An Improved Genetic Algorithm for Routing of Logistics Vehicles

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Abstract. As the logistical industry is increasingly global and integrated with information technologies, distribution of goods plays a bigger role in the logistics system overall. In this context, choosing an appropriate route for delivery of goods is considerably helpful in shortening the response time to customer needs, improving service quality, increasing customers’ satisfaction and reducing operation cost. In-depth studies are conducted on the vehicle routing problem (VPR), which is critical to efficient delivery of goods. A multi-constrained mathematical model is established. Meanwhile, the traditional genetic algorithm is improved by constructing chromosome for feasible path through integer coding, introducing penalty term to fitness function. The proposed algorithm is implemented on Visual Studio 2010. The results demonstrate the effectiveness and feasibility of the proposed algorithm.

1. Introduction

How to determine the route of vehicles is a critical problem to the modern logistics system. Optimizing the route of logistics vehicles can reduce operation cost, save time and improve efficiency. Therefore, performing systematic research on the theory and method for route optimization of vehicles is vital to modern logistics. It underlies the integrated development of modern logistics, construction of modern transportation system, development of modern visualized scheduling system, and improvement of intelligent transportation system.

2. Logistics VRP

2.1 Overview of VRP

VRP was first proposed by Dantzig and Ramser in 1959 [1]. The VRP problem can be described as follows. Given some customers located in specific locations with specific transportation requirements, a number of vehicles are instructed to drive from the central warehouse, determine optimal routes and then visit each of the customers as scheduled. The purpose of VRP is to minimize total transportation costs and deliver goods to destinations as soon as possible while satisfying specific constraints in terms of customer needs and vehicle carrying capacities.

VRP can also be described using the graph theory. Consider an undirected graph \( G = (V, A) \), where \( V = \{v_0, v_1, \ldots v_n\} \), \( V \) denotes the set of vertexes, \( E = \{(v_i,v_j): v_i, v_j \in V, i \neq j\} \), \( E \) denotes the set of edges connecting each pair of vertexes. The vertex \( v_0 \) denotes the location of distribution center, and other vertexes represent the set of customers that need to be served. A non-negative distance matrix or cost matrix \( D = \{d_{ij}\} \) can be defined on \( E \), where \( d_{ij} \) denotes the cost or distance from the vertex (customer) \( i \) to the vertex (customer) \( j \).

2.2 VRP classification

VRP can be classified into different types according to different criteria. For example, according to the characteristics of prior information, it can be classified into deterministic VRP and non-deterministic VRP; according to the constraints, it can be classified into the capacity-limited VRP,
distance-limited VRP and the VRP based on time window (VRPTW). Depending on whether the customer requirements can be divided, it can be classified into divisible VRP and non-divisible VRP.

The deterministic VRP problem is the most common category in practice, characterized by prior information on the location and requirement of customers/nodes. For example, the distribution center needs to address the demands of each department store for goods, working out the routes and schedules that will be followed in the next day for delivery of goods. This type of problem can be solved by the exact algorithm or the artificial intelligence algorithm. The former type includes the direct tree search method, dynamic programming method and integer linear programming method. The latter type includes the sweep method, tabu search method and the genetic method [2].

2.3 VRP model

In this paper, the time-unconstrained unidirectional VRP problem can be described as follows. Several vehicles drive from the distribution center for delivery of goods to several customers. Given the location and requirement of each customer, as well as the carrying capacity and maximum driving distance of each vehicle, we need to work out appropriate driving routes to optimize the objective function.

Consider there are N vehicles at the distribution center, each of which has a capacity of \( W_i \) and a largest driving distance of \( L_i \). A total of \( m \) customers need to be served. Let \( Q_{ij} \) denote the demand of each customer for goods, \( d_{ij} \) denote the driving distance between the customer \( i \) and the customer \( j \), and \( d_{0j} \) denote the distance between the distribution center and the customer \( j \). Also let \( I_i \) denote the number of customers served by the \( i \)th vehicle. If \( I_i = 0 \), it means that the \( i \)th vehicle is not used. Defining the total mileage traveled to deliver the goods as the objective function, we can establish a mathematical model for the time unconstrained unidirectional VRP problem as follows.

\[
\begin{align*}
\min s &= \sum_{i=1}^{N} \left[ \sum_{j=1}^{I_i} d_{ij} + d_{i0} \times \text{sign}(I_i) \right] \\
\sum_{j=1}^{I_i} Q_{ij} &\leq W_i \quad (2) \\
\sum_{j=1}^{I_i} d_{ij} + d_{i0} \times \text{sign}(I_i) &\leq L_i \quad (3) \\
0 &\leq I_i \leq m \quad (4) \\
C_i = \{c_{ij} | c_{ij} \in \{v_1,v_2,...,v_N\}, j = 1,2,...,I_i\} \quad (5) \\
\sum_{i=1}^{N} I_i &= m \quad (6) \\
c_i \cap c_j &= \emptyset, \forall i \neq j \quad (7) \\
\text{sign}(I_i) &= \begin{cases} 1, & I_i \geq 1 \\ 0, & \text{other} \end{cases} \quad (8)
\end{align*}
\]

where Eq. 1 is the objective function, designed to minimize the total mileage (i.e. the sum of length of all routes); Eq. 2 ensures that the sum of demands from all customers on each route does not exceed the carrying capacity of the vehicle; Eq. 3 ensures the length of each route does not exceed the largest driving distance of the vehicle; Eq. 4 ensures the number of customers on each route does not exceed the total number of customers; Eq. 5 ensures each customer will be served; Eq. 6 represents the set of all customers on each route; Eq. 7 ensures that each customer can only be served by one vehicle; Eq. 8 means that if the \( i \)th vehicle has one or more customers to serve, it participates in the delivery of goods and \( \text{sign}(I_i) \) is set to 1; otherwise, the \( i \)th vehicle has no customer to serve and thus is not used for delivery of any goods, and \( \text{sign}(I_i) \) is set to 0.

The number of vehicles necessary for delivery of goods needs to be estimated before determining the route. In the real-world scenario, a high level of complexity associated with goods loading (discharging) and a large number of constraints result in a small carrying capacity of vehicles. Here,
the method in [3] is used to determine the number of vehicles, i.e. \( M = [\sum Q_i / aW_i] + 1 \), where \( [\cdot] \) denotes the round operation, \( a \) is a parameter and \( 0 < a < 1 \). The more constraints there are, the smaller the value of \( a \); the more complicated the process of goods loading (discharging), the smaller the value of \( a \). It is set to 0.85 in this paper.

3. Overview of the Genetic Algorithm

The genetic algorithm (GA) provides a search method that can effectively address the optimization problem. It was a complete theory and method proposed by the U.S. Professor J. Hollnadt in the 1960s. It is actually a computation model that can emulate Darwin’s biological evolution of natural selection. Currently, it has been widely and effectively used for combinational optimization, artificial intelligence, artificial life, among others.

The steps of GA are described as follows.
1. Coding: the data in the solution space is first converted into the gene string in the genetic space. Different combinations of strings constitute different codes.
2. Generation of initial population: randomly generate \( N \) initial strings. Each string forms an individual (chromosome), and \( N \) individuals form a population.
3. Fitness evaluation: the fitness function indicates the quality of individual and solution.
4. Selection: note that the high-quality individuals are selected after considering the fitness of each individual and following certain criteria.
5. Crossover: randomly choose two from the selected individuals for crossover or recombination in order to produce two new individuals. Repeat this process until the crossover operation is performed on all individuals that need to perform this operation. It is the most important operation in GA.
6. Mutation: select several individuals from the optimal ones and then perform mutation on the selected individuals given a mutation probability \( P_m \). The mutation operation improves the ability of GA to find the optimal solution.
7. Conditional termination: terminate the process if the convergence condition is satisfied or the number of iterations is reached; otherwise, jump to Step (3) to follow the evolution procedures again. Every round of evolution produces a new generation of population.

4. Vehicle Routing Based on the Improved GA

4.1 The algorithm strategies are as follows
1. Coding: apply integer coding to chromosome.
   Let 0 denote the general warehouse, 1, 2, …, \( k \) denote the \( k \) sub-warehouses. The chromosome has a length of \( k + m + 1 \). In each chromosome, there are \( m + 1 \) 0s. The first and last element in it is 0, indicating that the vehicle drives from the general warehouse and finally returns to the general warehouse. The remaining \( m-1 \) 0s divides the code into \( m \) segments. These segments constitute \( m \) sub-routes for \( m \) vehicles to accomplish the transportation tasks. Consider a chromosome with code 0123045067890. It represents the schedule of three vehicles driving to nine sub-warehouses. Sub-route 1: general warehouse - sub-warehouse 1 - sub-warehouse 2 - sub-warehouse 3 - general warehouse; sub-route 2: general warehouse - sub-warehouse 4 - sub-warehouse 5 - general warehouse; sub-route 3: general warehouse - sub-warehouse 6 - sub-warehouse 7 - sub-warehouse 8 - sub-warehouse 9 - general warehouse.
2. Population initialization
   The size of population should reach a threshold to ensure that the algorithm can converge to global optimality. But the population size should also be controlled to reduce computational complexity.
3. Fitness function
   The penalty strategy which considers infeasible solution during genetic search is introduced to compute the fitness function. The schedule determined through direct permutation of customers can guarantee that the sum of all customers on a route does not exceed the vehicle’s carrying capacity and
that the length of each route does not exceed the largest driving distance of the vehicle. But it is unable to ensure that all customers will be served. If all customers are covered by the schedule, the number of infeasible routes \( M = 0 \), and it means that this solution is feasible. If the last few customers are not covered by the route, the number of infeasible routes \( M = 1 \) for this schedule. If this schedule’s objective function has a value \( Z \), the penalty weight of each infeasible route is \( P_w \) (set to a large positive number based on the domain of the objective function), the score of this solution, \( E \), can be computed in Equation (9). The smaller the value of \( E \) is, the higher the quality of solution. This method of solution evaluation embodies the idea of processing constraints using the penalty function.

\[
E = Z + M \times P_w
\]  

(9)

The fitness evaluation function is shown in Equation (10). The individual is first decoded to determine the number of infeasible routes \( M \) and the objective function value \( Z \). Then, the values of \( M \) and \( Z \) are substituted into the equation to obtain the individual’s fitness \( f \).

\[
F = 1/E = 1/(Z + M \times P_w)
\]  

(10)

4. Selection strategy: the selection strategy adopted in this paper involves best-individual storage and roulette wheel selection. Specifically, the \( N \) individuals are sorted out in descending order of fitness. The first individual is the best individual, which is thus directly passed down to the next generation. Note that this copy is the top individual of the new generation. The other \( N-1 \) individuals of the next generation are created through roulette wheel selection based on the fitness of the \( N \) individuals in the previous generation.

5. Crossover: the Order Crossover method is adopted.

6. Mutation: the multiple-swapping mutation technique is adopted.

5. System Implementation

5.1 Target problem

A company (0) performed statistical analysis of its sales in a region. After evaluating and sorting out about 100 customers, 20 major customers were finally selected (1-20). Their coordinates are as follows: 14.5, 13.0; 12.8, 8.5; 18.4, 3.4; 15.4, 16.6; 18.9, 15.2; 15.5, 11.6; 3.9, 10.6; 10.6, 7.6; 8.6, 8.4; 12.5, 2.1; 13.8, 15.2; 6.7, 16.9; 14.8, 7.6; 1.8, 8.7; 17.1, 11.0; 7.4, 1.0; 0.2, 2.8; 11.9, 19.8; 13.2, 15.1; 6.4, 5.6; 0.6, 14.8.

The demand of each customer for goods is: 100; 400; 1200; 1500; 800; 1300; 1700; 600; 1200; 400; 900; 1300; 1300; 1900; 1700; 1100; 1500; 1600; 1700; 1500.

The shortest route to these 20 customers needs to be determined while ensuring the vehicles are not overloaded and all customer requirements are satisfied. The vehicle has a carrying capacity of 8,000kg.

5.2 Related parameters

Parameter setting of the proposed GA is as follows. The number of individuals in the population is 20, the maximum number of generations is 400, the crossover probability is 0.9, the mutation probability is 0.09, and the penalty weight for vehicle overloading is 300.

The number of vehicles \( m \) needs to be estimated first before determining the route. From the method mentioned above for estimating the number of vehicles, it is learned that \( m = 4 \).

5.3 Operation results

The vehicle routing results obtained through the improved GA after 10 rounds of system operation are shown in Table 1. The average value is 123.9km, the optimal value is 130.3km, and the minimal value is 118.1km. It can be seen that the result is stable as the difference with the optimal value is small. The shortest driving distance is 118.1km, as shown in Fig. 1. The route of each vehicle is shown in Fig. 2.
Table 1. Vehicle routing results from the improved GA after 10 rounds of system operation.

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<td>122.9</td>
<td>120.5</td>
<td>130.3</td>
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Figure 1. Route of vehicles.

It is proved that this route absolutely satisfies the demand of each customer and the carrying capacity of vehicle. Therefore, it is a good feasible solution to VRP.

6. Conclusion

The optimization of route and schedule for logistics vehicles is studied in this paper. An improved GA is proposed to effectively address the vehicle routing problem. Our work contributes to the application of GA for combinational optimization, and lays the foundation for subsequent in-depth research on VRP and its algorithms. Hence, our work is of great theoretical and practical significance.

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References