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An Improved Path Optimization Method of Logistics Site Selection for Agricultural Products

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Abstract

Tracing the processing of agricultural products from raw materials to dining tables is an important means of guaranteeing food safety. Reasonable location selection for logistics distribution centers is an effective pathway for realizing the traceability of agricultural products. However, the traditional logistics site selection for agricultural products only considers a single constraint. In order to realize the optimal path in the traceability system, the logistics site selection problem of Aksu apple was transformed into a multiobjective optimization problem. Moreover, an improved bee colony algorithm for optimal location selection with multiple constraints was proposed. A mathematical model of location selection was constructed by considering several constraints of location selection for the distribution centers and the influencing factors, such as transport distance and operation cost. The local searching ability of the solving algorithm was improved using adaptive random-search strategies. The convergence rate of this solving algorithm was increased by introducing the particle swarm optimization algorithm. The accuracy and robustness of the algorithm were improved by adjusting parameters. The optimal location of a path in the traceability system was planned by using the improved algorithm. Results demonstrate that the improved bee colony algorithm is considerably superior to the artificial bee colony (ABC) algorithm and hybrid ABC algorithm in terms of performance. It can also realize multiobjective location selection. Thus, the optimal path is planned. This study provides a good reference for the construction and resolution of the traceability location selection model in different conditional regions.

Keywords: Swarm intelligence, Artificial bee colony algorithm, Location selection, Particle swarm optimization

1. Introduction

Market areas, transport routes, and inventory plans of agricultural products can be chosen reasonably by building a high-efficiency traceability system. Logistics distribution centers for agricultural products are the nodes mainly responsible for stocking, tallying, and delivery of agricultural products. As the key link of a traceability system for agricultural products, a logistics distribution center for agricultural products is an effective traceable pathway from the origin of raw materials to product processing [1]. The location of an agricultural logistics distribution center can be selected comprehensively with considerations such as geographical conditions and product demand to lower construction and operation costs of the center, thereby lowering logistics costs in the agricultural product traceability system and effectively tracing agricultural products [2]. Therefore, the location of an agricultural logistics distribution center must be selected scientifically to distribute and trace agricultural products reasonably and scientifically and achieve the maximum economic effects under the minimum comprehensive expenses.

The factors influencing the location selection for logistics distribution centers for agricultural products affect traffic conditions, existing infrastructure, and requirements for environmental protection, topographic conditions, meteorological conditions, social benefits, and socioeconomic needs. Traditional analytical methods for location selection for logistics distribution centers include the numerical analytical method, Baumol-Wolfe model, and capacitated facility location problem (CFLP) model. However, these methods generally focus only on the optimal transportation costs from the logistics distribution centers to the customers [3]. In practical decision-making, the location selection for a logistics distribution center must consider other factors. Moreover, it involves many constraints. The traditional analytical method cannot effectively optimize the location selection. Swarm intelligence (SI) applies group intelligence behavior and provides a new solution to multiobject optimization problems when the global object model is unnecessary [4]. The artificial bee colony (ABC) algorithm implements the global optimization of multivariable functions by simulating the group behaviors of a bee colony. It can also effectively solve the problem of multiconstraint in the location selection model. However, this algorithm still has many disadvantages, such as a low convergence rate and easy trapping into early mature [5].

Hence, the location selection problem of distribution centers for agricultural products was transformed into a typical optimization problem and solved by the SI algorithm. A new, improved algorithm was proposed for location selection by considering some common disadvantages of the SI algorithm, such as low accuracy, low rate of convergence, easy convergence of local minimum, and parameter sensitivity. It acquired the optimal location selection method under the premise of no increase in hardware expenses. Thus,

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the problem of the traditional analytical method in which only a single constraint is considered is addressed.

2. State of the art

At present, the model for the location selection for logistics distribution centers views transport routes as the major considering factor. Increasing constraints, such as geographical environment and operation cost, may decrease positioning accuracy. Moreover, the location selection algorithm cannot be optimized effectively. For instance, on the basis of the Baumol-Wolfe model, Guan constructed a location selection model for the overseas warehouses of cross-border E-commerce based on game theory [6]. However, this model was solved using the successive approximation method, which cannot ensure an optimal solution. Srisuwandee selected the location of an infectious waste incinerator by using the CFLP model; however, this model possessed limitations in the capacity and quantity of distribution centers and demonstrated poor general applicability [7]. The study and analysis of the existing location selection models of logistics distribution centers showed that the SI algorithm has good solving ability, even though it has some disadvantages in multiobject optimization problems. For instance, Hua and Gong suggested solving the location selection model of distribution centers by using the particle swarm optimization (PSO) algorithm [8-9]. However, the PSO algorithm has a strong searching ability in the early stage. It can also easily produce premature convergence. Tong optimized the location selection model of logistics distribution centers by using the improved condor algorithm [10]. Given the expansion of the location selection area, this algorithm exhibited obvious disadvantages in global searching ability. Miao proposed a new adaptive strategy for pheromone volatile factors to realize the adaptive-oriented improved ant colony optimization algorithm [11]. Nevertheless, the ant colony optimization algorithm has a slow convergence rate in the early stage. Improper setting of initial parameters may influence the optimization capability of the ant colony algorithm. Yonghui proposed an improved particle swarm clustering algorithm, which introduced the adaptive mechanism into the PSO algorithm [12]. This improved algorithm adjusted the algorithm parameters automatically to appropriate values during its operation. However, this algorithm exhibited poor performances in discrete optimization problems, and it could be easily trapped into local optimal. Karaboga and Kaya tested the performances of the ABC algorithm and studied its applications to combinatorial optimization. The results demonstrated that the ABC algorithm has good optimization performances, which are the same as those of the genetic algorithm, PSO algorithm, and differential evolutionary (DE) algorithm [13-14]. Baysal solved multiobject distributed flow shop scheduling by using the ABC algorithm. They concluded that the ABC algorithm can effectively solve two target optimization problems, namely, fuzzy processing time and expiration date [15]. Durgut introduced the adaptive hybrid strategy into the ABC algorithm and solved the discrete optimization problem by using the multidimensional complementary binary coding method [16]. Ustun replaced the onlookers in the bee colony by employing the mutation-crossing operation in the DE algorithm to increase the accuracy and the rate of convergence of the ABC algorithm [17]. For the DE algorithm, Abraham applied rule of elimination during the iteration of the ABC algorithm, which can effectively avoid the early maturity of the ABC algorithm [18]. Alatas introduced chaotic thought into the ABC algorithm and improved the global searching ability of the algorithm by using randomness and ergodicity of chaotic motion [19]. Özdemir added the adaptive searching formula into the ABC algorithm to decrease the relative error of the algorithm to some extent [20].

The location selection models in the above studies possess the disadvantages of difficult optimization and demonstrate limitations on the capability and quantity of distribution centers when applied to multiconstraint decision-making. In the present study, the locations of logistics distribution centers were selected using the ABC algorithm. The algorithm was initialized by taking advantage of the fast searching ability of the PSO algorithm in the early stage. Setting random parameters in the formula for updating positions of the new bee source guided the searching direction of the algorithm. Moreover, adding a two-way random optimization prevented the algorithm from the local optimal solution due to repeated searching along the single direction. The improved algorithm was applied to the location selection model. Thus, it provided references for the planning of the optimal route of the traceability system.

The remainder of this study is organized as follows. Section 3 constructs the location selection model of logistics distribution centers and describes the optimization method of the improved ABC algorithm. Section 4 tests the performances of the improved algorithm through a comparative test with the reference functions. Moreover, the feasibility and accuracy of the model were tested based on a case study in Wushi County, Aksu. Section 5 summarizes the conclusions.

3. Methodology

3.1 Location selection model

The location selection for logistics distribution centers in the agricultural product traceability system is a complicated NP-hard problem. A location selection model was built according to multiple constraints against location selection. Among different types of influencing factors, transport distance has the most prominent influence on the location selection results of logistics centers. Operation cost is also an important factor that enterprises consider during location selection decision-making. The location of logistics distribution centers were finally determined through the following three major stages by combining the two types of factors:

1) **Stage 1:** The positions of distribution points in the location selection area were determined, and the actual positions of distribution points were recorded. According to the transport route for the logistics distribution of agricultural products and the network distribution of logistics chains, the distances of each distribution point to the nearest distribution point on the adjacent route had to be recorded. The cost weight coefficients among distribution points were determined according to the adjacent distance and operation cost of locations. In this way, the minimum weight coefficient between each distribution point and adjacent distribution points was gained.

2) **Stage 2:** For each distribution point, the mean of unit weight cost was calculated according to Eq. (1):

$$C_{\text{aver}} = \sum_{i \neq j} \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \Big/ \sum_{j \neq i} SW_{ij} \quad (1)$$

where C_{aver} is the mean of unit weight cost. (x_i, y_i) and (x_j, y_j) are the coordinates of distribution points i and j, respectively. SW_{ij} is the cost weight coefficient between distribution points i and j.

3) **Stage 3:** The cost weight coefficients from logistics distribution centers to each distribution point were set reasonably according to the topographic conditions of location selection area, traffic conditions, operation costs, and product needs. Thus, the estimated distance between logistics distribution centers and distribution points (d_i) was obtained. Logistics distribution centers were positioned using the improved ABC algorithm.

3.2 ABC algorithm

The ABC algorithm simulated the behaviors of bees and searched for the global optimal solution through iteration based on local optimization. In the ABC algorithm, the bee colony was divided as follows according to behaviors: employed bees, onlookers, and scouts [21]. Each employed bee corresponded to one determined nectar source. During the initialization of the ABC algorithm, the initial nectar sources in the same quantity as the employed bees were generated randomly. The honey quality (fitness) of the employed bees from the current nectar source was calculated and recorded. Moreover, the adjacent domain was searched during the iteration. The onlookers evaluated the current nectar source according to the value recorded by the employed bees. The nectar source was updated according to practical situations. If a nectar source was abandoned, the employed bees of this nectar source were changed to scouts to search for a new nectar source in the adjacent areas and replace the original nectar source. Finally, the optimal nectar source was acquired through iteration. New nectar sources in the adjacent area were produced according to the searching rule of Eq. (2):

$$v_{ij} = x_{ij} + \varphi_{ij}(x_{ij} - x_{kj}) \quad (2)$$

where k ($k \in \{1,2,\cdots,\text{SN}\}$) is another random nectar source, except i. j is the subscript of the randomly selected nectar source. φ_{ij} is a random number between $[-1,1]$. Onlookers determine whether to abandon or keep the nectar source according to the greedy strategy. The probability for a nectar source to be chosen by the onlookers was determined by the following equation:

$$p_i = \frac{fit(\theta_i)}{\sum_{n=1}^{SN} fit(\theta_n)} \quad (3)$$

where SN is the total number of nectar sources, θ_i is the ith nectar source, and $fit(\theta_i)$ is the fitness of the nectar source at θ_i.

A nectar source was viewed to be exploited completely after the cyclic search for *limit* times. It had to be abandoned to avoid the local optimal of the ABC algorithm. At this moment, the employed bee from the current nectar source was changed into a scout to search for a new random nectar source to replace the original nectar source. *limit* is an important control parameter in the ABC algorithm. It is used to control the quantity of scouts. The random new nectar sources are generated according to Eq. (4):

$$x_{ij} = x_{\min,j} + rand(0,1)(x_{\max,j} - x_{\min,j}) \quad (4)$$

where x_{ij} ($i \in \{1,2,\cdots,\text{SN}\}$) is the D-dimensional vector, and D is the number of areas of distribution points in the traceability system, $j \in \{1,2,\cdots,\text{D}\}$.

3.3 PSO algorithm

The PSO algorithm is a new SI optimization algorithm developed by Kennedy and Eberhart in 1995. The PSO algorithm searches for the global optimal solution through iteration from random solutions by following the current optimal value. On the basis of the basic PSO algorithm, Shi and Eberhart proposed an improved PSO algorithm added with linear decreasing inertia weight (w) to balance the global and local searching abilities of the algorithm. The basic process of the PSO algorithm is as follows:

Step 1: Initialize the particle swarm with a scale of SN and randomly set the position and the initial speed of each particle.

Step 2: Calculate and evaluate the fitness value of the current particle position.

Step 3: Compare the fitness value of the current position (X_i) of each particle and the recorded fitness value of the optimal position (P_i). If the former is better than the latter, update P_i; otherwise, keep the recorded value.

Step 4: Compare the fitness value of the current position (X_i) of each particle and the fitness value of the optimal position (P_g) recorded by this particle swarm. If the former is better than the latter, update P_g ; otherwise, keep the recorded value.

Step 5: Update the speed and position of the particles according to Eqs. (5) and (6).

$$V_i(t+1) = wV_i(t) + c_1 r_1 (P_i(t) - X_i(t)) + c_2 r_2 (P_g(t) - X_i(t)) \quad (5)$$

$$X_i(t+1) = X_i(t) + V_i(t+1) \quad (6)$$

Step 6: If the number of iterations reaches the maximum limit or P_g meets the preset minimum fitting threshold, end the process; otherwise, turn to Step 2.

In Eqs. (5) and (6), $i \in \{1,2,\cdots,\text{SN}\}$. t is the number of iterations. V_i is particle speed. w refers to the linear decreasing inertia weight. P_i is the optimal position recorded by a particle. X_i refers to the position of the particle. P_g refers to the optimal position recorded by the particle swarm. c_1 and c_2 are learning factors. r_1 and r_2 are random numbers that distribute uniformly within [0,1].

3.4 Adaptive random optimizing strategy

3.4.1 Updating the formula of the improved ABC algorithm

The ABC algorithm updates the positions of the nectar sources through Eq. (2), where φ_{ij} is a random number within [-1,1]. An experimental test demonstrated that the convergence rate of the algorithm could be increased by setting the values of φ_{ij} reasonably [22]. In the early stage of the algorithm, high-quality nectar sources could be obtained by setting a high value of φ_{ij} . In the late stage of the algorithm, the local searching ability of the algorithm could be increased by setting a low value of φ_{ij} , thereby accelerating the convergence of the algorithm. Therefore, φ_{ij} was set as a function that decreases with the increase in the iteration times in the improved ABC algorithm.

$$\varphi_{ij}^{k} = \varphi_{ij}^{k-1} - \frac{C(w_{\max} - w_{\min})}{C_{\max}} \tag{7}$$

where C is the current iteration times, $C_{\max}$ is the maximum iteration times, and $w_{\max}$ and $w_{\min}$ are initial and terminal weights, respectively. The following is the rule for nectar source searching after the improvement:

$$v_{ij} = x_{ij} + \varphi_{ij}^{k}(x_{ij} - x_{kj}) \tag{8}$$

The updated formula of φ_{ij} with the iteration times can guide the searching scope of scouts to some extent. It improves the strong randomness of the algorithm and increases the convergence rate of the algorithm.

3.4.2 Two-way random searching mechanism

In the ABC algorithm, when a nectar source is chosen by the onlookers, the positions of the rest nectar sources in the adjacent area are determined according to Eq. (9):

$$\theta_{i+1} = \theta_i + \varphi_i \tag{9}$$

where φ_i is the random step length from the nectar source in the adjacent area to θ_i . According to the evaluation of onlookers, θ_{i+1} is chosen if the quality of the nectar source at θ_{i+1} is higher than that of the nectar source at θ_i ; that is, $fit(\theta_{i+1}) > fit(\theta_i)$. Otherwise, the original nectar source is kept. After the cyclic search for limit times, the nectar source is abandoned if the fitness value is not increased yet. This nectar source searching method has the disadvantage of a single direction. It may also produce a local optimal solution under a certain cardinal number of probability. According to the two-way random wandering searching mechanism proposed by Adamu [23], the searching characteristics under the dynamic network environment could be increased. The two-way random strategy was introduced into the ABC algorithm to realize the two-way random searching mechanism. The searching step length was set to *l*.

$$\theta_i = \begin{cases} \theta_i + d \ , \ fit(\theta_i + l) < fit(\theta_i) \\ \theta_i - d \ , \ fit(\theta_i - l) < fit(\theta_i) \\ \theta_i \ , \ other \end{cases} \tag{10}$$

3.4.3 Initialization of PSO algorithm

The PSO algorithm is considerably superior to the ABC algorithm in terms of the convergence rate. The advantage of the PSO algorithm can be used directly to realize an improved ABC algorithm by combining the PSO algorithm with the ABC algorithm. In particular, the PSO algorithm was introduced into the initialization stage of the improved algorithm to search for the global optimal solution quickly. Then, random initial nectar sources were produced near the optimal solution according to the search results. The ABC algorithm was used for follow-up optimization and iteration. The improved ABC algorithm initializes the positions of nectar sources:

$$X_i = P_{g,best}^{M} + \varphi_i^{M} \cdot P_{g,best} \tag{11}$$

where $P_{g,best}^{M}$ is the optimal fitness value of the swarm in SN-dimensional vectors. φ_i^{M} is the M-dimensional ([-1,1]) vector, which is generated randomly.

3.5 Logistics centers location selection algorithm based on the improved ABC algorithm

If the estimated distance between the logistics distribution centers and different distribution points is d_i (i = 1,2,⋯SN), the coordinates of the logistics distribution centers shall meet $\sqrt{(x-x_i)^2-(y-y_i)^2}=d_i$. Influenced by the quantity of distribution points and cost weight coefficient, d_i gains a certain amount of error. Suppose the positioning error is $fit_i = \sqrt{(x-x_i)^2-(y-y_i)^2}-d_i$. In this case, as the positioning error $fit(x,y)$ decreases, the calculation accuracy of the coordinates increases. Therefore, the fitness function of the improved ABC algorithm is

$$fit_i = \sum_{i=1}^{M} \left| \sqrt{(x-x_i)^2-(y-y_i)^2} - d_i \right| \tag{12}$$

Based on the above analysis, the main idea of the location selection algorithm of logistics distribution centers is to calculate first the mean of the unit weight cost (C_{aver}). The distance (d_i) between the logistics distribution centers and distribution points were calculated according to practical needs. The PSO algorithm was applied for initialization. The fitness function was optimized using the improved ABC algorithm to realize the location selection for logistics distribution centers. The steps are introduced as follows:

Step 1: Initialize the algorithm. Set the initial parameters, randomly produce a particle swarm with a scale of SN, and randomly set the positions and the initialization speed of each particle.

Step 2: The optimal swarm position (P_g) and the optimal fitness ($P_{g,best}$) are gained through the calculation and comparison using the PSO algorithm within the *limit*.

Step 3: Initialize the nectar source positions by the ABC algorithm according to Eq. (11). Calculate and record the fitness of the current nectar source. Search the nectar sources in the neighboring area according to Eqs. (7) and (8).

Step 4: Onlookers choose the nectar sources in the adjacent area according to Eq. (3). New nectar sources are produced near the current source according to the two-way random searching mechanism. Calculate and record the fitness of the new nectar sources.

Step 5: Onlookers choose the nectar source according to the greedy strategy.

Step 6: Decide whether to abandon the nectar source. If yes, the employed bees are changed into scouts. A new nectar source is produced randomly according to Eq. (4) for replacement.

Step 7: Record the current optimal position and fitness value.

4. Result Analysis and Discussion

The proposed improved algorithm was realized through Matlab (version: R2016b). The experimental hardware equipment used the 64-bit Linux PC server equipped with two 4-core Xeon E5 2.50 GHz processors, two pieces of 1TB 7.2K RPM hard disks, and 32 GB memory. The improved ABC algorithm verified the validity of the server through a comparative test of the reference functions. The performance of the improved algorithm was tested by drawing the optimization and iteration curves. The improved algorithm can select the locations for agricultural product logistics centers in a certain geological scope through a case study in Wushi County, Aksu. Moreover, the feasibility and accuracy of the location selection model were analyzed.

1) Performance test of the improved ABC algorithm

Four reference functions were chosen for the comparative test. The validity and performance of the improved ABC algorithm for the location selection for agricultural products (LSAP-ABC) were verified. The performance of the LSAP-ABC algorithm was compared with those of the standard ABC algorithm and the hybrid ABC (HABC) algorithm proposed in Reference [24].

a. Sphere function

$f(x)=\sum_{i=1}^{n} x_i^2$ is a continuous and single-peak convex function, and the searching range is [−100,100]. The global minimum point of the function is 0.

b. Rastrigin function

$f(x)=\left(\sum_{i=1}^{D} x_i^2-10\cos(2\pi x_i)+10\right)$ is a multipeak function, and its optimal solutions distribute uniformly. The searching range is [−20,20], and the global optimal solution is 0.

c. Rosenbrock function

$f(x)=\sum_{i=1}^{n-1}[100(x_{i+1}-x_i^2)^2+(x_i-1)^2]$. The searching range is [−30,30], and the optimal solution of the function is 0.

d. Pathological function

$$f(x)=\sum_{i=1}^{n-1}\left(0.5+\frac{\sin^2(\sqrt{100x_i^2+x_{i+1}^2})-0.5}{(1+0.001(x_i^2+x_{i+1}^2+2x_ix_{i+1})^2)}\right)$$

The searching range is [−100,100], and the global minimum point of the function is 0.

The algorithm was set as follows: the particle swarm and the number of cycles were set as 60 and 100, respectively. The swarm scale of the LSAP-ABC algorithm was 60, and the *limit* was 60. The swarm scale and the *limit* of the ABC algorithm and HABC algorithm were set consistent with those of the LSAP-ABC algorithm. The maximum number of iterations was 2500, and the running times were 30. The comparisons of the maximums, minimums, means, and variances of the three algorithms are shown in Table 1.

Table 1 shows that for the Sphere function, the optimization results were not relatively far from the ideal results. However, the optimization results were improved to some extent compared with the results of the ABC algorithm and HABC algorithm. The multipeak Griewank function proved that the LSAP-ABC algorithm had considerably better accuracy than the HABC algorithm and ABC algorithm with respect to the complicated nonlinear global optimization problem. For the Rosenbrock function, the global optimal solution was difficult to be converged. The means of the three algorithms were relatively large. However, the mean of the LSAP-ABC algorithm was far lower than the means of the two other algorithms. For the pathological function, the test results in Table 1 show that the searching accuracy and searching stability of the LSAP-ABC algorithm were better than those of the two remaining algorithms. According to the test results of the four reference functions in Table 1, the LSAP-ABC algorithm had the characteristics of the ABC algorithm. Compared with the ABC algorithm and HABC algorithm, the LSAP-ABC algorithm improves calculation accuracy and stability.

The optimization and iterative curves of the ABC algorithm, HABC algorithm, and LSAP-ABC algorithm to the four reference functions under 30 dimensions are shown in Fig. 1. In particular, the x-axis is the number of iterations, and the y-axis represents the optimal value in logarithmic coordinates.

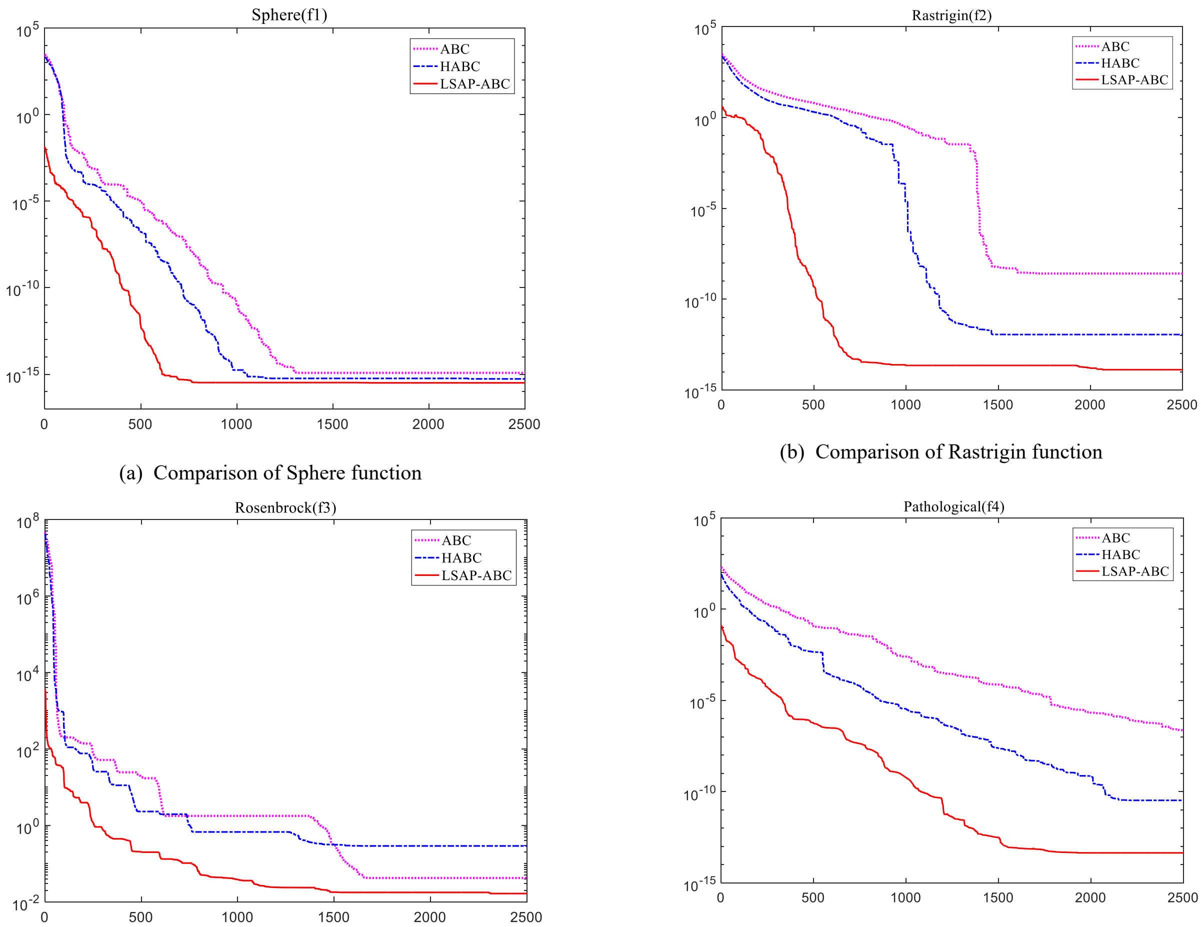
The optimization and iteration processes of the Sphere function are shown in Fig. 1(a). In the early stage, the LSAP-ABC algorithm used the optimal results of the PSO algorithm to replace the initial random nectar sources. Thus, it can realize fast-decreasing convergence to the optimal solution. The convergence rate of the LSAP-ABC algorithm was considerably better than the convergence rates of the two other algorithms. The optimization and iteration processes of the Rastrigin function are shown in Fig. 1(b). Given the fixed number of iterations in the early stage, the LSAP-ABC algorithm could realize linear decreasing convergence to the optimal solution. Moreover, its convergence rate was obviously superior to the convergence rates of the ABC algorithm and HABC algorithm. Given the fixed number of iterations, the accuracy of the optimal value of the LSAP-ABC algorithm was far higher than the accuracies of the ABC algorithm and HABC algorithm, as shown in Fig. 1(c). The algorithm converged gradually to the optimal solution and tended to stabilize with the increase in iterations. As shown in Fig. 1(d), the initial searching accuracy of the LSAP-ABC algorithm was better than the initial searching accuracies of the ABC algorithm and HABC algorithm. Moreover, the algorithm converged gradually to the optimal solution and tended to stabilize with the increase in iterations.

Table 1. Test results of functions

Function	Algorithm	D	Mean	Variances	Maximum	Minimum
(f1) Sphere	ABC	30	1.32153E-015	2.03142E-016	1.81147E-015	6.30578E-016
	HRABC		4.23667E-016	9.00306E-017	6.11458E-016	3.36774E-016
	LSAP-ABC		3.01731E-016	6.02294E-017	5.15621E-016	1.34771E-016
(f2) Rastrigin	ABC	30	9.92251E-010	9.8758E-009	4.22133E-008	3.45721E-012
	HRABC		1.00281E-012	1.65348E-012	7.75532E-012	2.28454E-015
	LSAP-ABC		1.44562E-014	1.89227E-014	5.37682E-014	0
(f3) Rosenbrock	ABC	30	0.233401	0.188744	0.948642	0.0182269
	HRABC		0.198655	0.247764	1.367612	0.0467822
	LSAP-ABC		0.010023	0.009232	0.039986	0.000865

(f4) Pathological	ABC HRABC LSAP-ABC	30	0.009188 0.001863 1.002652E-005	0.008726 0.002060 1.07344E-005	0.030243 0.007734 2.64322E-005	2.45191E-005 7.9192E-005 4.5733E-008

According to the analysis of the optimization and iteration processes of the LSAP-ABC algorithm, the adaptive random searching strategy realized by the PSO algorithm narrowed the optimal searching space in the early stage, thereby guiding the algorithm to the global optimal solution to some extent. Meanwhile, the LSAP-ABC algorithm was far superior to the ABC algorithm and HABC algorithm in terms of accuracy and rate of convergence, thereby preventing the early maturity of the algorithm. The LSAP-ABC algorithm could effectively solve the location selection problem of logistics centers, thereby increasing positioning accuracy.



(a) Comparison of Sphere function

(b) Comparison of Rastrigin function

(c) Comparison of Rosenbrock function

(d) Comparison of Pathological function

Fig. 1. Comparison of four reference function

2) Test of the positioning algorithm

All positions of the distribution points in the area were marked in Wushi County, Aksu, Xinjiang. A total of 24 distribution points exist. According to the geological conditions and quantity of distribution points in the study area, three logistics distribution centers were determined in the area. In particular, logistics distribution center A is responsible for 1 – 10 distribution points. Logistics distribution center B is responsible for 11 – 21 distribution points. Logistics distribution center C is responsible for 22 – 24 distribution points. The cost weight coefficients from logistics distribution centers to each distribution point were set according to topographic conditions, traffic conditions, operation costs, product needs, and other factors. The cost weight coefficients among distribution points beyond the distribution ranges of logistics distribution centers can be set infinitely large according to conditions. A relatively high value can also be set according to practical needs if a crossing distribution problem exists. This planning scheme can be flexibly applied to regions with different numbers of logistics distribution centers, different numbers of distribution points, or different sizes of geographic areas. The algorithm was set as follows: swarm scale, 60; number of cycles, 100; bee colony scale, 60; *limit*, 60. The distributions of logistics centers are shown in Fig. 2.

In Fig. 2, A, B, and C are the location selections of the logistics distribution centers. Logistics distribution center A is responsible for 22 – 24 distribution points. Distribution point 1 was used as the candidate distribution point of logistics distribution center A during location selection. Hence, the location of distribution center A is close to distribution point 24. Logistics distribution center B is close to the distribution point dense area. It can decrease the transport cost to the maximum extent. Logistics distribution center C is located at the center positions of the covered distribution points. According to location selection results, the location selection scheme can determine the locations of logistics distribution centers reasonably according to the positions of distribution points. Moreover, this scheme has good universality.

Fig. 2. Distribution of logistics centers in Wushi County, Aksu, Xinjiang (i = 3)

5. Conclusions

To plan the optimal route of the agricultural product traceability system and select the locations for logistics distribution centers reasonably and accurately, a location selection model of locations distribution centers was constructed. The ABC algorithm was optimized and improved using the PSO algorithm and the adaptive random optimization strategy. The LSAP-ABC algorithm was analyzed through reference function tests. It realized the positioning tests of the locations distribution centers in a certain region. The following conclusions could be drawn:

(1) The PSO algorithm is added in the initialization. The search results are used for further iteration and optimization. Hence, the LSAP-ABC algorithm can realize fast-decreasing convergence to the optimal solution and accelerate convergence.

(2) The adaptive random searching strategy increases the calculation accuracy of the LSAP-ABC algorithm. The stability of the LSAP-ABC algorithm is superior to that of the ABC algorithm.

(3) According to the experimental test of the positioning algorithm, the LSAP-ABC algorithm can determine locations for the logistics distribution centers of agricultural products accurately.

The proposed LSAP-ABC algorithm has good adaptability. It can be applied flexibly in areas with different locations and different numbers of logistics distribution centers and distribution points according to cost weight coefficients. It also has excellent general applicability. The number of the needed logistics distribution centers increases when the cover area of the traceability system exceeds a certain range, possibly increasing the difficulties in the optimal path planning in the traceability system. How to introduce other optimal path selection factors into the LSAP-ABC algorithm is worthy of further discussion.

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