Verification and Optimization of Metro Fare Clearing Models Based on Travel Route Reconstruction

Pu Yichao

School of Electronics and Information Engineering, Tongji University, Shanghai 201804, China. Email: puyichao07@163.com

© The Authors 2020

ABSTRACT

How to verify and optimize metro fare clearing models efficiently and accurately is a research focus in metro operations. Metro fare clearing models are mostly based on probability distributions. In such models, the normal distribution of travel time corresponding to the section probabilities is used to calculate the route choice probabilities of passengers on a multi-route metro network. By integrating the operating mileage proportions of each metro line operator and the corresponding route choice probabilities, the fare clearing proportions are calculated for all the operators of the metro network. To verify the accuracy of the fare clearing proportions, we propose a travel route reconstruction approach based on cell phone data acquisition technique. With wireless access point (AP) sensors installed at transfer stations, the unique medium access control (MAC) address of the smartphone with Wi-Fi function turned on is recorded and transmitted to a data analysis platform. After matching the MAC address information with time and location, the travel route of the smartphone user is reconstructed. Then, the parameters in the fare clearing model are verified and optimized according to the travel route choice probabilities. The proposed methodology is applied in Hangzhou metro network for experiment, and the metro fare clearing model is verified and modified by reconstructing the actual travel routes of the local passengers.

ARTICLE HISTORY

Received: 16-07-2020
Revised: 10-09-2020
Accepted: 18-09-2020

KEYWORDS

Fare clearing model
Cell phone data
Automatic fare collection
Travel route reconstruction

1. Introduction

According to the public-private partnership (PPP) cooperation mode, private companies participate in both the construction and the operation of metro lines in the metropolitans of some countries, e.g., Sydney (Gordon et al., 2013), London (Phang, 2007), Beijing (Chang, 2013), Shenzhen, Hangzhou, and Chongqing. Generally, metro lines are operated by different private companies instead of the government. Therefore, the revenue of metro network needs to be cleared to each line operator.

Fare clearing system is a key component of a metro network, not only because it is used to clear the revenue of each metro line operator, but also because
it can calculate the passenger flow distribution in the whole line network, which can be further used to study the supply and demand relationship of the metro line network. Fare clearing system consists of fare clearing model (core component), automatic fare collection (AFC) system, etc. AFC system offers services to passengers and operators, while provides metro operation data (such as daily entry-exit passenger flow and daily revenue of a line/station) to the fare clearing model. After receiving metro operation data, the fare clearing model begins to calculate the revenue and patronage of each metro line. The fare clearing system keeps working 24/7. Since the actual travel routes of passengers in metro network are hard to be detected, the metro fare clearing models in most cities are based on experimental models without highly accurate verification. Therefore, the clearing model results may not be consistent with the actual situations (Gao et al., 2011). Moreover, the upgrade frequency of a fare clearing model is quite low. In China, metro operators revise the fare clearing model once every one or two years (Zhou, 2014). Hence, fare clearing models cannot timely illustrate the patronage characteristics and travel route selection evolution of passengers. In this paper, we propose a cell phone data based travel route reconstruction approach to verify the accuracy of existing metro fare clearing model, and calibrate the parameters in the existing model to optimize the fare clearing model for the whole metro network.

The paper is arranged as follows. In Section 2, the recent studies conducted in both metro fare clearing and cell phone data based travel route reconstruction fields are reviewed. In Section 3, the metro fare clearing models in metropolitans of China are briefly introduced. In Section 4, a new metro travel route reconstruction approach is proposed. In Section 5, Hangzhou metro network is used as an example to verify and optimize the fare clearing model based on cell phone data acquisition. Finally, the conclusions are summarized in Section 6.

2. Literature review

The core algorithm in metro fare clearing model is the travel route reconstruction approach of passengers. The reconstruction is based on building the connection between the travel route choice and its influence factors. In this section, both fare clearing model and cell phone based travel route reconstruction are discussed.

2.1. Metro fare clearing models

For metro fare clearing models, a consistent conclusion has been achieved (Zhao et al., 2007; Wang et al., 2013; Lu, 2012; Yu & Wang, 2013) that travel time, transfer time, and the number of transfers have significant effects on the passenger route choice.

According to the sensitive analysis of passenger decision-making in Zhao et al. (2007), the transfer time and passenger familiarity of metro network affect the traveler route choice significantly. However, the parameters related to social economy, degree of convenience, and crowding were set as constant values. In Wang et al. (2013), the attributes mostly related to a route choice were analyzed. The results showed that travel time and transfer length were the most significant influencing factors, train headways and degree of crowding were the secondary significant influencing factors, and the degree of comfort was also a significant factor. However, this research was conducted from the prospect of metro designer instead of passenger. In Lu (2012), the metro clearing algorithm of Shenzhen was studied, and the existing transfer modes, basic influencing factors of route choice behavior were analyzed. In combination with theoretical analysis and traffic survey, a more realistic fare clearing model was built. It was suggested that the parameters of the fare clearing model could be optimized by means of regular traffic survey. However, the passenger travel behavior survey in that paper is simply based on questionnaires, and the reliability of the survey results needs to be further verified.

In Zhou (2014), the actual route choices were used to revise the parameters in Shanghai metro fare clearing models. Since the metro network was really large and
there are several routes in an origin-destination (OD) pair, it was not easy to figure out the actual OD routes. The author used the entry-exit time of each passenger recorded by AFC system to match the most possible travel route, and regarded the obtained route as the actual OD one. However, this approach does not work for routes with similar travel time.

In Sun et al. (2015), an integrated Bayesian statistical inference framework was proposed to develop a passenger flow assignment model in a complex metro network. The integrated approach was applied to the metro network in Singapore, and the estimation of parameter route choices was consistent with the previous survey-based studies. However, the assumed travel time reliability and service reliability have not taken temporal dynamics into consideration, and the proposed framework is still a theoretical model, lacking actual travel route choice data for verification.

In general, metro fare clearing models are similarly developed based on route choice theory, where travel time and transfer times are two major influence factors of passenger choice making. How to develop a fare clearing model in line with the actual situation is still unresolved.

2.2. Cell phone data based travel route reconstruction

With the blooming development of cell phone in the information era, big data methodology becomes increasingly popular in all scientific fields, especially in travel route reconstruction. Iqbal et al. (2014) used mobile phone call detail record (CDR) data to calculate the travel OD matrix. The CDR data of 2.87 million users over a month was used, and the traffic flow data of 13 key locations over 3 days of that month were used to verify the accuracy of the methodology. Alexander et al. (2015) used CDR data from 8 billion users over 2 months to estimate the average daily OD trips, and validated the applicability of the proposed method against the temporal and spatial distributions of trips reported in local and national surveys. Dong et al. (2015) used CDR data and mobile phone base stations to divide the traffic zone and characterized a traffic zone by working or residential. The results were consistent with the known distributions of typical working and residential areas in Beijing, China.

Aguilera et al. (2014) used cell phone data to measure the passenger flow in an underground transit system. The proposed method was applied to Paris underground transit system. Compared with direct field observations and AFC data, cell phone data could dynamically reflect the passenger quantities, including travel times, train occupancy levels, etc. In this paper, we propose a travel route reconstruction approach based on a new cell phone data acquisition method, with which the metro fare clearing model can be verified and optimized. The application of the proposed approach in Hangzhou metro network proves its reliability. The improved fare clearing model is highly consistent with the actual results.

3. Metro fare clearing model

Metro fare clearing models can be divided into three categories, i.e., metro fare clearing models based on network scale (Pan, 2014), metro fare clearing models based on the shortest route (Hoffman & Pavley, 1959), and metro fare clearing models based on multi-route choices (Raveau et al., 2014). In metro fare clearing models based on network scale, the revenue is cleared according to the operating mileage ratio of each metro line operator without the consideration of patronage distributions. This simplified clearing model has defects in both accuracy and rationality. In metro fare clearing models based on the shortest route, all the passengers are assumed to choose the shortest route in an OD pair. The revenue is cleared to the operators of the shortest routes. It is a feasible model under a simple metro network.

In metro fare clearing models based on multi-route choices, there are multiple rational travel routes for each OD pair. Each route has its own passenger flow assignment proportion according to a certain algorithm. By integrating the passenger flow distribution proportion and the operating mileage
proportion on every route in each OD pair, clearing proportions are calculated for all the metro line operators. Fare clearing models based on multi-route choices have been widely used in China, Sydney, Korea, etc. We integrate the algorithm of metro fare clearing models from related technical reports. The flowchart of clearing proportion calculation is shown in figure 1.

![Flowchart](image.png)

**Figure 1.** Flow chart of clearing proportion calculation.

We integrate the main influence factors for route choices, e.g., travel time, stop time, transfer walking time, transfer waiting time, and transfer number, as a function of the total travel time of a given route as follows:

$$ Rp = \sum_{i=1}^{m-1} T_i + \sum_{j=1}^{n} (T_{xj} + E_{xj})P_j \quad (1) $$

where $Rp$ is the total travel time of a certain route. The smaller $Rp$ is, the larger the choice probability on this route is. $m$ is the number of stops on this route. $n$ is the number of interchange stations on this route. $T_i$ is the travel time in the $i$th section. $T_{xj}$ and $E_{xj}$ are the transfer waiting time and the transfer walking time at the $j$th interchange station, respectively. $P_j$ is the transfer amplification coefficient at the $j$th interchange station, which converts the perception of passengers toward the transfer to travel time. For instance, when we set the transfer amplification as 1.5, the actual transfer time of 5 minutes will have the same influence on the choices of passengers as the travel time of 7.5 minutes.

According to the metro fare clearing models in China (Lu, 2012), normal distribution has been widely used to simulate the relationship between the total travel time of a route and its choice probability by passengers. We assume that there are $w$ effective routes in an OD pair. The scaled travel time is calculated by

$$ X_i = \frac{Rp_j}{Rp_{\text{min}}} \quad (2) $$
where $R_{p_i}$ and $R_{p_{\text{min}}}$ are the total travel time for route $i$ and the shortest route which shares the same OD pair with route $i$, respectively. The normalized scaled travel time is

$$S_i = \frac{1}{\sqrt{2\pi \sigma}} e^{-\frac{(X_i-1)^2}{2\sigma^2}}$$

(3)

where $\sigma$ is the standard deviation of the normal distribution, and is an empirical constant (Lu, 2012).

The normalized probability is

$$P_i = \frac{S_i}{\sum_{i=1}^{w} S_i}$$

(4)

The relationship between the total travel time and the route choice probability is illustrated in figure 2. The smaller $\sigma$ is, the more sensitive the route choice probability of passengers is to the total travel time (Lu, 2012). In Palma & Picard (2005), the route choice probability of passengers is quite sensitive to the increase in the travel time when the total travel time is short, and vice versa. It is due to the marginal effect. Usually, $\sigma=0.238$. It is an empirical value from Fare Clearing Model Technical Report.

Elongation ratio is used to eliminate the ineffective routes and improve the calculation efficiency. The elongation ratio is empirically 2. In general, if the travel time of a route is more than 2 times that of the shortest route, the route will be listed as an ineffective one.

The clearing proportion of a certain metro line operator $a$ in an OD pair is

$$CP_a = \sum_{i=1}^{w} \left( P_i \times \frac{L_i}{L_{a_i}} \right)$$

(5)

where $w$ is the number of effective routes in the OD pair. $P_i$ is the route choice probability derived from Eq. (4). $L_a$ is the operating mileage of operator $a$ on the $i$th route. $Li$ is the total operating mileage on the $i$th route. $\frac{L_a}{Li}$ is the revenue assignment proportion. After the clearing proportions of all OD pairs in the metro network are obtained, the revenue can be cleared to the operator of each line. According to China Metro Fare Clearing Model Technical Report, we list the major parameters in the fare clearing models of different metropolitans in table 1.
### Table 1. Major parameters in the fare clearing models of different metropolitans in China.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Beijing</th>
<th>Shenzhen</th>
<th>Shanghai</th>
<th>Hangzhou</th>
</tr>
</thead>
<tbody>
<tr>
<td>Section mileage</td>
<td>Operation map</td>
<td>Operation map</td>
<td>Operation map</td>
<td>Operation map</td>
</tr>
<tr>
<td>Section travel time</td>
<td>Timetable</td>
<td>Timetable</td>
<td>Timetable</td>
<td>Timetable</td>
</tr>
<tr>
<td>Transfer waiting time</td>
<td>Half of the headway</td>
<td>Half of the headway</td>
<td>Half of the headway</td>
<td>Half of the headway</td>
</tr>
<tr>
<td>Transfer walking time</td>
<td>In-field survey</td>
<td>In-field survey</td>
<td>In-field survey</td>
<td>In-field survey</td>
</tr>
<tr>
<td>Transfer amplification coefficient</td>
<td>1.5</td>
<td>1</td>
<td>$1.1^N$</td>
<td>1.5 for the 1st and 2nd time, and 3 for the 3rd time</td>
</tr>
<tr>
<td>Standard deviation $\sigma$</td>
<td>0.25</td>
<td>0.28</td>
<td>(depends on actual situation)</td>
<td>0.238</td>
</tr>
<tr>
<td>Elongation ratio</td>
<td>2 times</td>
<td>2 times</td>
<td>2 times</td>
<td>2 times</td>
</tr>
<tr>
<td>Consider operating time?</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Conser other influence factors (service quality, degree of crowding)?</td>
<td>No</td>
<td>Yes, degree of crowding</td>
<td>Yes, degree of crowding</td>
<td>No</td>
</tr>
</tbody>
</table>

### 4. Travel route reconstruction based on cell phone data

A newly developed cell phone data acquisition technique allows us to acquire cell phone data without analyzing CDR or GSM data. We install a wireless access point (AP) sensor on the ceiling of concourse or platform in metro stations. The AP sensor will automatically search for signals sent by the cell phones whose Wi-Fi function is turned on. After the signals are received, the AP sensor will record the unique medium access control (MAC) address of each cell phone and the recording time. With the AP sensors installed on the key nodes of a metro network, the travel trajectory (travel route and time of each smartphone user) can be reconstructed. Compared with CDR data, the acquisition technique proposed in this paper can better protect the privacy of customers.

There are three steps for the reconstruction of passenger travel routes:

1. Collect cell phone data. Input all the MAC addresses and acquisition times of every AP sensor to the database.
2. Reduce the data. Order the MAC addresses by time and eliminate the unusual data.
3. Reconstruct the route. Since every AP sensor has its own location, the travel route of each passenger (smart phone user) can be reconstructed by integrating all the captured data, such as MAC address, acquisition time, and location.

Figure 3 shows the network topology of the proposed travel route reconstruction methodology based on cell phone data.
In a metro network, AP sensors can be installed at the transfer stations and other key stations. With the proposed travel route reconstruction approach, the actual route choices of passengers (patronage distribution in metro network) can be calculated accurately. Then, the metro fare clearing model is able to be verified and the parameters in the fare clearing model can be optimized according to the results of the actual patronage distribution.

5. Verification and optimization of fare clearing models

To illustrate the proposed methodology, we use Hangzhou metro network as an experimental site.

5.1. Background introduction

Till now, Hangzhou has three metro lines in operation. Line 1 is operated by Hangzhou MTR Co., Ltd., and Line 2 and Line 4 are operated by Hangzhou Metro Operation Co., Ltd. The total length of Hangzhou metro network is 81.5 km, including 57 stations. We install AP sensors at six stations in the metro network, covering both the station platforms and the concourses. The six AP sensor equipped stations include four transfer stations and two large patronage stations. The detailed information is shown in figure 4.
Figure 4. Hangzhou metro map with six AP sensor equipped stations.

The entry-exit data from the AFC system can identify the travel routes for those OD pairs with only one route. For the OD pairs with multiple routes, we apply the proposed travel route reconstruction approach to calculate the actual patronage distributions. In Hangzhou metro network, there are four types of OD pairs with multiple routes, i.e., Type-I, Type-II, Type-III, and Type-IV.

Type-I is from the south part of Line 1 to the north part of Line 1, i.e., from Xianghu Station to Xiasha Jiangbin Station. Passengers can travel through Line 1 without transfer or transfer at Jinjiang Station to Line 4, and then transfer back to Line 1 at Pengbu Station.

Type-II is from the north part of Line 1 to the south part of Line 4, i.e., from Wenze Road to Jiangling Road. Passengers can travel through Line 1 without transfer or transfer at East Railwang Station to Line 4, and then transfer back to Line 1 at Jinjiang Station.

Type-III is from Line 2 to the middle part of Line 1, i.e., from Renmin road to Wulin Square. Passengers can transfer to Line 4 at Qianjiang Road, and then transfer to Line 1 at East Railway Station or Jinjiang Station.

Type-IV is from the middle part of Line 1 to Line 2, i.e., from Longxiangqiao to Remin road. Passengers can transfer to Line 4 at East Railway Station or

Jinjiang Station, and then transfer to Line 2 at Qianjiang Road.

To figure out the route choice probabilities of the above four types of OD pairs, we select three stations, i.e., East Railway Station, Jinjiang, and Jiangling Road, to analyze the first two types of OD pairs. This is because passengers from Jiangling Road to East Railway Station have two travel routes. We also select Renmin Road, Longxiangqiao, and Qianjiang Road (transfer station) to calculate the route choice probabilities for the last two types of OD pairs, since the two travel routes from Renmin Road to Longxiangqiao share similar operating mileage. In total, six stations in Hangzhou metro network are selected as the cell phone data acquisition sites.

According to the layout of the six stations, we decide the numbers of data acquisition devices as those listed in Table 2.

Table 2. Data acquisition devices installed at six stations in Hangzhou metro network.

<table>
<thead>
<tr>
<th>Category</th>
<th>Station</th>
<th># of Primary devices</th>
<th># of AP sensors</th>
<th>Illustration</th>
</tr>
</thead>
<tbody>
<tr>
<td>Central computer room</td>
<td>Qibao</td>
<td>3</td>
<td>N/A</td>
<td>1 central switch</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>2 servicers</td>
</tr>
<tr>
<td></td>
<td>Jiangling Road</td>
<td>3</td>
<td>9</td>
<td>1 router</td>
</tr>
<tr>
<td>Normal station</td>
<td>Longxiangqiao</td>
<td>3</td>
<td>9</td>
<td>2 POE switches</td>
</tr>
<tr>
<td></td>
<td>Renmin Road</td>
<td>3</td>
<td>9</td>
<td>9 AP sensors</td>
</tr>
<tr>
<td></td>
<td>East Railway Station</td>
<td>4</td>
<td>16</td>
<td>1 router</td>
</tr>
<tr>
<td></td>
<td>3 POE switches</td>
<td>16 AP sensors</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Transfer station</td>
<td>Qianjiang Road</td>
<td>4</td>
<td>12</td>
<td>1 router</td>
</tr>
<tr>
<td></td>
<td>3 POE switches</td>
<td>12 AP sensors</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Jinjiang</td>
<td>4</td>
<td>14</td>
<td>14 AP sensors</td>
</tr>
<tr>
<td></td>
<td>3 POE switches</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>7</td>
<td>24</td>
<td>69</td>
<td></td>
</tr>
</tbody>
</table>

5.2. Acquisition and analysis of cell phone data

We conduct this experiment for 23 days from January 26, 2016 to February 18, 2016. Since AP sensors are installed at both the platform and the concourse of each station, the passenger flow can be divided into entry-exit passenger flow, transfer passenger flow, passing passenger flow, and unusual passenger flow. Since not all passengers use smart phones and turn on the WiFi function, here, we compare the collected entry-exit cell phone data with the actual passenger flow data in the AFC system, and obtain the sampling rates, as shown in figure 5.

From figure 5, the average sampling rates at normal stations and transfer stations are about 86% and 45%, respectively. Since transfer stations are larger and the passenger flow distributions are more complex, it is
rational that the sampling rates at transfer stations are lower. In addition, one passenger may have more than one smart phones but only has one record in the AFC system, while his smart phone data will be captured more than once. Besides, the smart phone data of the working staff are not recorded in the AFC system but are recorded in the cell phone database. Therefore, it is rational that the sampling rate of Jiangling Road is over 100%.

After matching the acquired unique MAC address of each smart phone according to the record time and location, we can reconstruct the travel route and also calculate the sampling rates of patronage on the four typical OD pairs with multiple routes, as shown in figure 6.

**Figure 5.** Sampling rates of entry-exit flow at six AP sensor equipped stations, where the station name with star mark means it’s a transfer station of it.

**Figure 6.** Sampling rates of four typical multi-route OD pairs.
The average sampling rate of patronage is 23%. As the AP sensors are forbidden to be installed in the track area, only a small amount of cell phone data can be recorded for the passengers on the train. To analyze the effects of different sampling rates on the route choice probability, a sensitivity analysis is conducted. The detailed results are shown in Table 3.

From Table 4, one can figure out that the difference between the maximum and minimum sampling rates does not significantly affect the route choice probability. The travel route reconstruction system based on cell phone data is quite stable.

### Table 3. Sensitivity analysis results.

<table>
<thead>
<tr>
<th>OD pair type</th>
<th>Maximum sampling rate</th>
<th>Minimum sampling rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual route choice probability</td>
<td>Date</td>
<td>Actual route choice probability</td>
</tr>
<tr>
<td>Route 1%</td>
<td>Route 2%</td>
<td>Route 1%</td>
</tr>
<tr>
<td>Type-I</td>
<td>92.03</td>
<td>7.97</td>
</tr>
<tr>
<td>Type-II</td>
<td>83.62</td>
<td>16.38</td>
</tr>
<tr>
<td>Type-III</td>
<td>94.35</td>
<td>5.65</td>
</tr>
<tr>
<td>Type-IV</td>
<td>93.18</td>
<td>6.82</td>
</tr>
</tbody>
</table>

### Table 4. Route choice probability of four typical OD pairs.

<table>
<thead>
<tr>
<th>OD pair type</th>
<th>Actual route choice probability</th>
<th>Route choice probability from existing models</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual route choice probability</td>
<td>Route choice probability</td>
<td>Route</td>
</tr>
<tr>
<td>Route 1%</td>
<td>Route 2%</td>
<td>Route 1%</td>
</tr>
<tr>
<td>Type-I</td>
<td>92.16</td>
<td>7.84</td>
</tr>
<tr>
<td>Type-II</td>
<td>86.18</td>
<td>13.82</td>
</tr>
<tr>
<td>Type-III</td>
<td>94.74</td>
<td>5.26</td>
</tr>
<tr>
<td>Type-IV</td>
<td>94.95</td>
<td>5.05</td>
</tr>
</tbody>
</table>

### 5.3. Verification of the fare clearing model

Referring to the reconstructed travel routes of the 23% recorded passengers, we can verify and optimize the fare clearing model of Hangzhou metro network. Although the route choice probabilities present slight fluctuations, we can mix all the cell phone data to calculate the average route choice probability for each OD pair. The average route choice probabilities of the four typical OD pairs are listed in Table 4.

The actual route choice probabilities are significantly different from those of existing model, indicating that the travel behavior of passengers is not consistent with the empirical model. The route choice probabilities of Type-I and Type-II OD pairs illustrate the willingness of passengers toward transfer. Route 1 has a long travel time without interchange, while Route 2 has a short travel time with one or more interchanges. Obviously, passengers in Hangzhou dislike transfer. This may be caused by the unfamiliarity of passengers with the metro network structure. Furthermore, a large amount of passengers are tourists, and they prefer travel convenience to time saving.

The route choice probabilities of Type-III and Type-IV OD pairs illustrate the behaviors of passengers toward two routes with a similar length. In Route 1, passengers transfer from Line 4 to Line 1. In Route 2, passengers transfer from Line 1 to Line 4. The headways of Line 1 and Line 4 are 4 minutes and 8 minutes, respectively. This means that transferring to Line 1 can save more waiting time than transferring to Line 4. This is the reason why most passengers prefer Route 1.
We conclude from Table 4 that the route choice probabilities from the current Hangzhou metro fare clearing model are not consistent with the actual situations. An optimized clearing model should be provided according to the actual route choice probabilities.

5.4. Optimization of the fare clearing model

With the travel route reconstruction approach based on cell phone data, we can acquire the route choice probabilities of certain OD pairs. According to the algorithm in the metro fare clearing model, the sampling route choice probabilities can be used to calibrate the empirical parameter \( \sigma \) and the transfer amplification coefficients so as to optimize the fare clearing model for the whole network. In the existing Hangzhou metro fare clearing model, \( \sigma \) is 0.238, and the transfer amplification coefficient is 1.5 for the 1st and 2nd transfer time.

We use the least square estimation method to calibrate the empirical parameters in the Hangzhou metro fare clearing model on MATLAB. In Table 5, \( \alpha \) and \( \beta \) are the transfer amplification coefficients for the 1st and 2nd transfer time, respectively.

<table>
<thead>
<tr>
<th>Empirical parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \sigma )</td>
<td>0.243 2</td>
</tr>
<tr>
<td>( \alpha )</td>
<td>4.169 8</td>
</tr>
<tr>
<td>( \beta )</td>
<td>3.298 2</td>
</tr>
</tbody>
</table>

The average actual route choice probability of 8 days is used to verify the calibration results. The details are shown in Table 6. From Table 6, we can conclude that the optimized fare clearing model has much higher accuracy than the empirical model. The travel route choice probabilities and revenue assignments obtained from the optimized fare clearing model of Hangzhou metro network for each operator are more consistent with the actual situations. Since the cell phone data acquisition system keeps working, we can figure out the changes in the travel behaviors of passengers and optimize the parameters in the fare clearing model timely.

<table>
<thead>
<tr>
<th>OD type</th>
<th>Actual route choice probability</th>
<th>Route choice probability from the optimized model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Route 1%</td>
<td>Route 2%</td>
</tr>
<tr>
<td>Type-I</td>
<td>92.93</td>
<td>7.07</td>
</tr>
<tr>
<td>Type-II</td>
<td>86.90</td>
<td>13.10</td>
</tr>
<tr>
<td>Type-III</td>
<td>95.04</td>
<td>4.96</td>
</tr>
<tr>
<td>Type-IV</td>
<td>94.94</td>
<td>5.06</td>
</tr>
</tbody>
</table>

6. Conclusions

To verify and optimize metro fare clearing models, we propose a travel route reconstruction approach based on cell phone data acquisition technique. The cell phone data with Wi-Fi function turned on are recorded by AP sensors installed at key nodes. By matching the recorded time, location, and MAC address of each cell phone, we can reconstruct the actual travel route of each recorded cell phone user. With the actual route choice probabilities, the empirical parameters in the metro fare clearing model can be calibrated. Then, the revised fare clearing model can be applied to the whole metro network.

According to the conclusions of implementation in Hangzhou metro network, the sampling rate of cell phone data acquisition at each station is quite rational, and the travel route choice probabilities have slight fluctuations. Assumptions are made in this paper. First, since the AP sensor cannot be installed in the track area, the average sampling rate is 23% of all OD pairs. We assume that 23% is enough for illustrating the travel route choice probabilities. Second, only cell phones with Wi-Fi function turned on can be recorded by AP sensors. The manual questionnaire results in Hangzhou metro conducted by Hangzhou MTR Co. Ltd. show that nearly 73% of passengers prefer to turn on Wi-Fi function during traveling. Third, we
optimize the three empirical parameters in Hangzhou metro fare clearing model according to the average actual route choice probabilities. Although the results of the travel route reconstruction approach are quite accurate, the installation and maintenance costs of the proposed cell phone data acquisition system are high. This is the major limitation of this approach.

Metro fare clearing models can be verified and optimized with the approach proposed in this paper. How to apply the proposed approach to more complex metro network and how to develop a new fare clearing model which is more consistent with the actual situation are our further research directions.

Acknowledgment

This research is supported and sponsored by the Hangzhou Metro Group and Hangzhou MTR Corporation Limited in China. The installation of data acquisition devices in this research is conducted by Zhejiang Escan Technology Corporation Limited. The second author is supported by the Fundamental Research Funds for the Central Universities.

References


Publisher’s note: Eurasia Academic Publishing remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Open Access This article is licensed under a Creative Commons Attribution-NoDerivatives 4.0 International (CC BY-ND 4.0) licence, which permits copy and redistribute the material in any medium or format for any purpose, even commercially. The licensor cannot revoke these freedoms as long as you follow the licence terms. Under the following terms you must give appropriate credit, provide a link to the license, and indicate if changes were made. You may do so in any reasonable manner, but not in any way that suggests the licensor endorsed you or your use. If you remix, transform, or build upon the material, you may not distribute the modified material.
To view a copy of this license, visit https://creativecommons.org/licenses/by-nd/4.0/.