ABSTRACT

Passenger exchange coefficient is a significant factor which has a great impact on the pricing model of urban rail transit. This paper introduces passenger exchange coefficient into a bi-level programming model with time differential pricing for urban rail transit by analysing variation regularity of passenger flow characteristics. Meanwhile, exchange cost coefficient is also considered as a restrictive factor in the pricing model. The improved particle swarm optimisation algorithm (IPSO) was applied to solve the model, and simulation results show that the proposed improved pricing model can effectively realise stratification of fares for different time periods with different routes. Taking Line 2 and Line 8 of the Beijing rail transit network as an example, the simulation result shows that passenger flows of Line 2 and Line 8 in peak hours decreased by 9.94% and 19.48% and therefore increased by 32.23% and 44.96% in off-peak hours, respectively. The case study reveals that dispersing passenger flows by means of fare adjustment can effectively drop peak load and increase off-peak load. The time differential pricing model of urban rail transit proposed in this paper has great influences on dispersing passenger flow and ensures safety operation of urban rail transit. It is also a valuable reference for other metropolitan rail transit operating companies.

KEYWORDS

urban rail transit; time differential pricing; bi-level programming model; passenger exchange coefficient.

1. INTRODUCTION

In recent years, the rate of using public transport has become higher and higher. Under the circumstances, optimisation of game between urban rail transit and conventional bus which account for over 80% transport volume together is regarded as a key to distribute passenger flows and make effective use of public transport. Additionally, balancing passenger demands and profits of public transport operating companies remains a hot research topic. This paper establishes a new time differential pricing model for urban rail transit from the perspective of regulatory role of economic leverage and urban rail transit operational efficiency. The purpose is to guide passengers to arrange their travels rationally.

The fare optimisation issue of public transport has been extensively studied by many scholars. Currie [1] studied Melbourne’s 'early bird' fare system (free train travel before 7 a.m.) and found that, while reducing fare revenue to some extent, it significantly reduced level of full trains in the first peak hour (7 a.m. to 8 a.m.). Following the introduction of the five-zone fare system with no transfer fees in Haifa, Israel, Sharaby [2] found an 18.6% increase in the number of passengers switching from the private car system to the public transport system, demonstrating that fare optimisation provides better route choices for passengers. Kamel [3] proposed...
a time-based system fare strategy based on factors such as passenger travel choice patterns and departure times, and tested in Toronto, Canada. Results showed that time-based fare strategy spreads traffic demand to the shoulder of peak period and alleviates congestion during peak period. Yook [4] developed a distance-based bi-level programming fare model and used the Utah transit system as an example for experiments, proving that the model can effectively increase the demand for public transport and make the travel structure more rational. Borndörfer [5] argued that fares for public transport should not be based solely on the welfare maximisation perspective, developed a cost-constrained cooperative game model and applied it to the Dutch transport network. The reliability of the model is demonstrated. Zhang [6] compared and analysed a generalised cost minimum model and a bi-level programming model based on a generalised cost function in terms of multiple generalised utility values, and the study results showed the latter was superior in terms of both iterative results and efficiency. Liu [7] constructed a bi-level programming model based on the minimum travel time of an urban passenger transport system and confirmed that a reduction in urban rail transit fares would result in a reduction in the total generalised travel cost for passengers.

From the above literatures, it can be seen that all the public transport systems in different countries have the same characteristics, are time-varying and restricted by multiple factors. Neither maximisation of passenger welfare nor minimisation of travel distance alone can reasonably alleviate congestion during peak periods. Therefore, pricing strategies and models need to be systematically optimised. By combining time differential pricing strategies and models, a bi-level programming model can be built to better achieve multi-objective optimal decision making. The upper level model carries out profit maximisation of an operating company as the main objective, whereas the lower level model does minimisation of generalised cost of passenger travel as the main objective. The optimal value of fare can be solved by iteratively solving fare through mutual constraints relationship between the upper level and low level models. It is worth noting that for urban rail transport, the same line would present different passenger utilisation rates as city function changes over time. Generally, passenger utilisation rates of different lines represent a dynamic change. Unfortunately, the current pricing model is not flexible enough to cope with this problem.

From the viewpoint of algorithmic solution, Cheraghalipour [8] utilises and compares two kinds of traditional heuristic algorithms–genetic algorithm (GA) and particle swarm optimisation algorithm (PSO), as well as two hybrid algorithms (PSO-GA and GA-PSO) and a modified algorithm (GPA) to solve bi-level programming model respectively. Results showed that the GPA has a good performance among them. Mostafa [9] proposes a fast heuristic algorithm and two hybrid meta-heuristic algorithms. Although the former converges faster, the optimal solution performance of the latter is significantly higher in a comprehensive comparison. Liu [10] established a bi-level programming model based on elastic demand by using a simulated annealing algorithm for the upper level and the method of successive average (MSA) for lower level to solve them separately. The model solution achieved convergence in less than ten instances. Tafti [11] designed a bi-level congestion pricing problem and solved it using both the PSO and the GA. The final iterative results were the same, but the computation time of the PSO was 45% shorter than that of the GA, and the overall performance was better. Hao [12] applies a dynamic inertia factor to the particle swarm optimisation algorithm with a range of update rates. The merit is that it avoids slow iterations due to initial particles being too dispersed, and updates towards optimal solution and reaches convergence quickly to improve iteration efficiency. Generally, the particle swarm optimisation algorithm has a certain stability and accuracy to solve the bi-level programming model. PSO is applicable to a wide range of scenarios.

To our knowledge, there are as of yet no publications on time differential pricing models for urban rail transit based on passenger exchange coefficients for different time periods and route. In this paper, we will consider the impact of the passenger exchange coefficient on fare pricing from the perspective of urban rail transit and construct a bi-level programming model for urban rail transit from peak and off-peak hours, respectively. The upper level model serves as profit maximisation of an urban rail transit operating company, while the lower level model aims at generalised cost minimisation of passengers. Both passenger exchange coefficient
Passenger exchange coefficient

Fares

Operating costs

Government
macro-control

Minimise
generalized
cost

Operating companies

Profit of urban rail transit

Figure 1 – Outline of the bi-level programming model considering passenger exchange coefficient

Figure 1 – Outline of the bi-level programming model considering passenger exchange coefficient

and fare adjustment coefficient are fed to models for governing fares. The outline of the model is shown in Figure 1.

2. METHODOLOGY

2.1 Generalised cost model with passenger exchange coefficient

In an urban rail transit network, key stations with larger passenger exchange volume, relative long-stay of train, high passenger loads and variation costs, which have great impact on the departure interval, train punctuality and operation, make constraints on the whole line. Passenger exchange volume is commonly measured by a passenger exchange coefficient which indicates the degree of passenger utilisation of trains within a certain transport interval [13]. It is assumed that the passenger exchange coefficient is characterised by the passenger exchange coefficient, which can be expressed as Equation 1

\[ \eta = \frac{Q_i}{Q_{\text{max}} + \sum_{i=1}^{n} \min(a_i, b_i)} \]

where \( Q \) denotes total number of boarding passengers along the line, \( \min(a_i, b_i) \) indicates the smaller value between the numbers of boarding passengers and alighting passengers at station \( i \) of the \( n \) stations, where \( a_i \) is the number of boarding passengers at a station and \( b_i \) is the number of alighting passengers at the same station. Change the form of Equation 1 into Equation 2

\[ \eta = \frac{\sum_{i=1}^{n} a_i}{\sum_{i=1}^{n} b_i} \]

where \( k \) indicates the station where the numbers of boarding and alighting passengers become equal (assuming more there are more boarding than alighting passengers at each station before the point \( k \) and more alighting than boarding passengers at each station after the point \( k \)), \( Q_{\text{max}} \) denotes the maximum cross-sectional passenger flow. For solving parameter of the passenger exchange coefficient \( \eta \), we need three variables, namely, flow imbalance coefficient \( \eta_f \) average distance \( L_a \) [14] and passenger turnover volume \( Q \), which are expressed as Equation 3–5, respectively.

\[ \eta_f = \frac{Q_{\text{max}}}{Q_a} \]

\[ L_a = \sum_{i=1}^{n} l_i \cdot q_i \]

\[ Q = \sum_{i=1}^{n} b_i \cdot q_i \]

In Equation 3, \( Q_a \) denotes the average cross-sectional passenger flow. In Equation 4 and 5, \( l_i \) indicates the distance of the \( i \)th station interval in a line and \( q_i \) is the cross-sectional passenger flow of the \( i \)th station interval in a line. By substituting Equation 3–5 into Equation 2, the relationship among \( \eta, \eta_f \) and \( L_a \) can be described as Equation 6

\[ \eta = \frac{L}{\eta_f \cdot L_a} \]

where \( L \) indicates the total length of a route. Passenger exchange coefficient is an indicator to evaluate frequency utilised by passengers in a line at a certain period. The generalised cost function of the passenger exchange coefficient \( \eta \), to the lower level model for those current time differential pricing model studies. In this paper, we integrate passenger exchange coefficient \( \eta_f \) to the lower level model for increasing sensitivity of fare model to different lines in terms of passenger flow. To do this, the model has the ability to generate different fares accordingly by
recognising the differences in passenger exchange. The lower level model proposed in this paper is expressed as follows:

\[
\min Z(Q) = \sum_{k \in \mathcal{K}} \sum_{i \in \mathcal{I}} \phi_i \left[ \left( Q_i \right)^{\alpha_1} - \left( \alpha_1 v_i + \alpha_2 s_i + \alpha_3 m_i + \alpha_4 t_i \right) \right] dQ_i
\]

\[\sum_{k \in \mathcal{K}} \sum_{i \in \mathcal{I}} Q_i = Q \geq 0 \quad \text{s.t.} \quad e_m = \left[ \frac{\eta_i}{\eta_i} \right] \quad m \in k \]

where the generalised cost function takes form of a power function \( f(Q_i) = a(Q_i)^\delta - V_k \). The parameter \( V_k \) denotes generalised utility of the \( k \)-th mode of transportation at time period \( i \), and which includes \( P_{k}^{i} \) (economy, simplified for fares), \( S_{k}^{i} \) (quickness), \( M_{k}^{i} \) (comfort), \( T_{k}^{i} \) (punctuality). The parameter \( e_m \) describes the exchange cost coefficient which indicates the ratio of the passenger exchange coefficient \( \eta_i \) of a line to the average value of the passenger exchange coefficient \( \hat{\eta}_i \) in a time period \( i \). Parameter \( e_m \) is used to evaluate the relationship between the degree of passenger exchange of a line and the average level of the same time period. The exchange cost coefficient is set to 1 for all transportation modes except urban rail transit.

### 2.2 Time differential pricing model for peak hours

The main objectives are to control passenger interaction behaviour at stations and reduce the overload rate during peak hours when passenger flow is high. The upper level model in the bi-level programming model aims at realising the interests of urban rail transit operator while taking into account certain social welfare. From the perspective of the publicity of urban rail transit, fares are limited under the guidance of the government. The lower level model serves as a generalised cost minimisation model which integrates passenger exchange coefficients. The time differential pricing model for peak hours is expressed as Equation 9–11.

\[\max E^v(P,Q) = \sum_{i \in \mathcal{I}} \left( \delta e_m P_i^{v} - C_i \right) \]

\[\min Z(Q) = \sum_{k \in \mathcal{K}} \sum_{i \in \mathcal{I}} \phi_i \left[ \left( Q_i \right)^{\alpha_1} - \left( \alpha_1 v_i + \alpha_2 s_i + \alpha_3 m_i + \alpha_4 t_i \right) \right] dQ_i \]

\[1 \leq \delta e_m \leq \delta_{\text{max}} \]

\[\sum_{k \in \mathcal{K}} \sum_{i \in \mathcal{I}} Q_i = Q \geq 0 \quad \text{s.t.} \quad e_m = \left[ \frac{\eta_i}{\hat{\eta}_i} \right] \quad m \in k \]

In the constraints, \( \delta \) is the fare adjustment coefficient. The increase of \( \delta \) during peak hours should not be higher than the limit \( \delta_{\text{max}} \) set by the government. The exchange cost coefficient \( e_m \) is integrated during peak hours only for lines with the passenger exchange coefficient higher than the average. The parameters \( P_{k}^{i} \), \( C_{k}^{i} \) and \( Q_{k}^{i} \) indicate fare, operating cost per capita and passenger flow of urban rail transit in the \( i \)-th time period, respectively. Other parameters are explained in the previous sections.

### 2.3 Time differential pricing model for off-peak hours

During off-peak hours, passenger volume keeps a low status and the full load rate is also not high. The main goal of the urban rail transit operator is to attract passenger flow and improve income. We build the upper level model for maximising company benefits and the lower level model for minimising passengers' generalised costs to establish a bi-level programming model. They are described as follows:

\[\max E^v(P,Q) = \sum_{i \in \mathcal{I}} \left( \delta e_m P_i^{v} - C_i \right) Q_i \]

\[\min Z(Q) = \sum_{k \in \mathcal{K}} \sum_{i \in \mathcal{I}} \phi_i \left[ \left( Q_i \right)^{\alpha_1} - \left( \alpha_1 v_i + \alpha_2 s_i + \alpha_3 m_i + \alpha_4 t_i \right) \right] dQ_i \]

\[\delta_{\text{min}} \leq \delta e_m \leq 1 \quad \text{s.t.} \quad e_m = \left[ \frac{\eta_i}{\hat{\eta}_i} \right] \quad m \in k \]

Parameters in the model are defined as mentioned above and downward adjustment of \( \delta \) during the off-peak hours should not be lower than the lower limit \( \delta_{\text{min}} \) set by the government. The exchange cost coefficient \( e_m \) is added during off-peak hours only for lines with the passenger exchange coefficient lower than the average.
2.4 Algorithm design

In this paper, we take the particle swarm optimisation (PSO) algorithm based on dynamic inertia factor $\omega$ to solve our pricing model for urban rail transit. The flowchart of the PSO algorithm is described in Figure 2. The description of the algorithm is as follows:

Step 1: Initialisation. Initialising each parameter in the PSO algorithm, setting population size, generating particle population with fare adjustment coefficient $\delta$ as the upper level model variable (initialise the position $X_i^t$ and velocity $V_i^t$ of each particle within the constraints), recording the current position of the particle, the optimal position of population $g_{best}$ and corresponding fitness function value of each particle.

Step 2: Calculating the lower level model. Particle position $X_i^t$ is brought to the lower level for computing, and passenger flow $Y_i^t$ of different traffic modes at different periods is obtained as the optimal solution of the lower level model.

Step 3: Obtaining fitness function value and updating it. The parameters $X_i^t$, $Y_i^t$ are fed to the upper level model to calculate the fitness function value and compare it with the previous fitness function value, update particle optimal position $p_{best}$ and population optimal position $g_{best}$, and update inertia factor $\omega$. The update rule for $\omega$ is: $\omega'(t)=(\omega_{max}-\omega_{min})(T-t)/T+\omega_{min}$. $\omega'$ is the inertia factor of the $t$th iteration, $T$ is the maximum number of iterations and $t$ is the current number of iterations.

Step 4: Determining whether the convergence conditions are met. If requirements are met, then move to Step 5; if not, then move to Step 2.

Step 5: Optimal solution interference. The interference is calculated for the population optimal position $g_{best}$ and it is judged whether the corresponding fitness function value needs to be updated. If it needs to be updated, go to Step 3. If it does not require to be updated, go to Step 6.

Step 6: Output the optimal solution and the corresponding objective function value to end the algorithm.

Figure 2 – Flowchart of improved particle swarm optimisation algorithm
3. ANALYSIS

The data used in the case study include data borrowed from the Beijing Transportation Development Annual Report 2020 [15] and data collected from our social survey and investigation means.

3.1 Case design

In 2019, passengers from both urban rail transit and conventional bus exceed 6 million in the metropolitan public transport. The rate is roughly 1:1. Here we just consider two public transports – urban rail transit and conventional bus. As shown in Figure 3, it is assumed that the peak hours are 7:00–9:00 a.m. and 5:00-7:00 p.m., and the rest of the hours are assumed as off-peak hours. The peak traffic volume of urban rail transit (including morning peak and evening peak) accounts for about 78.6% of the whole day traffic volume. Therefore, conventional bus accounts for 62.8%. The total number of passenger trips during peak hours is about 862,000, and the total number of passenger trips during off-peak hours is about 359,000 (all data are calculated on weekdays).

The survey utility value indicators, referring to the methodology of the literature [16], are calculated in conjunction with the current state of the market and summarised in Table 1.

The lower limit of the discount rate and the upper limit of the price increasing rate for urban rail transit are set to 0.5 and 1.5, respectively. For determination of parameters of the generalised cost function, a and b equal 1 and 0.25, respectively, in combination with the fitting results of previous data. The weight coefficients of utility values are determined by using the hierarchical analysis method AHP as shown in Table 2. The research individuals of the model are single lines in different time periods. Line 2 and Line 8 are selected as the objects of analysis in this case study and their initial values are shown in Table 3. After calculation, the average value of passenger flow exchange coefficient $\tau^i$ of Line 2 and Line 8 equals 2.18. Assuming that the passenger flow exchange coefficient of the same line is equal to peak hours during off-peak hours. Combined with the Annual Statistics and Analysis Report of Urban Rail Transit 2019 [17], the discounted operation cost per capita is nearly $1.

![Figure 3 – The proportion of peak hours of each travel mode in the whole day in the central urban area](image)

Table 1 – Index of generalized utility value

<table>
<thead>
<tr>
<th>Transportation mode</th>
<th>Time period</th>
<th>Average fares ($)</th>
<th>Quickness $S^i_k$</th>
<th>Comfort $M^i_k$</th>
<th>Punctuality $T^i_k$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rail transit</td>
<td>Peak hours</td>
<td>0.75</td>
<td>24.64</td>
<td>11.53</td>
<td>0.77</td>
</tr>
<tr>
<td></td>
<td>Off-peak hours</td>
<td>0.75</td>
<td>15.36</td>
<td>8.05</td>
<td>0</td>
</tr>
<tr>
<td>Conventional bus</td>
<td>Peak hours</td>
<td>0.28</td>
<td>15.71</td>
<td>10.43</td>
<td>1.99</td>
</tr>
<tr>
<td></td>
<td>Off-peak hours</td>
<td>0.28</td>
<td>9.60</td>
<td>6.06</td>
<td>0.68</td>
</tr>
</tbody>
</table>
Figures 4 and 5 illustrate iterations of peak hours and off-peak hours, respectively. As seen in Figures 4 and 5, business profits reach peak value and keep stability at the duration of 20 and 30 iterations. From Table 4, it can be seen that the passenger flow of Line 2 and Line 8 during peak hours decreases by 9.94% and 19.48%, respectively, conventional bus increases by 10.56%. During off-peak hours, passenger flow of Line 2 and Line 8 increased by 32.23% and 44.96%, conventional bus decreased by 9.19%. Table 5 shows fare of Line 2 and Line 8 increase by $0.32 and $0.09 during peak hours and decrease by $0.11 and $0.16 during off-peak hours. The results show that time differential pricing model integrated with passenger exchange coefficients can effectively differentiate Line 2 and Line 8, allowing them to take different fares depending on the different level of passenger exchange volume during peak hours and off-peak hours. Time differential pricing strategy guides passengers to arrange their travel mode and travel time rationally. This effectively diverts passenger flow to reduce traffic load in peak hours and increase traffic volume in off-peak hours.

3.2 Result

The two models are programmed separately using the MATLAB software. The initial parameters of the particle swarm algorithm are set (e.g. population size is 20, iterations are 50, $c_1=2$, $c_2=2$, $r_1=0.6$, $r_2=0.3$, $\omega_{\text{max}}=0.9$, $\omega_{\text{min}}=0.3$). After iterative calculations by the improved particle swarm optimisation algorithm, the change in passenger flow for urban rail transit and conventional bus after the implementation of time differential pricing can be obtained, as shown in Table 4.

The fare adjustment coefficients $\delta$ and fare variation for urban rail transit are calculated as shown in Table 5.

### Table 2 – Weight coefficients of each utility value index

<table>
<thead>
<tr>
<th>Service indicators</th>
<th>Fares</th>
<th>Quickness</th>
<th>Comfort</th>
<th>Punctuality</th>
</tr>
</thead>
<tbody>
<tr>
<td>Peak hours</td>
<td>-21.09%</td>
<td>-8.13%</td>
<td>-13.29%</td>
<td>-57.50%</td>
</tr>
<tr>
<td>Off-peak hours</td>
<td>-28.65%</td>
<td>-8.96%</td>
<td>-22.08%</td>
<td>-40.31%</td>
</tr>
</tbody>
</table>

### Table 3 – Initial operation data of Line 2 and Line 8 of Beijing rail transit network

<table>
<thead>
<tr>
<th>Line</th>
<th>Average daily passenger flow (10,000 passengers)</th>
<th>Peak hours’ passenger flow (10,000 passengers)</th>
<th>Daily average distance [km]</th>
<th>Operating distance [km]</th>
<th>Peak hours’ passenger flow exchange coefficient $n_x^i$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Line 2</td>
<td>98.6</td>
<td>77.5</td>
<td>5.07</td>
<td>23</td>
<td>2.78</td>
</tr>
<tr>
<td>Line 8</td>
<td>44.42</td>
<td>34.9</td>
<td>9.30</td>
<td>31</td>
<td>2.00</td>
</tr>
</tbody>
</table>

### Table 4 – Public transport passenger flow after the implementation of time differential pricing

<table>
<thead>
<tr>
<th>Transportation mode</th>
<th>Time period</th>
<th>Passenger flow (10,000 passengers)</th>
<th>Passenger flow change rate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Line 2</td>
<td>Peak hours</td>
<td>69.8</td>
<td>-9.94</td>
</tr>
<tr>
<td></td>
<td>Off-peak hours</td>
<td>27.9</td>
<td>+32.23</td>
</tr>
<tr>
<td>Line 8</td>
<td>Peak hours</td>
<td>28.1</td>
<td>-19.48</td>
</tr>
<tr>
<td></td>
<td>Off-peak hours</td>
<td>13.8</td>
<td>+44.96</td>
</tr>
<tr>
<td>Conventional bus</td>
<td>Peak hours</td>
<td>95.3</td>
<td>+10.56</td>
</tr>
<tr>
<td></td>
<td>Off-peak hours</td>
<td>32.6</td>
<td>-9.19</td>
</tr>
</tbody>
</table>

### Table 5 – Adjustment coefficient $\delta$ of urban rail transit ticket price in each time period

<table>
<thead>
<tr>
<th>Time period</th>
<th>Fare adjustment coefficient $\delta$</th>
<th>Fare changes on Line 2 ($)</th>
<th>Fare changes on Line 8 ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Peak hours</td>
<td>1.12</td>
<td>+0.32</td>
<td>+0.09</td>
</tr>
<tr>
<td>off-peak hours</td>
<td>0.86</td>
<td>-0.11</td>
<td>-0.16</td>
</tr>
</tbody>
</table>
of passenger flow between peak and off-peak hours of urban rail transit has decreased a lot. In the case of this paper, the ratio changes from 3.67 to 2.35, a decrease of 1.32, while in the case of literature [16], the ratio changes from 2.37 to 1.55, a decrease of 0.82. It can be seen that the model proposed in this paper is more effective in solving the overcrowded problem during the peak hours, resulting in a more rational passenger travel structure. Meanwhile, with the addition of the passenger exchange coefficient, which is the biggest innovation of this paper, the model can set different fares according to the difference in passenger flow of the rail lines, so that time differential pricing can be achieved specifically for each rail line. The advantage of this is that both lines in core areas and lines in remote areas can generate more appropriate fares according to their characteristics. It achieves a balanced transportation system by shifting passenger flow to reduce full capacity during peak hours and attracting passenger flow to improve utilisation during off-peak hours. The limitation of the model is that the competition with other transportation modes in the region is not considered. Sensitivity analysis should be added to the values of some parameters in the next research to further verify the rationality.

Compared with the literature [16], the model proposed in this paper focuses more on the comparison between urban rail transit lines and divides the fare based on the passenger flow level of lines themselves, which improves the sensitivity of the model while forming a self-restraint. We know that passengers can be divided into elastic travellers and inelastic travellers based on their travel characteristics. Elastic travellers are those who can flexibly adjust their travel plans, such as tourists. The majority of inelastic travellers are workers and students.

### 3.3 Analysis

Here we compare this our findings with the existing literature [16]. Based on the passenger flow characteristics of peak hours and off-peak hours, two bi-level programming models that aim at time differential pricing are developed in literature [16]. In the lower level model, the generalised cost function is also used in literature [16] considering different service indicators. Due to the differences between these two cases, it is not possible to directly compare the results of our paper with [16]. However, we can compare the results by introducing a method to represent the ability between models indirectly.

We know that the larger the ratio of the passenger flow of peak hours and off-peak hours is, the more irrational the structure of passenger travel becomes. Figure 6 clearly shows that after the calculation of the time differential pricing model proposed in this paper, the ratio (slope of the straight line in Figure 6)
Through reading literatures and surveys, we found that if the price model is implemented, the majority of the population being shifted are the elastic travellers (they adjust their travel plans for a better price). In other words, inelastic travellers can trade a certain fare cost for better comfort during peak hours, but the total generalised cost is still optimal. Essentially, people always tend to travel with the lowest generalised cost. We know that transport systems are complex and that public transport pricing should take safety, social welfare, regional coordination and economy of the passengers into account. The model proposed in this paper still has some shortcomings in treating these aspects.

4. CONCLUSION

Compared with other time differential pricing models, the proposed model in this paper integrates passenger exchange coefficient into time differential pricing model, constructing a bi-level programming model for peak and off-peak hours, solving the models with an improved particle swarm optimisation algorithm. The simulation results conclude that the proposed model effectively distinguishes the degree of passenger exchange in different lines of urban rail transit network at different durations and improves flexibility of fares adjustment with time-variation. Thus, fares adjustment relying on this model are in accordance with real passenger flow characteristics.

Due to limited data, only a few lines are selected and assumptions are made on the passenger exchange coefficients during off-peak hours. The subsequent study will expand the sampling area and sample size, refine and enrich the generalised utility of passenger trips, delineate time periods in more detail and further investigate the changing patterns of rail transit more systematically.

ACKNOWLEDGEMENT

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