Research on Model Fitting Capacity of Vehicle Routing Problem

Chenghua Shi, Xiaofeng Zhao

1 College of Economics & Management, Huazhong Agricultural University, Wuhan 430070, P.R. China, chenghuashi@hebeu.edu.cn
2 School of Economics and Management, Hebei University of Engineering, Handan 056038, P.R. China, Qboy_best@163.com

Abstract

Existing vehicle routing researches always focus on the methods of finding the optimal path, losing sight of the dynamic characteristics of real vehicle routing problem. In this paper, some indicators that can reflect the traffic condition of cities are added into the mostly used vehicle routing model to improve the application result in practical situation. Experimental results demonstrate that the dynamic fitting capacity of model and algorithm for logistics situation is very important in the practical application of vehicle routing problem, and this field should be more in-depth studied.

Keywords: Logistics Distribution, Vehicle Routing Problem, Genetic Algorithm, Refuse Time, Time Window

1. Introduction

In recent years, with the rapid development of economic globalization, supply chain system is becoming more and more important to economy. Vehicle routing problem (VRP) is one of the important research fields of supply chain. Selecting the appropriate vehicle routing methods can shorten the response time to customer needs, improve service quality, enhance customer satisfaction with the logistics chain, and reduce the operating costs of service providers. So the vehicle routing problems have always been the hotspot of operational research, management science and computer science. However, most of the researches in this field are focused on finding the optimal path, losing sight of the dynamic characteristics of real vehicle routing problem. In practice, how much impact do the dynamic factors (such as traffic flow and so on) have on the routing selection, or are they can be neglected? In this paper, two algorithms and an experiment are carried out to make it clear.

2. Literature review

Many different VRP mathematical models have been proposed for different problems with the deep study of Routing Problem. Generally, there are integer programming model, graph theory based model and other theories based models in VRP. Fisher [1] presented the three subscript VRP model with capacity and time window constraints. Clarke and Wright [2] proposed c-w saving algorithm, and the algorithm first constructs the same number of paths by the nodes needed to be visited (not including the starting point), and then computes the saved cost after combining arbitrary two paths. Asim Munawar etc [3] designed cellular Genetic Algorithm with Local Search (LS) to solve Capacitated Vehicle Routing Problem (CVRP) over Cell Broadband Engine (Cell BE). The algorithm firstly constructs a series of solutions, and then continuously improves them. Taillard etc.[4] pointed out that optimal solution got by the algorithm is often superior to local extreme value obtained by the traditional algorithm. What’s more, the algorithm has better convergence and higher search efficiency. Genetic algorithm is another important method in solving TSP and VRP, William Ho [5] introduced the method into VRP with time window. Yang Peng and Ye-mei Qian [6] solved VRP with fuzzy demands (FVRP) using Particle Swarm Optimization. It can be seen that most of the researches are focus on “how to solve the NP-Hard problem of VRP”, but few research has been conducted on the affect of dynamic factors in practical situation on the VRP, which is the key problem researched in this paper.

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3. Problem formulation and preliminaries

A cold drink chain enterprise, which deals with various brands of ice-cream and cold drink, sets its chain stores in over 50 cities of China. There are several stores in each city. The enterprise has set 7 regional distribution centers in 7 different cities taking charge of the distribution of goods to cities in its own region. Each city has been set one city logistics center. The area for the experiments is with one logistics center and 12 cities in the area.

The original logistics distribution process is: A store will send inventory request to city logistics center when the chain stores’ inventories are lower than minimum stock, and the city logistics will send its inventory request when its inventory is lower than minimum stock. For our research, however, we want to involve both highway transportation process and urban transportation process in one distribution, so as to study how much impact dynamic traffic conditions have on the optimization algorithm of VRP. Therefore, the original distribution process is changed as follows: In our research, no city logistics center will be established in all cities, when the inventory is lower than minimum stock, the store sends its inventory request directly to the regional distribution center, and the logistics management system will set the latest arrival time according to the minimum stock of the store. A logistic center can have several refrigerator cars for the delivery, and an optimal routing scheme should be designed in order to reduce logistics cost.

Two algorithms have been designed. One is a genetic algorithm based on the traditional algorithm of VRP, which does not take the dynamic traffic condition of practical situation into account, and the other is a improved algorithm, to which the dynamic factors that can reflect the practical traffic situation are added. Several experiments have been carried out to compare how the algorithms work out in the practical dynamic situation.

3.1. Mathematical model of the problem

The problem described in the previous section is a VFVRPTW(Variable Fleet Vehicle Routing Problem with Time Window), and the latest arrival time of vehicles is computed by the minimum stock of each chain store. The stores open all day, and there is no special requirement for the earliest arrival time, so it is set 0. According to the most prevalent integer programming method, the mathematical model of the problem is as follows:

\[
\text{min } \sum_{i=0}^{N} \sum_{j=0}^{N} \sum_{k=1}^{K} c_{ij} x_{ijk} \quad (1)
\]

\[
\text{min } \sum_{i=0}^{N} \sum_{k=1}^{K} x_{ijk} i=0 \quad (2)
\]

\[
s_d \sum_{i=0}^{N} d_i \sum_{k=1}^{K} x_{ijk} \leq q \quad 1 \leq k \leq K \quad (3)
\]

\[
\alpha_i \leq t_{ik} \leq \beta_i \quad 1 \leq k \leq K, 0 \leq i \leq N \quad (4)
\]

\[
\sum_{j=0}^{N} x_{ijk} = 1 \quad 1 \leq k \leq K \quad (5)
\]

\[
\sum_{i=0}^{N} x_{ihek} - \sum_{j=0}^{N} x_{ijk} = 0 \quad 1 \leq k \leq K, 0 \leq h \leq N \quad (6)
\]

\[
\sum_{i=0}^{N} x_{i,k+1} = 1 \quad 1 \leq k \leq K \quad (7)
\]

\[
x_{ijk} = \begin{cases} 
0 & \text{Otherwise} \\
1 & \text{If vehicle } k \text{ doesn’t arrive at node } j \text{ from node } i 
\end{cases} \quad (8)
\]

In the model, \( i, j \in \{0,1,2,\ldots,N\} \). We suppose that: \( c_{ij} \) denotes the distance from city \( i \) to city \( j \). \( q \) denotes the maximum load of vehicles. \( d_i \) (\( i=1,2,\ldots,N \)) denotes demand of customer \( i \) and \( d_i<q \). The objective functions (1) and (2) minimize the total distance and vehicle number. Constraints (3) ensure that vehicle capacity will not be exceeded; Constraints (4) guarantee that \( t_{ik} \), which is the arrival time
of vehicle \( k \) at store \( i \), should be between \( \alpha_i \) (earliest arrival time of store \( i \)) and \( \beta_i \) (latest arrival time of store \( i \)); Constraints (5), (6) and (7) present that each vehicle should leave from the depot, visit each city one after another, and finally return to the depot. For most models, \( c_{ij} \) is constant. Genetic algorithm is one of the most effective methods of solving VRP, and it has got good results when used in the simulated experiments in many papers. In this paper, genetic algorithm is chosen to solve the vehicle routing problem.

3.2. The genetic algorithm for the problem

The delivery process has two steps for this case:

First, compute the needed vehicle number and the vehicle routing among cities, in which the vehicle capacity demand of a city is the sum of all stores’ demand, and the priority of cities is computed by formula (9).

When the vehicle routing among cities is worked out, the vehicle routing in city should be computed. For this step, the problem is degenerated into a vehicle routing problem with soft time windows (vehicle number is 1), and the method in literature [6] is used (set the vehicle number to be 1).

The genetic algorithm GAFVRPTW (Genetic algorithm for VRP with time windows) designed for step 1 is as follows:

3.2.1. City priority evaluation function

The city priority evaluation function is as formula 9:

\[
P(j) = \omega_1 \frac{|t_{o_j} - \tilde{a}_j|}{|\tilde{b}_j - \tilde{a}_j|} + \omega_2 \frac{|t_{o_j} - \tilde{b}_j|}{|\tilde{b}_j - \tilde{a}_j|} + \omega_3 \frac{c_{o_j}}{\max_{i \in S_j} c_{o_i}}
\]

In which, \( \omega \) denotes the weight of each item and \( \omega_1 + \omega_2 + \omega_3 = 1 \); \( t_{o_j} \) denotes the time from starting city to city \( j \); \( \tilde{a}_j \) denotes the average value of all earliest arrival time of all stores in the city; \( \tilde{b}_j \) denotes the latest arrival time of all stores in the city.

3.2.2. Chromosome encoding method

The decimal coding is used as chromosome encoding method. The vector \( \{l_1, l_2, \ldots, l_N\} \) represents a chromosome \( G \), in which element(gene) \( l_i \) is a non-repeated decimal number between 1 and \( N \), that is \( l_i \in [1, N] \). The first generation of population is a set of randomly generated chromosomes \( G_h \) (\( h = 1, 2, \ldots, N_p \)), in which \( N_p \) denotes the individual number of every generation, and \( N \) denotes city number. The city priority can be represented by value of the decimal number, the bigger of the value the higher of the priority, and a gene segment that meets precedence relationship determines a rational vehicle routing. For instance, the precedence relationship of 16 cities is \( 1 > 2 > 3 > \ldots > 16 \), and the chromosomes: (3), (1, 4, 7, 9, 10, 13, 16), (2, 8, 11, 12), (5, 6, 14, 15) mean that the delivery needs 4 vehicles.

Population initialization strategy is the same as the GRASP method in literature [7], and the chromosome crossover is the same as the DAX method in literature [8].

3.2.3. Fitness function

The process of mapping encoding vectors of the chromosome to meet all the constraints is called feasible process. The feasible process is as follows:

(1) According to the order from left to right, the gene segment in chromosome that meets precedence relationship determines a vehicle route. Otherwise, use another vehicle to start a new route. For example, the precedence relationship of 10 customers is 1,2,3,4,5,6,7,8,9,10, and then for chromosome S: 8 9 2 3 4 6 1 5 7 10, gene segment (8,9), (2,3,4,6), and (1,5,7,10) meet the precedence relationship. Thus S represents the number of vehicles for the use is 3.
(2) Check each gene segment to see if they meet vehicle capacity constraints and the time window constraints of each city. Then the chromosome corresponds to a feasible solution of the problem if the answer is yes, otherwise, the chromosome corresponds to an infeasible solution.

Fitness function is used to evaluate individuals in the population. Each chromosome $G_h (h = 1, 2, \ldots, Np)$ in the population can obtain the corresponding feasible solution after the feasible process. The objective function value $Z_h$ of the feasible solution is obtained according to formula (2), and if the chromosome corresponds to an infeasible solution, give it a big integer $M$. We assume the fitness function $f_h = \frac{1}{Z_h}$. The greater value $f_h$ indicates the better the performance of $G_h$ and the closer to the optimal solution.

3.2.4. Selection operator

Selection operators sort the $k$ chromosomes of population of each generation by $f_h$ value, and copy the chromosome with the maximum $f_h$ value into the next generation. The rest $k-1$ chromosomes of next generation are dealt with Roulette Wheel Selection—the probability of each individual being selected into the next generation is equal to the ratio of its fitness value to the sum of entire population. The higher the fitness value, the greater the possibility being selected.

3.2.5. Mutation operator

Mutate the population of each generation by a certain probability. Randomly generate two mutation points, and reverse the mutation segments to get a new individual, for example, $C=51|2438|679$, $C'=51|8342|679$.

3.3. The improved model with refuse time

Modify the model in section 3 to get the following model. Revise formula (2) and (3) to formula (10) and (11), and add formula (12) to the constraints.

$$
\min \sum_{i=0}^{N} \sum_{j=0}^{N} \sum_{k=1}^{K} (t'_{ij} + t'_{ji})x_{ijk} \quad (10)
$$

$$
\min \sum_{i=0}^{N} \sum_{j=0}^{N} x_{ijk} \quad i=0 \quad (11)
$$

$$
nd<ND \quad (12)
$$

As a city can contain multiple stores, we suppose that: $t'_{ij}$ in the model denotes the travel time from finishing the delivery of last store in city $i$ to leaving the city, $t'_{ij}$ denotes delivery time for multiple stores in the city $j$, and $t'_{ji}$ denotes the time from city $i$ to city $j$. Owing to the cities linked by highway, we assume that traffic condition doesn’t affect the speed of vehicles on the highway, which means that the speed in all highway is constant $v_h$, and $t'_{ij}$ is proportional to distance $t'_{ij} = c_{ij}/v_h$. The $ND$ in constraint (12) represents the number of failing to reach the stores on time in all the cities, and $ND$ is the maximum number of stores allowing the occurrence of delay.

We still use formula (9) to determine the evaluation function of city priority, and code chromosome by using decimal coding. Each bit represents a city. Feasible function is as follows:

1. According to the order from left to right, the gene segment in chromosome that meets precedence relationship determines a vehicle route, otherwise use another vehicle to start a new route.
2. Check each gene segment determined in accordance with the precedence relations to see if they meet the capacity constraints.
If they meet the capacity constraint, check the time constraints. For a chromosome, if the gene fragments it contains are determined (that is, the order of reaching the cities has been determined), \( t' \) can be determined. Each city may contain multiple stores, so the calculation for \( t' \) should also consider the route of multiple stores in cities. Once the gene segments are identified, the time to reach the city \( j \) can be determined. If the time is within \( T_j \), we consider vehicle speed in city \( j \) to be \( v' \); otherwise the speed is \( v'' \). Then the routing problem of the city becomes vehicle routing problem with time windows (the vehicle number is 1). We should remove constraints ---“finally return to the starting city”, because the vehicle will turn to next city after the last store supplied. In addition, since the evaluation function to determine city precedence relations is the average value of time window for all the stores in the city, if using hard time window, we can not ensure a feasible solution, so the soft time windows should be chosen to solve the routing problem in city \( j \). In this step, the method in literature [6] is used to acquire the shortest path in city \( j \), whose delivery time is \( t'_j \). As soft time windows allow delay, we record \( nd \), which means the number of delayed stores of all cities. If \( nd < ND \), we hold that the chromosome is a feasible solution, otherwise infeasible solution.

Then we acquire the corresponding feasible solution \( G_h (h = 1, 2, \ldots, N_k) \) for each chromosome of the population, where \( N_k \) is the number of chromosomes in a feasible solution, supposing that the set of all feasible solutions is \( G \). For a defined chromosome segment \( y \in G_h \), the time that the fragment requires \( t_y = \sum_{i,j \in y} t_{ij} + t'_{ij} \) (\( i, j \) are the nodes in the segment \( y \)) can be calculated, that is \( t_h = \sum_{y \in G_h} t_y \). If the chromosome corresponds to the infeasible solution, assign \( t \) a large integer \( M \), and make the fitness function \( f_h = \frac{1}{t_h} \). The greater \( f_h \), indicate the better performance of \( G_h \), which means the closer to the optimal solution.

The calculation of crossover operators, selection operators, and mutation operators for chromosome is the same as GAFVRPTW.

4. Experiment and result analysis

As logistics center is no longer set up in each city, to ensure the ease of loading and unloading, vehicles are loaded by arrival sequence: last-come, first-loaded, and should also run in strict accordance with the calculated path.

Nine groups of contrast experiments were carried out, and 5 distributions were conducted in each group. Both of the algorithms in the section 3 were adopted to solve the distribution orders for the same group which are the practical orders of the stores in each distribution, and the average of the 5 distributions was taken to be the result of an experimental group. Because not all of the 12 cities have distribution orders each time, and for the comparability of the experiments, 8 fixed cities were chosen to be the experiment cities. A certain quantity of distribution orders of the stores in the 8 cities were chosen in each distribution. In group 1, one distribution order of the store in each city was chosen for the experiment; In group 2, a total of 10 stores distribution orders were chosen; In group 3, a total 12 stores distribution orders were chosen; In group 4, 14 ones were chosen, and so on. The number of store distribution order for the other groups is shown as the ASC in table 1. The store distribution order number of all groups is rising at a rate of 20%, so as to get a better comparison of each group.

The upper limit of refrigerated car’s capacity is 8 ton. 10 min is the unloading time for stores.
<table>
<thead>
<tr>
<th>group</th>
<th>algorithm</th>
<th>ACR (min)</th>
<th>ARCT (km/h)</th>
<th>ASC (km)</th>
<th>ARDH (km)</th>
<th>AS (min)</th>
<th>ADS (min)</th>
<th>ASS (km/h)</th>
<th>ARST (km)</th>
<th>ARDC (km)</th>
<th>SDR (%)</th>
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<td>1870</td>
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<td>1952</td>
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<td>110</td>
<td>1918</td>
<td>10</td>
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<td>172</td>
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<td>2021</td>
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<tr>
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<td>1103</td>
<td>104</td>
<td>1912</td>
<td>12</td>
<td>1.0</td>
<td>331</td>
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<td>100</td>
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Figure 1. The average speed in cities

Figure 2. Average number of delayed stores each group

Figure 3. Average actual traveling distance on highways

Figure 4. Delayed stores and serviced stores ratio each group
For the GAMSC method, the refuse time corresponds to the periods of time that the vehicle speed of the city is less than 20km/h in the city. The data are from the statistics of each urban traffic department. ND is set to be 5% of the number of stores for the service. The results are shown in table 1.

ACR: the average number of vehicles each group; ARCT: The average actual traveling time on high ways; ARDH: The average actual traveling distance on high way each group; ASC: average speed on high ways; AS: The average number of stores serviced each group (the sum of 12 cities); ADS: the average number of delayed stores each time; ARST: The average actual traveling time in cities each time(not including the laytime); ASS: average speed in cities; SDR: delayed stores and serviced stores ratio each time; ARDC: The average actual traveling distance in cities each group.

It can be seen from ASC in table 1, that the vehicle speed among cities changes little. That is because all the cities are linked by high ways, so the vehicle speed is affected little by traffic condition. It can be seen from ARCT and ARDH in table 1 and Figure 3 that the total distance and time cost on highway of GAFVRPTW is better than GAMSC’s. That is because the refusal time introduced by GAMSC is a constraint that only considers urban traffic condition, and it is a redundant constraint for highway and fixed speed condition which will increase the total distance.

As is shown by ARDC in table 1 and Figure 5, the total distribution distance of GAFVRPTW is shorter than the one of GAMSC in cities. But with the increase of store order number, the total distribution time of GAFVRPTW increases faster than GAMSC’s, which is shown as ARST in table 1 and Figure 6. The speed in cities decreases faster too, which is shown in figure 1. That is because GAFVRPTW is based on distance, and dose not consider the dynamic traffic condition. For further analysis, we should divide the entire logistics transportation process into two stage.-- highway and urban area. The traffic condition and road condition have little influence on the speed of the vehicle in highway, so the transportation time is proportional to the distance, which applies to the formula (2). However, many logistics transportation processes include not only just the stage on highway, but also in the urban ---the stage of delivering goods off the highway. In urban, the traffic situation is relatively complex, and the vehicle speed is greatly influenced by traffic conditions, the transportation time is often not proportional to the distance. Therefore, the way that uses distance to evaluate the distribution in formula (2) is not applicable. So that when constructing the model we can not just ignore the traffic impact on the transportation time to set the Cij value as a fixed value.
It is shown by ADS and SDR in table 1 and figure 2, figure 4 that the delay delivery rate of GAFVRPTW increases rapidly. The delay to a certain store caused by some unexpected situations will cause the delay of subsequent store. For instance, suppose that a distribution sequence is 4, 7, 9, 10, 13, and the vehicle arrives city 4 during its rush hour, which makes the arriving time at the store in the city delayed by the traffic jam. It will cause the delay of 7, 9, 10, 13. However, GAMSC algorithm avoids the situation to a large extent, so the delay delivery rate is much lower than GAFVRPTW’s. Nonetheless, for the dynamic variable is relatively simple and can not fit the practical dynamic condition perfectly, the delay delivery rate in group 9 is 12.6%, which is much higher than ND in the algorithm.

Because algorithm GAMSC introduced new constraint, the average number of vehicles every time is higher than GAFVRPTW’s, which is shown as ACR in table 1.

The result of the experiments shows that the traditional static method base on distance can get better solution in simulation environment and some situation that vehicle speed changed little. Whereas, when it is used in the dynamic situation that vehicle speed changed much by the practical traffic condition and other ones, the performance will decrease much. It will get a better result if using speed and time as the measures, and introducing some dynamic factors into the model and algorithm. And the model fitting capacity of vehicle routing problem is very important to VRP in practical situation.

5. Conclusions

In order to study how much impact does dynamic traffic conditions have on the VRP algorithms, a serious of experiments are conducted. Furthermore, the performance is discussed by numerical experiments. The results show that the dynamic fitting capacity of the model is more important than obtaining the optimal solution of NP-hard problem for the practical application of routing optimization. Although better solutions can be got by this model, due to the complexity of the problem, presently, the solution of this paper can still not meet the need of practical applications, which is worth following up deeply.

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6. References