

1 **EVALUATING OFF-PEAK PRICING STRATEGIES IN PUBLIC TRANSPORTATION**  
2 **USING AN ACTIVITY-BASED APPROACH**

6 **Milan Lovrić, Corresponding Author**

7 Singapore-MIT Alliance for Research and Technology (SMART)  
8 1 CREATE Way #09-02, CREATE Tower. Singapore, 138602.  
9 Tel: +65-6601-1637; Email: lovric.milan@gmail.com

11 **Sebastián Raveau**

12 Singapore-MIT Alliance for Research and Technology (SMART)  
13 1 CREATE Way #09-02, CREATE Tower. Singapore, 138602.  
14 Tel: +65-6601-1636; Email: sebastian.raveau@smart.mit.edu

16 **Muhammad Adnan**

17 Singapore-MIT Alliance for Research and Technology (SMART)  
18 1 CREATE Way #09-02, CREATE Tower. Singapore, 138602.  
19 Tel: +65-6601-1637; Email: adnan@smart.mit.edu

21 **Francisco C. Pereira**

22 Singapore-MIT Alliance for Research and Technology (SMART)  
23 1 CREATE Way #09-02, CREATE Tower. Singapore, 138602.  
24 Tel: +65-6601-1635; Email: camara@smart.mit.edu

26 **Kakali Basak**

27 Singapore-MIT Alliance for Research and Technology (SMART)  
28 1 CREATE Way #09-02, CREATE Tower. Singapore, 138602.  
29 Tel: +65-6601-1634; Email: kakali@smart.mit.edu

31 **Harish Loganathan**

32 Singapore-MIT Alliance for Research and Technology (SMART)  
33 1 CREATE Way #09-02, CREATE Tower. Singapore, 138602.  
34 Tel: +65-6601-1638; Email: harish@smart.mit.edu

36 **Moshe Ben-Akiva**

37 Massachusetts Institute of Technology  
38 77 Massachusetts Avenue, Room 1-181. Cambridge, MA 02139.  
39 Tel: +1-617-253-5324; Email: mba@mit.edu

41 Word count: 4,491 words text + 11 tables/figures x 250 words (each) = 7,241 words

48 Submission Date: August 1, 2015

## ABSTRACT

Public transportation authorities across the world are implementing various peak and off-peak pricing strategies to manage travel demand and improve the overall system performance. In this study, an activity-based demand framework is used to evaluate two off-peak pricing policies currently in use in Singapore. These policies consist of a free pre-peak travel on MRT and an off-peak discount for an integrated transit (public buses and MRT). Smart card data collected before and after the implementation of the first policy was used to calibrate the behavioral models involved, in order to properly capture travelers' preferences and choices. To evaluate both pricing strategies, a comprehensive set of key performance indicators was considered, including the changes in peak ridership, average trip fare, operator's revenue, the number of public transportation trips and mode share. The results indicate that off-peak discount pricing strategies are a viable policy option for spreading demand peaks, and that they are more effective in the afternoon peak. This study also demonstrates the capabilities and the advantages of an agent-based modeling platform SimMobility as a tool for policy analysis.

## 1 INTRODUCTION

Peak and off-peak pricing strategies are common revenue management techniques nowadays used with varying degrees of success by public transportation authorities across the world. The motivation for using such pricing strategies is an expectation they can shift travel demand away from the commuting peaks, which would result in a more balanced capacity utilization and, by reducing the peak congestion, also in an improved level of service. These pricing strategies usually take the form of peak price surcharges or off-peak discounts (free off-peak travel being the ultimate discount) (1). In addition to time-based criteria (i.e., time windows during which they apply), pricing strategies can also have location-based requirements (e.g., smart card tap-in and/or tap-out must occur within certain areas of the city or at specific stations), or they can be user-based, (i.e. tailor-made for specific passenger types such as senior citizens or students and children).

Singapore has considerable experience with (off-)peak pricing in both private and public transportation. It is the first country in the world to introduce an Electronic Road Pricing scheme for private traffic (2). Furthermore, Singapore's Land Transport Authority (LTA) has already experimented with early travel discount schemes in the Mass Rapid Transit (MRT) system. In June 2013, LTA implemented its Travel Smart initiative which provides free MRT travel to commuters who end their journey before 7:45 AM on weekdays at one of the designated stations in the Central Business District (CBD). According to LTA, "the aim of Travel Smart is to influence travel behavior change, to shift traveling commuters to off-peak periods, encourage a switch to more sustainable modes of travel such as public transportation, walking and cycling, car pooling, and car sharing, or reduce travel demand altogether" (3).

The widespread use of smart card technology for transit fare collection means that operators now have access to "big data" that can be utilized to detect changes in travel behavior, as well as to evaluate the efficacy of their pricing policies, whether implemented on a temporary or a permanent basis. However, worldwide experiences also show that it takes time before pricing strategies can have any perceptible effect on shifting peak ridership to off-peak periods (4). Nevertheless, in practice, it can be difficult to disentangle the effects of pricing strategies from the effects of other demand trends, changes in transit schedule, new infrastructure developments, etc. Furthermore, implementing new pricing strategies in practice is often a costly process of trial and error.

Meanwhile, agent-based models have achieved wide acceptance in transportation planning and policy analysis, as with increasing computational power it is now possible to run large-scale people-centric mobility simulations (5). In this line of research, SimMobility is a new simulation platform, developed at the Singapore-MIT Alliance for Research and Technology (SMART). SimMobility integrates various mobility-sensitive behavioral models within a multi-scale framework (Long-term, Mid-term and Short-term) that considers land-use, transportation and communication interactions (5). In this study, SimMobility Mid-term and its Pre-day activity-based demand models are used to evaluate two off-peak discount pricing strategies currently being deployed in Singapore public transportation: (i) Free pre-peak travel on MRT and (ii) Off-peak discount for an integrated transit (i.e. public buses and MRT).

The contribution of this paper lies in the use of an activity-based approach to evaluate different time-based, location-based and mode-based pricing strategies for travel demand management in public transportation. With this approach it is possible to analyze the effects of such policies on different layers of mobility and activity. The use of smart card data collected before and after the deployment of the free pre-peak travel in Singapore MRT allowed the calibration of behavioral models in terms of price sensitivity, so that SimMobility can now be

applied to evaluate other innovative pricing policies. The paper is organized as follows: Section 2 presents a literature review on travel demand management in public transportation using pricing policies; Section 3 describes the methodology, including the model overview, the experimental design, data analysis and model calibration; Section 4 presents results and discussions; and finally, Section 5 presents the main conclusions and lines of future research.

## 2 LITERATURE REVIEW

Excessive demand for travel on mass transit systems of major cities, especially during peak hours, is becoming a growing issue worldwide. The majority of literature on travel demand management for transit systems discusses policies and plans through which private transportation users may be shifted to public transportation. There are a few studies on the topic of smoothing peak demand for transit systems (6). A study for San Francisco (7) suggested pricing strategies in the form of peak fare pricing, station-specific pricing, fare passes discounts for certain classes of travelers and peak parking pricing. Shifting travelers' time of travel by means of demand management strategies is classified as *active peak spreading*. Daniels and Mulley (8) identified that a partnership between large trip generators and the government is the key for a successful implementation of peak spreading in public transportation. The study discusses various demand and supply side initiatives, including pricing in the context of Sydney rail transit, and determines their effectiveness in peak spreading.

Transit authorities across the world are nowadays implementing various peak and off-peak pricing strategies. For example, Melbourne and Singapore have adopted discounted fares in off-peak periods which can be considered as a reward to commuters who aid in spreading peak demand (9). Liu and Charles (10) reviewed several empirical studies in the context of fare differentiation in rail transit for peak spreading. They found that passengers tend to start their journeys outside the peak, provided there is a significant fare differentiation between peak and off-peak periods. They further concluded that free or discounted off-peak pricing make people happier than peak surcharges and that people are more willing to travel in pre-peak periods rather than in after-peak periods (especially morning commuters).

Various modeling techniques have been used to appropriately quantify the effects of pricing strategies on spreading the peak demand. Usually, departure time choice models have been developed in this context, by formulating the choice problem in a finite number of discrete time periods and modeling the choice using random utility maximization theory (11). However, more scheduling dimensions (such as mode choice (12), route choice, activity choice along with the changes in entire activity-travel patterns (13)) can also be integrated to examine the second order effects of those strategies. Most of the modeling work concentrates on road (rather than transit) networks, as congestion on roads during peak periods causes more problems. The seminal empirical study by Small (14) that follows Vickrey's schedule delay approach, concludes that commuters make a trade-off by changing departure times only when the marginal rate of substitution between journey time for schedule delay is significantly large. Maunsell (15) pointed out the differences between peak spreading scenarios for road and transit networks. These stem not from different ways in which commuters perceive pricing strategies, but mainly from different conditions and options they face. For example, car drivers have greater flexibility when deciding time of day for travel than do transit users who are usually limited by service schedules.

Very few modeling attempts have been made in relation with transit systems. Whelan and Johnson (16), presented a bi-level model, in which the upper level models the mode choice between rail, other modes and not traveling at all, and the lower level models the passengers' choice from a number of combinations of different services and ticket types, based on their

generalized cost. Passengers were assumed to select trains from a given time frame around their most desired departure time. Using this model structure, a simulation was performed to examine the effects of peak and off-peak differential fares, and it was found that peak surcharge of 10% and 30% reduced peak loading ratio (load to seat capacity) from 130% to 126% and 119%, respectively. Maunsell (15) presented an equilibrium-based temporal train assignment model for the morning trip that is split into five 30-minute time periods. The model considered factors such as: required arrival time at destination and the degree of flexibility; available rail services for the journey in each time period in terms of expected journey time and frequency; fare for travel in each time period; and level of crowding experienced in each time period.

Besides the modeling and simulation approach, a few studies have also analyzed observed data before-and-after the policy intervention. For example, studies (4, 9) presented an analysis of the data in relation to the fare-free transit service employed in Melbourne known as the "Early Bird" scheme. The results showed that 23% of "Early Bird" ticket users had shifted their trips away from the morning peak (i.e. before 7:00 AM) with an average time shift of 42 minutes. Similarly to Melbourne, Singapore's Land Transport Authority (LTA) has further extended the free pre-peak travel on the MRT network up to June 2016 (17). This policy was initiated in year 2013, and based on the observational analysis, LTA has noticed a sustained reduction of 7% to 8% in the number of commuters during the morning peak. Finding out the impacts of pricing strategies in this manner can provide useful estimates of demand changes and can aid in understanding of the factors that underly the peak spreading phenomenon.

### 3 METHODOLOGY

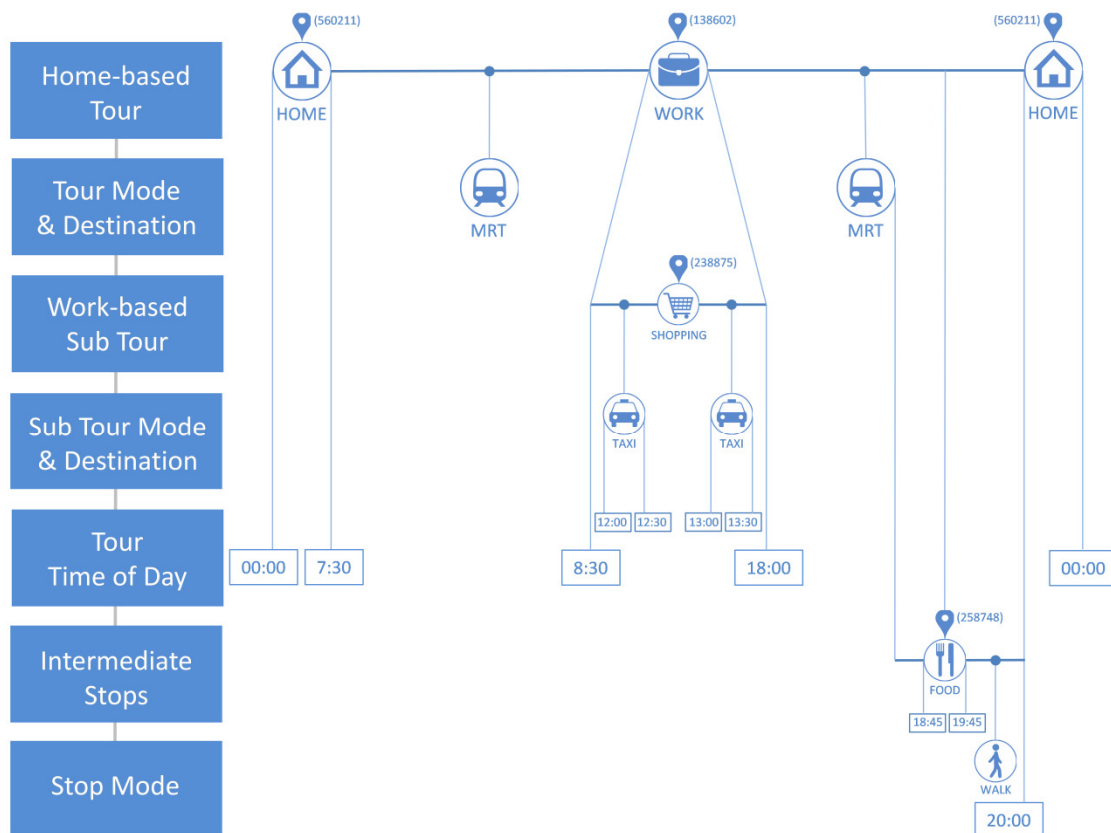
For this study, we have used SimMobility's Mid-term modeling framework, which combines an econometric activity-based demand model with a simulation-based dynamic traffic assignment within an agent-based environment. Mid-term consists of three interacting simulators: the Pre-day simulator, which is responsible for modeling and simulating individual daily activity and travel patterns; the Within-day simulator, which utilizes an event-driven mechanism to simulate departure times and route-choice behavior; and the Supply simulator that takes care of network attributes and the supply system in relation to both public and private transportation (5). Models within these simulators have been developed and calibrated using various datasets from Singapore, including household survey data, GPS data and smart card data. For the purpose of this study, Pre-day simulator is used in order to model pricing strategies for public transportation and analyze their effects on the mobility and activity patterns of individuals.

#### 3.1 Model Overview

Pre-day simulator follows an activity-based approach to modeling transportation demand (18, 19) and it consists of a series of hierarchical discrete choice models, further described in (5). The output of Pre-day is a full activity schedule for each agent, consisting of activities (classified into work, education, shopping and others) and trips using nine possible transportation modes (public bus, MRT, private bus, drive alone, shared ride with 2 passengers, shared ride with 3 passengers, motorcycle, taxi, and walk). The time resolution of departure time for each trip is a 30-minute time interval, and the origin and destination of each trip are 1169 traffic analysis zones. The most relevant models for passengers' response to a pricing strategy are time-of-day and mode-destination choice models which contain cost variables. These models also contain socio-demographic variables to account for the population heterogeneity (i.e. different user types). Also, these level of service models provide welfare indicators (in the form of Logsums) to day pattern level models, so as to capture the second-order effects of the policy.

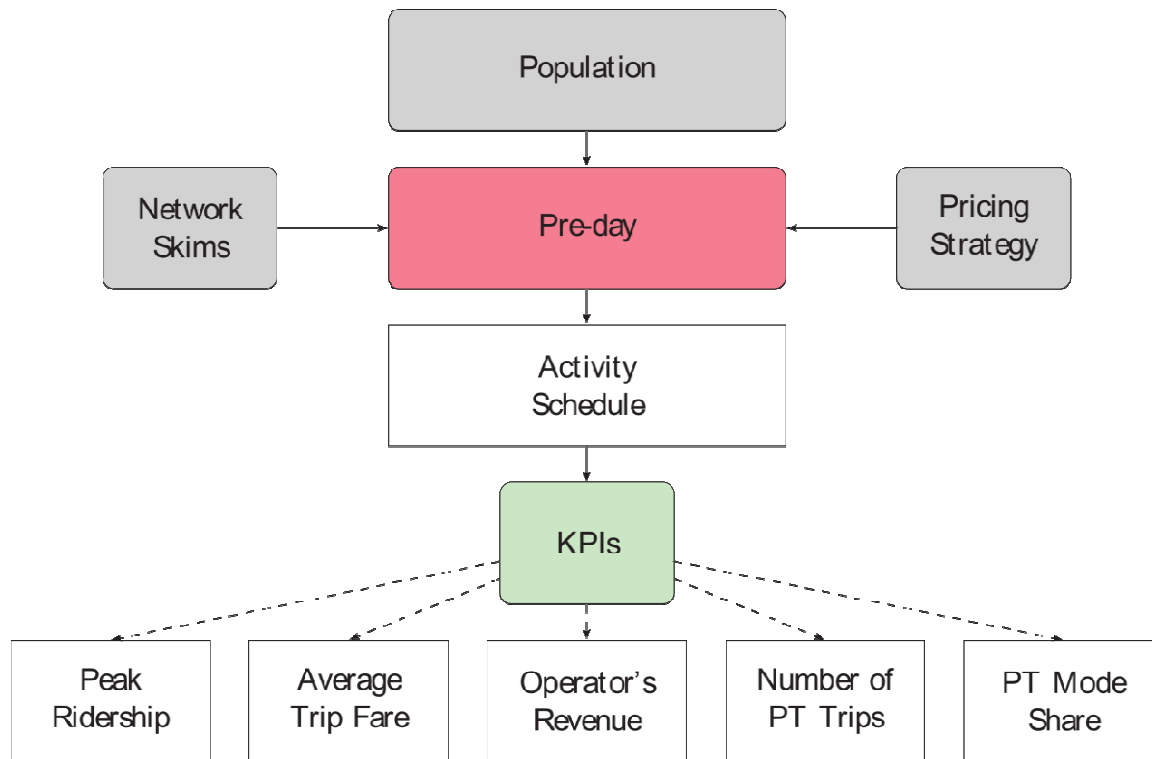
Figure 1 illustrates activity-based models in Pre-day simulator with an example, by identifying all the individual decisions that are modeled. These decisions can be roughly aggregated into seven stages:

- The first modeled decision is the number of home-based tours (if any) to be performed during the day, distinguished by the purpose. It is important to note that for home-based tours the origin is known beforehand.
- The second decision is the destination (when possible, as for fixed-worker and students the destinations are also known beforehand) and travel mode, depending on the availability.
- The third and the fourth decision deal with potential work-based sub-tours, distinguished by the purpose. If such sub-tours are performed, the destination and mode are modeled.
- The fifth decision is the time of day for all tours and sub-tours to be performed during the day, which leads to effective activities durations.
- Finally, the sixth and the seventh decision relate to intermediate stops to be performed during any of the trip legs, also distinguished by the purpose. If an individual decides to make an intermediate stop, the destination and mode are modeled.



**FIGURE 1 Pre-day Structure for Modeling Activities and Trips.**

Figure 2 shows a high-level overview of the modeling framework used for this case study. The input into the Pre-day simulator is a synthetic population that includes agents' socio-economic characteristics, vehicle ownership and land use information. The population was synthesized from household interview travel survey data (HITS 2012), by expanding the sample to a full Singapore population. Alternatively, the population could also come from a long-term model, such as the one currently being developed within SimMobility (20). Furthermore, Pre-day uses the information from network skims about zone-to-zone travel times and private and public travel costs distinguished by three periods in a day: AM peak (7:30 AM to 9:30 AM), PM peak (5:30 PM to 7:30 PM) and off-peak. Pricing strategy is an input to the simulator and it needs to be explicitly incorporated into its behavioral models.



**FIGURE 2 Framework Overview.**

To evaluate the effects of pricing strategies, it is necessary to consider a comprehensive set of key performance indicators (KPIs) that can measure different dimensions of economic, societal and environmental performance (21). This study considers the following KPIs for all scenarios:

- *Peak ridership* is represented by the sum of transit network loadings during the morning peak (7:30 AM to 9:30 AM) or the afternoon peak (5:30 PM to 7:30 PM). For the free pre-peak policy, peak ridership is calculated from total arrivals (tap-outs) into the policy area (CBD) from 8:00 AM to 9:30 AM.
- *Average trip fare* is based on the actual prices paid by the passengers taking into account the discounts and the specific rules of the pricing policy.
- *Operator's revenue* is calculated as the sum of trip fares collected from all the passengers

during one simulated day. This is a simplified calculation of revenue that assumes the same policy applies to all the passengers and that they are paying transit charges using their smart card's electronic purse (there are no holders of a monthly travel pass).

- *Number of public transportation trips* is the number of single transit trips made by all the passengers during one simulated day.
- *Public transportation mode share* is the percentage of trips made using transit modes (public bus or MRT).

### 3.2 Experimental Design

In this study the following pricing strategies are implemented and simulated:

#### *Nominal pricing*

This policy with no fare reduction serves as the baseline scenario, against which the changes in KPIs are calculated for other pricing policies. In this scenario a total of 5,758,366 trips are performed: 57.8% for Work, 27.9% for Education, 1.8% for Shopping, and 12.4% for Other purposes. The aggregated daily modal shares are: 28.8% Public Bus, 25.1% MRT, 8.7% Private Bus, 13.7% Drive Alone, 8.4% Share Ride 2, 3.6% Share Ride 3, 2.0% Motorcycle, 1.2% Taxi, and 8.5% Walk. Average trip fare on public transportation (public bus and MRT) was SGD \$1.17.

#### *Free pre-peak travel on MRT*

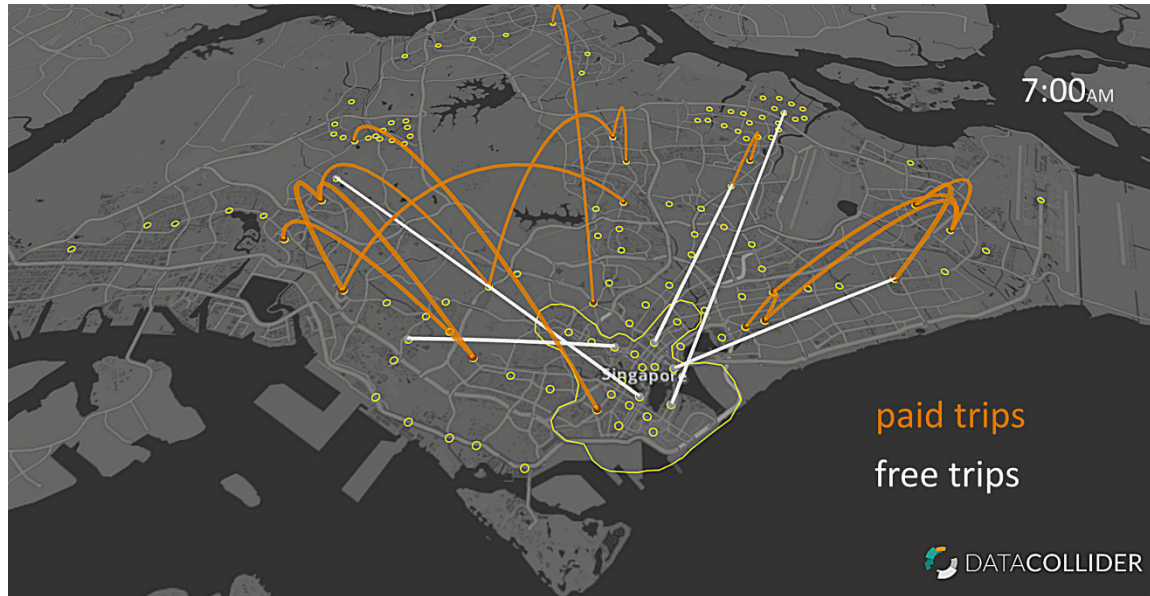
This policy, implemented by LTA in June 2013 on weekdays, enables free travel using MRT service for those passengers who tap-in outside of Singapore's CBD area and tap-out at one of the 16 designated stations inside the CBD area before 7:45 AM. A discount of up to 50 cents is offered to those who miss the cut-off time but manage to exit these stations between 7:45 AM and 8:00 AM. As Pre-day simulator considers 30-minute intervals, this time-, location- and mode-based policy was modeled as a free MRT travel for arrivals at CBD stations before 8:00 AM. Figure 3 shows top origin-destination flows from the simulator at the moment of arrival (which is in the pre-peak period). White flows represent free MRT trips, while orange flows represent paid MRT trips (the height of the arc is proportional to the trip fare). Since Pre-day model operates on a zonal level, but the policy operates on a station level, zones needed to be assigned to MRT stations. This was achieved by using the nearest neighbor method which mapped zones to the stations closest to their centroids (see Figure 4). The justification for such a procedure is the finding that walking is the main access and egress mode to MRT stations in Singapore (only 1.3% of travelers access or egress the public transportation network by motorized modes). An extension of this study would be to obtain an even more accurate mapping, by using route choice models with multi-modal access and egress to public transportation systems (22).

#### *Off-peak discount in public transportation (bus + MRT)*

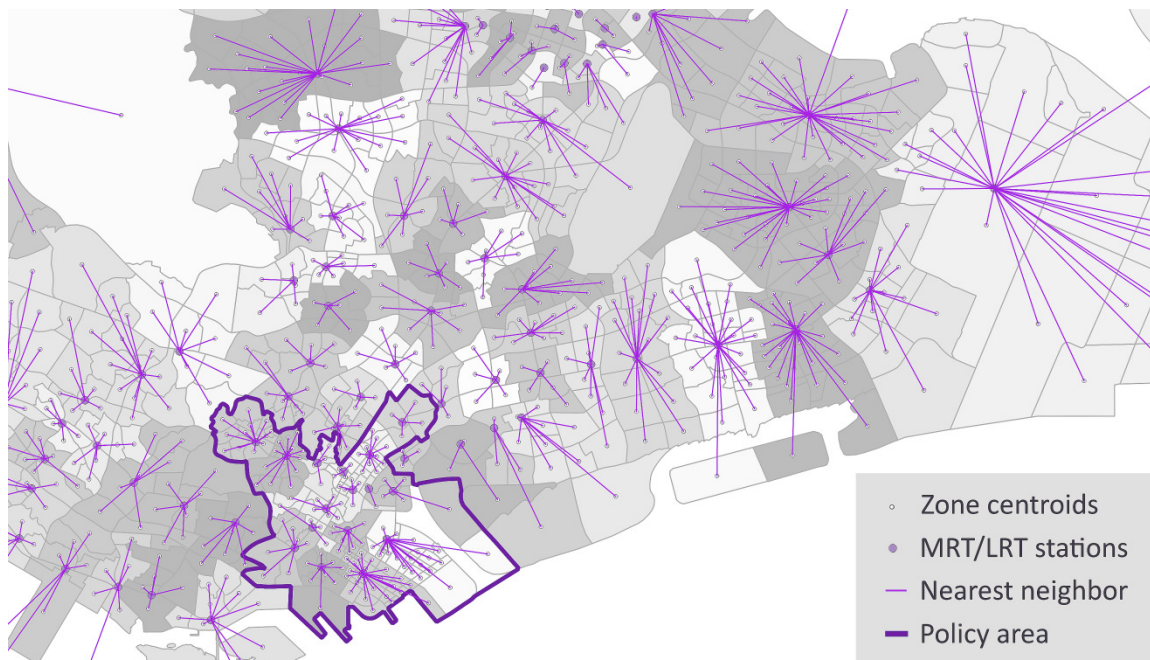
This is a time-based policy that applies to the integrated transit system across the city. The trips for which tap-ins are during one of the off-peak periods (before 6:00 AM, from 9:00 AM to 5:00 PM, or after 7:30 PM) have a discounted fare. In July 2015, Singapore's Ministry of Transport implemented a trial of a similar policy by introducing a new type of the public transportation concession card called *Off-Peak Monthly Travel Pass*. This pass enables unlimited free travel that begins in one of the three off-peak periods, and it costs 2/3 of the regular concession card. For the simulation experiments, four discount levels are considered: 25%, 50%, 75% and free



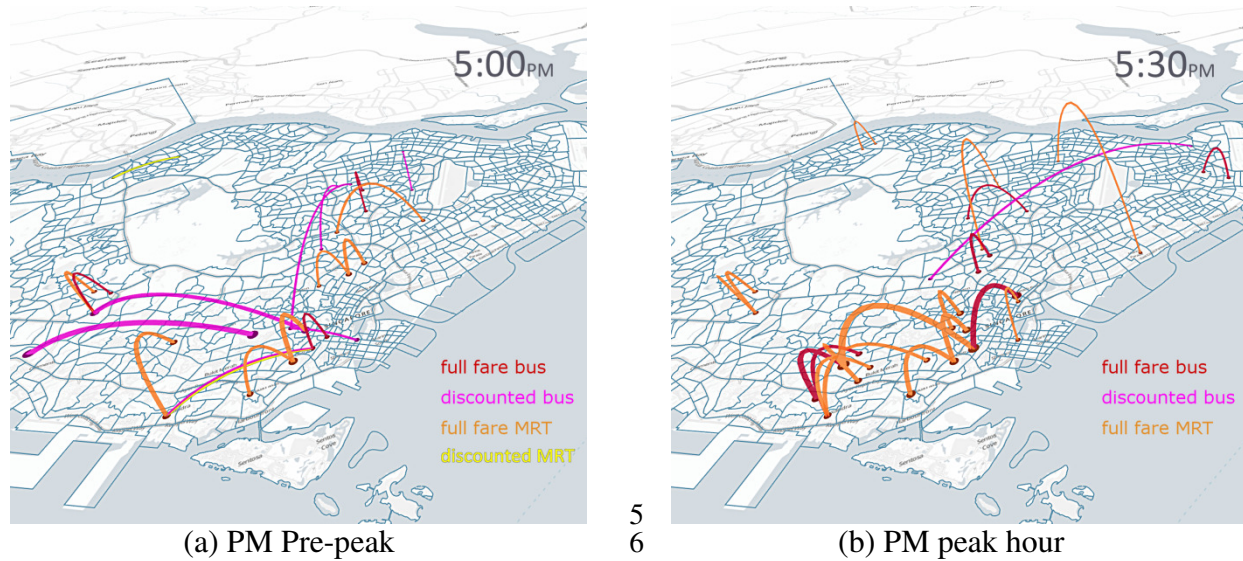
(100%). Figure 5 shows top origin-destination flows obtained for the 50% off-peak discount pricing policy. For arrivals in the period before the afternoon peak (5:00 PM to 5:30 PM), the flows show a combination of discounted and non-discounted bus and MRT trips, depending on whether trips started before or after 5:00 PM. On the other hand, arrivals in the afternoon peak period (5:30 PM to 6:00 PM) are mostly non-discounted, except for the long bus trip that started before 5:00 PM. This policy applies to all stations, so the mapping between zones and stations was not necessary.



**FIGURE 3 Top Origin-Destination Flows on MRT for the Free Pre-peak Policy.**



**FIGURE 4 Mapping Zones to MRT/LRT Stations using the Nearest Neighbor Method.**



**FIGURE 5 Top Origin-Destination Flows on Public Transportation for the 50% Off-peak Discount Policy.**

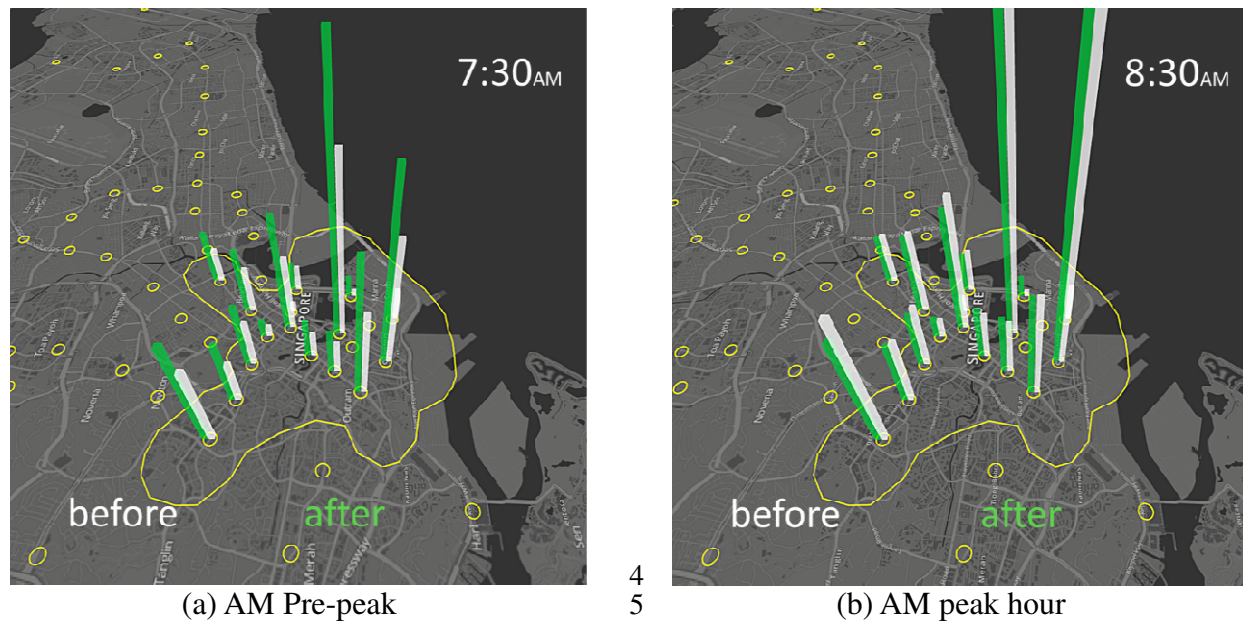
### 3.3 Data Analysis and Model Calibration

By comparing smart card data from April 2011 (before the free pre-peak policy) and August 2013 (after the free pre-peak policy) it is possible to evaluate the policy implications on peak ridership into the CBD area. Figure 6 shows smart card tap-outs across the 16 stations in the CBD area where the free pre-peak policy was implemented. It can be seen that ridership after the policy is higher in the pre-peak period (Figure 6a), while it is lower in the peak hour (6b). This indicates a demand shift occurred from peak hour into an earlier period, and therefore the policy had a desired peak spreading effect. To obtain representative weekdays (before and after the policy), smart card transactions from all weekdays in the dataset (excluding Fridays, Saturdays, Sundays and holidays) were combined and relative frequencies of arrivals at CBD stations were plotted. As Figure 7a shows, there has been a discernible change in the shape of the morning peak after the implementation of the policy. This information was used to calibrate Pre-day models, by changing the travelers' sensitivity to cost, in order to obtain a comparable change in the simulated demand curve shown on the right (Figure 7b).

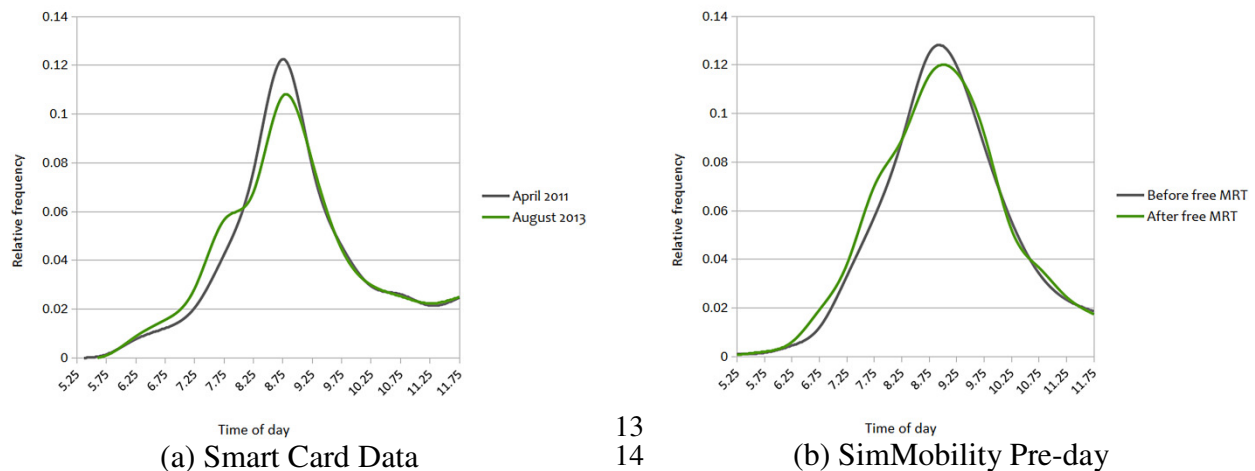
The calibration of Pre-day affected two models:

*Tour Time of Day choice models* The cost parameter for work tours was adjusted to produce the change in MRT demand observed before/after the free early MRT policy in smart card data (comparing a representative weekday from April 2011 with a representative weekday from August 2013). The same calibrated parameter was used to test the off-peak discount policy. It was not necessary to calibrate parameters for other purposes.

*Tour Mode and Destination choice models* Fare reduction was introduced for morning MRT trips from outside CBD into CBD, based on the proportion of the morning peak demand affected by the policy (7:30 AM - 8:00 AM), which was also estimated from smart card data. Similarly, for the off-peak discount policy, fare reductions were introduced for bus and MRT trips taking into account the proportion of demand that falls within three discounted off-peak periods.



**FIGURE 6 Pre-peak and Peak Hour Ridership into CBD Before and After the Policy (Smart Card Data).**



**FIGURE 7 Relative Frequency of Tap-outs in CBD Before and After the Free Pre-peak MRT Policy.**

#### 4 RESULTS AND DISCUSSION

Table 1 shows the performance of the free pre-peak travel policy measured by the changes in KPIs. It can be seen that the policy was effective with respect to the peak hour ridership into the CBD area, which was reduced by 3.48%. As regards the affordability of MRT travel, average MRT trip into CBD became 15.06% (or 19 cents) cheaper. However, the system-wide impact was not that noticeable, as the average MRT trip for the whole network was only 2.03% (or 2 cents) cheaper. Since the policy was based on discounts (free trips), it had a negative impact on the operator's revenue, resulting in a 2.16% loss. The policy also resulted with more MRT trips into CBD. However, as the total number of trips differs between simulation runs (agents make not only the mode choice but also the decision whether to travel or not), it is more meaningful to consider the



changes in the MRT mode share, which are also reported in Table 1. We can see that there was a 4.24% increase in the MRT mode share during the free period (before 8:00 AM), but when the morning peak (and the whole day) were included in the analysis, the change in MRT mode share became much smaller. This indicates the mode share increase in the free period was mostly due to a time shift, rather than due to new passengers attracted to the MRT.

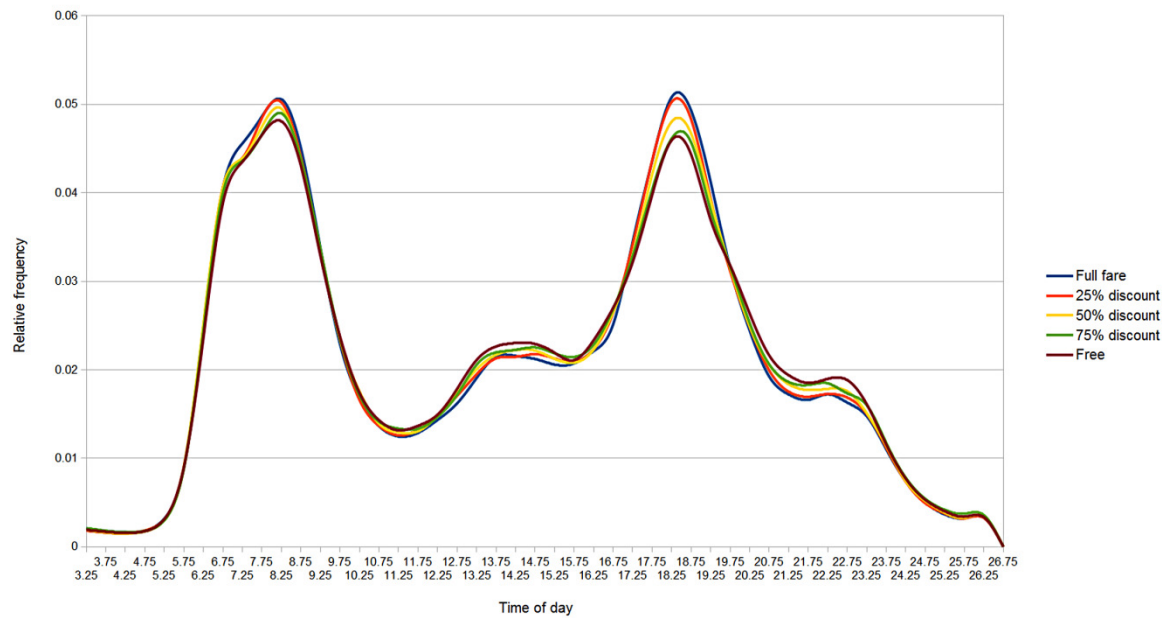
**TABLE 1 Changes in KPIs After the Free Pre-peak MRT Policy**

KPI	Change
Peak hour ridership into CBD	-3.48% (-2,570 trips)
Pre-peak ridership into CBD	+21.67% (+4,540 trips)
Average MRT trip fare	-2.03% (-2 cents)
Average MRT trip fare into CBD	-15.06% (-19 cents)
Operator's revenue	-2.16%
Number of MRT trips into CBD	+0.93%
MRT mode share for trips into CBD (before 8:00 AM)	+4.24%
MRT mode share for trips into CBD (before 9:30 AM)	+0.48%
MRT mode share for trips into CBD (whole day)	+0.39%

Table 2 shows the effects of the off-peak discount policy for an integrated public transportation mode. It can be observed that the policy increases off-peak ridership and decreases peak ridership (in the afternoon peak more so than in the morning peak). This can also be seen in Figure 8 which shows combined load profiles for public buses and MRT, for different levels of off-peak discount. The higher levels of discount will translate into lower average trip fares and higher losses in daily revenue (however, this calculation of a daily revenue is simplified as it does not take into account that in reality the revenue loss would be somewhat offset by the purchase of off-peak monthly travel passes). The more affordable public transportation also resulted in the higher number of trips and somewhat higher public transportation modal shares of public transportation. It is interesting that the peak ridership was reduced despite the increased number of public transportation trips, which may suggest the potential benefits of off-peak discount strategies for controlling the demand growth in a desired way. The increased public transportation mode share suggests that off-peak pricing strategies are not only effective in terms of peak spreading but may also improve the environmental sustainability of the transportation system as a whole. This is because an increased public transportation mode share comes with a reduction of all other mode shares, all of which are motorized (with exception of walking). However, the percent changes in mode shares indicate this policy effect is rather small in magnitude.

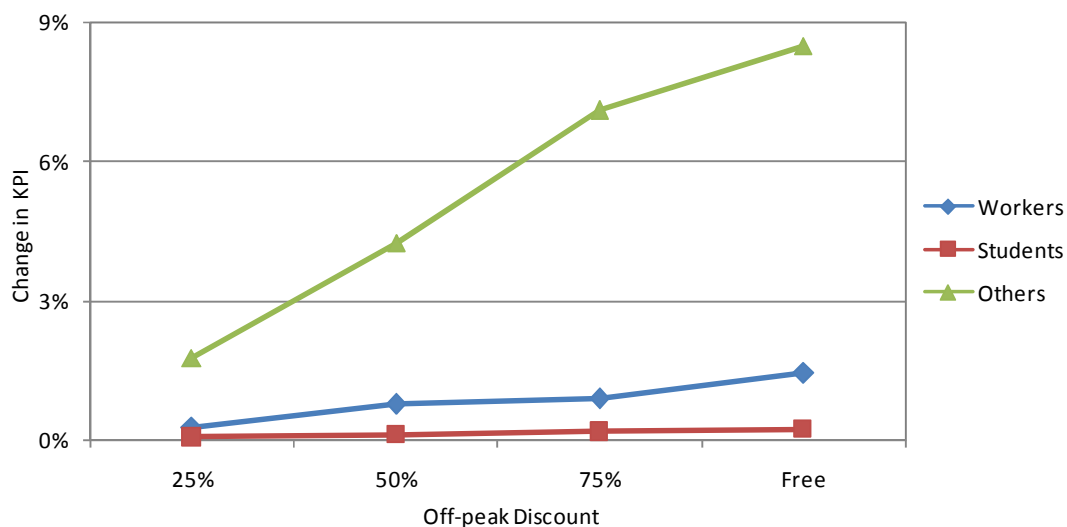
**TABLE 2 Changes in KPIs After the Off-peak Public Transportation (Bus + MRT) Discount Policy**

KPI \ Discount	25%	50%	75%	Free
AM peak ridership	-1.00%	-2.29%	-2.81%	-4.21%
PM peak ridership	-1.84%	-4.91%	-7.97%	-9.72%
Off-peak ridership	+0.81%	+2.07%	+3.20%	+4.00%
Average public transport trip fare	-13.59% (-16 cents)	-27.49% (-32 cents)	-41.97% (-49 cents)	-54.87% (-66 cents)
Operator's revenue	-12.93%	-25.93%	-40.58%	-56.33%
Number of public transportation trips	+0.79%	+2.13%	+2.32%	+3.71%
Public transportation mode share	+0.31%	+0.81%	+1.11%	+1.61%



**FIGURE 8 Combined Bus and MRT Load Profiles for Off-peak Discount Policies (SimMobility Pre-day).**

To understand the effect of the off-peak discount policy on different types of travelers, Figure 9 shows the changes in public transportation mode share for different levels of off-peak discount (compared to the nominal pricing case), distinguished by traveler's occupation. Students present the lowest increase in public transport mode share (from 0.06% for the 25% discount case to 0.22% for the free case), which is expectable as students already tend to travel in off-peak periods in the nominal pricing case. Workers are slightly more sensitive, with an increase of up to 1.44% in public transportation mode share. Other travelers (e.g. retired, homemakers, unemployed, etc.) are the most responsive, with increases in public transportation mode share between 1.76% and 8.48%, depending on the off-peak discount, as they have more flexibility when choosing the time of their trips.



**FIGURE 9 Changes in Public Transportation Mode Share for Off-peak Discount Policies (SimMobility Pre-day).**

## 5 CONCLUSIONS

This paper evaluated off-peak pricing policies in Singapore public transportation using an activity-based demand model SimMobility Pre-day. First, we replicated the free pre-peak travel policy currently used in Singapore MRT. By comparing smart card data before and after the implementation of this policy, it was possible to observe the changes in transit demand induced by the policy and use that knowledge to calibrate behavioral models. Subsequently, this calibrated model was used to evaluate an additional pricing policy - off-peak discount for an integrated transit (public bus + MRT) - that has only recently been deployed in Singapore. To evaluate the implications of these policies, several key performance indicators were obtained from the simulation output and compared with the nominal pricing scenario. The results suggest that off-peak pricing strategies have a measurable impact on the travel demand (reducing the peak ridership) as well as on the affordability of transit, which in turn has the potential to increase the number of public transportation trips and mode share.

In future work, we will enhance the simulator capabilities in terms of behavioral models (e.g. public transportation route choice with multimodal access and egress), inputs such as the synthetic population (e.g. from a long-term model), and a more detailed level of service (e.g. travel times including denied boarding for buses and MRT). We will further utilize this model to test and propose additional innovative pricing policies for Singapore public transportation, for example to find the optimal pricing policy that maximizes social welfare. Finally, we are also interested in developing models for pricing in public and private transportation based on tradeable travel grants.

## ACKNOWLEDGMENTS

The research described in this project was funded by the Singapore National Research Foundation (NRF) through the Singapore-MIT Alliance for Research and Technology (SMART) Center for Future Mobility (FM). The data for this research was generously provided by the Singapore's Land Transport Authority (LTA). The authors would like to thank Carlos Carrion, Siyu Li, Maya Abou-Zeid, and other researchers and developers from SMART for their contributions in the development of SimMobility. We would also like to thank the LIVE Singapore! team for their help with the visualization.

## REFERENCES

1. Cervero, R., Time-of-day transit pricing: comparative US and international experiences. *Transport Reviews*, Vol. 6, No. 4, 1986, pp. 347–364.
2. Santos, G., Urban Congestion Charging: A Comparison between London and Singapore. *Transport Reviews*, Vol. 25, No. 5, 2005, pp. 511–534.
3. Land Transport Authority, *Travel Smart in Singapore*, Retrieved from: [www.lta.gov.sg/content/ltaweb/en/public-transport/mrt-and-lrt-trains/travel-smart.html](http://www.lta.gov.sg/content/ltaweb/en/public-transport/mrt-and-lrt-trains/travel-smart.html), 2015.
4. Gwee, E. and G. Currie, Best practices: review of time-based public transport fare pricing. *Journeys*, 2013, pp. 59–68.
5. Lu, Y., M. Adnan, K. Basak, F. Pereira, C. Carrion, V. Saber, H. Loganathan, and M. Ben-Akiva, SimMobility Mid-term simulator: a state of the art integrated agent based

- 1 demand and supply model. In *Transportation Research Board 93rd Annual Meeting*,  
2 Washington D.C., 2015.
- 3
- 4 6. Henn, L., G. Karpouzis, and K. Sloan, A review of policy and economic instruments for  
5 peak demand management in commuter rail. In *Proceedings of Australasian Transport*  
6 *Research Forum*, Planning and Transport Research Centre, Curtin University of  
7 Technology, Bentley, WA, 2010.
- 8
- 9 7. Nelson Nygaard Consulting Associates, *BART demand management study: Working paper*  
10 *no.1 - Research on TDM strategies*. Report to the Bay Area Rapid Transit Authority, San  
11 Francisco, 2008.
- 12
- 13 8. Daniels, R. and C. Mulley, The paradox of public transport peak spreading: Universities  
14 and travel demand management. *International Journal of Sustainable Transportation*, Vol.  
15 7, No. 2, 2013, pp. 143–165.
- 16
- 17 9. Currie, G., Quick and effective solution to rail overcrowding: free early bird ticket  
18 experience in Melbourne, Australia. *Transportation Research Record: Journal of the*  
19 *Transportation Research Board*, Vol. 2146, 2010, pp. 35–42.
- 20
- 21 10. Liu, Y. and P. Charles, Spreading peak demand for urban rail transit through differential  
22 fare policy: a review of empirical evidence. In *Proceedings of Australasian Transport*  
23 *Research Forum*, 2013.
- 24
- 25 11. Cervero, R., Transit pricing research. *Transportation*, Vol. 17, No. 2, 1990, pp. 117–139.
- 26
- 27 12. De Jong, G., A. Daly, M. Pieters, C. Vellay, M. Bradley, and F. Hofman, A model for time  
28 of day and mode choice using error components logit. *Transportation Research Part E:*  
29 *Logistics and Transportation Review*, Vol. 39, No. 3, 2003, pp. 245–268.
- 30
- 31 13. Adnan, M., D. Watling, and T. Fowkes, Model for integrating home-work tour scheduling  
32 with time-varying network congestion and marginal utility profiles for home and work  
33 activities. *Transportation Research Record: Journal of the Transportation Research*  
34 *Board*, Vol. 2134, 2009, pp. 21–30.
- 35
- 36 14. Small, K. A., The scheduling of consumer activities: work trips. *The American Economic*  
37 *Review*, 1982, pp. 467–479.
- 38
- 39 15. Faber Maunsell, Ltd., *Demand management techniques: peak spreading*. Final report to  
40 department for transport, Transport for London and Network Rail, 2007.
- 41
- 42 16. Whelan, G. and D. Johnson, Modelling the impact of alternative fare structures on train  
43 overcrowding. *International Journal of Transport Management*, Vol. 2, No. 1, 2004, pp.  
44 51–58.
- 45
- 46 17. Land Transport Authority, *News release on free pre-peak travel extended until June 2016*,  
47 Retrieved from: [www.lta.gov.sg](http://www.lta.gov.sg), 2015.

18. Ben-Akiva, M., J. Bowman, and D. Gopinath, Travel demand model system for the information era. *Transportation*, Vol. 23, No. 3, 1996, pp. 241–266.
19. Bowman, J. and M. Ben-Akiva, Activity-based disaggregate travel demand model system with activity schedules. *Transportation Research Part A: Policy and Practice*, Vol. 35, No. 1, 2001, pp. 1 – 28.
20. Lima Azevedo, C., K. Marczuk, S. Raveau, H. Soh, M. Adnan, K. Basak, H. Loganathan, N. Deshmunkh, E. Frazzoli, and M. Ben-Akiva, Microsimulation of Demand and Supply of Autonomous Mobility On-Demand, *95th Annual Meeting of the Transportation Research Board*, Washington D.C., 2016.
21. Lovrić, M., T. Li, and P. Vervest, Sustainable revenue management: A smart card enabled agent-based modeling approach. *Decision Support Systems*, Vol. 54, No. 4, 2013, pp. 1587–1601.
22. Tan, R., S. Raveau, D. Lee, and M. Ben-Akiva, A Public Transport Route Choice Model with Multi-Modal Access and Egress: Application to the Large-Scale Network of Singapore, *95th Annual Meeting of the Transportation Research Board*, Washington D.C., 2016.