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The Impact of Bus Priority Policies on Peak Commuters Behavior: An Agent-Based Modelling Perspective

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Abstract. By using micro-simulation method and the BushCMosteller reinforcement learning model, this paper modeled the behavior of urban commuters departure time choice on a many-to-one transit system during the morning peak-period. Three kinds of typical urban public transport priority policies were studied. Result shows that if we can choose the right time for free public transportation, the pre-peak-free policy will have certain effects on staggering the commuting peak by influencing commuters decision-making on departure-time. As for the bus-accelerating policy, it can lower commuters cost, but it is likely to cause more congested volume and add more pressure on the public transit system. The departure-frequency increasing policy can partially alleviate the peak congestion problem, but cannot fundamentally eliminate the congestion, instead, it may increase the operating costs. This research is helpful in acquiring a better understanding of commuters departure time choice and commuting equilibrium during the peak-period. The research approaches also provide an effective way to explore the formation and evolution of complicated traffic phenomena.

1. Background

With the acceleration of urbanization and the rapid development of the national economy, the bottleneck effect of urban transportation on its economic development has drawn more and more public attention. As an important urban infrastructure, public transportation is a principal body to meet urban residents daily travel demand. Compared with private transportation, urban public transportation has obvious development advantages such as: high transportation capacity and efficiency; economical traffic resources; low energy consumption; low transportation costs and less automobile exhaust pollution.

The major problem faced by urban public transportation (represents by buses) is the traffic congestion during the morning peak-period. If the departure-time distribution of bus commuters centralized in one specific period, it will have a negative impact on the normal operation of public transportation and commuters traveling comfort. Thus, it will further weakened peoples willingness of traveling by bus, consequently the social utility caused by ”bus priority policy” will be reduced. Therefore, the studies into the factors influencing peoples travel choice behavior is conducive to improving the implementation of the bus priority policy and also provide an important reference for people to travel around.

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Commuters departure time has become a focal point in the study of traffic demand management. Thus the research on commuters departure time choices during morning peak-period will be very helpful to alleviate urban traffic congestion problems through providing an important reference for traffic management measures such as the congestion charging policy and staggering different working hours.

Vickrey (1955) firstly studied the commuters departure time choices. In his model, a road with limited capacity connects residential locations and workplaces; commuters drive daily from their home to work and minimize commuting costs by departing at a proper time. Commuting costs include the costs of travel time, delay penalty costs and queuing time. All commuters costs are equal when equilibrium is reached. This model is called the bottleneck model which has been extensively studied by Daganzo (1985) and Arnott et al. (1993). After the 1990s, researchers studied the departure time choice of commuters who utilize mass transit in peak hours experiencing an increasing process. Sumi et al. (1990) proposed an optimization model of commuters departure time and route choice in mass transit systems, in which a commuters departure time is mainly determined by his or her scheduled arrival and the operational features of the system. Alfa and Chen (1995) designed an algorithm studied on the commuters morning departure time decisions. Commuters expected waiting time is regarded as the congestion cost in their model. However, due to the complex calculation process, this algorithm failed to provide the final analytical results of the model. Huang et al. (2004, 2005) used a Discomfort function to make an analysis on commuters dynamic travel behaviors on public transportation. Their model considered commuters congestion costs as an increasing function of travel time and in-vehicle population and this study has been conducted to investigate the decision-making process of commuters during peak-periods. Tian et al. (2007) analyzed the equilibrium properties of a variant of the bus-corridor problem; within their model the traffic congestion presents a feature that the increase of congestion costs with a growing number of passengers on board will not stop till an equilibrium property is reached and their numerical results are in agreement with Arnott et al. (1993).

Based on computational experiments approaches, this thesis explores the impact of "bus-priority" policy on commuters departure-time choices. This experiment is conducted with reinforcement learning model, in which a bus line with multiple origins and a single destination is designed so as to investigate the decision-making process of commuters departure-time. By introducing bus fare, in-vehicle travel time, crowding costs, and early/ late arrival penalty we stimulate three different policy environments, under which bus commuters departure-time choice behaviors were investigated.

2. Methods

2.1. Situation design

As shown in figure 1, there is a bus line with multiple origins and a single destination. Buses set out from the furthest residential location,H_1, stop by at $H_2, \cdots, H_(k-1), H_k$, and finally stop at workplace W. Given $N_1, N_2, \cdots, N_k$ commuters take the bus line form stations $H_2, \cdots, H_(k-1), H_k$ to workplace in the morning peak period. Considering a daily commuting situation, we assumed that commuters have full information of the bus timetable. Thus, the waiting time at a station is assumed to be zero for simplicity. Supposing that the buses speed is constant, constants $\tau_1, \tau_2, \cdots, \tau_k$ are utilized to indicate the moving time in each segment form H_1 to W .

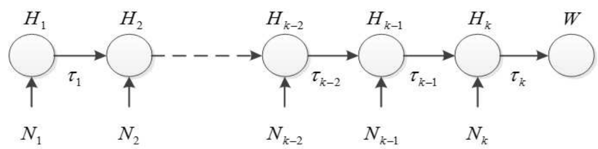

Figure 1: The bus line with multiple origins and a single destination

The total commuting cost of a commuter at station H_i selecting bus j is provided by TC_j^i , which contains bus fare, in-vehicle travel time, total crowding cost, and early/late arrival penalty. In the experiment, according to the different research point of view, major factors affecting total costs and the form of TC^i_j will remain in diversity.

In the experiment, all the commuters knowledge of departure time choice will be constantly updated through their work on the reinforcement learning mechanism. Hence, commuters would like to minimize their individual commuting costs by selecting different departure-times. During the course of learning and selecting, departure time-table as a complete information is conducted openly with non-cooperative game rules to all commuters. After a long-term learning process, a state of User-Equilibrium will be achieved within the whole experimental system. At equilibrium, the total commuting costs of commuters departing from the same station are identical, and no one experiences lower individual cost by unilaterally changing his/her departure time. Mathematically, this condition can be expressed as follows:

$$\begin{cases} TC^i_j = TC^i, n^i_j > 0 \\ TC^i_j \geq TC^i, n^i_j = 0 \end{cases} \tag{1}$$

Where n^i_j is the number of commuters from station H_i taking bus j and TC^i_j is the equilibrium commuting cost from station H_i. This equation indicates that if some commuters who utilized bus j depart from H_i , then their individual commuting cost is equal to the equilibrium commuting cost; otherwise, the commuting cost by bus j is not less than the equilibrium cost.

2.2. *Commuters reinforcement learning mechanism*

In this research, the commuters basic behavior pattern is to take the bus at a proper time to workplace every simulation period (day). After a simulation period, commuters update their knowledge of departure time by reinforcement learning; through countless repetition of the simulation process, ultimately achieve the goal of learning. Bush-Mosteller (BM) model was adopted in commuters learning process. BM model is a classical reinforcement learning model, which has been widely used in various research fields (Wynne 1995; Macy and Flache 2002; Zhou et al. 2012).

The standard BM model includes a learning algorithm and stochastic decision rules. Supposing that the BM model was applied to this research, the potential strategy set for commuters is the collection of all the bus shifts in the morning peak period. Each bus represents an option of strategy (departure time); each strategy corresponds to a certain probability. Hence, the strategy set as a whole corresponds to a probability vector, which presents commuters learning outcomes of the BM model as well as their knowledge of departure time. This probability vector also indicates commuters preference for departure choice and commuters action strategy within one simulation period is determined by stochastic decision rules. Figure 2 shows the learning process of the commuter:

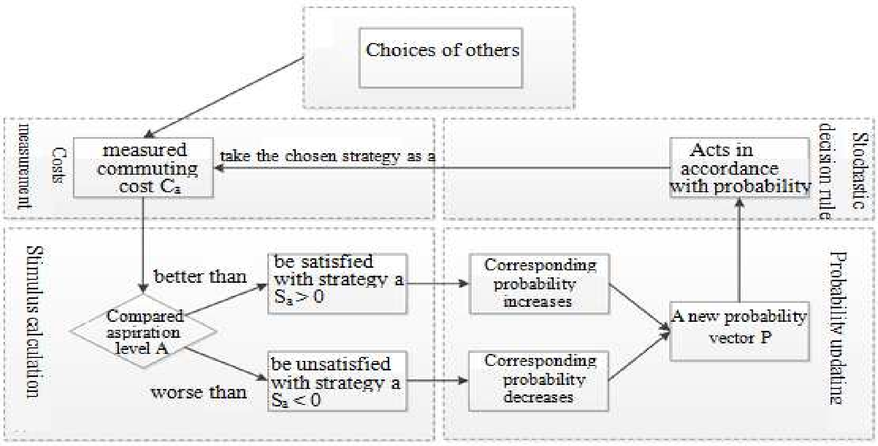

Figure 2: commuters learning process

In Figure 2, the "external environment" mainly refers to other commuters departure time choices. While the cost measurement is relevant to the simulation environment; generally speaking, commuters costs consist of travel time, early/late arrival penalty, crowding cost and currency expenses etc. Commuters self-selection and other commuters decisions co-determine his or her commuting cost in one simulation period. In figure 2, the BM reinforcement learning model consists of three core components including stimulus calculation, stochastic decision rules and probability updating.

The key of the BM reinforcement learning is the process of stimulus calculationŀła measurement of a commuters travel stimulation. If the calculating result s_a is greater than 0, which indicates that commuters are satisfied with the decision-making (a positive stimulus); otherwise, it may indicates that commuters are not satisfied with the decisions (a negative stimulus). The direction of reinforcement learning could be distinguished to be rewards or punishments according to the sign of s_a, while the learning intensity is determined by absolute value of s_a. Thus the calculation of stimulus s_a is the most important factor that affects the learning efficiency of the BM model, which is expressed as:

$$s_a = \frac{A - c_a}{max[|A - c_{min}|, |A - c_{min}|]} \tag{2}$$

Where

c_a — the average commuting cost of decision

A —the commuters aspiration level

c_{max}— the highest commuting cost perceived

c_{min}— the lowest commuting cost perceived

What presented by this formula is that commuters aspiration level A provides a reference point to the calculating process when commuting costs exceed commuters expectations. A positive s_a indicates commuters positive attitude towards his or her decision; otherwise, a negative attitude would be provided. In this thesis, commuters aspiration level A equals to his/her historical average commuting cost. c_{max} and c_{min} refer to the highest and lowest commuting cost perceived respectively, including the current turn. The denominator in Equation (2) represents the supremum of the absolute value of the difference between any cost the commuter ever perceived and his/her aspiration. With this scaling factor, the absolute value of s_a is ensured to be not more than unity, which provides a standardized stimulus to the probability updating process. As a result, it will benefit the calculating process, at the meantime, the differences in c_{max} and c_{min} among each commuter also embodied the idea of distributed self-learning to the fullest extent.

The "probability updating" stage is the core of BM reinforcement learningŀłit transforms the commuters travel stimulus into his/her travel experience. There are too rounds of updating exist in this phase; the first is to update the corresponding probability of the current turn and then update the others in an appropriate way in order to make the probability equals to unity in total. After the utilization of strategy a in one commuting process, its corresponding probability updating rules is presented in below:

$$p_{a,t+1} = \begin{cases} p_{a,t+1} + (1 - P_{a,t})\imath s_{a,t} & s_{a,t} \geq 0 \\ p_{a,t} + p_{a,t}\imath s_{a,t} & s_{a,t} < 0 \\ a \in T & \end{cases} \tag{3}$$

Where $P_{a,t}$ represents the probability of strategy a at day t ; $\imath$ is the learning rate ($0 < \imath < 1$) showing commuters learning speed; $s_{a,t}$ is the stimulus experienced after taking strategy a at day t . Supposing that the selected strategy can bring the commuter a positive stimulus, then the growth rate of the corresponding probability that a commuter continues to choose the same departure time in his/her next commute is $\imath s_{a,t}$ times higher than that of the remaining strategies in total. Otherwise, its corresponding probability will decrease $-\imath s_{a,t}$ than the original ($s_{a,t}$ is negative).

The probabilities of other unsorted strategies are updated as follows:

$$p_{other,t+1} = \begin{cases} p_{other,t}(1 - ls_{a,t}) & s_{a,t} \geq 0 \\ p_{other,t}(1 - \frac{p_{a,t}\imath s_{a,t}}{1-p_{a,t}}) & s_{a,t} < 0 \\ other \in T \ and \ other \neq a & \end{cases} \tag{4}$$

This ensures that when the action brings commuters a satisfied result, its corresponding probability will increase accordingly. Otherwise, it may be decreased on the original basis. Thus, it is able to guarantee that the sum of all probabilities is always equal to unity. It also ensures that the probability fluctuation range of those unsorted strategies will be determined by their original probability.

In the ”stochastic decision-making” process, commuters choose their departure time according to the simplest ruleł”Acts in accordance with the probability”. It means that if the probability to choose one specific bus is P, it will not be changed when commuters continue to take on the same bus. This rule of decision-making is simple, intuitive and can also ensure the fairness among those selected strategies.

3. Results and discussion

3.1. *The influence of ”pre-peak-free” policy*

In order to alleviate traffic congestion problem in large cities, many areas have implemented a variety of policies to control urban public transportation, among which charter by time policy is a typical one proposed under the environment of public transit priority. In June 2013 Singapore implement a ”pre-peak discount” policy on subway operation system. Under this new policy, 16 major metro stations located in urban areas are free of charge before 7:45am ; form 7:45 am to 8:00am commuters can enjoy 0.5 dollars discount ($1 for about 5 RMB) form those metro stations; during the other periods passengers have to buy full price tickets. Similarly, Chengdu the capital city of Sichuan Province in China also implements a ”pre-peak free” policy on bus operation system since July, 2013. Buses are free to take in central urban areas during 5:00am to 7:00 am every day. The core of such policies is to reduce passengers off-peak commuting costs, so as to encourage commuters to travel during off-peak hours.

In order to investigate the influence of ”pre-peak free” policy, we design an experiment as follows: the way to calculate the total commuting cost of a commuter at station H_i choosing bus j is:

$$TC_j^i = p_j + C_j^i + \delta(j) \tag{5}$$

Where p_j represents the bus fare of bus j and a fixed price-system is adopted here, which indicates that the bus fare does not vary with the change of distance. Actually, this is a very common situation in the daily life. Regarding to pre-peak free policy, the usual practice is to set a critical time; citizens are free to take those buses which departure (or arrive) before this critical time and other remaining trips will be charged in full price as follows:

$$p_j = \begin{cases} 0 & j > j^* \\ p_{full} & j \leq j^* \end{cases} \tag{6}$$

j^* functions as a bounded line; passengers are can enjoy the pre-peak free policy to take those buses depart before bus j^* ; to take those buses depart later than bus j^* ,you have to pay in full price P_{full} .

C_j^i represents a commuters in-vehicle crowding cost. We utilize the crowding costs by Tian (2007) to calculate C_j^i :

$$C_j^i = \sum_{s=i}^{k} g[\sum_{m}^{s} = 1n_j^m]\tau_s \tag{7}$$

Where n_j^m is the number of commuters taking bus j from station H_m ($n_j^m \geq 0$), τ_s represents the travel time between H_s and H_{s+1} , and crowding function g(n) reflects a commuters perception of in-vehicle crowding.

When there is no one in the bus, congestion cost is 0, namely, $g(n) = 0$. $g(n)$ can be generally described by a simple linear function. $\sigma(n)$ refers to the early/late arrival penalty which is proposed by Vickrey (1955). Under his basic assumption, all commuters are willing to get to work on time. Neither late arrival nor an early one will cause a negative effect. In this paper, a calculating model similar to Vickrey (1955) is conducted, in which $[T = \xi, \cdots, 2, 1, 0, -1, -2, \cdots, -\varsigma]$ was employed as the tab set of bus services, where ζ and ς are sufficiently large to ensure that all commuters can arrive at the workplace during the peak period considered. Only one bus is assumed to arrive at workplace W on time (arrival at work-start time); this bus is denoted by 0. Thus, $j > 0$ denotes trains arriving early, and the early arrival time is $j * t$. t denotes departure intervals of the buses. $t < 0$ denotes trains arriving late, and the late arrival time is $-j * t$. $\sigma(j)$ is provided by:

$$\begin{cases} \delta(j) = \beta jt, j > 0 \\ 0, j = 0 \\ -\gamma jt, j < 0 \end{cases} \tag{8}$$

Where β and γ are both positive numbers denoting the early and late arrival penalties per unit time, respectively.

In this group of experiment, the parameters are taken as follows:$t = 0.05(h)$, $(\beta, \gamma) = (0.1, 0.3)(RMB/h)$, $\tau_1 = 0.2$, $\tau_2 = 0.2$, $\tau_3 = 0.3$,$\tau_4 = 0.1(h)$, $N_1 = 100$, $N_2 = 160$, $N_3 = 180$, $N_4 = 100(persons)$, $g(n) = 0.005n(RMB/h)$, $j^* = 7$, $p_{full} = 3(RMB)$; while the pre-peak free policy is not employed in the experiment of comparative group, under this condition, each bus has an identical price. The experiment results (1500 days of evolution) are presented as follows:

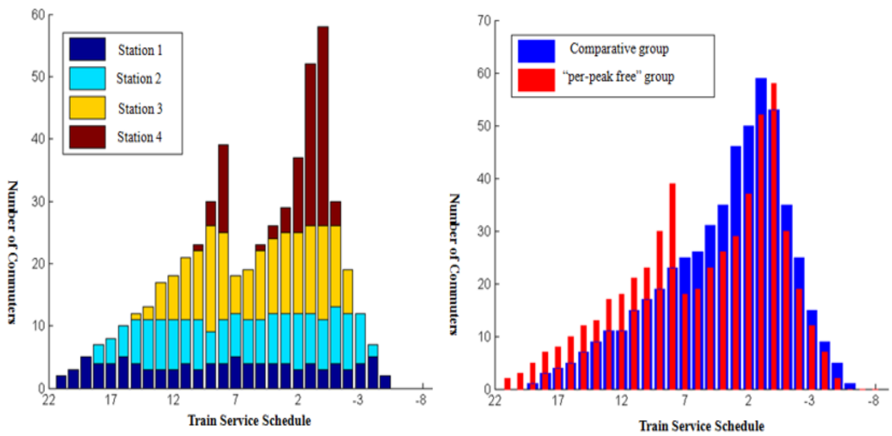

Figure 3: an simulation experiment under the per-peak free policy

The experiment shows that:

1. There is a big difference in the distribution of commuters departure time (bus choice); the experiment designed based on the "pre-peak free" policy has a double-peak feature in distribution, while only one peak can be seen form the distribution of comparative group. The first peak appears when bus $j^* + 1$departs from the bus station; bus $j^* + 1$ is the last free bus, on which commuters do not have to get up too early in the morning. The second peak appears during the rush hours (the departure time of bus 0), which is the time when the majority of commuters take their way to workplaces.

2. By observing the distribution of commuters in each station, figure 3a reflects that the pre-peak free policy has a weak influence on the departure time choice of commuters living near station 1 and station 2; On the contrary, it has a more apparent influence on the distribution of downstream commuters departure time. Compared with downstream commuters double-peak distribution, the policy equipped upstream commuters distribution with a broader range but fewer passengers for each bus. Therefore, we can see that the specific public transport environment must be taken into consideration before the pre-peak free policy is carried out.

3. Generally speaking, the ”pre-peak free” policy plays an effective role in relieving the traffic jam during peak periods (as seen in figure 3b). Compared with the verification experiment, this group of experiment has an increasing number of passengers enjoying this free-ticket policy. The number of passengers is increasing as the arrival time goes to check in. Compared with the verification experiment, there is a decreasing number of passengers on those buses remaining in full charge (except bus 0). Among them, the number of passengers on bus [7, 2] dropped considerably. So we can see that the pre-peak free policy has certain effects on staggering the commuting peak by attracting a group of commuters from the verification experiment to change their schedule and take free bus in rush hours.

3.2. The influence of ”bus-accelerating” policy

Except for the ”pre-peak free” policy, a variety of preferential policies and measurements have been conducted in many big cities across the country in order to accelerate the speed of their public transportation. Beijing became a typical example by piloting transit priority signal control system. The implementation of bus lanes was vigorously promoted in many cities in China such as: Hangzhou, Chengdu and Guangzhou etc. These measures were proposed to guarantee the rights of public transportation and accelerate its speed, under this condition, the policy of priority of public transport also became a research hotspot (Chen et al. 2006; Ge et al. 2009).

In this experiment, the total commuting cost of a commuter to take bus j from station H_i can be presented as follows:

$$TC_j^i = aT^i + C_j^i + \delta(j) \tag{9}$$

Where αT^i represents the cost of in-vehicle travel time; α represents the cost per unit time. In the comparative group (without acceleration), the parameters are taken as follows: $t = 0.05(h)$, $(\beta, \gamma) = (0.1, 0.3)(RMB/h)$, $N_4 = 100(persons)$, $\alpha = 0.1(RMB/h)$, $\tau_1 = 0.2$, $\tau_2 = 0.2$, $\tau_3 = 0.3$,$\tau_4 = 0.1(h)$, $N_1 = 100$, $N_2 = 160$, $N_3 = 180$, $g(n) = 0.005n(RMB/h)$. In the experiment group (under the bus-accelerating policy) supposing that we accelerate the speed of public transport by 50%, the time buses travel across different stations is changed into $\tau_1 = 0.13$, $\tau_2 = 0.13$, $\tau_3 = 0.2$, $\tau_4 = 0.7(h)$,the remaining parameters remain unchanged.

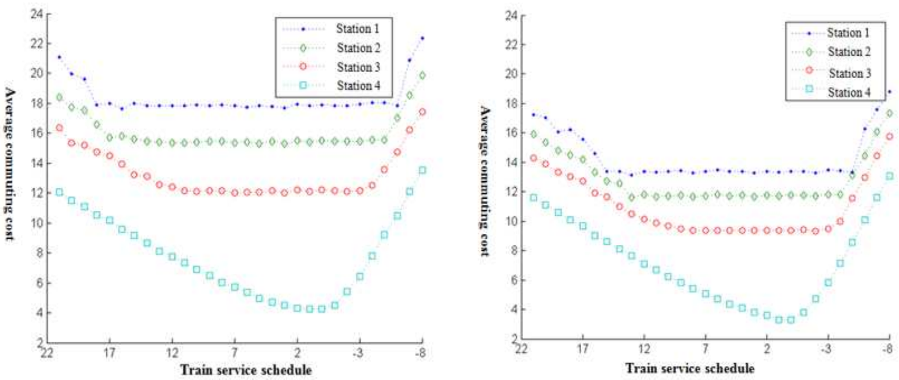

Figure 4: the average commuting cost under the bus-accelerating policy (a. the normal group; b. the bus-accelerating group)

Through experiments we can find that:

1. From passengers average commuting costs (shown in Figure 4), we can see that bus-accelerating policy has an significant impact on reducing passengers commuting costs, especially for those upstream commuters. For example, the average costs of commuters living near station 1 have been decreased by 23%.

2. As can be seen from Figure 5, the distribution of commuters departure time is more centralized under the ”bus-accelerating” policy. That is to say, from the time perspective, the traffic conjunction becomes

a more severe problem under this policy. The number of commuters on bus [7, -1] is no less than that of commuters without conducting the ”bus-accelerating” policy, while the number of commuters on the remaining buses has a slight decrease after accelerating their speed. This is not accordance with our common sense, because that we adopted the ”bus-accelerating” policy is to achieve the purpose of alleviating traffic congestion in rush hours, however, the experiment results show that under this policy, the distribution of commuters departure time is more centralized than before, thus it is more likely to cause congestion problems.

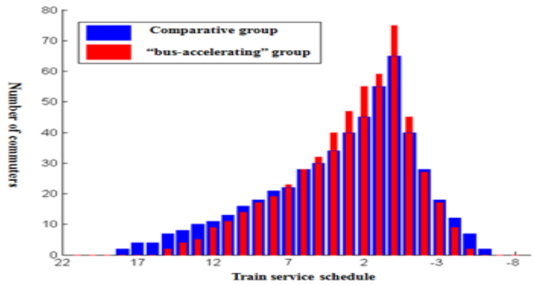

Figure 5: an simulation experiment under the bus-accelerating policy

One possible reason is that when we accelerate the bus speed, the interval travel time of each bus among different stations will be shortened and consequently, it will benefit commuters by reducing their costs of travel time. The calculation process of C_j^i , can also prove this point. Under the premise that each bus has the same passenger capacity, we can find that the shorter the interval time is, the smaller their crowding cost will be. By this way, we can reduce the impact of these two kinds of costs, so that they will have a weaker influence on the equilibrium. While the bus-accelerating policy doesnt have a directly influence on the early/late arrival penalty, as a result, commuters will be more sensitive to reducing their early/late arrivals by selecting a proper departure time, rather than feel sensitive to crowding, which leads to a more centralized distribution of commuters departure time. This phenomenon inspired us to have a new understanding on the ”bus-accelerating” policy. Undoubtedly, accelerating the speed of public transportation during the peak-period can not only save commuters travel time, but also improve their satisfaction. From a macro perspective, it also reflects the development strategy of ”public transport priority”. Regarding to the distribution of commuters departure time this policy, however, doesnt play a positive role in peak shifting and averting. On the contrary, it is likely to cause more congested volume and add more pressure on the public transit system and this is what policy-makers should truly taking into considerations.

3.3. The ”departure-frequency increasing” policy

The ”departure-frequency increasing” is also a kind of public transport priority policy which has been implemented or will be implemented in many cities. The influence of this policy on the traffic environment and peoples commuting arrangements need to be assessed carefully. In the baseline experiment:$t = 0.05(h)$, $(\beta, \gamma) = (0.1, 0.3)(RMB/h)$, $\alpha = 0.1(RMB/h)$, $\tau_1 = 0.2$, $\tau_2 = 0.2$, $\tau_3 = 0.3$, $\tau_4 = 0.1(h)$, $N_1 = 100$, $N_2 = 160$, $N_3 = 180$, $N_4 = 100(persons)$, $g(n) = 0.005n(RMB/h)$, the work time is assumed to be and learning rate . While for the experiment based on ”departure-frequency increasing” policy, we assumed that the departure frequency will be increased form to during right before bus 0 setting out. al 6 to 10 during. The remaining parameters are unchanged and the experimental results are shown as follows:

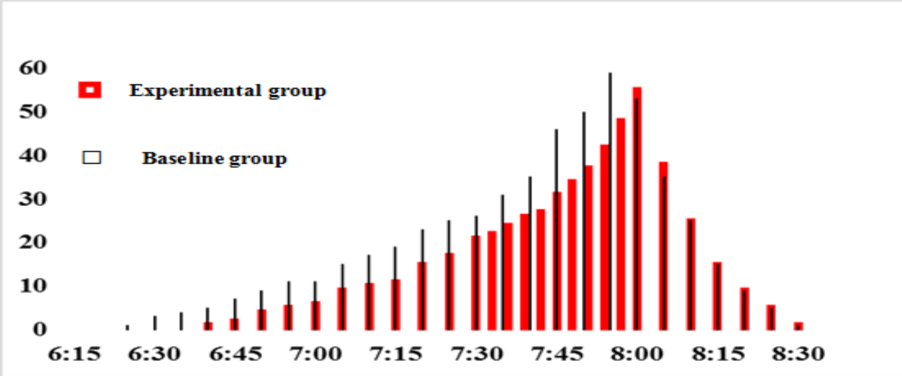

Figure 6: The distribution of bus passenger capacity

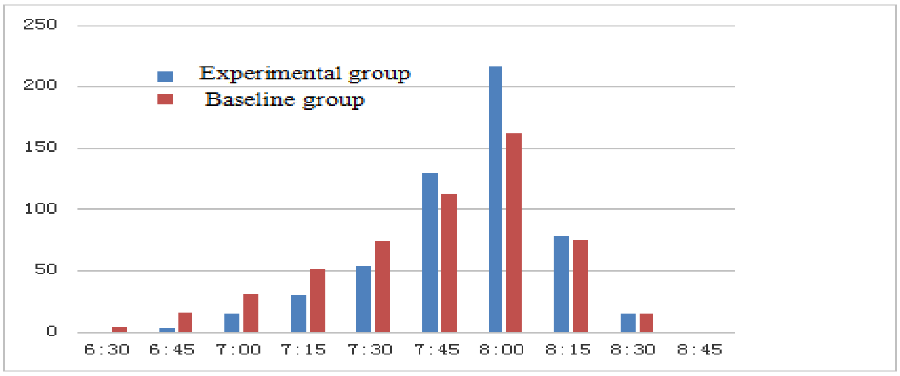

Figure 7: The distribution of bus travel volume

The results of this set of experiments indicate that:

1. From figure 6 we can find that since we have shortened the departure time interval during 7:30 to 8:00AM and improve the bus frequency, there is an oblivious decline in the number of passengers per bus during the peak-period; especially for those buses setting out before 8:00 AM, their average number of passengers per bus fell by 45.7%. Simultaneously, people change their time of departure due to our improvement of bus frequency. Namely, the earliest time of departure in the baseline group is 6:25AM, but for the experiment group it has been changed into 6:40AM and regarding to the empty buses, there are four empty ones in the baseline group, while 7 ones remain in another group.

2.Figure 7 shows the trip volumes for each half an hour. Form this figure we can find that during the period when we improve the bus departure frequency, there is a 24.7% increase of trip volumes occurred suddenly. Therefore, it is not difficult for us to conclude that the ”departure-frequency increasing” policy can improve the comfortability of taking peak-period busesłłthe bus is not so crowded as before and we improve commuters time utilityłłpeople can choose a proper departure time; we, however, should also notice that the increasing departure frequency may cause a waste of public resources. For example, there are three more empty buses in the experiment group. Therefore, before the implementation of this policy, a reasonable time span and frequency quantity both should be taken into consideration.

4. Conclusions

In the study on the impact of commuters departure time, Bush-Mostellers reinforcement learning model is used to represent commuters departure time choice equilibrium in different conditions.

Under the ”pre-peak free” policy commuters departure time choice equilibrium has a double-peak feature in distribution. The first peak appears at the last free bus and the second peak appears during the rush hours when the majority of commuters take their way to workplaces. The simulation experiment indicates that the pre-peak free policy has certain effects on staggering the commuting peak and it us conducive to reduce the pressure on public transportation in rush hours. A variety of ”bus-accelerating” policies such as setting up a public transit signal control system and bus lane planning etc. have been conducted in many cities in China. These policies, however did not play an effective role in peak shifting and averting. Though under the ”bus-accelerating” policy, commuters cost can be decreased, yet the distribution of commuters departure time is more centralized than before, which is likely to add more pressure on the public transit system. The departure-frequency increasing policy can reduce commuters crowding but we should also notice that the increasing departure frequency may cause a waste of public resources.

In conclusion, every bus priority policy has advantages and disadvantages; the implementation of these policies should be based on the specific circumstances of the public transport. At the same time, this study provides a set of pre-estimating and assessment methods for the implementation of ”public transport priority” policies. Based on this study we can have a well prediction on the influence of these policies, in order to avoid

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