Solving the Optimization of Physical Distribution Routing Problem with Hybrid Genetic Algorithm

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Abstract. In view of the deficiency of genetic algorithm in local search ability, a simulated annealing algorithm for optimization of physical distribution routing problem is constructed. Compared with the traditional optimization algorithm, the hybrid genetic algorithm has faster convergence speed, better distribution result and better application value.

1. Introduction
The Logistics distribution path optimization is a NP hard problem in the field of combinatorial optimization, which has a wide range of engineering applications and real life background. How to solve the distribution path problem quickly and effectively has a high practical value. At present, the main algorithms used to solve the distribution path optimization problem are: genetic algorithm, simulated annealing algorithm, ant colony algorithm, neural network algorithm and hybrid strategy algorithm[1-6]. This paper analyzes the genetic algorithm in the intelligent algorithm, improves its application in solving the distribution path problem, and introduces the simulated annealing algorithm to strengthen its optimization ability. The experimental results show that the hybrid genetic algorithm is more reliable in the case of small population size.

2. Modeling building
The demand of a logistics distribution problem is as follows: knowing the specific location of users, the quantity of goods transported, the load of vehicles and the maximum distribution distance of vehicles, solving the optimal vehicle distribution route and the shortest distribution route. Requirements: 1) the distribution volume of users on each line shall not exceed the vehicle load; 2) the total distance of each line shall not exceed the critical value of vehicle driving distance; 3) each customer's demand can only be served by one vehicle.

Suppose K is the maximum number of vehicles; \(Q_k\) (k = 1, 2, ..., K) refers to the carrying capacity of the vehicle; \(D_k\) refers to the maximum driving distance of the vehicle; L refers to the number of users; \(q_i\) refers to the number of goods to be transported by the user; \(d_{ij}\) refers to the distribution distance from location point i to location point j; \(d_{0j}\) refers to the distance from the center point to each distribution point; \(n_k\) refers to the number of users serving the k-th vehicle; \(R_k\) refers to the k-th distribution route.

\[
\min z = \sum_{k=1}^{K} \left[ \sum_{l=1}^{n_k} d_{x_l(i-1)j_l} + d_{x_kd_0} \text{sign}(n_k) \right]
\] (1)
\[ \text{s. t. } \sum_{i=1}^{n_k} q_{ki} \leq Q_k \quad (2) \]

\[ \sum_{i=1}^{n_k} d_{k(i+k+k)} + d_{k(2i+2k)} \text{sign}(n_k) \leq D_k \quad (3) \]

\[ 0 \leq n_k \leq L \quad (4) \]

\[ \sum_{k=1}^{K} n_k = L \quad (5) \]

\[ R_k = \{ r_{ki} | r_{ki} \in [1, 2, \ldots, L], i=1,2, \ldots, n_k \} \quad (6) \]

\[ R_{x1} \cap R_{x2} = \emptyset \quad (\forall k_1 \neq k_2) \quad (7) \]

\[ \text{sign}(n_k) = \begin{cases} 1 & (n_k \geq 1) \\ 0 & \text{(other)} \end{cases} \quad (8) \]

3. **Construction of hybrid genetic algorithm**

The algorithm used in this paper is mainly to introduce simulated annealing into the crossover operation of genetic algorithm, so that the genetic algorithm can not only receive good solutions, but also receive poor solutions, so as to avoid falling into the "premature" solution.

3.1. **Algorithm steps**

1) Determine population size n, crossover probability Pc, mutation probability Pm and initial temperature T0;
2) Randomly generate L individuals and calculate their fitness;
3) Select individuals;
4) Cross operation and simulated annealing operation were carried out for individuals;
5) Mutation operation;
6) Cooling, \( T = T_0 \cdot \theta^k \), \( \theta \) is a constant between \([0,1]\), k is the number of iterations;
7) If an evolutionary algebra is reached, terminate the operation, otherwise skip back to step (3).

3.2. **Algorithm design**

1) Coding rules. Take the natural number encoding of 0, 1…N.
2) Fitness function. For an individual, if the number of distribution paths and the total number of vehicles is reduced by M, then the fitness function is as follows:
\[ F = 1 / \left( Z + M * \alpha \right) \]
3) Selection operators. The roulette method is used.
4) Crossover operator. Cross method similar to OX method is adopted.
5) Simulated annealing algorithm. Suppose that the parent generation before crossing is f1, f2, and the offspring after crossing is c1, c2. The fitness of the parent generation and the offspring is F(fi), F(ci), i = 1, 2, respectively. Then simulated annealing operation is carried out. If the offspring F(ci) is larger than the parent F(fi), the offspring ci is used to replace the parent fi. Otherwise, the offspring ci is accepted with probability \( \exp(F(ci) - F(fi)/T) \). In the formula, T is the current temperature;
6) Mutation operator. The mutation method of continuous and multiple commutation is used.
4. Construction of hybrid genetic algorithm

4.1. Coding
According to the characteristics of logistics distribution path optimization, this paper adopts a simple and intuitive natural number coding method, using 0 for distribution center, 1, 2, ..., L represents each demand point. As the distribution center has k vehicles, there are at most k distribution paths, each of which starts from the distribution center and ends at the distribution center. In order to reflect the vehicle distribution path in the code, k-1 virtual distribution centers are added, which are expressed as L+1, L+2, ..., L+K-1. In this way, 1, 2, ..., L+K-1 constitute an individual and correspond to a distribution path scheme. The chromosomes thus formed are simple, intuitive and easy to understand.

4.2. Fitness function
For the distribution path scheme corresponding to an individual, to judge whether it is excellent or not, first of all, it needs to see whether it meets the constraints of distribution; second, it needs to calculate the value of the objective function. For an individual, set the difference between the number of corresponding distribution paths and the total number of distribution vehicles as m (if the number of distribution paths is not greater than the total number of distribution vehicles, then take M = 0, which means that the individual corresponds to a feasible solution; if the number of distribution paths is greater than the total number of vehicles, then M > 0, which means that the individual corresponds to an infeasible solution), assuming that the target function value is Z, M is the infeasible path, then the fitness Z of the individual can be calculated by formula (9).

\[
F = \frac{1}{Z + M \cdot \alpha} \quad (9)
\]

In the formula: \( \alpha \) is the penalty weight for each infeasible path, and a relatively large positive number can be taken according to the value range of the objective function.

4.3. Selection operation
Using the combination of optimal individual retention and roulette selection strategy: N individuals in each generation group are arranged from large to small according to the fitness, and the individual performance in the first place is the best. Copy it directly into the next generation, and rank first. The other N-1 individuals of the next generation group need to be generated by the roulette selection method according to the fitness of N individuals of the previous generation group. Specifically, it is to first calculate the sum of all individual fitness in the previous generation group \( \sum F_j \), and then calculate the proportion of each individual's fitness \( F_j / \sum F_j \quad (j=1,2,...,N) \) as the probability of being selected. In this way, it can not only ensure the survival of the best individual to the next generation, but also ensure that individuals with larger adaptability have a greater chance to enter the next generation.

4.4. Crossover operation
In this paper, a cross method similar to ox method is adopted, which is introduced as follows:

(1) Randomly select a mating region in the string, and select two strings and mating regions as follows:

\[
\begin{align*}
A &= 1 \ 2 \ 3 \ 4 \ 5 \ 6 \ 7 \ 8 \ 9 \\
B &= 9 \ 8 \ 7 \ 6 \ 5 \ 4 \ 3 \ 2 \ 1
\end{align*}
\]

(2) Add the mating area of B to the front of a, and the mating area of a to the front of B to get:

\[
\begin{align*}
A' &= 7 \ 6 \ 5 \ 4 \ 1 \ 2 \ 3 \ 4 \ 5 \ 6 \ 7 \ 8 \ 9 \\
B' &= 3 \ 4 \ 5 \ 6 \ 9 \ 8 \ 7 \ 6 \ 5 \ 4 \ 3 \ 2 \ 1
\end{align*}
\]
In A' and B', the same natural number as the mating area is deleted successively after the mating area, and the final two individuals are obtained:

\[ A^{''} = 7 6 5 4 1 2 3 8 9 \]
\[ B^{''} = 3 4 5 6 9 8 7 2 1 \]

Compared with other cross methods, this method can still produce a certain degree of variation effect under the same condition of two parents, which has a certain role in maintaining the diversity of population.

4.5. Mutation operation
In order to keep the diversity of individuals in the group, we use the technology of continuous and multiple alternation to change the order of individuals. The mutation operation occurs with a certain probability. Once the mutation operation occurs, the random method is used to generate the exchange times J, and the individual gene of the required mutation operation is exchanged J times (the position of the exchange gene is also randomly generated).

4.6. Mountaineering operation
For the optimal individuals in each generation of population formed by genetic operation, mountain climbing operation should be carried out by neighborhood search. In this paper, we use gene transposition operator to achieve mountain climbing operation. The operation method is as follows:

1. Randomly select two genes in individuals and exchange their positions;
2. Judge whether the adaptive value increases after gene transposition. If the adaptive value increases, replace the original individual with the transposed individual;
3. Repeat (1) and (2) until a certain number of exchanges is reached.

5. Experiment analysis
A logistics center has two distribution vehicles with a capacity of 8t and 7t respectively. The maximum driving distance of each vehicle distribution is 60 km. The distance between the distribution center (its number is 0) and six customers, as well as between six customers are \( d_{ij} \), 6 customers’ demand for goods \( d_{ij} \) (i=1,2,...,6) for goods \( d_{ij} \) refer to the corresponding literature [1]. Six customers’ demand \( d_{ij} \) for goods \( d_{ij} \) (i=1,2,...,6) are referred to the corresponding literature [1]. It is required to arrange vehicle distribution route reasonably to minimize the total mileage of distribution.

In this paper, the following parameters are used to solve the problem: population size is 30, evolution algebra is 25, crossover probability is 0.8, mutation probability is 0.08, penalty weight of infeasible path is 200km, and climbing times is 20. The example is solved 10 times randomly, and the calculation results are shown in Table 1.

| Computation order | 1    | 2    | 3    | 4    | 5    | 6    | 7    | 8    | 9    | 10   | Average |
|-------------------|------|------|------|------|------|------|------|------|------|------|---------|
| Total distribution distance | 42.00 | 44.50 | 46.00 | 50.50 | 42.00 | 43.50 | 45.50 | 49.50 | 42.00 | 46.50 | 45.20   |
| The evolutionary algebra of finding the final solution for the first time | 2.00  | 4.00  | 6.00  | 8.00  | 2.00  | 1.00  | 3.00  | 5.00  | 22.00 | 2.00  | 5.50    |
| Computing time | 0.18  | 0.11  | 0.22  | 0.15  | 0.11  | 0.16  | 0.16  | 0.16  | 0.11  | 0.11  | 0.15    |
It can be seen from table 1 that the optimal solution of the problem is 42km for 3 times out of 10 times and approximate optimal solution for 7 times. In terms of calculation efficiency, the average calculation time of 10 solutions is 0.15s, and the calculation efficiency is high.

In order to facilitate the comparison, genetic algorithm is used to solve the example for 10 times, and the search times for each solution are 1000 times. See Table 2 for the comparison of the calculation results of genetic algorithm and hybrid genetic algorithm.

| Algorithm type                  | Genetic algorithm | Hybrid genetic algorithm |
|---------------------------------|-------------------|-------------------------|
| Total distance of average distribution | 50.1              | 45.2                    |
| Standard deviation of solution  | 1.84              | 1.15                    |
| The number of times to get the optimal solution | 1                 | 3                       |
| The average number of searches to find the optimal solution for the first time | 85                | 130                     |
| Average calculation time        | 0.3               | 0.15                    |

It can be seen that from the optimization results, the hybrid genetic algorithm is superior to the genetic algorithm; from the calculation efficiency, the hybrid genetic algorithm is significantly higher than the genetic algorithm; from the robustness of the algorithm, the stability of the hybrid genetic algorithm is better than the genetic algorithm.

6. Conclusions

Aiming at the deficiency of genetic algorithm in local search ability, this paper combines it with mountain climbing algorithm which has strong local search ability, constructs hybrid genetic algorithm, and obtains good calculation results. At present, there are many algorithms with strong local search ability, such as ant colony algorithm, discrete Hopfield network and so on. It will be an important direction for the development of genetic algorithm to combine genetic algorithm with these local search algorithms.

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