Research Article
Research on Food Vehicle Routing Problem Based on Improved Genetic Algorithm

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Abstract: The study proposed an improved genetic algorithm to solve this food logistics routing problem. the rationality of the model was validated and the effectiveness of the algorithm. Research conclusion can provide reference for the research on food logistics distribution business in the pursuit of minimizing total cost to optimize route choice, vehicle size and departure time. It also has great application value. With the boom of economics, people's standards of living are increasing, so we are paying more and more attention to the fresh food quality problem.

Keywords: Application value, food vehicle distribution, improved genetic algorithm

INTRODUCTION

With the improvement of people's living standard and the fast rhythm of people's work, the demand for food is growing fleetly. However, the increasing demand not only promotes food's market supply increasing, also has brought great pressure and challenge for logistics enterprises. It is vital for them to provide high quality shipping services for retailers in the required delivery time. On the other hand, the traffic congestion makes the distribution time and the shipping cost for food rising. For distribution companies, in considering the time window constraints, they must also take into account the characteristics that may effects the distribution such as potential congestion in urban road transport and the perishable of the commodities for the purposes of achieving the minimum cost. Therefore, considering the condition of road traffic situation is of theoretical and practical significance in the study of vehicle routing problem for food (Likar and Jevsnik, 2006).

This paper from the basic theory of logistics and vehicle routing problem, introduces the characteristic and the system structure of food logistic, the classification and the algorithm of vehicle routing problem, etc., the periodic vehicle routing problem is analyzed in detail. On this basis, with consideration of food characteristics, such as perish-ability and time sensitivity etc., a periodic vehicle routing model for vehicle routing is constructed to optimize vehicle routing, vehicle allocation and departure time. This model minimizes the total distribution cost which includes the assigned vehicle costs, transportation costs, overtime cost and the cost of damage distribution. After that, an improved genetic algorithm is promoted to solve this model. Finally, the rationality of the model was validated and the effectiveness of the algorithm.

MATERIALS AND METHODS

Initialization of the algorithm: Compared to other algorithms, the genetic algorithm has its own merits. The genetic algorithm adopts the evolution mechanism and it carries out the searching process in the whole situation, averting the localization. Even if the adaptive function is discontinuous or irregular, the genetic algorithm can find the optimized solution of whole situation. And also, it has wonderful parallel processing and can realize the combination with other algorithms, especially adapted to the issues which has large scale and broad distribution:

- Divide the feasible region $[L,U]$ of the problem to be optimized into B subspaces according to the following equation:

$$u_k - l_k = \max_{1 \le i \le n} \{u_i - l_i\}$$
$$\begin{cases} L_i = L + (i-1)\left[(u_k - l_k)/B\right]1_k \\ U_i = U + (B-i)\left[(u_k - l_k)/B\right]1_k \end{cases}, \quad i = 1, 2, \mathrm{L}, B$$

Here, $L = \left[l_1, l_2, \cdots, l_n\right]^T$ and $U = \left[u_1, u_2, \cdots, u_n\right]^T$ respectively denote the lower boundaries and upper boundaries of n independent variables of the problem. B denotes the design parameter. 1_k is the n-dimensional vector of which the kth bit is 1 and other bits are 0. L_i and U_i denote n-dimensional vectors respectively similar to L and U. In this way, the feasible region of the problem can be divided into B subspaces, namely $\left[L_1, U_1\right], \left[L_2, U_2\right], \cdots, \left[L_B, U_B\right]$.

- Discretize each independent variable in each subspace according to the following equation.

Suppose the domain of the independent variable x_i is $[l_i, u_i]$ then x_i can be quantized in to Q_1 (the design parameter) levels $a_{i1}, a_{i2}, L, a_{iQ_1}$ and the detailed computation method for a_{ij} is:

$$a_{ij} = \begin{cases} l_i & j = 1 \\ l_i + (j-i)\left[(u_i - l_i)/(Q_1 - 1)\right] & 2 \leq j < Q_1 \\ u_i & j = Q_1 \end{cases}$$

- **Select M₁ chromosomes from each subspace:** First construct the orthogonal table $L_{M_1}(Q_1^N) = [a_{ij}]_{M_1 \times N}$ in which N denotes the dimensionality of the problem, $M_1 = Q_1^{J_1}$ and J_1 denote the positive integers that satisfy the condition $\frac{Q_1^{J_1} - 1}{Q_1 - 1} \geq N$. Then select M_1 combinations from the Q_1^N ones to form M_1 chromosomes.
- Select the best G (the size of the initial population) chromosomes from the M_1 B potential ones to form the initial population according to their fitness value.

Genetic algorithm crossover operation: In order to realize the optimization of vehicles dispatching, the main content of genetic algorithm is as follows:

- **Number the researching object:** Only when we transform the spatial data issue into a bunch of genes data which can be dealt with by this algorithm can we use the genetic algorithm to handle this problem for the genetic algorithm has poor handling ability to spatial problems.
- **Initialize the population biology:** In order to achieve the operation of the spatial problems, we must optionally transform the spatial problems into population biology which has many individuals and these individuals can response the answer of one space optimized issue. Thus, the key issue is how to form the initialized population biology.
- **Using the fitness function:** Every individual in the transformed population biology will affect the merits of the whole issue. So we have to use the fitness function to evaluate the individuals' ability and apply the data to other genetic operation.
- **Select the excellent individual:** In the genetic algorithm, only the excellent past age can have great meaning to the younger generation, cause the great individual and gene can multiply the greater generation.
- **Intersect and form the new individual:** The intersection of single gene can influence the astringency and shorten the calculating time. We select the individual having the good genes to

intersect with the better genes and get the greater gene combination. Generally, the intersection has two steps (Kozenski and Behn, 2008). Firstly, we should pair the last generation randomly and confirm the intersection point of these individuals which can be paired randomly, then transform or intersect the partial information and then produce the new individual.

- **Creating the new generation through variation:** Variation can make the individual in population biology multiple, which preventing the algorithm to enter into the locality and effecting the optimized calculation of the overall situation. The variation also has two steps. Firstly, selecting part of the chosen individuals and creating a new individual through variation according to the projecting process. The whole implementation of the genetic algorithm crossover operation is shown as follows:
  - ○ Select two parent chromosomes for crossover operation according to the crossover probability. Suppose that the two selected parents are $\begin{cases} p_1 = (p_{11}, p_{12}, \cdots, p_{1N}) \\ p_2 = (p_{21}, p_{22}, \cdots, p_{2N}) \end{cases}$ and the defined solution space $\left[l_{parent}, u_{parent}\right]$ is:

$$\begin{cases} l_{parent} = \left[\min(p_{11}, p_{21}), \min(p_{12}, p_{22}), L, \min(p_{1N}, p_{2N})\right] \\ u_{parent} = \left[\max(p_{11}, p_{21}), \max(p_{12}, p_{22}), L, \max(p_{1N}, p_{2N})\right] \end{cases}$$

  - ○ Discetize the solution space $[l_{parent}, u_{parent}]$ of two parent individuals for crossover operation into Q_2 parts.
  - ○ Select some independent variables that will suffer crossover operations. The number of potential child individuals generated by each pair of parent individuals should be controlled to avoid a huge evaluation on the populations during the crossover operation. In this study, the crossover only operates on F genes of the parent chromosome. Discretize these F independent variables in each subspace.
  - ○ Select potential child points from the solution space of parents according to the orthogonal table. First generate the orthogonal table $L_{M_2}(Q_2^F) = [b_{ij}]_{M_2 \times F}$ in which Q_2 is an odd number, $M_2 = Q_2^{J_2}$ and J_2 is the smallest positive integer that satisfies the condition $\frac{Q_2^{J_2} - 1}{Q_2 - 1} \geq F$. Then select M_2 combinations from these Q_2^F ones to form M_2 potential child individuals.
  - ○ Select two with the best fitness value from the M_2 potential child individuals and two parents as the result of this crossover operation.
  - ○ If the number of the implemented crossover operations has reached the preset value, stop crossover immediately, or turn to (1).

RESULTS AND DISCUSSION

Path mutation operation:

- Randomly select a parent chromosome for mutation operation according to the mutation probability.
- Obtain the mutated child chromosomes according to the fine perturbation method. Here, the perturbation means generating four mutated child chromosomes through tuning the value of the selected parent gene respectively to its original $1-1-2\sigma, 1-\sigma, 1+\sigma$ times and $1+2\sigma$ times.
- Select the best one of the parent and child chromosomes as the result of this mutation operation.
- If the number of the implemented mutation operations has reached the pre-set value, stop mutation immediately, or turn to (1).

The example analysis of improved genetic algorithm in food logistics transferring path: To prove that the improved genetic algorithm can get the optimized solution of food logistics path dispatching in the multi-resources constraint condition and the reliably practical application, we carry on the data validation with the help of software. We use function rand (1) in the MATLAB to randomly produce 10 customers in the square of (0, 100) and set up a complete dispatching network, numbering them as 1, 2,…, 10. According to the require of need, we randomly produce the coordinate of the dispatching network center and all the customer in the field of (0, 8). The function inputted includes: the prime cost 1.2/k, the distance 123 m, 20 min each mission, the speed 45 k/h in dispatching and we get data of randomized distance of the algorithm produced at last (Table 1).

The straight-line distance of the selecting coordinate in the field is the practical distance of the nodal point. Transform the limitation of obeying the resource-constrain to the losing distance. We must estimate the total pcu which we need in the whole dispatching mission, making $\partial = 0.86$, the pcu satisfying $m = [\sum_{i=1}^{n} q_i / \partial Q] + 1 = 3$.

In the practical logistics vehicle dispatching, the dispatching issue constrained by the multi-resources can realized the better management and distribution. Because of the developed modern transportation, there are many chained gas station in each lattice point, so we consider the persistent driving ability of vehicles as unfailing. Thus, we just need to solve the dispatching optimized solution of the vehicle models (Abada and Aggarwal, 2005). After the improvement of traditional genetic algorithm, now we optimize the vehicle dispatching under loading resource-constraint condition: ruling the dispatching car as 3, in light of the

Table 1: The data of algorithm example randomly produced

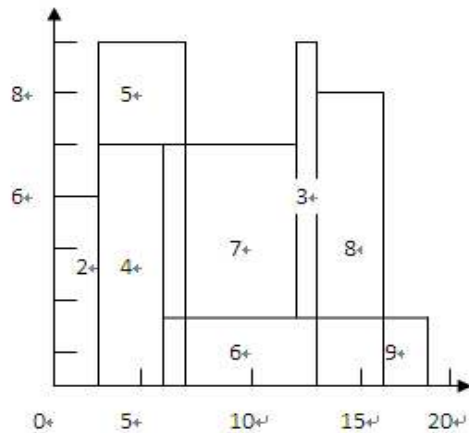| Code	Coordinate (km)	Temporal demand	Time window constraints
0	(55.56)	0.0t	-
1	(59.41)	2.2t	14:50-15:20
2	(32.94)	2.3t	9:00-9:30
3	(58.12)	6.8t	10:30-11:30
4	(60.85)	3.6t	10:05-10:45
5	(36.71)	1.2t	14:00-14:30
6	(14.66)	5.6t	11:05-11:45
7	(34.25)	3.2t	9:50-10:25
8	(67.40)	1.8t	14:00-14:30
9	(75.79)	3.4t	11:00-11:25
10	(19.46)	1.6t	15:40-16:20

Fig. 1: Dispatching path

detailed operating steps such as intersection and variation, function the program 26 times and finally we get the optimum solution convergence and we know that if the prime cost is 866.12¥, the dispatching is the most simple, so is the profit. The scheme of dispatching is shown in Fig. 1.

We can learn from the detailed data from this chart that the vehicle dispatching issue under loading resource-constraint can be reasonably optimized in driving routine, length, capacity tonnage and so on. And the iteration time as well as the time of calculation is less than former, the most important is the prime cost is much less. However, the vehicle dispatching under condition of time window resource-constraint is not satisfying with the punishing cost caused by time window, so it has to sacrifice the length to insure the time so as to meet demand, so the dispatching cost is much higher. We can see in the experimental example, the improved genetic algorithm can not only better optimize the localized demand vehicle dispatching issue under the condition of multi-resources constrain, but also can improve the efficiency of solving and the convergence of the overall situation.

CONCLUSION

We discuss the analyze the genetic algorithm of food logistic path with the improved genetic algorithm in detail, changing the disadvantage of slow convergence in the traditional genetic algorithm,

making the application of improved genetic algorithm become much wider, thus promote the application of vehicle dispatching in the genetic algorithm, the growth of food logistics, as well as the development and ability of the economy.

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