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An improved flower pollination algorithm for optimization of intelligent logistics distribution center

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A B S T R A C T

It is easy to fall into local optimal solution in solving the optimal location of intelligent logistics distribution center by traditional method and the result of optimization is not ideal. For this, the study puts forward an optimization method of intelligent logistics distribution center based on improved flower pollination algorithm. This method uses the logic self-mapping function to carry out chaotic disturbance to the pollen grains, so that the pollen grain set lacking the mutation mechanism has strong self-adaptability, and the convergence of the optimal solution in the later stage of the algorithm is effectively prevented. The boundary buffer factor is used to buffer the cross-boundary pollen grains adaptively so as to prevent the algorithm from the local optimization, and the convergence speed and the optimization accuracy of the algorithm can be improved obviously in processing the optimal location of intelligent logistics distribution center. The convergence of the algorithm is analyzed theoretically by using the real number coding method, and the biological model and theoretical basis of the algorithm are given. The experimental results show that the proposed method has better performance than the traditional one, and the algorithm outperforms a genetic algorithm and particle swarm algorithm. It provides a feasible solution for the intelligent logistics distribution center location strategy. It affords a good reference for improving and optimizing the internal logistics of the manufacturing system and the operational efficiency of the entire intelligent logistics system.

A R T I C L E I N F O

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Intelligent logistics;
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1. Introduction

With the increase of vehicle ownership in China, the problem of traffic jam becomes more and more serious. It's a bottleneck to choose the optimal route of distribution center in a real time manner according to the road condition in the field of intelligent logistics [1-2]. The traditional solution is to optimize the distribution center route under certain constraints, and realize the optimization of the distribution center route under the condition of only considering the single index such as the least cost or the shortest path [3-4]. With the increase of road condition and distribution task complexity, it is difficult to satisfy the demand of intelligent logistics distribution index with only single constraint condition. The optimization of distribution center's optimal route gradually evolves into a multi-constraint optimization problem that satisfies several expectations of distribution personnel in the road network [5-6]. Logistics distribution center is a bridge between supply and demand, its location optimization strategy is the core content of logistics network system analysis, and often determines the distribution system and mode of intelligent logistics system. Therefore, it's theoretically and practically significant to select a reasonable logistics distribution center, achieve the best balance between supply and demand, and thus improve the operation efficiency of the entire intelligent logistics system [7-8].

In recent years, researchers have adopted a lot of methods to study location strategies of intelligent logistics distribution center, and achieved a lot of influential results. Research scholars at home and abroad have deeply studied the location optimization of intelligent logistics center, and classified it into continuous location model and discrete location model [9-10]. The continuous method mainly solves the choice and decision-making of logistics node in plane area. Many scholars have studied the uncertainty of parameters in the model. Literature [11] studied the stochastic programming model of supply chain network under uncertain conditions. Document [12] delt with the location of commercial facilities in uncertain environments. Literature [13] established an interval node decision-making model of logistics network based on barycenter method, and constructed an interval decision-making model of multi-commodity and multi-node continuous logistics facility location. Literature [14] proposes a logistics distribution center location model based on bi-level programming. The distribution points and user cost are considered respectively in the upper and lower levels of the model, and a simple heuristic algorithm is used to optimize the model. Literature [15] used AFS and TOPSIS related theories to explore the location model of logistics distribution center. Literature [16] studied the location issue of distribution center based on rough set and interactive multi-objective fuzzy decision theory. These methods above focus on qualitative or quantitative research on the optimization of location of intelligent logistics distribution centers, and have achieved certain results, which provide a reference for further improving and optimizing the operational efficiency of the entire intelligent logistics system.

From existing researches, it's found that there are two problems in the route optimization of intelligent logistics distribution center: (1) Few researches focus on the specific application requirements of intelligent optimization algorithm in the route optimization of intelligent logistics distribution centers but the influence of the algorithm on the optimization precision and convergence speed is ignored; (2) The setting of the route optimization constraints is too simple to meet the optimization precision requirements under the current complex road conditions. Aiming at the problems in previous researches, this study proposes an optimization method of intelligent logistics distribution centers based on improved flower pollination algorithm.

Flower pollination algorithm (FPA) is a new swarm intelligence optimization algorithm. It is a stochastic global optimization algorithm which mimics the mechanism of self-pollination and cross-pollination of flowering plants in the biological world [17]. The algorithm has the characteristics of easy implementation, strong universality and fast convergence speed, and has wide application. The algorithm is simple to implement and has less parameters, the given conversion probability can set the conversion threshold of global search and local search, and the algorithm adopts Lévy flight mechanism, which has excellent global optimization effect, so the algorithm can be used to solve many complicated optimization problems. On the basis of analyzing the optimization nature of standard flower pollination algorithm, this study presents an improved flower pollination algorithm, analyzes the convergence of the algorithm, optimizes the location model of logistics distribution centers with this improved algorithm, and compares the obtained results with the results of genetic algorithm and standard particle swarm algorithm. The experimental results show that under the premise of satisfying supply and demand, the method proposed in this study obtains the best location scheme for intelligent logistics distribution centers, and its performance is superior to the other two algorithms. The scheme in this study has a good guiding significance for the concrete practice.

2. Intelligent logistics distribution center location model

The problem of the vehicle travel path belongs to the optimal scheduling problem, and the cost is reduced by solving the optimal driving route. The related theories and solving algorithms are of great significance for improving the efficiency of logistics transportation, so it has always been the focus of relevant experts. In recent years, research on the problem of vehicle travel paths has produced many results, such as vehicle routing problems with multiple stations, vehicle routing problems with time window constraints, and vehicle routing problems for loading and unloading cargo. At the same time, vehicle travel routes have applications in all aspects of life, such as product distribution, cargo transportation, and mitigation of traffic jams.

It is difficult to change the location of an intelligent logistics distribution center once it's determined. Therefore, in the process of constructing the distribution center location model, the factors such as fixed cost, management cost and maximum inventory capacity should be taken into account. In the logistics network system, the demand of the demand points should be less than or equal to the size capacity of the distribution center. Under the condition of satisfying the distance upper limit, it is necessary to find out the distribution center from the known demand points and distribute the goods to each demand point. Based on the above problems, the intelligent logistics distribution center location model can be expressed as:

$$\mathrm{Min}T \sum_{j=1}^{M} h_j C_j + \sum_{i=1}^{N} \sum_{j=1}^{M} g_j W_{ij} + \sum_{i=1}^{N} \sum_{j=1}^{M} W_{ij} d_{ij} z_{ij} \tag{1}$$

$$\text{s.t} \sum_{j=1}^{M} W_{ij} \leq B_i, \ \ (i = 1,2,\cdots,N) \tag{2}$$

$$\sum_{j=1}^{M} Z_{ij} = 1, \ \ (i = 1,2,\cdots,N) \tag{3}$$

$$Z_{ij} \leq h_j, \ \ (i = 1,2,\cdots,N) \tag{4}$$

$$\sum_{j=1}^{M} h_j = p \tag{5}$$

$$d_{ij} \leq l, \ \ (i \in M, j \in N) \tag{6}$$

where, N represents a set of ordinal numbers for all demand points; M is a set of demand points selected as the distribution center; C_j is the cost of building a distribution center; $h_j \in \{0,1\}$, when it is 1, the point j is selected as the distribution center; g_j indicates the unit management cost of material circulation in the distribution centers; W_{ij} represents the demand at the demand point i; d_{ij} represents the distance between demand point i and its nearest distribution center j; $Z_{ij} \in \{0,1\}$ represents the service allocation relationship between the demand point and the distribution center, when it's 1, it indicates that the demand of the demand point i is supplied by the distribution center j, otherwise $Z_{ij} = 0$. l indicates the upper limit of the distance between the demand point and the distribution center. Eq. 2 indicates that the demand of users should be less than or equal to the size capacity of the distribution center; Eq. 3 represents ensuring that each demand point is served by a distribution center closest to it; Eq. 4 indicates that there is no customer at a location without a distribution center; Eq. 5 shows that p demand point(s) is (are) selected as distribution center(s); Eq. 6 shows that the distribution center supplies the nearby demand points only within a limited range.

In the material and product distribution part of the manufacturing system, this method can also be used to select the distribution center, and the target function can be changed or added according to its own needs. For example, when distributing the materials needed for manufacturing, if the arrival time of materials has a certain limit, you can add time constraints, and then use the improved flower pollination algorithm to solve. It can be seen that the method can be used not only in the manufacturing system but also in any system that needs to be distributed.

3. Improved flower pollination algorithm

3.1 Standard flower pollination algorithm

Flower pollination algorithm is a kind of random search algorithm constructed by simulating the process of flower pollination in the nature, which embodies the preference mechanism of the nature [18]. The bionic principle is that flowers breed their offspring by pollination. The pollination process can be carried out by insects or natural wind and water. Butterflies are attracted by the color and smell of flowers, and fly to X_{best} after collecting nectar on the pollen X_i, so as to realize pollen transfer between flowers, which is called cross-pollination or global pollination. Under the action of wind, the pollen transfer between adjacent flowers X_i and X_i is realized. This kind of pollination is called self-pollination or local pollination. Through global pollination and local pollination, flowers flexibly achieve the process of pollen transfer. The ideal conditions of the algorithm are assumed as follows:

- In the process of cross-pollination, pollinators carry out pollination through Lévy flight.
- Self-pollination is the pollination process of adjacent flowers under the action of natural force. It is a kind of local pollination. The pollination mode is determined randomly by transition probability $p \in [0,1]$.
- In general, each flowering plant can bloom a lot of flowers, producing millions of pollen gametes, and in order to simplify the problem, we make the hypothesis that each plant only blooms one flower and each flower only produces one pollen gamete, which means that a flower or pollen gamete corresponds to a solution to the optimization problem.

For the formal description of the flower pollination algorithm, the following mathematical model is established:

In global pollination, pollinator carry pollen grains for large-scale and long-distance search, so as to ensure the optimal individual pollination and propagation. In the process of global pollination, the formula for updating the position of pollen is:

$$X_i^{t+1} = X_i^t + L(X_i^t - g^*) \tag{7}$$

where, X_i^t is the spatial location corresponding to the i-th pollen in the t-th iteration; g^* is the spatial position of the optimal solution in the current iteration (i.e., the t-th iteration). The parameter $L > 0$ is the step size and follows the Levy distribution, as shown in Eq. 8.

$$L \sim \frac{\lambda \Gamma(\lambda) \sin(\pi\lambda/2)}{\pi} \frac{1}{s^{1+\lambda}}, (s >> s_0 > 0) \tag{8}$$

where, $\Gamma(\lambda)$ is a standard gamma function, parameter $1 < \lambda \leq 3$ is $\lambda = 1.5$ in this study.

The formula of pollen grain position renewal for local pollination of adjacent flowers is as follows:

$$X_i^{t+1} = X_i^t + \varepsilon(X_j^t - X_k^t) \tag{9}$$

where, X_j^t and X_k^t are the spatial positions of two pollen grains randomly selected, and ε is a random operator uniformly distributed on the [0,1] interval.

The transition probability P is the probability determining whether pollen grains are pollinated globally or locally, and is a constant, with $p \in [0,1]$. The higher the value of P is, the higher the probability of carrying out the local pollination activity is, and the lower the chance of carrying out the global pollination is.

Due to the fact that adjacent flowers are easier to pollinate, the probability of local pollination will be higher than that of global pollination. Through the study of parameters, it is found that the optimization problem $p = 0.8$ is the best choice of parameters. The process of optimizing the algorithm: randomly disperse the population of pollen grains in solution space, and by comparing the size of random production number *rand* and transition probability P, and determine whether each pollen grain will carry on global pollination or local pollination; after several movements and updates of positions, all the pollen grains will converge to the place of optimum fitness; so, the successful pollination and insemination of pollen grains can be realized, and the optimization can be achieved. The steps of the algorithm are as follows:

Step 1: Initialize basic parameters of the algorithm. Set the number of pollen grains as n, transition probability as P and the maximum value of the number of iterations as $MaxT$;

Step 2: Randomly initialize the positions of all pollen grains x_i^0 (i = 1,…,n), find out the pollen grain individuals with the best fitness in the initial situation, and record the current position and fitness of the individuals;

Step 3: Start the iteration, and update the positions of all pollen grains. First generate a random number *rand* between [0,1] and if *Rand* > *p*, the pollen grains are pollinated globally according to Eq. 7; otherwise, the pollen grains are locally pollinated according to Eq. 9. After the position update of all pollen grains is completed in this iteration, the current optimal position and fitness of each pollen grain are calculated, and the position and fitness of the optimal individual in the population are updated;

Step 4: Go to Step 5 when it reaches the maximum number of iterations, otherwise go to Step 3 and start the next iteration;

Step 5: Get the global optimal solution and the target function value at this time.

3.2 Chaos optimization strategy

The principle of chaotic search: first, the variable of chaotic space is mapped to the solution space of the problem by some rules, and then the solution space is traversed by virtue of the chaotic feature. There are many chaotic mapping models. The research shows that the chaotic sequence obtained by using logical self-mapping function is better than Logistic mapping. Therefore, the logical self-mapping function is used in this study to construct chaotic sequences to realize chaotic traversal, and the following expressions are given:

$$cx_j^{k+1} = 1 - 2 \times (cx_j^k)^2 \tag{10}$$

where, cx_j^k is the *j*-th dimensional component of a chaotic variable, *k* is the number of iteration steps, $cx_j^0 \in (-1,1), j = 1,2,\ldots,d$. When $cx_j^k \neq 0$, the chaotic sequence obtained by logical self-mapping model possesses dynamic characteristics of chaos and is sensitive to initial values. The algorithm steps are as follows:

Step 1: Set $k = 0$, the decision variable x_j^k is mapped to the chaotic variable cx_j^k between –1 and 1 according to Eq. 11.

$$cx_j^k = 2 \times \frac{x_j^k - x_{\min,j}}{x_{\max,j} - x_{\min,j}} - 1 \tag{11}$$

where $j = 1,2,\ldots,d$, $x_{\max,j}$ and $x_{\min,j}$ are the upper boundary and the lower boundary of the *j*-th dimensional variable search, respectively.

Step 2: According to cx_j^k, the carrier operation is performed with Eq. 4, and the calculation iterates to the next generation of the chaotic variable cx_j^{k+1}.

Step 3: The chaotic variable cx_j^{k+1} is converted into decision variable x_j^{k+1} according to Eq. 12.

$$x_j^{k+1} = \frac{1}{2} \times [(x_{\max,j} - x_{\min,j}) \times cx_j^{k+1} + x_{\max,j} + x_{\min,j}] \tag{12}$$

where $j = 1,2,\ldots,d$.

Step 4: The performance analysis and evaluation on the newly generated solution are carried out according to decision variable cx_j^{k+1}. If the chaotic search has reached the preset limit or the new solution is superior to the initial solution, the new solution is output as the result of the chaotic search, otherwise, set $k = k + 1$ and return to Step 2.

3.3 Boundary buffer factor

In the process of optimization with flower pollination algorithm, the position of pollen grains is likely to break through its boundary value. In this case, the traditional method is to limit the position of pollen grains to the interval $[-x_{\max}, x_{\max}]$. The advantages of this method are simple operation and small computation, but the boundary compulsory processing method is unfavorable to the convergence of the algorithm, resulting in a lot of errors. In order to solve this problem, the method of dynamically changing interval is adopted, the size of the boundary is scaled according to the situation, the out-of-boundary grains are buffered by the boundary buffer factor and processed according to the out-of-boundary position of the pollen grains. The specific operation is as follows:

When $x_{ij}(t) < a_j$, $x_{ij}(t)$ can be represented as:

$$x_{ij}(t) = a_j((1 - \text{sgn}a_jL) + \text{sgn}a_jL(|v_{ij}(t)|/v_{j\max})rand) \quad (13)$$

When $x_{ij}(t) > b_j$, $x_{ij}(t)$ can be represented as:

$$x_{ij}(t) = b_j((1 + \text{sgn}b_jL) - \text{sgn}b_jL(|v_{ij}(t)|/v_{j\max})rand) \quad (14)$$

In Eq. 13 and Eq. 14, sgn is symbolic functions, $L \in [0,1]$, a_j and b_j are lower and upper limits of the grain in the j-th dimension, respectively. From Eq. 13 and Eq. 14, the boundary buffer factors are treated according to the actual situation of pollen grains, and the actual situation and movement of pollen grains are fully considered. The simulation results show that the boundary buffer factor can effectively improve the convergence speed and optimization accuracy of pollen pollination algorithm.

3.4 Specific steps of solution

The specific steps of optimizing the location problem of intelligent logistics distribution center by using the improved flower pollination algorithm are as follows:

Step 1: Initialize basic parameters of the algorithm. Set the number of pollen grains as n, transition probability as P, the maximum value of the number of iterations as $MaxT$, and the largest number of iteration steps for chaotic search as $MaxC$.

Step 2: Randomly initialize the positions of all pollen grains x_i^0 (i = 1,…,n), find out the pollen grain individuals with the best fitness in the current pollen grain set, and record the current position and fitness of the individuals;

Step 3: Start the iteration, and update the positions of all pollen grains. First generate a random number $rand$ between [0,1] and if $rand > p$, the pollen grains are pollinated globally according to Eq. 1; otherwise, the pollen grains are locally pollinated according to Eq. 3. After the position update of all pollen grains is completed in this iteration, the current optimal position and fitness of each pollen grain are calculated, and the position and fitness of the optimal individual in the population are updated;

Step 4: The individuals of pollen grains are evaluated, the n individuals(in percentage) with the best fitness are selected as the best pollen set, and the remaining $1 - n$ poorer individuals (in percentage) are selected and replaced with randomly generated individuals of pollen grains.

Step 5: The current optimal solution of the individual after chaos optimization is obtained, and the search region is dynamically shrunk by Eqs. 7 and 8.

Step 6: Turn to Step 7 when the number of iterations is equal to $MaxT$ or reaches the set search accuracy; otherwise, turn to Step 3 to perform the next iteration;

Step 7: Output the global optimal solution and the corresponding objective function value at this time.

4. Convergence analysis of chaotic flower pollination algorithm

In the chaotic flower pollination algorithm, the pollination process of flowers is the premise of convergence of the algorithm, the long-distance search and Lévy flight mechanism of pollinators in the cross-pollination guarantee the convergence stability and global optimization, the self-pollination enhances the local optimization ability of the algorithm, and the chaos strategy enhances the swing of the algorithm near the local solution, and reduces search range, gets rid of the local interference, and accelerates the search speed.

If the component x_i (i = 1,2,…,n) of the pollen set $X = (x_1,x_2,…,x_n)$ is represented by the τ dimensional binary coded string, the code string can take 2^τ discrete values, which is equivalent to the 2^τ discrete values dividing the defined interval [Lb_i, Ub_i], with the accuracy of $\varepsilon = (Ub_i - Lb_i)/2^\tau$. Therefore, according to this characteristic, the convergence of the chaotic flower pollination algorithm can be analyzed by real coding. If the search accuracy of the solution space is assumed to be ε, the solution space M can be understood as a discrete space, its size is $|M| = \prod_{i=1}^{n}(Ub_i - Lb_i)/\varepsilon$, where each point $x \in M$ is a pollen grain, so set its fitness $F = f(x)$ is a function of fitness, obviously $|F| \leq M$, so it can be written as $F = \{F^1,F^2,...F^{|F|}\}$, where $F^1 > F^2 >...> F^{|F|}$. According to the different fitness degree, the search space M can be divided into different non-empty subset $\{M^i\}$, which is defined as:

$$M^i = \{x|x \in M, f(x) = F^i\} \tag{15}$$

where i = 1,2,...,$|F|$, then:

$$\begin{aligned} &\textstyle\sum_{i=1}^{|F|}|M^i| = |M|; M^i \neq \varphi, \forall i \in \{1,2,\dots,|F|\}; \\ &M^i \cap M^j = \varphi; M^i \cap M^j = \varphi, \forall i \neq j; U_{i=1}^{|F|}M^i = M \end{aligned} \tag{16}$$

For any two elements $x_i \in M^i$ and $x_j \in M^j$,

$$f(x_i)\begin{cases} > f(x_j), & i < j \\ = f(x_j), & i = j \\ < f(x_j), & i > j \end{cases} \tag{17}$$

It is easy to know that F^1 can be considered a global optimal solution F^*, and that individuals with fitness equal to F^* should be in M^1. In the iterative process of the algorithm, the number N of pollen populations remains unchanged, $p = \{x_1,x_2,...,x_N\}$. Set P as a set, containing all populations, and since the pollen grains in the population are allowed to be the same, the number of possible populations is:

$$|\beta| = C_{|M|+N-1}^{N} \tag{18}$$

Then, in order to judge the quality of the populations, the fitness function of p can be defined as:

$$F(P) = \max\{f(x_i)|i = 1,2,\dots,N\} \tag{19}$$

Similarly, according to the different fitness, P can be divided into $|F|$ non-empty sub-sets (i = 1,2,...,$|F|$), where $|P^i|$ represents the size of the set P^i. The set P^1 includes all populations with fitness F^1.

Set p^{ij} (i = 1,2,...,$|F|$; j = 1,2,...,$|P^i|$) represents the j-th population of p^i. Under the action of the evolution operator, the probability $\mathrm{Pr}_{ij,kl}$ of p^{ij} transiting to p^{kl} represents the transition probability of any one of the populations from p^{ij} to p^k, and $\mathrm{Pr}_{i,k}$ represents the transition probability of any one of the populations from p^i to p^k, then:

$$\mathrm{Pr}_{ij,k} = \sum_{i=1}^{|p^k|}\mathrm{Pr}_{ij,kl}\,; \quad \sum_{k=1}^{|F|}\mathrm{Pr}_{ij,k} = 1\,; \quad \mathrm{Pr}_{i,k} \geq \mathrm{Pr}_{ij,k} \tag{20}$$

A square matrix $A \in R^{n\times n}$ is called:

- a nonnegative matrix, if $a_{ij} \geq 0, \forall i,j \in \{1,2,\dots,n\}$;
- a primitive matrix, if A is nonnegative, and there is an integer $k \geq 1$, so $A^k > 0$;
- a random matrix, if A is nonnegative and $\sum_{j=1}^{n} a_{ij} = 1$, then $\forall i \in \{1,2,\dots,n\}$;
- a reducible random matrix can perform a row-column transformation of the same form to obtain $A = \begin{bmatrix} S & 0 \\ R & T \end{bmatrix}$, where s is the m-order primitive matrix, and R and T≠0.

<u>*Definition 1*</u>**:** If an evolutionary algorithm converges to a global optimal solution, its sufficient and necessary conditions are:

$$\lim_{t\to\infty}\mathrm{Pr}\{f(P^t) = F^*\} = 1 \tag{21}$$

where, Pr represents probability and P^t represents the t-th generation population.

<u>*Theorem 1*</u>: Set $\mathrm{Pr} = \begin{bmatrix} S & 0 \\ R & T \end{bmatrix}$ is a reducible random matrix, S is the m-order primitive matrix and R and T≠0, then

$$\mathrm{Pr}^{\infty} = \lim_{n\to\infty}\mathrm{Pr}^n = \lim_{k\to\infty}\begin{bmatrix} S^n & 0 \\ \sum_{i=0}^{n-1}T^iRS^{n-i} & T^n \end{bmatrix} = \begin{pmatrix} S^{\infty} & 0 \\ R^{\infty} & 0 \end{pmatrix} \tag{22}$$

Obviously, Pr^{∞} is a stable random matrix and $\mathrm{Pr}^{\infty} = [1,1,\dots,1]^T[p_1, p_2, \dots, p_n]$, $\sum_{j=1}^{n} p_{ij} = 1$, and $p_j = \lim_{k\to\infty} p_{ij}^{(k)} \geq 0$, when $p_j \begin{cases} > 0 & (1 \leq j \leq m) \\ = 0 & (m+1 \leq j \leq n) \end{cases}$.

Theorem 2: In the chaotic flower pollination algorithm, for$\forall i, k \in \{1,2,\dots,|F|\}$,

$$\mathrm{Pr}_{i,k} \begin{cases} > 0, & k \leq i \\ = 0, & k > i \end{cases} \tag{23}$$

Prove: First, for $\forall P^{ij} \in p^i (j = 1,2,\dots,|p^i|)$, $\exists X^* = (x_1^*, x_2^*, \dots, x_n^*) \in p^{ij}$, so $f(x^*) = F^i$, $\forall p^{kl} \in p^k$, $k = 1,2,\dots,|F|$, $l = 1,2,\dots,|p^k|$, $\exists X' = (x_1', x_2', \dots, x_n') \in p^{kl}$ and $f(X') = F^k$. Under the action of evolutionary operators, p^{ij} is transited to be p^{kl}, if p^{ij} of the t-th generation is evolved to be p^{kl} of the $(t+1)$-th generation, and for convenience, record them as L^t and L^{t+1}. The chaotic flower pollination algorithm has the optimization strategy and the historical optimal solution F* is preserved in each pollination process. Therefore, the optimal position of pollen is F* at L^t, and under the condition that the population remains unchanged, the next generation L^{t+1} is produced through pollination behavior, and the best pollen grain F' in L^{t+1} is compared with F*, if F' is better than F*, the preserved historical optimal solution is replaced by F', otherwise unchanged, then:

$$f(L^{t+1}) \geq f(L^t) \Rightarrow k \leq i \Rightarrow \forall k > i,\ \mathrm{Pr}_{ij,kl} = 0 \Rightarrow \forall k > i,\ \mathrm{Pr}_{ij,k} = \sum_{l=1}^{|p^k|} \mathrm{Pr}_{ij,kl} = 0 \Rightarrow$$

$\forall k > i$ and $\mathrm{Pr}_{i,k} = 0$.

Secondly, in each pollination process, the algorithm is iterated and the optimal solution is found. The behavior selection is made according to the principle of the fastest or better speed. Therefore, set individual X', with the fitness of $f(X') = F^k$, $k \leq i$, and X' has r components $(x_1', x_2', \dots, x_r')$ different from X*, the probability of x' generated by x* through Levy flight operator is $\mathrm{Pr} = (1 - \frac{1}{n})^{(n-r)} \prod_{i=1}^{r} \phi(x_i^* - x_i') > 0$, where φ is the probability density function for levy distribution. So the probability of p^{ij} evolving to be p^k is greater than zero, so $\forall k \leq i$ and $\mathrm{Pr}_{i,k} \geq \mathrm{Pr}_{ij,k} > 0$.

Theorem 3: The chaotic flower pollination algorithm is globally convergent.

Prove: Each Pr_i, $i = 1,2,\dots,|F|$ can be viewed as a state on a time-aligned finite Markov chain. According to Theorem 1, the transition probability matrix of the algorithm is expressed as:

$$\mathrm{Pr} = \begin{bmatrix} \mathrm{Pr}_{1,1} & 0 & \cdots & 0 \\ \mathrm{Pr}_{2,1} & \mathrm{Pr}_{2,2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ \mathrm{Pr}_{|F|,1} & \mathrm{Pr}_{|F|,2} & \cdots & \mathrm{Pr}_{|F|,|F|} \end{bmatrix} = \begin{bmatrix} S & 0 \\ R & T \end{bmatrix}$$

where $R > 0$, $T \neq 0$ and $S = 1$.
According to Theorem 1,

$$\mathrm{Pr}^{\infty} = \lim_{k\to\infty} \mathrm{Pr}^k = \lim_{k\to\infty} \begin{bmatrix} S^k & 0 \\ \sum_{i=0}^{k-1} T^i R C^{k-i} & T^k \end{bmatrix} = \begin{bmatrix} S^{\infty} & 0 \\ R^{\infty} & 0 \end{bmatrix}$$

where $S^{\infty} = 1$ and $R^{\infty} = (1,1,\dots,1)^T$, so Pr^{∞} is a stable random matrix, and

$$\mathrm{Pr}^{\infty} = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ 1 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 0 & \cdots & 0 \end{pmatrix}$$

Therefore, regardless of the fitness state of the current population, it will converge to the optimal fitness state with probability 1 after infinite evolution, so the improved flower pollination algorithm is globally convergent.

5. Results and discussion

In this section, the results of optimization of the proposed method, genetic algorithm and standard particle swarm optimization algorithm are compared in Matlab environment to prove the effectiveness and feasibility of the proposed method. During the experiment, the coordinates of 31 cities are collected, and the position coordinates of each demand point and the material demand are given in Table 1. The material demand in the table is the standardized value and does not represent the actual value. The dimensionless process is applied to 31 logistics points. The dimensionless process uses the quotient of the mean value of each factor variable to obtain dimensionless data.

The parameters of flower pollination algorithm are as follows: p = 0.8, *beta* = 1.5, the number of chaos iterations k = 10, and the ratio of selecting the best pollen set is n = 20. The improved flower pollination algorithm is used to optimize the location model of the intelligent logistics distribution center. The point value is set to be 6, which indicates that 6 logistics distribution centers are selected from 31 demand points.

In the simulation experiment, the final data is the average result after running the program for 100 times, so as to reduce the error. The convergence curve of the improved flower pollination algorithm is shown in Fig. 1.

The location scheme of the intelligent logistics distribution center is shown in Fig. 2. The box represents the distribution center, and the dot represents the demand point. The connection between the box and the dot indicates that the logistics distribution center is responsible for the distribution of the materials at a demand point. The location model of the intelligent logistics distribution center is optimized by the method proposed in this study, and the location scheme is [22 17 6 29 6 11].

In the process of solving the location optimization of the intelligent logistics distribution center with the improved flower pollination algorithm, chaos optimization and boundary buffer factor are added to effectively avoid the algorithm falling into local optimization, so that the convergence speed and optimization accuracy of the algorithm are obviously improved, reflecting that the flower pollination algorithm needs no accurate description of the problem in solving the practical problem, but can quickly obtain the optimal solution within a certain limit. Table 2 shows the performance comparison between the proposed scheme, genetic algorithm and standard particle swarm optimization (PSO) in optimizing the location model of intelligent logistics distribution center.

Table 1 Position of demand point and material demand

No.	Coordinates	Demand	No.	Coordinates	Demand
1	(2378,3172)	50	17	(4462,3641)	90
2	(1689,2623)	60	18	(2685,3252)	80
3	(4973,4582)	60	19	(4891,3431)	50
4	(2732,3452)	40	20	(2541,3964)	40
5	(1367,2473)	70	21	(4571,3115)	90
6	(3874,3994)	70	22	(2714,3574)	60
7	(4953,2363)	30	23	(4325,3683)	70
8	(3852,3372)	60	24	(4232,3231)	60
9	(2454,3068)	60	25	(2232,3462)	50
10	(2122,1374)	80	26	(4436,3285)	50
11	(4132,3879)	40	27	(3340,4112)	30
12	(2244,3896)	30	28	(1203,2183)	60
13	(4564,1598)	30	29	(4632,3461)	80
14	(3933,4212)	80	30	(2262,3365)	50
15	(3284,1475)	30	31	(3422,4316)	70
16	(3433,2756)	50			

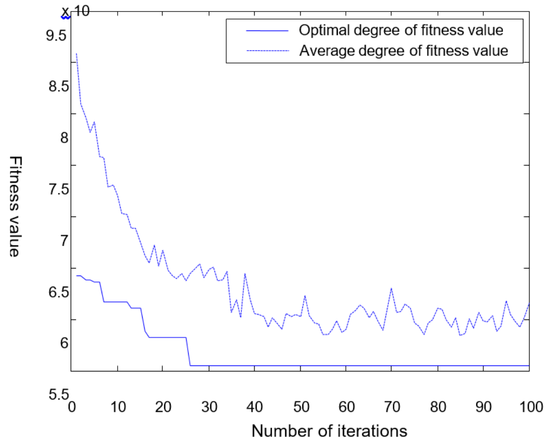

Fig. 1 Convergence curve

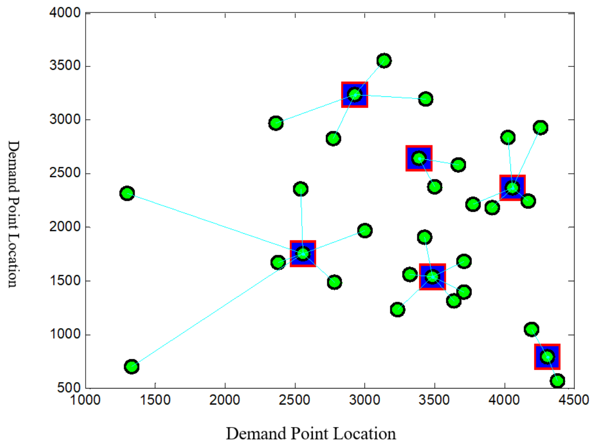

Fig. 2 Location scheme

Table 2 Performance comparison of several algorithms

Algorithm	Location scheme	Average distribution cost	Number of iterations	Running time/s
GA	22 17 6 29 6 11	1892	110	36.3
PSO	22 17 6 29 6 11	1363	60	15.5
Improved FPA	22 17 6 29 6 11	1012	26	11

Table 2 shows that when genetic algorithm, standard particle swarm optimization algorithm and the method in this study optimize the location model of the intelligent logistics distribution center, the optimal scheme can be obtained, The average delivery cost required by the genetic algorithm is 1892, the number of its iterations is 110, and its running time is 36.3 seconds. The average delivery cost required by the standard particle swarm optimization algorithm is 1363, the number of its iterations is 60, and its running time is 15.5 seconds. The average delivery cost required by the improved flower pollination algorithm is 1012, the number of its iterations is 26, and its running time is 11 seconds. Therefore, the performance of the improved flower pollination algorithm is generally better than the other two algorithms. In order to further verify the universality of the improved flower pollination algorithm in solving such problems, the number of logistics demand points is changed, and simulation experiments are carried out on different initial data respectively. The simulation results show that when the number of logistics demand points is large, the advantages of the algorithm presented in this study are more obvious. At the same time, we also find that the flower pollination algorithm has the advantages of self-organizing ability, distributed operation and positive feedback, and can perceive the change of surrounding road condition parameters in real time in complex road network. It is especially suitable for the path optimization problem of intelligent logistics distribution center under multi-constraint conditions.

6. Conclusion

The optimal location model of intelligent logistics distribution centers is a non-convex and non-smooth nonlinear model with complex constraints, which belongs to NP-hard problem. This study uses the intelligent optimization method to the path optimization problem of the intelligent logistics distribution center, and proposes an improved flower pollination optimization algorithm. According to the actual characteristics of the whole logistics network system, a location model of the intelligent logistics distribution center is constructed. According to the biological characteristics of flower pollination, the realization principle of the flower pollination algorithm is described from the mechanism, and the convergence of the algorithm is analyzed by real coding method. The optimization performance of the algorithm is analyzed in detail, and the biological model and theoretical basis of the algorithm are given.

In order to avoid the local optimization and improve the convergence speed and optimization accuracy of the algorithm, this study introduces chaos optimization and boundary buffer factor.

By means of logical self-mapping function, the pollen grains are disturbed by chaos, which makes the pollen grain set without mutation mechanism have strong self-adaptive ability. Meanwhile, the size of the boundary is dynamically scaled according to the actual situation, and the boundary buffer factor is used to buffer the pollen grains crossing the boundary. The experimental results show that compared with other methods, the method proposed in this study is more effective in solving the location optimization of the intelligent logistics distribution center, and can quickly and accurately find the best logistics distribution center for demand points.

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