Routing For Taxi-pooling Problem Based on Ant Colony Optimization Algorithm

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Abstract

With the increasingly global environmental awareness, the city transportation strategy tends to be low-carbon and energy-saving. The most focuses of this trend is intelligent transportation. As a supplementary transportation tools between private transportation and public transportation, taxis have been the useful complement of the city public transportation system. The low-carbon and energy-saving way for taxis is called taxi-pooling. In this work, we focus on the routing problem of taxi-pooling. Specifically, with the analysis of the taxi-pooling problem, we investigate the characteristics and restraints, and construct an optimization model which aims to minimize the cost of passengers, maximize the benefit of drivers and maximize the load rate. To solve the above model, we propose to employ a modified Ant Colony Optimization (ACO) model. Our simulation results show that our method can effectively solve the taxi-pooling routing problem with the above three objectives.

Keywords: Taxi-pooling, Ant Colony Optimization (ACO), Routing, Energy-saving.

1. INTRODUCTION

With the increasingly global environmental awareness, the city transportation strategy tends to be low-carbon and energy-saving. As a significant component of city transportation, public transportation has been the focus of this trend. However, the public transportation infrastructure is usually behind the regional expansion of cities; and meanwhile, it cannot efficiently solve the "last kilometer" problem (Wan and Chen, 2013) for private traffic demand. On the contrary, as a supplementary transportation tools between private transportation and public transportation, taxis have been the useful complement of the city public transportation system.

However, the load rate of the "one person per car" rental model for taxis is typically low. For example, in Changsha province of China, there are more than 7000 taxis in 2009, and the load rate is only 36.1%, and the average load rate of 36 cities in China is 42.2% (Lu and Wu, 2008). Obviously, the transportation capacity has not been fully explored yet due to road traffic resource scarcity, traffic congestion and high empty load. Considering taxi-pooling service, the situation can be improved in short-distance transportation, remote routes and peak traffic. Conducting people to use taxi-pooling instead of driving their own cars, can help to reduce the cost of public transportation, and also contribute to the energy conservation policy of governments. In this way, the overall transportation of the city can be greatly improved.
Generally, taxis employ the point-to-point shortest path as the driving path. However, in the taxi-pooling scenario, drivers have to detour to pick up more passengers. From the perspective of system optimization, the routing should be properly assigned so that the transportation efficiency is improved, the overall cost of all passengers is reduced compared to that of each individual trip, and the benefit of drivers is also ensured. Therefore, how to design an efficient routing algorithm to meet the above requirements is the focus of this study.

As one of the bionic evolutionary algorithm, Ant Colony Optimization (ACO) has the advantages such as positive feedback, robustness, parallel computing and collaboration. It has been widely employed in the transportation resource planning problems (Dorigo and Gambardella, 1997). In this work, considering the specific characteristics of taxi-pooling and the drawbacks of basic ACO, we propose a tailored ACO algorithm to calculate the optimal routes for taxi-pooling.

The contributions of this paper can be summarized as follows:

(i) We construct an optimization model to minimize the cost of all passengers, maximize the benefits of taxi drivers, and maximize the load rate, with consideration of a set of constraints.

(ii) To efficiently solve above optimization problem, we propose a modified ACO algorithm with the consideration of specific characteristics of taxi-pooling.

(iii) We design a simulation experiment to evaluate the efficiency of our method for taxi-pooling problem.

The remaining of this paper is organized as follows. Section 2 discusses the related work, and Section 3 describes the problem statement and provides the taxi-pooling modeling. In Section 4, the proposed modified algorithm based on ACO is presented, and in Section 5 we conduct some simulation experiments. Finally, the paper is concluded in Section 6.

2. RELATED WORKS

The first category of related work is taxi scheduling and routing. In 1994, Jeffrey et al., designed a task allocation and consultation solution for calling for taxis. Liao et al., (2001) conducted analysis on the taxi intelligent scheduling using GPS technology. Dorer et al., (2001) proposed an adaptive solution for optimizing dynamic transportation, which deals with the shortest path problem in taxi intelligence scheduling. Lee et al., (2004) designed a distributed intelligent taxi scheduling method. Chabini (1998) proposed to calculate the shortest path from any point to an end point by time discretization under the first in first out (FIFO) condition. Rilett et al., (1998) estimated the expected traveling time of specific route by considering the driving time as a continuous stochastic process. LAM et al., (1992) compared historical data and current traffic situation, only when there was an obvious difference, induced the offline results using historical data. Kim et al., (1999) proposed an induction method based on real-time data from GPS by using ARIMA (Auto-Regressive Integrated Moving Average) model to predict the driving time for next period. Athanasisos et al., (2001) regarded the driving time as a time-varied function along with its shortest path algorithm, and proposed a massive parallel algorithm to improve the efficiency of the algorithm.

Car-pooling has been studied by some researchers as well. From the perspective of the number of cars, car-pooling problem includes single car-pooling (Zhang et al., 2012) and multi-car pooling (Wu and Zhang, 2010). From the perspective of traveling time restriction, there are time window based car-pooling (Pillac et al., 2013) and no time window car-pooling (Nagy and Salhi, 2005). From the status of driving, there are
dynamic car-pooling problems (Agatz et al., 2011; Agatz et al., 2012; Sun et al., 2012) and static car-pooling problems (Jaw et al., 1986; Luo and Schonfeld, 2007; Parragh and Schmid, 2013; Parragh et al., 2010). From the perspective of transfer, there are car-pooling without transfer (Schilde et al., 2011; Diana and Dessouky, 2004; Zidi et al., 2012) and car-pooling with transfer (Agatz et al., 2011; Diana and Dessouky, 2004). However, the existing method for car-pooling routing is based on a one-to-N diagram and the heuristic algorithm and greedy algorithm are typically used (Barth and Todd, 1999; Cordeau and Laporte, 2006; Cordeau and Laporte, 2007; Tao and Chen, 2007). In this work, we employ an intelligent algorithm ACO to solve the taxi-pooling routing problem.


3. PROBLEM STATEMENT AND MODELING

Mr. Reed had been dead nine years: it was in this chamber he breathed his last; here he lay in state; hence his coffin was borne by the undertaker's men; and, since that day, a sense of dreary consecration had guarded it from frequent intrusion.

In this work, we focus on the route planning for taxi-pooling problem, which is formulated as an optimization problem similar to TSP (Traveling Salesman Problem) (César et al., 2011) and VRP (Vehicle Routing Problem) (Branda˜o de Oliveira and Vasconcelos, 2010). However, there are some major differences for taxi-pooling. First, taxi-pooling is one-way transportation where the passing positions are typically residential areas. Second, considering the real world marketing requirements of taxi service, some constraint factors, such as the capacity of taxi-pooling, driving time and waiting time, are also added into the model. Finally, the route planning objective for taxi-pooling problem is to optimize the route including starting point, passing points and the ending points with consideration of the cost of passengers and benefit of drivers.

There are some assumptions in our modeling. First, we suppose the number of stop sites and the unit cost per kilometer is fixed. Second, the speed of taxi driving is presumed to be unchanged all the time. Finally, no failures or accidents are considered in this work. All other possible situations are considered, for example, one pickup site can be visited more than once, if the number of demands exceeds the maximum capacity of specific taxi.

3.1 Objective functions

The objective of our taxi-pooling problem is to minimize the cost of passengers and maximize the benefit of taxi drivers as well as the load rate. Suppose \( G \) is the set of stop sites in the road network, \( D \) is the set of demand points, and \( X \) is the set of taxis.

The cost of passengers is the total time cost and price cost of each individual participated in taxi-pooling. The time cost of all passengers is calculated as follows.
\[
\sum_{x=1}^{X} \sum_{u,v=1}^{D} \sum_{i,j=1}^{G} \chi_{ij}^x t_{ij} \cdot s_{uv}^x \quad (1)
\]

where \( t_{ij} \) is the driving time from sites \( i \) to \( j \), \( s_{uv}^x \) is the number of passengers between demand points \( u \) and \( v \) for taxi \( x \), and \( \chi_{ij}^x \) denotes whether taxi \( x \) passes route \((i, j)\), which is defined as follows.

\[
\chi_{ij}^x = \begin{cases} 
1 & \text{if taxi } x \text{ passes } (i, j) \\
0 & \text{otherwise}
\end{cases} 
\quad (2)
\]

The price cost of passengers is the summary of all passengers’ price. However, in order to pick up more passengers, drivers may have to detour and the extra cost should be shared among passengers. Suppose the regular price of individual passenger if travel alone from \( u \) to \( v \) is \( C_{uv} \), and the boarding fee is \( C_0 \) listed below.

\[
C_{uv} = C_0 + r \cdot (d_{uv} - d_0)
\quad (3)
\]

Where \( d_0 \) is the distance within boarding fee \( C_0 \), \( r \) is the unit price after \( d_0 \), and \( d_{uv} \) is the driving distance from \( u \) to \( v \).

Suppose the rate of taxi-pooling for each individual of taxi \( x \) from \( u \) to \( v \) is \( R_{uv}^x \), and therefore the total price for all passengers is followed.

\[
\sum_{x=1}^{X} \sum_{u,v=1}^{D} R_{uv}^x s_{uv}^x C_{uv} \quad (4)
\]

Where \( C_{uv} \) is the normal price of individual traveler, and \( R_{uv}^x \leq 1 \) to ensure taxi-pooling is beneficial.

The benefit of drivers is defined as follows.

\[
\sum_{x=1}^{X} \sum_{u,v=1}^{D} (R_{uv}^x s_{uv}^x C_{uv} - \delta \cdot d_{uv}^x) \quad (5)
\]

where \( d_{uv}^x \) is the driving distance from \( u \) to \( v \) of driver \( x \), which could be a detour, and \( \delta \) is the unit cost of taxi including fuel cost, depreciation cost and service fee.

The load rate is defined as the ratio of the passengers participated in taxi-pooling to the total number of waiting passengers at each site as follows.

\[
\frac{\sum_{x=1}^{X} \sum_{u,v=1}^{D} \sum_{i,j=1}^{G} \chi_{ij}^x t_{ij} \cdot s_{uv}^x}{\sum_{x=1}^{X} \sum_{u,v=1}^{D} \sum_{i,j=1}^{G} \chi_{ij}^x \cdot s_{uv}^x} \quad (6)
\]

Therefore, the objective functions are as follows.

\[
\min \sum_{x=1}^{X} \sum_{u,v=1}^{D} \sum_{i,j=1}^{G} \chi_{ij}^x t_{ij} \cdot s_{uv}^x + \sum_{x=1}^{X} \sum_{u,v=1}^{D} R_{uv}^x s_{uv}^x C_{uv} \quad (7)
\]
Eq. (7) aims to minimize the total cost of all passengers, Eq. (8) aims to maximize the benefit of all drivers, and Eq. (9) tries to maximize the load rate.

### 3.2 Restrictions

Now we consider the specific restrictions for the taxi-pooling model. First, the cost of passengers in taxi-pooling should be less than the individual cost without taxi-pooling, that is followed.

\[
R_{uv}^x \leq 1 \tag{10}
\]

where \( R_{uv}^x \) is the cost rate of taxi-pooling compared to without taxi-pooling.

Second, the benefit of drivers should be more than that without taxi-pooling.

\[
\sum_{x \in X} \sum_{u,v \in D} R_{uv}^x s_{uv}^x c_{uv} \geq \sum_{x \in X} (C_0 + r \cdot (d_x - d_0)) \tag{11}
\]

where \( d_x \) means the route for taxi \( x \) without taxi-pooling. Note that one passenger is picked up within the driving route.

Third, the number of passengers is limited to the maximum capacity \( Q_x \) of taxi \( x \), and the available capacity of site \( j \) when taxi \( x \) leaves site \( i \) should be followed.

\[
Q_x \geq Q_j^x \geq (Q_x + s_{ij}^x) \cdot x_{ij}^x \tag{12}
\]

Where \( Q_j^x \) means that the number of passengers picked up at site \( j \) should be no more than the maximum capacity \( Q_x \) of the taxi and no less than the last pickup point.

In summary, the optimization model of taxi-pooling is built as follows.

\[
\begin{align*}
\max & \quad \sum_{x \in X} \sum_{i=1}^{N_x} \sum_{u,v \in D} \left( x_{uv}^x \cdot r \cdot (d_{uv}^x - d_0) + C_0 - \delta \right) \\
\text{s.t.} & \quad \sum_{x \in X} \sum_{i,j} x_{ij}^x t_{ij}^x s_{uv}^x + \sum_{x \in X} \sum_{i,j} R_{uv}^x s_{uv}^x c_{uv} \\
& \quad - \left( \sum_{x \in X} \sum_{i,j} x_{ij}^x t_{ij}^x s_{uv}^x + \sum_{x \in X} \sum_{i,j} R_{uv}^x s_{uv}^x c_{uv} \right) = 0
\end{align*}
\]
0 < R_{uv}^* \leq 1 \\
0 < \sum_{x \in X}(c_x + r \cdot (d_x - d_0)) \leq \sum_{x \in X, u, v \in D} \sum_{u} R_{uv}^* s_{uv}^* c_{uv} \leq \sum_{x \in X, u, v \in D} \sum_{u} R_{uv}^* s_{uv}^* c_{uv} \\
(Q_i^* + s_{ij}^*) \cdot \lambda_i^* \leq Q_j^* \leq Q_x \\
s_{ij}^* = \{0, 1\}

4. ROUTING AND PRICING ALGORITHM BASED ON ACO

4.1 ACO basics

ACO was proposed upon the behavior study of real ant colony. It’s been found that when ants are searching for food, they would release pheromones on the routes, so that other ants within certain range could be informed and then move towards the routes with high amount of pheromones. Therefore, the behavior of ant colony is positive feedback, the more numbers of ants in some routes, the more amount of pheromones remained. In addition, it is more likely that other ants choose the routes with more amount of pheromones, which in turn increases the pheromones strength. In this way, the amount of pheromones on the optimal route increases, while the pheromones on other routes decrease, which contributes to the optimal route solution.

As shown in Fig.1, the principles of ACO can be explained through the double-bridge experiment conducted by Deneubourg et al., (1990). Suppose we have two designed routes in Figure 1-A, and the upper route is longer than the lower one. Two groups of ants are put at each end of the bridge, denoted as L and R respectively. At the initial stage, the decision is randomly made at the cross, as shown in Figure 1-B. After a while, more and more ants go to the lower route because more pheromones are released on the lower route, which increases the selected probability. Thus, if there come new ants at the cross, they are more likely to choose the lower route, as shown in Figure 1-C and 1-D, where the dotted lines denote the amount of pheromones. Finally, with the accumulation of pheromone and positive feedback mechanism, almost all ants would gather on the lower route.

The basic ACO can be described as follows (as shown in Fig.2). Suppose ant $k$ is at node $i$ when time $t$, and the amount of pheromones on path $(i, j)$ at $t$ is $\tau_{ij}(t)$. Therefore, the probability of ant $k$ moving to node $j$ is calculated as follows.
if $j \in \text{allowed}_k$, \[ p^k_{ij}(t) = \frac{[\tau^t_{ij}(t)]^a[\eta^t_{ij}(t)]^\beta}{\sum_{s \in \text{allowed}_k}[\tau^t_{is}(t)]^a[\eta^t_{is}(t)]^\beta} \]  
otherwise, \[ p^k_{ij}(t) = 0 \]

where $\text{allowed}_k$ denotes the set of available nodes for ant $k$ to choose, $a$ is the heuristic factor denoting the importance of path, $\eta^t_{ij}(t)$ is the expectation of transition from node $i$ to node $j$, and $\beta$ is the heuristic factor denoting the importance of $\eta^t_{ij}(t)$.

![Figure 2. Flow chart of ACO.](image)

The update of pheromone $\tau^t_{ij}(t)$ is conducted as follows.

$$ \tau^t_{ij}(t) = (1 - \rho) \cdot \tau^t_{ij}(t - 1) + \Delta \tau^t_{ij} $$  

where $1 - \rho$ is evaporation parameter for pheromone, $\Delta \tau^t_{ij}$ is the increment on path $(i, j)$ after one iteration, $\Delta \tau^t_{ij}$ is the amount of pheromone on path $(i, j)$ at current iteration for ant $k$, and

$$ \Delta \tau^t_{ij} = \begin{cases} Q/L_{k} & \text{if ant } k \text{ passes } (i,j) \text{; } \\ 0 & \text{otherwise} \end{cases} (18) $$

where $Q$ is a constant, and $L_k$ is the total distance of route for ant $k$ at current iteration.

4.2 Modified ACO for taxi-pooling routing
Taxi-pooling routing problem can be solved by ACO algorithm as a resource optimization problem. However, there are some specific requirements compared to the basic ACO. First, compared with the single destination ACO problem, taxi-pooling needs to find out a sequence of destinations for pickup problem. Second, the route characteristic is related to time. For example, in rush hours, traffic jam happens in some routes, and therefore, those routes should be avoided by decreasing the amount of pheromone. Last, unlike the collaboration in ACO, taxi drivers compete each other for picking more passengers on each route.

Therefore, we modify ACO as follows. Suppose we have \( X \) ant colonies for \( X \) taxi drivers, and the amount of pheromones on route \((i, j)\) for driver \( X \) at \( t \) is \( \tau_{ij}(t, x) \). Then Eq.(15) is rewritten as follows.

\[
\text{if } j \in \text{allowed}_k, \quad p_{ij}^k(t, x) = \frac{[\tau_{ij}(t, x)]^\alpha [\eta_{ij}(t, x)]^\beta}{\sum_{s=1}^{\text{allowed}_j} [\tau_{is}(t, x)]^\alpha [\eta_{is}(t, x)]^\beta} \cdot \gamma \quad (19)
\]

\[
\text{otherwise, } \quad p_{ij}^k(t, x) = 0
\]

where \( \eta_{ij}(t, x) \) is the expectation of transition from \( i \) to \( j \), which is decided by the traffic situation. \( \gamma \) is the restraint factor from other ant colonies, which means that if route \((i, j)\) is already selected by other taxis, then decrease the passing probability.

\[
\gamma = \sum_{y=1, y \neq x}^{X} \theta_{ij}(t, y) \quad (20)
\]

\[
\text{if } j \in \text{allowed}_r, \quad \theta_{ij}(t, y) = \frac{[\tau_{ij}(t, y)]^\alpha [\eta_{ij}(t, y)]^\beta}{\sum_{s=1}^{\text{allowed}_j} [\tau_{is}(t, y)]^\alpha [\eta_{is}(t, y)]^\beta} \cdot \gamma \quad (21)
\]

\[
\text{otherwise, } \quad \theta_{ij}(t, y) = 0
\]

Then, update the pheromone as follows.

\[
\tau_{ij}(t, x) = (1 - \rho) \cdot \tau_{ij}(t - 1, x) + \Delta \tau_{ij} \quad (22)
\]

\[
\Delta \tau_{ij} = \sum_{k=1}^{X} \Delta \tau_{ij}^k \quad (23)
\]

5. SIMULATION

![Simulation road network.](image)
In this section, we design a case study to simulate the proposed model and algorithm and evaluate the validity. We use Matlab for programming.

Suppose the road network is shown in Fig.3, where the weight of edge denotes the distance between two nodes. There are 10 Origin-Destination (OD) pairs (as shown in Table 1), and 4 taxis initialized at positions 2, 3, 6 and 9. The basic price of taxi $C_0$ is 5 while no longer than 1 km. After that the unit price $r$ is 2 per km. The speed of taxi is 45 km/h, and the capacity of all taxis $Q$ is 4 passengers.

Table 1 Passengers distribution of OD pairs

<table>
<thead>
<tr>
<th>OD pair</th>
<th>Passengers</th>
<th>OD pair</th>
<th>Passengers</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-8</td>
<td>1</td>
<td>4-9</td>
<td>3</td>
</tr>
<tr>
<td>3-6</td>
<td>2</td>
<td>2-9</td>
<td>1</td>
</tr>
<tr>
<td>7-2</td>
<td>2</td>
<td>1-10</td>
<td>1</td>
</tr>
<tr>
<td>9-4</td>
<td>1</td>
<td>6-7</td>
<td>2</td>
</tr>
<tr>
<td>5-10</td>
<td>2</td>
<td>8-2</td>
<td>1</td>
</tr>
</tbody>
</table>

We compare the results with the famous shortest path Dijkstra’s algorithm solution, notated as DA. In DA, we simplify the objectives as to minimize the total driving distance and maximize the load (i.e. summation of the number of passengers picked up at each point). The results are shown in Table 2, and the results of each route for each taxi are shown in Table 3.

Table 2 Comparison of ACO and Dijkstra algorithms

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Fitness</th>
<th>Driver benefit</th>
<th>Cost per passenger</th>
<th>Load rate (%)</th>
<th>Average time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DA</td>
<td>-</td>
<td>96.48</td>
<td>4.70</td>
<td>75.54</td>
<td>60.03</td>
</tr>
<tr>
<td>ACO</td>
<td>198.24</td>
<td>115.31</td>
<td>4.24</td>
<td>87.26</td>
<td>72.58</td>
</tr>
<tr>
<td>Modified ACO</td>
<td>162.33</td>
<td>119.25</td>
<td>3.52</td>
<td>90.15</td>
<td>84.21</td>
</tr>
</tbody>
</table>

In Table 2, we can observe that modified ACO algorithm outperforms others, where the driver benefit, cost of passenger and load rate are improved, while the average convergence time increases. The reason is that our modified ACO adds more logic into the basic ACO, which is introduced earlier in this paper.

Table 3 Sequence of sites in routes of taxis

<table>
<thead>
<tr>
<th>Route</th>
<th>Taxi start</th>
<th>Site 1</th>
<th>Site 2</th>
<th>Site 3</th>
<th>Site 4</th>
<th>Site 5</th>
<th>Site 6</th>
<th>Site 7</th>
<th>Site 8</th>
<th>Site 9</th>
<th>Site 10</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>2</td>
<td>3</td>
<td>0</td>
<td>0</td>
<td>4</td>
<td>5</td>
<td>6</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>2</td>
<td>3</td>
<td>1</td>
<td>0</td>
<td>6</td>
<td>4</td>
<td>7</td>
<td>5</td>
<td>8</td>
<td>9</td>
</tr>
<tr>
<td>3</td>
<td>6</td>
<td>3</td>
<td>0</td>
<td>4</td>
<td>2</td>
<td>6</td>
<td>1</td>
<td>5</td>
<td>7</td>
<td>8</td>
<td>9</td>
</tr>
<tr>
<td>4</td>
<td>9</td>
<td>4</td>
<td>6</td>
<td>3</td>
<td>5</td>
<td>0</td>
<td>7</td>
<td>2</td>
<td>8</td>
<td>1</td>
<td>0</td>
</tr>
</tbody>
</table>

In Table 3, we listed the sequence of sites for each taxi. For example, for the taxi at position 2, the route for taxi-pooling is 2-4-5-8-9-10. For taxi at position 3, the route for taxi-pooling is 3-1-2-6-8-5-7-9-10. For taxi at position 6, the route for taxi-pooling is 6-4-1-3-7-5-8-9-10. For taxi at position 9, the route for taxi-pooling is 9-7-3-1-4-2-6-8.
Besides, the taxi-pooling routes of 10 OD pairs are shown in Fig.4. Also, the distance and cost comparison between without taxi-pooling and taxi-pooling are listed in Table 4.

**Table 4** Comparison of distance and cost between no taxi-pooling and taxi-pooling

<table>
<thead>
<tr>
<th>OD pair</th>
<th>Without taxi-pooling distance</th>
<th>Taxi-pooling distance</th>
<th>Detoured distance</th>
<th>Without taxi-pooling cost</th>
<th>Taxi-pooling cost</th>
<th>Cost saved</th>
<th>Cost rate R</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-8</td>
<td>11</td>
<td>22</td>
<td>11</td>
<td>14</td>
<td>10.45</td>
<td>3.35</td>
<td>0.75</td>
</tr>
<tr>
<td>3-6</td>
<td>16</td>
<td>19</td>
<td>3</td>
<td>18</td>
<td>13.02</td>
<td>4.98</td>
<td>0.72</td>
</tr>
<tr>
<td>7-2</td>
<td>13</td>
<td>19</td>
<td>6</td>
<td>15</td>
<td>9.50</td>
<td>5.50</td>
<td>0.63</td>
</tr>
<tr>
<td>9-4</td>
<td>11</td>
<td>17</td>
<td>6</td>
<td>13</td>
<td>10.01</td>
<td>2.99</td>
<td>0.77</td>
</tr>
<tr>
<td>5-10</td>
<td>15</td>
<td>15</td>
<td>0</td>
<td>18</td>
<td>12.28</td>
<td>5.72</td>
<td>0.68</td>
</tr>
<tr>
<td>4-9</td>
<td>11</td>
<td>13</td>
<td>3</td>
<td>13</td>
<td>8.95</td>
<td>4.05</td>
<td>0.69</td>
</tr>
<tr>
<td>2-9</td>
<td>16</td>
<td>18</td>
<td>2</td>
<td>18</td>
<td>12.38</td>
<td>5.62</td>
<td>0.69</td>
</tr>
<tr>
<td>1-10</td>
<td>22</td>
<td>30</td>
<td>8</td>
<td>25</td>
<td>18.26</td>
<td>6.74</td>
<td>0.73</td>
</tr>
<tr>
<td>6-7</td>
<td>13</td>
<td>13</td>
<td>0</td>
<td>15</td>
<td>11.79</td>
<td>3.21</td>
<td>0.79</td>
</tr>
<tr>
<td>8-2</td>
<td>13</td>
<td>27</td>
<td>14</td>
<td>16</td>
<td>9.93</td>
<td>6.07</td>
<td>0.62</td>
</tr>
</tbody>
</table>

Besides, the taxi-pooling routes of 10 OD pairs are shown in Fig. 4. Also, the distance and cost comparison between without taxi-pooling and taxi-pooling are listed in Table 4.
Moreover, we illustrate the convergence speed of ACO based algorithm in Fig. 5. Compared with the basic ACO algorithm, our modified ACO achieves less fitness value. Specifically, modified ACO convergences at approximately 38th iteration with the fitness value 162.33, while the basic ACO convergences at 40th iteration with the fitness value 198.24. The speed improvement is not obvious, because the modified algorithm assign each taxi with an ant colony, which is introduced earlier. However, modified method gets better accuracy.

**6. CONCLUSION**

In this work, we study the taxi-pooling problem to promote intelligent transportation and energy-saving. Specifically, we aim to minimize the cost of all passengers, maximize the benefit of drivers, and maximize the load rate as well. With the fully understand of taxi-pooling, we construct the optimization for taxi-pooling, and propose to employ a modified ACO algorithm to solve the routing results. However, we assume that all demands are known beforehand. In real world, real-time pricing demand is more commonly discussed. Therefore, in future, we would consider the scenario which the demand points are not completely determined in advance.

**7. ACKNOWLEDGMENTS**

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**8. REFERENCES**


