STUDY OF MULTI-VEHICLE ROUTING PROBLEM WITH TIME WINDOW

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Abstract

The vehicle routing problem (VRP) is an attractive topic in logistics research work. Multi-vehicle routing problem with time window (MVRTW) is a variant of VRP, which accommodates realistic system specifics such as capacity of multi-vehicle, time constraint and network constraint (one-way, banning of turning movement etc.). To solve the MVRPTW, an improved approach combining geographical information system (GIS) with parallel genetic algorithm (PGA) is proposed. Shortest paths could be calculated by spatial analysis module and topology construction of road network in GIS. In order to strengthen the search ability, an adaptive generation mechanism of the initial population and the evolutionary operators are used in PGA. The suggested approach proved to be efficient by a practical case of Changchun City.

1 Introduction

The development of ecommerce impuluses the increase of logistic demand intensely, and many logistical problems are becoming known. As a survey, the ratio of logistics cost to GDP in China is 18%, which far exceeds the average value of developed countries. In addition, the distribution process is the crucial section of logistics activity. Therefore, researching on vehicle distribution routing planning is very necessary.

Vehicle routing problem (VRP) consists of a fleet of vehicles, which leave a centralized depot, and serve a set of geographically dispersed customers exactly once. The goal of the problem is to find out the vehicle scheduling and routing plan and to minimize the total transportation cost or the total route distances. It is introduced by Dantzig and Ramser in 1959 [1]. The study of VRP will contribute to reduce the logistics cost of enterprises and society and urban environmental pollution. As a non-deterministic polynomial-time hard (NP-hard) problem, the practical vehicle routing problem is more intractable due to the data requirements and the complexity of transportation problems.

Most researchers tend to use a heuristic algorithm to solve it and there has been a growing interest in the use of geographical information system (GIS) to analyze these problems. Cheng-Liang Yang (2006) established an accurate distance matrix by a geographical information software and solved the simple VRP by traditional Genetic Algorithm [2]. Hongchun Hu (2006) proposed to establish a real time computer simulation system of urban logistics distribution vehicle routing optimization based on GIS. He explicated several key modules [3]. Chun-Yu Ren (2007) improved ordinal crossover operators and utilize dualistic coding in genetic algorithms to deal with VRPTM [4]. Zhi Can (2009) improved traditional genetic algorithms by dividing the population into three parts and designed a new punish factorial[5]. Fuce (2010) analyzed potential parameters, elements, reviewed the present VRP, and derived problem with it, finally put forward the human-computer interaction model [6]. Tong Zhen (2010) combined the VRP model for geographic information system (GIS) by analyzing the VRP model in grain logistics, and used the Particle Swarm Optimization (PSO) to identify the optimal route [7]. Hiroyuki Kawano (2010) used two spatial tools, “Photo Tracker” and “ArcGIS” to record and analyze trajectories of vehicle and moving objects, presented k-means clustering under the constraints of visiting sequence of VRP[8].

Considering the flaws of each algorithm, some researchers improved solving efficiency by modified or hybrid heuristic algorithms. Yue-Jiao Gong (2012) proposed a set-based PSO to solve the discrete combinatorial optimization problem VRPTW [9]. Andrés Muñoz-Villamizar (2013) discussed the combined location routing problem (LRP) in urban scenarios, then proposed a simulation-optimization approach, which employs Monte Carlo simulation to add biased random behavior to different heuristic procedures in order to search for a near-optimal solution efficiently [10]. Xianghu Meng (2014) improved a population-based incremental learning algorithm to solve the vehicle routing problem with soft time windows (VRPSTW) by an objective to minimize the count of vehicles as well as the total travel distance [11]. Djamaladdine Mahamat Pierre (2014) presented a new crossover operator, called Partially Optimized Cyclic Shift Crossover (POCSX) to improve the multi-objective genetic algorithms [12].

In this paper, an approach, which combines the geographical information system (GIS) with modified parallel genetic algorithm, is proposed for solving the multiple-vehicle routing problem with time window (MVRPTW). In this method, the GIS is used for analyzing the roads network and calculating shortest paths, considering the realistic system specifics like the prohibited turns, which are ignored by Euclidean distances. And some modifying techniques, such as designing better operators and enrich-
ing genotype, are employed to improve the parallel genetic algorithm and guide the search for the global optimum instead of getting trapped in the local optimum. This algorithm is applied to find the optimal sequence of customers to each employed vehicle with the constraints of multiple capacities and time windows.

2 The Method

2.1 An introduction to MVRPTW

In these multi-vehicle routing problems with time windows (MVRPTW), a number of distribution vehicles with different types locate at a central depot in order to serve a number of demand customers, and each demand customer has its requirement of served time range. And if the goods couldn’t be sent to customers in the time window, the logistics enterprise will have to take the responsibility for the loss of customers. The optimized optimal sequence of vehicles needs to be found to minimize the total cost. Unlike the primary VRPTM, the logistics enterprise has more vehicles with diversified types to select, and vehicles with different type have different capacities, speeds and different employing charges. In this situation, different sets of employing vehicles have different cost even the same routes, so employing cost of vehicles needs to be factored. Meanwhile, it is supposed that plenty of vehicles can be used and the time of driver’s private activities is not taken into account. The unloading time consists of the constant time for parking and the absolute unload time which is proportional to the amount of goods.

An abundant fleet of vehicles with diversified capacity is not taken into account. The unloading time consists of the constant time for parking and the absolute unload time which is proportional to the amount of goods. In this situation, different sets of employing vehicles have different cost even the same routes, so employing cost of vehicles needs to be factored. Meanwhile, it is supposed that plenty of vehicles can be used and the time of driver’s private activities is not taken into account. The unloading time consists of the constant time for parking and the absolute unload time which is proportional to the amount of goods.

The MVRPTW is defined on a directed graph \( G = (V, A) \), where \( V = \{v_0, ..., v_N\} \) is the set of nodes and \( A = \{(v_i, v_j): i, j \in V, i \neq j\} \) is the set of arcs. Vertex \( v_0 \) is a depot node; other vertexes are customer nodes. \( C = \{1, 2, ..., K\} \) is the set of the vehicle type and \( C = \{c_1, ..., c_K\} \). \( T \) is also defined as a set of all the non-overlapping delivery time windows with equal or different lengths. The positive travel time \( t_{ij} \) is associated with each arc \((v_i, v_j)\). The demand of each customer \( v_i \in V/v_0 \) is set by \( g_i \). In addition, \( c_1 \) and \( c_2 \) are the time cost of node \( v_i \in V/v_0 \) for early arrival and late arrival, respectively. An abundant fleet of vehicles with diversified capacity \( Q_k \) is available to serve the customers. The distribution time cost has the following general piecewise function:

\[
P_{ij}(t_i) =
\begin{cases}
  c_1, & t_i < e_i \\
  c_2, & t_i > e_i
\end{cases}
\]

where \( t_i \) is the arrival time of customer \( v_i \), \( \{e_1, f_1\}, \{e_2, f_2\}, ..., \{e_K, f_K\} \) is the set of all the non-overlapping time windows, and \( c_1, c_2 \) are unit time cost for early arrival and late arrival, respectively. The parameters and decision variables of the mathematical model are presented in Table 1.

| Table 1. Notations of the parameters and decision variables of the mathematical model. |
|----------------------|---------------------------------------------|
| Parameter/decision variable | Definition |
| \( b_i \) | The demand of the customer \( v_i \) |
| \( Q_k \) | Capacity of vehicle with type \( k \) |
| \( v_k \) | Speed of vehicle with type \( k \) |
| \( M_d_k \) | Maximum distance of vehicle with type \( k \) |
| \( f_c_k \) | The fixed charge of vehicle with type \( k \) used once |
| \( d_{c_k} \) | The cost per mileage of the k-th type vehicle |
| \( d_{ij} \) | The distance of arc \((v_i, v_j)\) |
| \( \{e_i, f_i\} \) | Time window of customer \( v_i \) |
| \( c_1, c_2 \) | The unit time cost for early arrival and late arrival |
| \( t_i \) | The arrival time of arc \((v_i, v_j)\) |
| \( t_{ij} \) | Traveling time of arc \((v_i, v_j)\) |
| \( l_k \) | The variable is equal to vehicles amount with type \( k \) |
| \( \Gamma \) | The utilization rate of vehicle capacity , and \( 0 < \gamma < 1 \) |
| \( X_{ijlk} \) | This variable is equal to 1 if arc \((v_i, v_j)\) is used by vehicle \( l_k \) and 0 otherwise |

2.2 Mathematical formulation

Using the notation introduced in the above section, we propose a mathematical model for the multi-vehicle routing problems with time windows as follows.

\[
\begin{align*}
\text{Min} Z &= \sum_{k=1}^{K} f_c_k L_k + \sum_{i=0}^{N-1} \sum_{j=0}^{N} \sum_{l_k=0}^{K} \sum_{k=1}^{K} d_{c_k} d_{ij} X_{ijkl} \\
&+ \sum_{i=0}^{N} \sum_{j=0}^{N} \sum_{l_k=0}^{K} \sum_{k=1}^{K} P_{ij}(t_i) \\
&\sum_{i=0}^{N} \sum_{j=0}^{N} X_{ijkl} g_j \leq \gamma Q_k \\
t_j &= t_i + t_{ij} + t_{l_i} \\
t_{ij} &= d_{ij} X_{ijkl} / v_k \\
t_{l_i} &= t_0 + \tilde{c} g_i \\
L_k &= \sum_{j=0}^{N} \sum_{l_k=0}^{K} \sum_{k=1}^{K} \frac{X_{ijkl}}{Q_k} \\
\sum_{l_k=0}^{K} \sum_{i=0}^{N} \sum_{j=0}^{N} X_{ijkl} &= 1
\end{align*}
\]

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\[
\sum_{i=0}^{V} \sum_{j=0}^{V} X_{ij} d_{ij} \leq M d_k \quad (8)
\]
\[
X_{ij} = 0 \quad \text{or} \quad 1 \quad (9)
\]
\[
t_{ij} \neq 0, \quad L_k \geq 0 \quad (10)
\]

The objective function (1) is to minimize the total cost concluding vehicle employing cost, vehicle travel cost and delivery time cost. Considering that the different vehicles have the different fixed cost and the different transportation cost per mileage, this function could get the minimum cost by the strategy with the most appropriate numbers and types of vehicles. Further, the multi-vehicle routing problems with time windows (MVRPTW) could be solved.

Constraint (2) ensures the load of each vehicle within its capacity limit. Constraint (3) means that arrival time at customer \( v_i \), the traveling time of arc \( (v_i, v_j) \) and the unloading time at customer \( v_i \). Constraint (4) presents the traveling time of arc \( (v_i, v_j) \). Instead of the simple Euclidean distances, the practical road distances between all depots and the distribution center would be imported as the parameter \( d_{ij} \). Constraint (5) calculates the unloading time of goods at customer \( v_i \). Constraint (6) means that the required amount of vehicles with type \( k \) is less than the total demand divided by the available capacity. Constraint (7) guarantees that every demand point is just served by one vehicle. Constraint (8) ensures vehicle distances within the maximum.

### 2.3 Shortest paths calculation based on GIS

The Euclidean distance between two sites is always used as the input parameter in vehicles routing model. In fact, that's not the case and the urban traffic of actual distribution is quite complicated. For example, drivers could not turn direction immediately at most crossings, so the routing plan with Euclidean distances becomes inoperative. It is quite necessary to find an approach to calculate that distances and take the road network and traffic regulations into consideration.

The Geographic Information System (GIS) software is a good choice, such as ArcGIS, MapInfo and MapGIS. That software has been applied successfully in many areas, for instance, electronic navigation, traffic and tourism, electric power communication network and its pipeline layout. Detailed digital specific information about the special transportation topology and infrastructure in the form of appropriate geographical objects is stored in the spatial data base of GIS. In particular, the road network in the form of polyline objects, the administrative boundaries in the form of polygon objects, the road characteristics and complex path constraints such as the number of the street lanes, the road direction, the prohibited turns onto network roads, the overpasses and underpasses, are maintained.

In supermapGIS, the relevant information is loaded in a workspace with “smwu” formats. The topology network is built and the simulated traffic regulations are set, such as the turning table of nodes, the nodes or lines with barriers, and resistance values of roads. At last, the spots of the distribution center and demands are remarked. In addition, the shortest paths are obtained by the optimal path analysis module in spatial analysis group. As a case study of Changchun City, the topology network is built as Fig. 1 and the setting as Fig. 2.

![Roads network topology.](image1)

![Setting of traffic regulation.](image2)

![A case of the representative point.](image3)
2.4 Improved parallel genetic algorithm

The genetic algorithm especially in solving complex non-linear problem has its own unique advantages. The advantages root in the intrinsic parallelism of the algorithm, the unbound without space constraints and the dispensable requirements of continuity, derivative and peak. Certainly, it still has some shortages such as the lack of demonstrative theories on convergence and effectiveness of random search mechanism. It is a crucial issue to guide the targeted algorithms search to a global optimal solution and avoid an invalid search, to improve algorithms efficiency and accuracy. Therefore, we improve the parallel genetic algorithm for the multiple-vehicle routing problem with time window.

2.4.1 Representation and encoding method

Integer 0 presents the depot, and the integers, like 1, 2, ..., N, present the index numbers of the index of present customer stops. The array fills with these integers represents a chromosome. $L_k$ is the amount of employee vehicles with type $k$, and $L_k \neq 0, k \in C = \{1, 2, ..., K\}$, C is the set of the vehicle type. $r_1$ represents one of the customers and $i \in V = \{1, 2, ..., N\}$. The array shows as Fig. 5.

![Figure 5. Genotype with sequence of depots/customers indexes.](image)

When one vehicle with type 1 and two with type 2 are used, the genotype just like the Fig. 6. Route 1 represents the visiting order of the first vehicle with a first type, route 2 represents the route of the second vehicle with the first type, and route 3 represents the visiting sequence of the first vehicle with the second type. In each route, the vehicle starts from the depot, visits one by one, and returns the depot.

![Figure 6. An example of a chromosome.](image)

2.4.2 Initial population generation

In the parallel genetic algorithm, the evolutionary subprocess runs with each vehicle strategy, and the optimal solutions of all strategies are compared for the global optimal solution. The preliminary visiting order is randomly generated and the initial population is created by inserting 0 into orders according to the capacity constraints. This inserting process is that the capacity of the order numbers is summed one by one, and when $\sum_{i=1}^{\rho} g_i \leq \gamma Q_k$ and $\sum_{i=1}^{\rho+1} g_i > \gamma Q_k$, the virtual depot 0 is inserted between the positions, $\rho$ and $\rho + 1$. The insertion should be continued until the amount $\sum_{k=1}^{K} L_k - 1$ of virtual depot 0 are done. The improvement makes sure that the initial population is feasible.

2.4.3 Fitness function construction

Fitness function represents the method for the evaluation of individuals. It can be very simple or very complex method, which includes a lot of parameters. The fitness function can be calculated by adding or multiplying the length of the penalty constant or its square. When the objective function is $f(x)$ and constraints are $h(x) \leq H$ and $g(x) \geq G$, the fitness function will be $f(x) + \gamma_1 \max(0, h(x) - H) + \gamma_2 \min(0, g(x) - G)^2$.

2.4.4 Selection operator

The roulette wheel method and best individual saving strategies are used together in this process. In roulette wheel method, we simulate the game of roulette and choose the individual by throwing a ball in the wheel. Each individual occupies a spot on the wheel and the size of its spot is determined by the fitness of the individual – more fit the individual, more space it occupies on the wheel, thus there are more chances for those individuals falling into the space. is the chances of all falling to its space. Meanwhile, the best individual will be one member of the next population straightforwardly so that the loss of the best genotype due to randomness will be averted.

2.4.5 Crossover operator

The simple crossover operator to combine two arrays always simply choose a random point in arrays and take the first part from parent and the second part from the other parent. As it is expected, the operator result could be infeasible and the diversity between parents and children is paltry especially when the individual length is long. To improve feasibility of children, the appropriate crossover operator is requisite. The crossover part is one random part of route, it moves in front of the other parents and the repeated numbers will be removed, nevertheless, the virtual depot position in offspring should remain same as parents. For instance, the second route is chosen as the crossover part, the parents and children are shown as Fig. 7.
2.4.6 Mutation of chromosome

Mutation is an operator that enriches the genotype and widens the search space. In nature, the mutation has a small chance of happening, and so as GAs, where researchers define a mutation probability factor. This factor has to be small enough because mutation brings randomness to the genetic principle. Compared with other mutation methods, the swap mutation is a comparatively simple technique. In this technique, two random customers swap their spots. To keep the feasibility of the chromosome, the depot should not be chosen. It is shown as Fig. 8.

2.4.7 Updating the population

In order to avoid local optimization and keep the population scale, we replenish the population by adding some new supplementary chromosomes in the population, when the search still stagnates in the local optimal solution after much iteration. This modification both enriches the population genotype and contributes to find the global optimum.

2.5 Solution flow

To summarize, the solving process of this problem is shown as Fig. 9.

Step 1: Solving the shortest paths
Import space and distance information such as the coordinates of customers and distributor center, build GIS network and set network environment parameters, executive shortest path planning module to obtain the shortest paths.

Step 2: Getting the vehicle strategies
According to the shortest distances between the customers and other delivery information, the possible vehicles strategies could be obtained.

Step 3: Genetic algorithm execution
Initial the population, carry on the selection, crossover, and mutation operator in turn, then judge whether the population needs the evolution again by ending criterion, compare these results of different strategies to choose the best one.

Step 4: Display the VRP solution on GIS map
Display the global optimum in supermap GIS.

2.6 The analysis of computational complexity

The time complexity of the algorithm is the iteration time, including the time complexity of a subset D1 in selection operator to make sure it feasible, O(N(D1)) and the time complexity of a subset D2 to ascend sort of fitness, O(N(D2)). N(∗) stands for the element number of one certain set and . When the maximum number of iterations is Gmax, the total time complexity of this genetic algorithm is O((N(D1))∗N(D0)+(N(D2))∗∗Gmax, and the D0 is the set of constraints including the constraints transferred from the objective function.

3 Applications and Results

In this section, we apply the approach proposed above on a distribution case of Changchun city. In this problem, eight customers are distributed by one central depot. Table 2...
represents the coordinates in plane coordinate system which are transformated from GPS coordinate system. Table 3 represents the demand and the time windows from the eight customers. Two kinds of vehicles can be used, and some useful parameters of them are in table 4. In addition, we assumed the start moment of vehicles from despot is 0, the unit unloading time is 0.1 and the fixed time of vehicle parking for unloading is 1.2. Effective utilization rate of all vehicles is 0.95. The unit time cost for early arrival is 5 and 20 for late arrival.

Table 2. The coordinates of the distribution centre and customers.

<table>
<thead>
<tr>
<th>DC</th>
<th>Cus1</th>
<th>Cus2</th>
<th>Cus3</th>
<th>Cus4</th>
<th>Cus5</th>
<th>Cus6</th>
<th>Cus7</th>
<th>Cus8</th>
</tr>
</thead>
<tbody>
<tr>
<td>X- Coordinate</td>
<td>489</td>
<td>480</td>
<td>480</td>
<td>487</td>
<td>496</td>
<td>500</td>
<td>513</td>
<td>496</td>
</tr>
<tr>
<td>Y- Coordinate</td>
<td>7.79</td>
<td>1.45</td>
<td>1.76</td>
<td>4.14</td>
<td>9.69</td>
<td>8.85</td>
<td>7.87</td>
<td>9.51</td>
</tr>
</tbody>
</table>

Table 3. The demands and time windows of customers.

<table>
<thead>
<tr>
<th>Customer</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>Demand [e, f]</td>
<td>2</td>
<td>1.5</td>
<td>4.5</td>
<td>3</td>
<td>1.5</td>
<td>4</td>
<td>2.5</td>
<td>3</td>
</tr>
</tbody>
</table>

Table 4. The vehicles parameters.

<table>
<thead>
<tr>
<th>Type</th>
<th>Capacity</th>
<th>Employed Cost</th>
<th>Freight Rate</th>
<th>Speed</th>
<th>Max Distance</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>8</td>
<td>350</td>
<td>2</td>
<td>45</td>
<td>30</td>
</tr>
<tr>
<td>2</td>
<td>6</td>
<td>300</td>
<td>1.5</td>
<td>35</td>
<td>20</td>
</tr>
</tbody>
</table>

3.1 The achievement of distances by GIS

We mark the representative position of the distribution centre and customers on the map of Changchun city in supermapGIS and achieve the shortest paths and distances. As is shown in table 5 and Fig. 10.

Table 5. The shortest distances.

<table>
<thead>
<tr>
<th>Spots</th>
<th>DC</th>
<th>Cus1</th>
<th>Cus2</th>
<th>Cus3</th>
<th>Cus4</th>
<th>Cus5</th>
<th>Cus6</th>
<th>Cus7</th>
<th>Cus8</th>
</tr>
</thead>
<tbody>
<tr>
<td>DC</td>
<td>0</td>
<td>255</td>
<td>0</td>
<td>138</td>
<td>0</td>
<td>101</td>
<td>0</td>
<td>0</td>
<td>16</td>
</tr>
<tr>
<td>Cus1</td>
<td>255</td>
<td>0</td>
<td>138</td>
<td>0</td>
<td>16</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Cus2</td>
<td>255</td>
<td>0</td>
<td>138</td>
<td>0</td>
<td>16</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Cus3</td>
<td>255</td>
<td>0</td>
<td>138</td>
<td>0</td>
<td>16</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Cus4</td>
<td>255</td>
<td>0</td>
<td>138</td>
<td>0</td>
<td>16</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Cus5</td>
<td>255</td>
<td>0</td>
<td>138</td>
<td>0</td>
<td>16</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Cus6</td>
<td>255</td>
<td>0</td>
<td>138</td>
<td>0</td>
<td>16</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Cus7</td>
<td>255</td>
<td>0</td>
<td>138</td>
<td>0</td>
<td>16</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Cus8</td>
<td>255</td>
<td>0</td>
<td>138</td>
<td>0</td>
<td>16</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

3.2 Solving the model by improved parallel genetic algorithm

The parameters of the modified genetic algorithm are as follows: the sum of generation: 50, the population size: 30, the probability of crossover: 0.9 and the probability of mutation: 0.1. The infeasible route would get the penalty value of 1000. This improved genetic algorithm of this MVRPTW runs for ten times, and the optimal result is shown as table 6.

Table 6. The optimal solution.

<table>
<thead>
<tr>
<th>Type</th>
<th>Visiting order</th>
<th>Load</th>
<th>Transport cost</th>
<th>Visiting moment</th>
<th>Total cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>07810</td>
<td>7.5</td>
<td>183.55</td>
<td>0.41</td>
<td>2.22</td>
</tr>
<tr>
<td>1</td>
<td>0340</td>
<td>7.5</td>
<td>69.93</td>
<td>0.23</td>
<td>2.15</td>
</tr>
<tr>
<td>1</td>
<td>02560</td>
<td>7</td>
<td>198.68</td>
<td>2.39</td>
<td>4.62</td>
</tr>
</tbody>
</table>

In the optimal result, the vehicles with type one are used and their routes are 0-7-8-1-0, 0-3-4-0, and 0-2-5-6-0, respectively. The total cost 1358.56 consists of operating cost 900, transport cost 452.16 and time cost 6.4. We can see the vehicles routes as Fig. 11. The experimental result indicates a good performance of the proposed approach in this paper.
3.3 Comparison between this solution with, without GIS information

The advantages and disadvantages of the method with and without GIS information can be summarized as Table 7.

<table>
<thead>
<tr>
<th>Method</th>
<th>Applicable solution scale</th>
<th>Solution speed</th>
<th>Visibility</th>
</tr>
</thead>
<tbody>
<tr>
<td>With GIS</td>
<td>large</td>
<td>fast</td>
<td>perfect</td>
</tr>
<tr>
<td>Without GIS</td>
<td>small</td>
<td>slow</td>
<td>bad</td>
</tr>
</tbody>
</table>

The introduction of GIS improves the efficiency of solving VRP problems obviously, especially in scenarios with large scales, even though more time would be paid to build roads topology network. This genetic algorithm method with GIS would solve the VRP problem very fast, and the optimal vehicles route could be displayed vividly on the map online.

The result of the method without GIS and with Euclidean distance will be seen like Fig. 12. It, at most circumstances, is not the most optimal due to the coarse distances, and the solution always could not provide the drivers a realistic instruction.

4 Conclusions

In this paper, we analyze the practical transportation condition for logistics distribution environment, and address the multi-vehicle routing problem with time window. We propose that the shortest paths between spots are obtained by the geographic information system, and the parallel genetic algorithm for MRPTW performs more efficient search by introducing an adaptive generation mechanism of the initial population, improving the evolutionary operators. Our approach has been proved effective by a real case of Changchun. According to the obtained results, our method for MVRPTW seems to perform quite well. For further research, this more efficient genetic algorithm would be applied in the GIS platform based on the mobile network in real-time and visualization distribution.

References
