Research on Vehicle Routing Problems Based on the Improved Pareto Ant Colony Algorithm

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Abstract

The paper describes the problems of route optimization for logistics delivery vehicles with time windows with the mathematics model being put forward as well. Then, it makes some improvement for transition probability and pheromone update strategy representing the transition strategy and puts forward the improved Pareto ant colony algorithm according to the disadvantages of ant colony algorithm which is easy to slump into local optimum when solving the problems of vehicle optimization in the logistics system. What is more, the Mat lab simulation tool is used to makes simulation of IPACA. It also verifies the effectiveness of skills used by IPACA to improve the disadvantages of ant colony algorithm which is easy to slump into local optimum when solving the problems of vehicle optimization in the logistics system after comparing one experimental data to the simulation results of three algorithms and comparing one experimental data to the simulation results of two algorithms.

Keywords: vehicle routing, ant colony algorithm, improved Pareto algorithm

1. INTRODUCTION

The vehicle routing problems with time windows are often described as: a warehouse (No.0), a number of customers L, the position coordinate \((x_i, y_i)\) of each customer in delivery, the amount of goods demanded by each customer \((i = 0, 1, 2, ..., L)\), the loading capacity of the vehicle Q which is pre-set(Dou, 2014). Each vehicle starts from the delivery center 0 and comes back later when the delivery work is completed. Suppose that each customer is visited only one time and the total goods demand of each city which is visited by each vehicle will not surpass the loading capacity of the vehicle, each customer is endowed with a time window \((T_e_i, T_l_i)\), \(T_e_i\) is the earliest time for service permitted by the customer \(i\), \(T_l_i\) is the latest time for service permitted by the customer \(I\) (Yi and Kang, 2015).

In terms of the vehicle routing problems with soft time windows, except for the situation that the delivery vehicle arrives at the destination point of the customer \(i\) within the scope of the time window, another two situations should be considered as well(Li, 2014): one is that the delivery vehicle arrives at the customer \(i\) before \(T_e_i\), which means the service only starts up until the earliest time point \(T_e_i\), what is more, in the waiting process, the cost of opportunity is lost(Ming, 2013); another situation is that if the vehicle arrives at the destination after \(T_l_i\), punishment for being late is inevitable. If the punishment for being late is too high, the degree of satisfaction for customers is greatly affected(Ming, 2013).

In terms of the vehicle routing problems with hard time windows, the service time of the vehicle must be within the scope of the time window with the opportunity cost and...
punishment for being late not allowed at all (Petr, 2014). On such basis, the actual situation should be considered, that means all the tasks must be completed with the minimum quantity of vehicles and the minimum quantity of mileages (total cost) of the vehicle.

2. THE DESCRIPTION OF VEHICLE ROUTING OPTIMIZATION PROBLEMS WITH TIME WINDOW

According to the above description, the VRPTW model is actually:

\[
\min Z = \sum_{j=0}^{N} \sum_{i=0}^{N} \sum_{k=0}^{K} z_{ij} x_{jk}
\]

s.t. \[x_{ijk} = \begin{cases} 
1 & k \in m, m \in M \\
0 & \text{otherwise} \end{cases} \]

\[
\sum_{j=0}^{N} \sum_{i=0}^{N} d_{ij} x_{ijk} \leq Q
\]

\[
\sum_{j=0}^{N} \sum_{k=1}^{K} x_{ijk} = 1
\]

\[
\sum_{i=0}^{N} \sum_{k=1}^{K} x_{ijk} = 1
\]

\[a_i \leq a_i \leq b_i\]

\[a_t_j = a_t_i + w_t_i + s_j + t_{ij}\]

\[w_t_j = \max \{T_e_j - a_t_i, 0\}\]

\[width_j = b_j - a_t_j\]

\[lt_j = \min \{t_i - T_l_j, 0\}\]

\[Lost_j = a \times wat_j + b \times alt_j\]

In the model: equation(1) represents the target function and \(z_{ij}\) can be time cost-distance, which is determined according to the goal of solving practical problems; equation(2) represents a judgment of the vehicle from customer \(i\) to customer \(j\) and \(m\) is the number of the vehicles involved in the delivery while \(M\) is the total number of vehicles possessed by the delivery center; equation(3) represents the limitation of vehicle loading capacity which ensures that each vehicle is never overloaded; equation(4) and equation(5) ensure that each customer is only served by one vehicle for only one time; equation(1) to (5) consist the model of vehicle routing problems with the
restriction of time window being neglected; equation (6), (7), (8) are the restriction conditions of VRPTW with \( t_{ij} \) being used as the time of vehicle going from customer \( i \) to customer \( j \), \( i, j = 0, 1, 2, \ldots, L \); \( s_i \) is the service time spent for the customer \( i \); \( a_t_j \) is the time for the vehicle to arrive to customer \( i \). Equation(8) represents that fact that the vehicle has arrived at customer \( i \) earlier than the earliest permitted service time \( T_e \). \( W_t \) is the time for the vehicle to wait at \( i \). Equation(9) represents the difference between the time for the vehicle on road to get to \( i \) and the limitation of time window (that is the latest service time permitted by the customer) (Yuvraj and Tarek, 2015); equation(10) represents the time duration of being late for vehicles in VRP with soft time window; equation(11) represents the cost of punishment if the vehicle arrives at the point too earlier or too late with \( a, b \) represent the punishment coefficient for vehicles arriving at the destination customers being earlier or being late (Wang et al, 2012).

3. THE IMPROVED PARETO ANT GROUP ALGORITHM

3.1 State transition rules of ants improved by IPAGA

Just as the basic ant colony algorithm, when IPACA solves the routing problems, ants with quantity of \( m \) will start from the delivery center and each ant will select the next city according to the state transition rules. When the IPACA designs the state transition rules for selecting the next city, the selection strategy is adapted in which the deterministic selection and random selection are integrated with on another (Petr, 2014).

The probability of being selected for a city is judged according to the limitation of time window changed according to the mileage of vehicles, the pheromone on the route and the saved route.

\[
P^*_j = \frac{\left[ \tau_{ij} \right]^\alpha \left[ \eta_{ij} \right]^\beta \left[ 1/wt_i \right]^\gamma \left[ 1/width_j \right]^\gamma \left[ \mu_{ij} \right]^\phi}{\sum \left[ \tau_{ij} \right]^\alpha \left[ \eta_{ij} \right]^\beta \left[ 1/wt_i \right]^\gamma \left[ 1/width_j \right]^\gamma \left[ \mu_{ij} \right]^\phi}
\]

(12)

In equation (12): the information heuristic factor is all the possible values expressed by 1; \( \tau_{ij} \) represents the route intensity of arc edge \((i, j)\); \( \alpha (\alpha > 0) \) is the information heuristic factor which represents the comparative importance of the movement route of ants; \( \eta_{ij} \) is the visibility of arc edge \((i, j)\); its equation is:

\[
\eta_{ij} = \frac{1}{d_{ij}}
\]

(13)

In equation (13), \( d_{ij} \) is the distance between two adjacent cities; \( \beta (\beta > 0) \) is the expected heuristic factor, representing the visibility of arc edge \((i, j)\); the bigger the value is, the shorter the route selected by ants will be:

\[
\mu_{ij} = d_{i0} + d_{j0} - d_{ij}
\]

(14)

In equation (14), \( \mu_{ij} \) is the variable introduced for taking the distance between takes points and delivery center into consideration and it also reflects the amount of route being saved by the method that the two points are connected to each other directly compared to that the two points are connected to delivery center respectively. It is also called the value of saving. \( \phi \) is the heuristic factor of value of saving for \( \mu_{ij} \) in transferring probability. It reflects the comparative importance of value of saving. Obviously, the bigger the \( \phi \) is, the bigger the probability for selecting \( j \) is. The idea of saving method is absorbed here.
When solving the problems of VRTPW, the next mobile customer point determined by state transition rules may be not just one, but multiple, therefore, it is necessary to screen the multiple transferring probabilities. As the ants are also randomly seeking food within an area, a random number within $[0, 1]$ is set up and the transferring probability and the random number are compared to one another. When some transferring probability is bigger than the random number, the ant will transfer to the customer point consistent to the transferring probability.

### 3.2 Global update rule of IPACA based on Pareto optimal solution set

The ants will update the pheromone according to the local pheromone updating strategy, which will make the ants search for other optimum set of solution within a certain scope all the time. But when the iteration number is too big, the aunts will converge the speed and search ability as they are limited by the scope so that they slump into local optimum. Therefore, the paper introduces a new global pheromone update rule according to the characteristics of artificial ants. The new rule will make improvement and updating for the global pheromone by adopting Pareto dominant mode so as to judge the situation of pheromone obtained by Pareto frontier similar to the results of optimum solution. What is more, the pheromone is updated by adopting some strategies according to the situation of corresponding pheromone so as to improve the convergence rate of the algorithm and prevent it from slumping local optimum.

**Definition 1.** The dominance of Pareto: if the vector $F=(f_1, f_2, \ldots, f_m)$ and the vector of dominance of Pareto $V=(v_1, v_2, \ldots, v_m)$, it will be recorded as $F<V$, which means that $F<V$ if and only if $\forall i \in (1, 2, \ldots, m), f_i \leq v_i \land \exists j \in (1, 2, \ldots, m), F_j \leq v_j$. Decision making vector $x_f \in \Omega$ is the optimum of Pareto if and only if there is no $x_r \in \Omega$ and it meets $F(x_{ij}) \leq F(x_f)$. The Pareto optimal set existing in the problems of vehicle routing optimization in logistics system is the set of optimal decision vector of Pareto. Target vector set expressed accordingly is called non-dominant set or Pareto frontier.

The thought of definition 1 is added in ant colony algorithm for solving VRPTW with the following three strategies being used to update the optimal solution set of Pareto: strategy one: if there is an inferior new route in optimal solution set of Pareto, it should be deleted and the new route should also be added into optimal solution set of Pareto. At this time, the pheromone situation of the new route is actually the new Pareto frontier.

Strategy two: if new route generated after the research is completed has the equal value with the existing routes in optimal solution set of Pareto, the new route should be added into solution set of Pareto. If the appearing times of the new route surpasses a certain frequencies insolution set of Pareto, the Pareto frontier should be updated.

Strategy three: if the number of solution set of Pareto reaches the certain value $N$ and a new solution of route is to be added, a solution which is not the Pareto frontier should be selected and deleted from the existing set of solution randomly.

IPACA is determined according to strategies 1-3 after the ants have finished searching for new routes which will then be judged so as to confirm whether it shall be installed into Pareto solution set or not and the Pareto frontier is judged so as to confirmed whether it shall be updated or not (that is to say, the previous solution set includes the pheromone situation between cities). If the updating shall be carried out according to Pareto frontier, the pheromone of route of Pareto solution corresponded in Pareto frontier shall be updated. What is more, IPACA will make updating operation for the pheromone currently according to the following equation:

$$
\tau_{ij}^{'} = (1-\alpha)\tau_{ij} + \alpha \delta \eta_{ij}
$$

(15)
In the equation, \( \alpha \) represents the pheromone volatile factor with its value scope being \([0, 1]\). \( \delta \) represents the pheromone penalty factor. The standard test set is adopted to carry out testing for ant colony algorithm. In the experiment, when \( \delta = 0.25 \), it will exert the punishment for pheromone more effectively.

3.3 Steps of the algorithm

Step 1 is parameter initialization. The cycle index \( N_{c} = 0 \), the maximum cycle index \( N_{c_{\text{max}}} \), the number of ants \( m \), the initialized pheromone of arch edge \( (i, j) \) \( r_{ij}(0) = 1 \), the amount of legacy information which is in the same route \( \Delta r_{ij}(0) = 0 \), the city \( o \) will all be listed in Tabu table;

Step 2: the initiative point will be listed in the current set of solution; at that time, the transition probability \( p_{ij} \) of each ant \( k \) will be calculated according to the rules of transition probability, the waiting time for service of the cities which are to be chosen and time span. On such basis, the next transition city will be selected. If the loading capacity of the current ant can not meet the requirement of even one customer, the ant will be forced to return to the delivery center and its loading capacity will be zero, afterwards, it will restart from the delivery center, otherwise, the driving time, the time window of the vehicle will be updated for selecting the next city;

Step 3: when all the cities currently are added into Tabu table, the number of ant \( m \leftarrow k \) will be recorded, otherwise, if \( k \leftarrow k + 1 \), turn back to step 2;

Step 4: the 2-opt local search mechanism will be adapted to optimize the route of every ant. The initiative circuit is improved and the functional value of the object is reduced by exchanging for two sides every time. If there is time node breaching time window after the exchange, the change shall be terminated;

Step 5: record the functional value of each ant \( L(k)(k = 1, 2, \ldots, m) \) with the best solution currently being recorded;

Step 6: According to strategy 1-3, the optimum solution of Pareto will be updated with the current Pareto frontier being marked;

Step 7: according to the equation (15), the global pheromone will be updated according to the Pareto solution set;

Step 8: each arch edge \( (i, j) \) will be set by \( \Delta r_{ij} \leftarrow 0 \), if \( N_{c} \leq N_{c_{\text{max}}} \), it will be transferred to step 2;

Step 9: the optimum solution will be output.

4. SIMULATION EXPERIMENT AND ANALYSIS OF THE RESULTS

The paper makes simulation for the improved Pareto ant colony algorithm (IPACA) which will be used to solve the route problem of vehicle in the Mat lab 2010a simulating environment so as to demonstrate the effectiveness of the algorithm. When solving VRPTW, the parameter scope of the algorithm is referred to TSP. That is to say, when \( \beta \) is within 1-3, \( \alpha \) is within 1-2 and the value scope of \( \rho \) is 0.7-0.9, a better result will be obtained to some extent.
4.1 Simulation experiment 1

In the environment stated in the previous content, the data of experiment 1 is from literature (Li, 2014). The three algorithms of tabu algorithm of literature (Li, 2014), the improved ant colony algorithm and the IPACA in the paper are used to solve the three problems which are respectively the vehicle route problem with the time window being neglected, the vehicle route problem with soft time window and the vehicle route problem with hard time window.

For the problem, there are 15 customers who need goods delivery (the number is 1, 2, ..., 15). The coordinate, demand, time window and other data are all shown in table 1. The delivery task of these cities is completed by some vehicles with the delivery capacity of 5t which starts from delivery center 0. The speed of the vehicle is 1 km/h and the transformation cost per unit is 1Yuan/mile.

The parameter of IPACA is set as: \( \alpha=1, \beta=3, \theta=2, \sigma=3, \varphi=3, \varsigma=0.85 \). Tabu algorithm (TS) and the improved ant algorithm (IACA) will be set by adopting the methods and parameters in literature (Li, 2014) and (Ming, 2013) with the iteration number of each algorithm being 100 times. \( DisZ \) is used to represent the total cost of the vehicles involved in delivery and \( MinZ \) represents the minimum transportation cost.

(1) The results comparison of three algorithms for optimization problems of vehicle routes with the restraint of time window being neglected.

It is shown in table 2 that the number of vehicles of IPACA application in optimization problems of vehicle routes with the restraint of time window being neglected is the same as TS and IACA. But in terms of the delivery route, it is more optimized than TS and IACA so as to make the minimum transportation cost of the corresponding scheme being just 509.86 Yuan which is 39.5Yuan and 39.23 Yuan less than 549 Yuan of TS and 549.06 of ACA respectively.

### Table 1 The data of experiment 1

<table>
<thead>
<tr>
<th>Client</th>
<th>( x_i )</th>
<th>( y_i )</th>
<th>( d_i )</th>
<th>( T_{e_i} )</th>
<th>( T_{l_i} )</th>
<th>Client</th>
<th>( x_i )</th>
<th>( y_i )</th>
<th>( d_i )</th>
<th>( T_{e_i} )</th>
<th>( T_{l_i} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>49</td>
<td>49</td>
<td>0</td>
<td>0</td>
<td>9999</td>
<td>0</td>
<td>59</td>
<td>8</td>
<td>0.2</td>
<td>9</td>
<td>80</td>
</tr>
<tr>
<td>1</td>
<td>19</td>
<td>0</td>
<td>1.0</td>
<td>75</td>
<td>145</td>
<td>1</td>
<td>19</td>
<td>48</td>
<td>1.9</td>
<td>39</td>
<td>105</td>
</tr>
<tr>
<td>2</td>
<td>32</td>
<td>6</td>
<td>1.9</td>
<td>59</td>
<td>129</td>
<td>2</td>
<td>69</td>
<td>76</td>
<td>0.9</td>
<td>25</td>
<td>124</td>
</tr>
<tr>
<td>3</td>
<td>36</td>
<td>22</td>
<td>1.1</td>
<td>16</td>
<td>86</td>
<td>3</td>
<td>45</td>
<td>11</td>
<td>0.8</td>
<td>78</td>
<td>153</td>
</tr>
<tr>
<td>4</td>
<td>52</td>
<td>20</td>
<td>0.5</td>
<td>48</td>
<td>169</td>
<td>4</td>
<td>82</td>
<td>46</td>
<td>1.8</td>
<td>48</td>
<td>129</td>
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<td>5</td>
<td>71</td>
<td>95</td>
<td>1.8</td>
<td>81</td>
<td>119</td>
<td>5</td>
<td>29</td>
<td>90</td>
<td>1.6</td>
<td>19</td>
<td>156</td>
</tr>
<tr>
<td>6</td>
<td>29</td>
<td>48</td>
<td>1.5</td>
<td>25</td>
<td>159</td>
<td>6</td>
<td>73</td>
<td>28</td>
<td>1.9</td>
<td>53</td>
<td>165</td>
</tr>
<tr>
<td>7</td>
<td>11</td>
<td>69</td>
<td>1.6</td>
<td>21</td>
<td>92</td>
<td>7</td>
<td>71</td>
<td>13</td>
<td>0.9</td>
<td>81</td>
<td>198</td>
</tr>
</tbody>
</table>

### Table 2 Three kinds of algorithms of vehicle routing problems with ignoring the time window constraints

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Reference</th>
<th>TS</th>
<th>IACA</th>
<th>IPACA</th>
</tr>
</thead>
<tbody>
<tr>
<td>MinZ(Yuan)</td>
<td>549.3</td>
<td>549.08</td>
<td>509.12</td>
<td></td>
</tr>
<tr>
<td>DisZ(Yuan)</td>
<td>549.1</td>
<td>549.26</td>
<td>509.12</td>
<td></td>
</tr>
<tr>
<td>Routes</td>
<td>0-4-2-1-0</td>
<td>0-8-2-1-4-0</td>
<td>0-11-2-1-3-0</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0-13-6-7-0</td>
<td>0-9-7-6-0</td>
<td>0-4-5-15-14-12-0</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0-9-5-9-0</td>
<td>0-10-5-9-10-0</td>
<td>0-10-5-13-0</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0-11-1-8-15-14-12</td>
<td>0-12-14-15-11-0</td>
<td>0-6-9-0</td>
<td></td>
</tr>
</tbody>
</table>

(2) The results comparison of H algorithms for optimization problems of vehicle routes with the restraint of soft time window.
When solving the optimization problems of vehicle routes with the restraint of soft time window, one more variable needed to be considered--punishment cost which is generated by arriving at the customer point of vehicles too late or too early. The punishment cost of one point is presented according to equation (11) and Lostj. The total punishment cost is presented by LostZ. The results comparison of the three algorithm is shown in Table 3.

From Table 3, it is found out that the minimum cost when solving the optimization problems of vehicle routes with the restraint of soft time window is:

\[ MinZ = DisZ + LostZ \]  

(16)

Although the number of vehicles involved in delivery of the three algorithm is four, the transportation cost of the three algorithm is different. In IPACA, every vehicle involved in delivery arrives at the destination of the customer within the time scope required by the customers with no cost of loss. In TS, the situation that there is vehicle arriving earlier at time point 15 occurs, so the loss of the opportunity cost is up to 9.6. In IACA, the losses of opportunity cost at customer time point 12 and 15 are respectively 12.13 Yuan and 0.20 Yuan. The total cost of vehicles involved in delivery for IPACA is actually the minimum transportation cost. What is more, the total cost of vehicle and the minimum transformation cost are the minimum value obtained by three algorithms.

Therefore, in terms of solving the problems of vehicle routes with the restraint of soft time window, IPACA companies have decreased the transformation cost, at the same time, the extra cost of punishment cost is avoided. What is more, it is also conductive for companies to increase opportunities of serving new customers.

(3) The results comparison of many algorithms for optimization problems of vehicle routes with the restraint of hard time window.

### Table 3 Three kinds of algorithms of vehicle routing problems with soft-time window constraints

<table>
<thead>
<tr>
<th>AlgorithmReference</th>
<th>TS</th>
<th>IACA</th>
<th>IPACA</th>
</tr>
</thead>
<tbody>
<tr>
<td>MinZ (Yuan)</td>
<td>573.31</td>
<td>549.08</td>
<td>563.12</td>
</tr>
<tr>
<td>DisZ (Yuan)</td>
<td>569.15</td>
<td>549.26</td>
<td>568.12</td>
</tr>
<tr>
<td>LostZ (Yuan)</td>
<td>9.7</td>
<td>13.23</td>
<td>0</td>
</tr>
<tr>
<td>Lostj (Yuan)</td>
<td>Lost15:9.6</td>
<td>Lost12:12.13, Lost15:0.20</td>
<td>0</td>
</tr>
<tr>
<td>Routes</td>
<td>0-3-15-14-12-0</td>
<td>0-3-8-2-1-4-0</td>
<td>0-8-2-1-11-4-0</td>
</tr>
<tr>
<td></td>
<td>0-13-76-0</td>
<td>0-9-6-7-0</td>
<td>0-3-12-15-0</td>
</tr>
<tr>
<td></td>
<td>0-9-5-10-0</td>
<td>0-10-5-13-0</td>
<td>0-10-5-16-0</td>
</tr>
<tr>
<td></td>
<td>0-8-1-2-11-4-0</td>
<td>0-12-14-15-11-0</td>
<td>0-9-6-7-0</td>
</tr>
</tbody>
</table>

In the optimization problems of vehicle routes with the restraint of hard time window, the vehicles must arrive at the customer points within the time scope required by...
customers. They should not arrive earlier or later. The results of solving the optimization problems by three algorithms of vehicle routes with the restraint of hard time window are shown in table 4.

Table 5 Two kinds of algorithms of vehicle routing problems with Hard Time Window

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>IACA</th>
<th>IPACA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reference</td>
<td></td>
<td></td>
</tr>
<tr>
<td>distribution routing</td>
<td>1266.01</td>
<td>1224.5</td>
</tr>
<tr>
<td>Routes</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0-5-14-12-9-19-0</td>
<td>0-5-14-4-3-17-11-0</td>
<td></td>
</tr>
<tr>
<td>0-18-3-4-17-11-6-0</td>
<td>0-7-8-16-5-21-19-0</td>
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<td>0-1-7-8-15-16-13-20-0</td>
<td>0-1-10-2-12-9-19-15-16-0</td>
<td></td>
</tr>
</tbody>
</table>

The above experimental results show that: in solving the problems of vehicle routes with the restraint of hard time window, the minimum transportation cost obtained by IPACA which is 562.76 Yuan is smaller than 585.77 Yuan of TS and 585.77 Yuan of IACA. But the result in the table is the same as the one obtained by IPACA when solving the problems of vehicle routes with the restraint of hard time window. In order to further verify the effectiveness of IPACA when solving the problems of vehicle routes with the restraint of hard time window, the simulation experiment 2 should be carried out.

4.2 The simulation experiment 2

The experiment 2 is carried out by adapting the cases in literature 4 relevant to the problems of vehicle routes with the restraint of hard time window, in which the simulation is made for the problems of vehicle routes of customer points with one delivery center and 20 hard time windows, then it will be compared to the improved ant colony algorithm in literature (Ming, 2013); the parameter of IPACA is still set as $\alpha=1, \beta=3, \theta=2, \sigma=3, \varphi=3, \rho=0.85$ and the iteration number of each algorithm is 100.

From table 5, it is found out that the number of vehicles in the two algorithm is 3 units, but the delivery route obtained by IPACA in the paper is 1224.10km which is more optimized than 1266.01km in the results of literature (Ming, 2013), therefore, the WIPACA is suitable for solving the problems of vehicle routes with the restraint of hard time window. It is found out by analyzing the experimental results: in the new state transition rule W and Pareto solution set being integrated into ant colony algorithm, an improved IPACA of Pareto for solving the vehicle route problem is put forward. In terms of the transition rule, the saving method is adopted to increase the saving factors, at the same time, in the updating stage of global pheromone, the incentive renewal mechanism based on Pareto optimum solution set is introduced with the hope to enhance the global search capability and convergence velocity of the algorithm. The simulation results show that IPACA has some certain superiority when compared to the current algorithm in terms of solving the route problems of vehicles.

5. CONCLUSION

Firstly, the paper describes the problems of route optimization for logistics delivery vehicles with time window with the mathematics model being put forward as well. Then, it makes some improvement for transition probability and pheromone update strategy representing the transition strategy and puts forward the improved Pareto ant colony algorithm according to the disadvantages of ant colony algorithm which is easy to slump into local optimum when solving the problems of vehicle optimization in the logistics system. What is more, the Mat lab simulation tool is used to makes simulation of IPACA. It also verifies the effectiveness of skills used by IPACA to improve the disadvantages of ant colony algorithm which is easy to slump into local optimum when solving the problems of vehicle optimization in the logistics system after comparing one
experimental data to the simulation results of three algorithms and comparing one experimental data to the simulation results of two algorithms.

6. REFERENCES