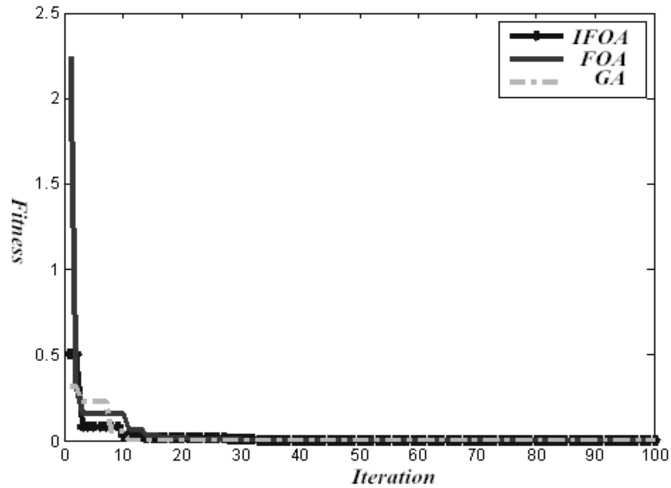

Fig. 5. Convergence graph of $F4$ function

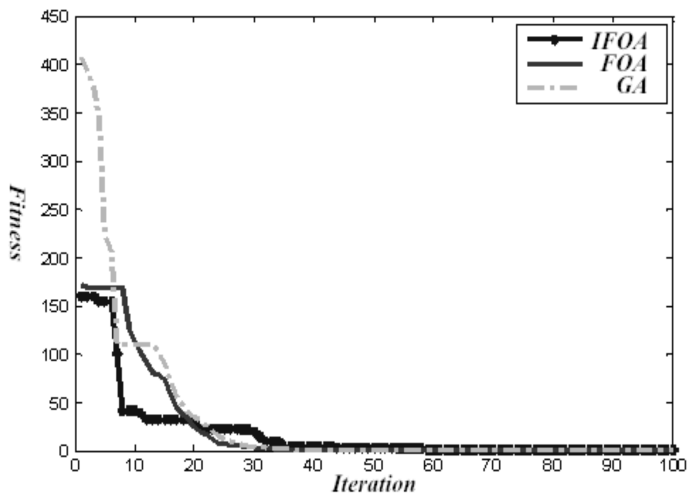

Fig. 6. Convergence graph of *Sphere* function

From Figs. 3–6 it is obvious that the convergence rate of IFOA algorithm superior to that of FOA algorithm and GA algorithm. This verifies superiority of IFOA. Its convergence rate is faster, and its fitness function value further approaches the theoretical value.

In order to prove the feasibility and effectiveness of IFOA during optimizing distribution center site selection, the coordinates of 31 cities in China are gathered, the position and the goods demand of each user are shown in Table 1. The data in this paper go through standardized processing. 6 cities are chosen as logistics distribution centers.

Table 1. Users' position and their goods demand

j	(U_j, V_j)	b_j	j	(U_j, V_j)	b_j
1	(1304, 2312)	20	17	(3918, 2179)	90
2	(3639, 1315)	90	18	(4061, 2370)	70
3	(4177, 2244)	90	19	(3780, 2212)	100
4	(3712, 1399)	60	20	(3676, 2578)	50
5	(3488, 1535)	70	21	(4029, 2838)	50
6	(3326, 1556)	70	22	(4263, 2931)	50
7	(3288, 1229)	40	23	(3429, 1908)	80
8	(4196, 1044)	90	24	(3507, 2376)	70
9	(4312, 790)	90	25	(3394, 2643)	80
10	(4386, 570)	70	26	(3439, 3201)	40
11	(3007, 1970)	60	27	(2935, 3240)	40
12	(2562, 1756)	40	28	(3140, 3550)	60
13	(2788, 1491)	40	29	(2545, 2357)	70
14	(2381, 1676)	40	30	(2778, 2826)	50
15	(1332, 695)	20	31	(2370, 2975)	30
16	(3715, 1678)	80			

Set fruit fly population size $sizepop = 20$ and the maximum iteration times $Iteration = 100$. The optimization results of logistics distribution center for 6 centers are shown in Fig. 7.

When there are 5 and 4 logistics distribution centers and the iteration times are different, the principle of calculation is similar to the above, convergence curves and distribution path maps of IFOA are shown in Figs. 8 and 9.

According to the optimization result of IFOA algorithm under different iteration times and different population size (Fig. 10), as iteration times and population size rise, the optimal iteration times and different population size tends to be better. The simulation experiment shows that IFOA algorithm has high feasibility and effectiveness during optimizing logistics distribution center site selection problem.

4. Conclusion

Although fruit fly optimization algorithm has such advantages as few control parameters, fast convergence rate and high convergence precision, it has local optimum problem and thus may be easily caught in local minimum. In order to achieve reasonable allocation of the site of logistics distribution center and improve work efficiency and economic benefit of logistics distribution system, this paper combines ergodicity, regularity and randomness advantages of logistic chaotic system and proposes fruit fly optimization algorithm based on logistic chaotic system to overcome

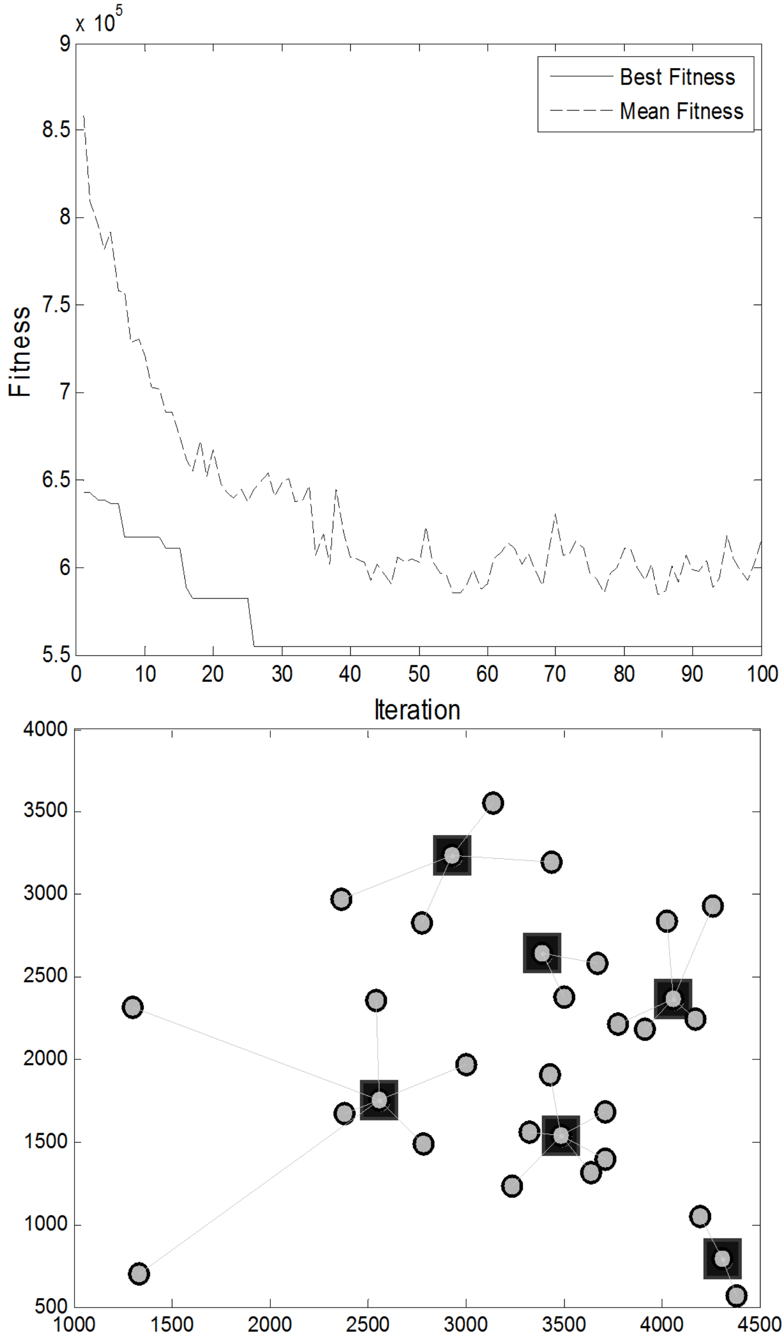

Fig. 7. Distribution path and convergence map when there are 6 distribution centers

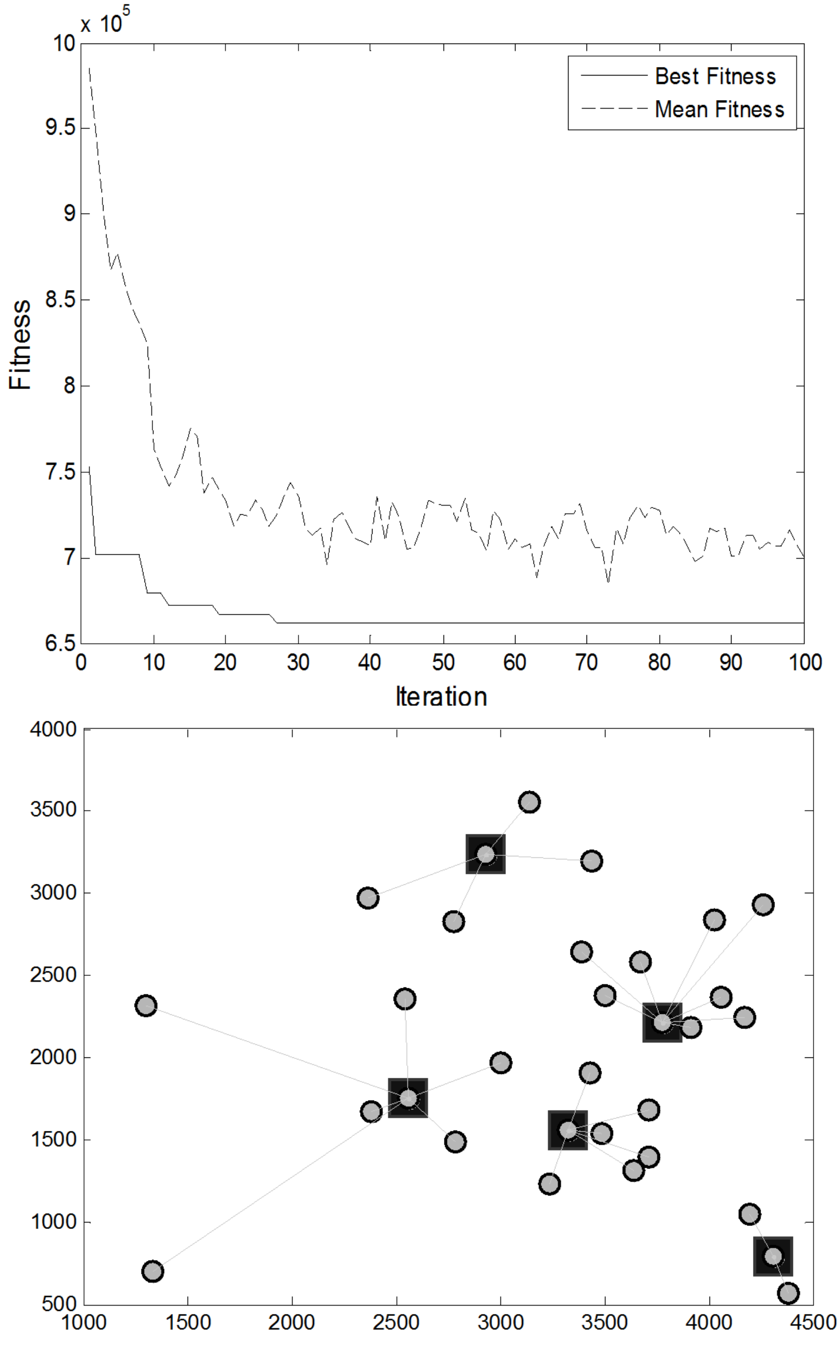

Fig. 8. Distribution path and convergence map when there are 5 distribution centers

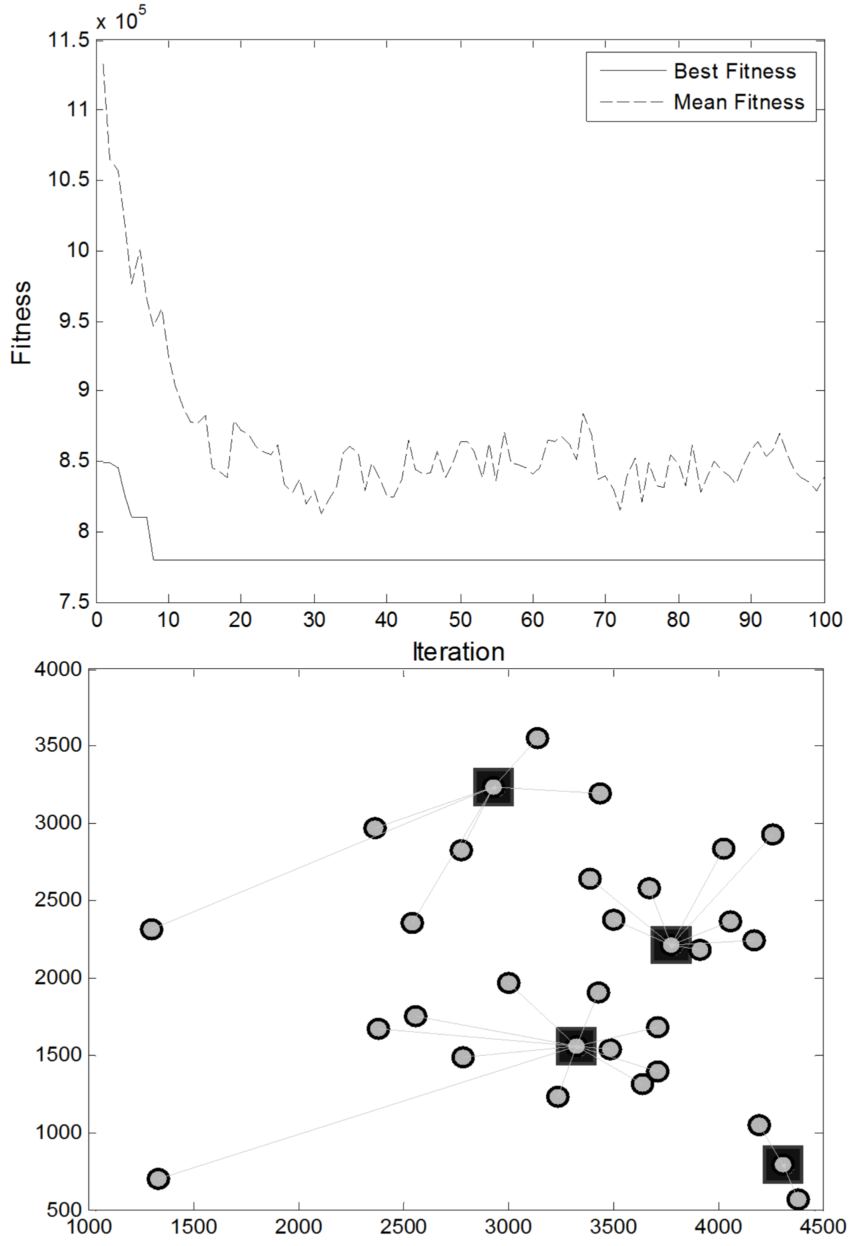

Fig. 9. Distribution path and convergence map when there are 4 distribution centers

local optimum problem of fruit fly optimization algorithm. A mathematical model for site selection of logistics distribution center is established according to the coordinates of logistics distribution centers in 31 cities and their demand for goods

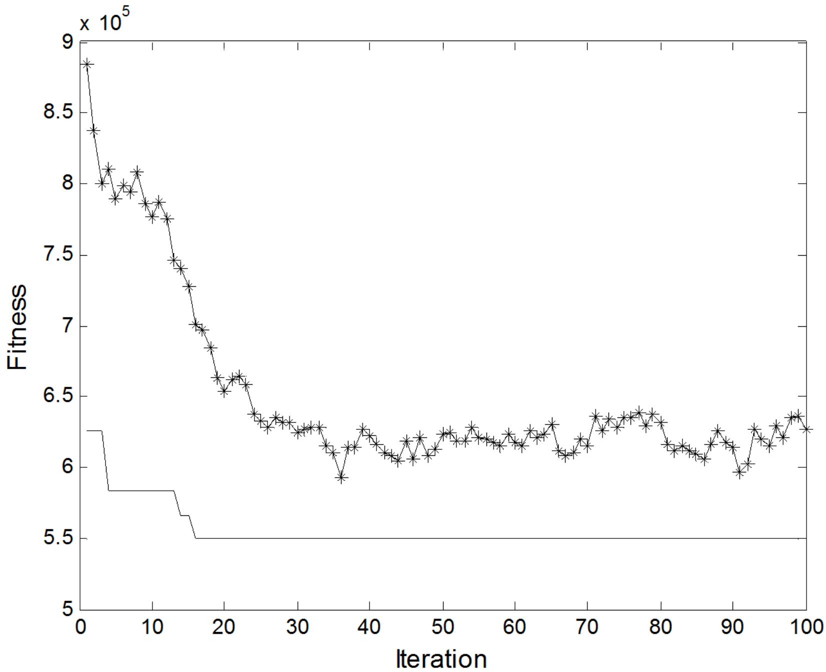

Fig. 10. Convergence comparison diagram of IFOA algorithm and FOA algorithm

and materials. Besides, improved fruit fly optimization algorithm is applied for optimization solution to achieve the optimal allocation of distribution path and save cost. The simulation result indicates that, the algorithm has the advantages of fast convergence rate and high precision. On this basis, distribution paths under different number of distribution centers and distribution paths under different iteration times and population size are compared to achieve optimization of objective function and the lowest cost.

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