Transportation Research Part A 140 (2020) 127–141

Contents lists available at ScienceDirect

Transportation Research Part A

journal homepage: www.elsevier.com/locate/tra

Examining impacts of time-based pricing strategies in public transportation: A study of Singapore

Muhammad Adnan[a,b,*], Bat-hen Nahmias Biran[c,d], Vishnu Baburajan[a], Kakali Basak[a], Moshe Ben-Akiva[d]

[a] Singapore-MIT Alliance for Research and Technology, 1 CREATE Way, #09-02 CREATE Tower, 138602, Singapore
[b] UHasselt- Hasselt University, Transportation Research Institute (IMOB), Agoralaan, 3590 Diepenbeek, Belgium
[c] Department of Civil Engineering, Ariel University, Ariel 40700, Israel
[d] Department of Civil and Environmental Engineering, Massachusetts Institute of Technology, 77 Massachusetts Avenue, Cambridge, MA 02139, USA

ARTICLE INFO

Keywords:
Pricing strategies
Public transportation
SimMobility
Singapore

ABSTRACT

Peak and off-peak pricing strategies are an important policy tool used to spread peak demand in public transportation systems. This study uses an agent-based simulator (SimMobility Mid-term) to examine the impact of pricing (off-peak fare discounts) strategies used in Singapore. The aim of the paper is to demonstrate the capabilities of the simulator, and types of detailed performance indicators it can provide, in order to examine the effects of complex public transport pricing policies. Behavioral models within the simulator are calibrated with relevant datasets such as household travel survey, smart card, GPS probe data from taxis and traffic counts for the Singapore network. Nine (09) time-based pricing strategies are examined that consist of a combination of free pre-peak travel on Mass Rapid Transit (MRT) and an off-peak discount for integrated transit (public buses, MRT and Light Rail Transit (LRT)).

Changes in public transport ridership, mode shares, operator's revenue and denied boarding are used as indicators to examine the impacts of pricing strategies. The effects of these policies are also examined on segments of the population in terms of income level, person type and gender. Results indicate that off-peak discounts spread PM peak demand and attract individuals to public transportation. However, the availability of fare discounts in all off-peak periods results in adverse impacts during the AM peak because many commuters shift the return leg rather than the initial leg of their journey. The study concludes with suggestions on how to explore more effective pricing strategies, i.e. providing fare discounts only during off-peak periods that surround AM peak.

1. Introduction

In recent years, major cities have introduced off-peak discounted fares and free travel on urban passenger rail networks to encourage commuters to travel before the morning peak period (Ge et al., 2015; Smith, 2009). Singapore has considerable experience with time-based pricing in both private and public transportation. It was the first country to introduce an Electronic Road Pricing scheme for private traffic (Cheong and Nadiah, 2013) and provides extensive public transportation throughout the city. Public

* Corresponding author at: UHasselt- Hasselt University, Transportation Research Institute (IMOB), Agoralaan, 3590 Diepenbeek, Belgium.
E-mail addresses: muhammad.adnan@uhasselt.be (M. Adnan), bat-hen@smart.mit.edu (B.-h. Nahmias Biran), vishnub87@gmail.com (V. Baburajan), kakali.basak@smart.mit.edu (K. Basak), mba@mit.edu (M. Ben-Akiva).

https://doi.org/10.1016/j.tra.2020.08.010
Received 6 December 2019; Received in revised form 29 July 2020; Accepted 17 August 2020
Available online 29 August 2020
0965-8564/

transport (PT) consists of the Mass Rapid Transit (MRT) system, Light Rapid Transit (LRT) system and buses. MRT and LRT routes cover major residential and business areas of Singapore and are augmented with an efficient supply of public buses. Singapore's Land Transport Authority (LTA) has experimented with early travel discount schemes in the 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 MRT stations in the Central Business District (CBD). In line with LTA's efforts to manage public transport demand, this paper examines pricing strategies employed in Singapore with an emphasis on the capabilities of the SimMobility agent-based simulation platform (Adnan et al., 2016; Lu et al., 2015; Azevedo et al., 2017). Key highlights of the work presented include: 1) Using inputs from the SimMobility long-term module to form the synthetic population for Singapore. The population is generated using a modified iterative proportional fitting procedure that draws on rich data sources such as Singstat (national census) and the Household Interview Travel Survey (HITS collected in year 2008 and 2012). The procedure to generate this population is explained in Zhu and Ferreira (2014); 2) Using the SimMobility Mid-term simulator (comprised of an integrated demand and supply model) to provide nine (09) different off-peak discounts (including free pre-peak travel); 3) Using a variety of indicators from the Mid-term simulator, such as ridership and revenue from the demand-side and denied boarding from the supply-side, to examine impacts; and 4) Analysing results using different socio-demographic characteristics such as person type (in terms of occupation), gender and income.

SimMobility (Adnan et al., 2016) integrates various mobility-sensitive behavioral models within a multi-scale simulation platform that considers land-use, transportation and communication interactions. It was developed at the Singapore-MIT Alliance for Research and Technology (SMART). Long-term (Adnan et al., 2016), Mid-term (Lu et al., 2015) and Short-term (Azevedo et al., 2017), simulators are embedded in a flexible framework that ensures simultaneous integration and modularity. The platform focuses on impacts on transportation networks and intelligent transportation systems, and it simulates a portfolio of technology, policy and investment options under alternative future scenarios. The rest of the paper is structured as follows. Section 2 provides a literature review of recent time-based pricing policies for public transport, as well as agent-based platforms used to test these policies. Section 3 introduces the methodology and presents the model overview, experimental design and data analysis. Section 4 includes results and discussions. Finally, Section 5 presents the main conclusions and findings of this work.

2. Literature review

Urban transportation is characterized by large-scale temporal and spatial variations in demand patterns (Andrea et al., 2009). Travel Demand Management (TDM) has traditionally focused on road congestion using road pricing (Halvorsen et al., 2019). There is a wide body of knowledge regarding the use of road pricing schemes to reduce traffic congestion; such schemes are Fixed or Dynamic Pricing, Congestion Pricing or Distance Based Pricing (for a comprehensive review see: (de Palma and Lindsey, 2011; Chen et al., 2018; Cipriani et al., 2019). Road pricing aims to change the traveler's route, departure time or travel mode (mainly by transferring passengers to public modes) (Lindsey and Verhoef, 2000). But, as cities face increasing congestion on passenger rail systems due to population growth (Sarkar and Jain, 2016), a key priority for local policymakers becomes to maintain or increase the market share of Public Transport (PT) (Cats et al., 2017). As it is resource intensive to expand PT capacity to meet increases in travel demand, cities are turning to TDM measures such as time-based pricing strategies to help spread peak hour travel demand and reduce rail overcrowding (Gwee and Currie, 2013).

A variety of PT pricing policies have been implemented worldwide. Fare Free Public Transit (FFPT) policies exists in nearly 100 cities (Kębłowski, 2019) and are aimed at attracting car passengers to PT (Cats et al., 2014). However, results show a considerable and undesirable shift from walking to public transit. For example, a year after the introduction of FFPT in Tallinn, most of the increase in PT usage was caused by a 40% decrease in walking trips (Cats et al., 2017).

PT demand management strategies are also driven by social goals such as enhanced mobility, economic and efficient operation of PT, and to encourage commuters to travel before or after the peak period (Štraub and Jaroš, 2019). For instance, Volinski (2012) studied an off-peak pricing strategy implemented in Melbourne, Australia – "the early bird ticket". It offers passengers free rail travel on trips completed before 7:00 am. Results indicate that 23% of passengers shifted the time of travel by an average of 42 min. This shift reduced demand during peak time by between 1.2% and 1.5%, which is equivalent to a maximum of five average train loads (or 3% of total peak trains). However, demand growth during this period has far outweighed this effect. Overall, it is unclear to what degree the early bird ticket program has reduced overloading. A similar peak spread experiment was conducted in the Netherlands in which participants could earn monetary rewards for traveling outside peak hours (Peer et al., 2016). The research found that, compared to the pre-measurement, the relative share of peak trips decreased by 22% during the reward period, and by 10% during the post-measurement. Implementation of temporally differential fares in Taipei revealed that peak-hour Metro riders shifted to off-peak periods, or even chose other modes. Metro riders were sensitive to the tested differential fare levels, especially the peak-hour surcharge, and afternoon riders were more sensitive to proposed fare changes than morning riders (Lan et al., 2010).

Bianchi et al. (1998)) using an SP experiment, modelled the implications of off-peak discounts for Santiago Metro travellers by estimating ordinal probit models. Their model predicted decrease in the demand for morning and evening peaks varying from 8% to 3.5% for two lines. The decrease in the demand for morning peak is higher compared to evening peak. However, validation with real data showed more slightly more decrease in the demand for evening peak compared to morning peak. Analysis of an off-peak fare discount policy for subway use in Hong-Kong revealed mixed results (Halvorsen et al., 2016; Yang and Tang, 2018). Overall, a 3% decrease was noted for peak hour trips in response to a reduction in average pre-peak hour fare of approximately 25%. Halvorsen et al. (2016) recently tested a fare-reward scheme to manage peak-hour congestion of urban rail transit bottlenecks in four metro lines in Hong-Kong. A free ride during the shoulder periods was granted after a certain number of paid trips during peak hours. They found that the performance of the fare-reward scheme depended on the original fare. The optimal scenario was one in which 50% of commuters travelled for free during the shoulder periods, which led to at least a 25.0% reduction in total time costs and 20.0% reduction in average equilibrium trip costs.

Singapore also turned to demand management techniques as a result of high passenger volumes and limited seat availability in the PT (Chakirov and Erath, 2011). Theseira and Qiyan (2018) presented an analysis of pre-peak free travel and pre-peak fare discounts implemented in Singapore using smart card data collected 6 months before and after the policy launch date. The policy included a free ride for all trips that ended in the city center (at designated MRT stations) before 7:45 am on weekdays. For trips that ended between 7:45–8:00 am, a discount of 0.5 SGD was given. They concluded that the effect of free travel is minimal and negligible for 30 min beyond the policy window. In addition, the reduction in price down to free has a diminishing marginal effect rather than increasing the marginal effect that is predicted in the literature. The 0.5 SGD discounts achieve up to 2/3 of the policy effect of free travel, suggesting 1) that the point-based fare elasticity varies highly over the smaller reductions in fare and 2) opportunity cost of time (waking up early) seems to be high among commuters. Tirachini et al. (2016) investigated the observed behavior of a subset of metro users in Singapore who are willing to travel a longer time (in the opposite direction or backwards) to secure a seat for the actual trip in the direction towards their destination as a way of analyzing crowding effects in the metro system. Overall, time-based strategies seem to have effective results in spreading the demand in peak hours although the magnitude of the effect is unclear.

Demand management techniques may provide monetary compensation or other incentives at the expense of the government or transit operator (Smith, 2009). Perone (2002) reported a loss of approximately one-quarter of revenue when a fare-free policy for off-peak hours was implemented in Mercer County, New Jersey. The results show that a fare-free strategy produces excessive off-peak ridership predominantly by untargeted passengers who would otherwise travel by modes such as walking or bicycling. Smith (2009) studied five major rail systems in the US that used peak pricing. Results showed that flat fares may financially hurt the transit organization because they do not address cost variability by time, distance, or mode. In a flat-fare environment, relatively expensive trips (peak, long-distance, rail) are used more often than if they were priced according to the cost of service. Conversely, relatively cheap trips (off-peak, short-distance, bus) are over-priced and used less often than if the price was based on service cost. Transit agencies end up supplying a greater number of under-priced trips while losing ridership and revenue from over-priced trips. Overall, analyses support the assertion that peak pricing policies enhance service effectiveness and improve social equity.

The measure of elasticity is used to determine the impact of fare changes on PT demand (Paulley et al., 2006). Paulley et al. (2006) reviewed and synthesized a large number of previous studies which tested the elasticity values of PT demand in response to change in fares. They found significant variation in the elasticity value across studies. Most studies found fare elasticity to be between 0 and -1 (inelastic), but some studies found that long-run elasticity exceeded -1. The authors observed that fare elasticity may significantly vary depending on time of day, transport mode, type of area, trip purpose and distance and traveler characteristics. Unlike work that focused only on the potential effects of PT fare discounts, Burguillo et al. (2017) examined actual PT fare increases in Spain. Even in years with the highest price increase, demand remained inelastic. These results are consistent with results of other studies that found the PT demand to be inelastic [e.g. 18,32]. Cross-elasticity with other transport modes is also an important factor to understand the effects of fare reduction. In Litman's (2017) comprehensive review of PT elasticity studies, he estimated that 10%-50% of PT added trips will substitute for an automobile trip due to reduced fares.

Although a range of analytical models are used to estimate large-scale transport pricing reforms (Anas and Lindsey, 2011), activity-based models offer an advantage in testing such scenarios. They capture the entire picture of an individual's activities, and are able to account for trade-offs among various activities and travel alternatives in one's daily activity pattern (Ben-Akiva et al., 1998). Kaddoura et al. (2015) used MATSim as an activity-based simulation platform for the optimization of PT fares. They implemented a marginal social cost pricing approach: External delay effects among PT users charging the equivalent monetary amount. This study considers the effect of boarding/alighting passengers on in-vehicle time, waiting time without an active capacity constraint, and waiting time induced by an active capacity constraint. Results found that the marginal social cost pricing yields higher social welfare than charging an optimized flat fare. However, the scenarios were not tested using a real transport network. Lovrić et al. (2016) used SimMobility, an activity-based microsimulation model, to evaluate time-based policies implemented in the Singapore PT. They evaluated the free pre-peak travel policy and off-peak discount for an integrated bus and MRT/LRT systems. They found that free travel and discounts in pre-peak travel in PT reduce peak-period ridership, although the microsimulation model used was not fully calibrated. In addition, the authors did not test combinations of free travel together with a pre-peak discount to find the optimal pricing solution.

TDM has focused mostly on road pricing as a solution for road congestion. Various TDM schemes, such as FFPT and off-peak travel discounting, have been studied in PT. These studies focused on transferring passengers from private cars to PT, while improving social welfare and PT efficiency by spreading peak demand, and found mixed results. A shift from private vehicles to PT and from peak period to off-peak period was observed. But the variance of the changes was large, and a significant shift from non-motorized modes to PT modes was found. Most studies focused on estimating the effects of PT demand management using analytic models, based on known implemented strategy. These models are limited in their ability to predict the effects of different travel demand strategies, taking into account the large variability of PT demand elasticity on change in costs. Only a few studies used activity-based models, which are more suitable for the examination of TDM strategies. This paper uses the advantages offered by the activity-based approach, and addresses the study limitations of Lovrić et al. It offers a thorough examination of passenger behavior and system performance under different combinations of time-based pricing policies in the PT system of Singapore.

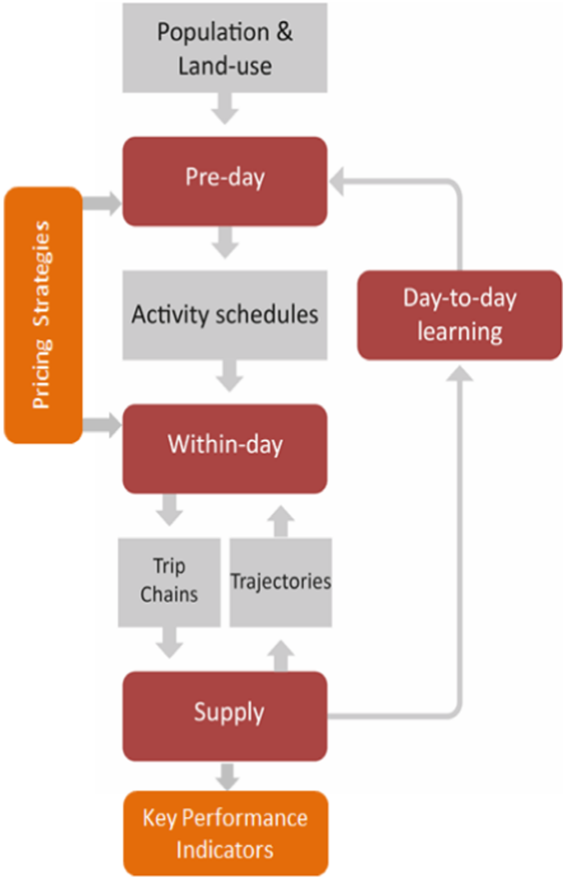

Fig. 1. SimMobility Mid-term Overview with Pricing Strategies Induction.

3. Methodological framework

3.1. SimMobility Mid-term simulator

SimMobility Mid-term (MT) simulates daily travel at the household and individual level. It is a mesoscopic simulator that combines an activity-based micro simulator on the demand side with mesoscopic traffic simulation on the supply side. Fig. 1 presents the modeling framework of the MT simulator. A detailed description of each component of the MT model can be found in Lu et al. (2015). The demand side comprises two groups of behavior models: pre-day and within-day.

3.1.1. Pre-day model

The Pre-day model provides an enhanced version of the econometric Day Activity Schedule approach (presented in Bowman and Ben-Akiva (2001)); it determines the initial overall daily activity schedule of the agent, particularly the activity sequence (including tours and sub-tours), preferred modes, departure times by half-hour time slots, and destinations for discretionary activities. This approach is based on the sequential application of hierarchical discrete choice models using Monte-Carlo simulation. Fig. 2 provides the structure of the Pre-day modeling framework; different discrete choice models (consisting of three levels: Day pattern, Tour and Intermediate stop) are linked and generate daily schedules of individuals. The Pre-day models are developed for four different activity types: work, education, shopping and others. Home, work and education locations are not modelled at the Mid-term level because they are explicitly modeled at the long-term level. Work is modeled within the Pre-day framework for individuals whose work location is not fixed. In destination/location choice models, traffic analysis zones (TAZ) are considered as alternatives. Nine different modes are modeled within Pre-day: MRT/LRT, Bus, Private Bus, Car-drive alone, Car-with 2 passengers, Car-with 3 passengers, Motorcycle, Taxi and Walk. From the mode and mode-destination choice models, the individual-based logsums for each activity type are transferred to day pattern level models, which helps capture the second-order effects of the policy (in terms of selection of changed daily patterns). Time-of-day models at the tour level jointly predict choice of arrival and departure times by incorporating alternative specific constants, their combination, time pressure effect and time-dependent level of service variables (i.e. travel time and travel cost). The time of day model specification uses the cyclical and continuous indirect utility functions to solve the discontinuity issue of utilities due to the discretization of time (as explained in Ben-Akiva and Abou-Zeid (2013). Alternatives for time-

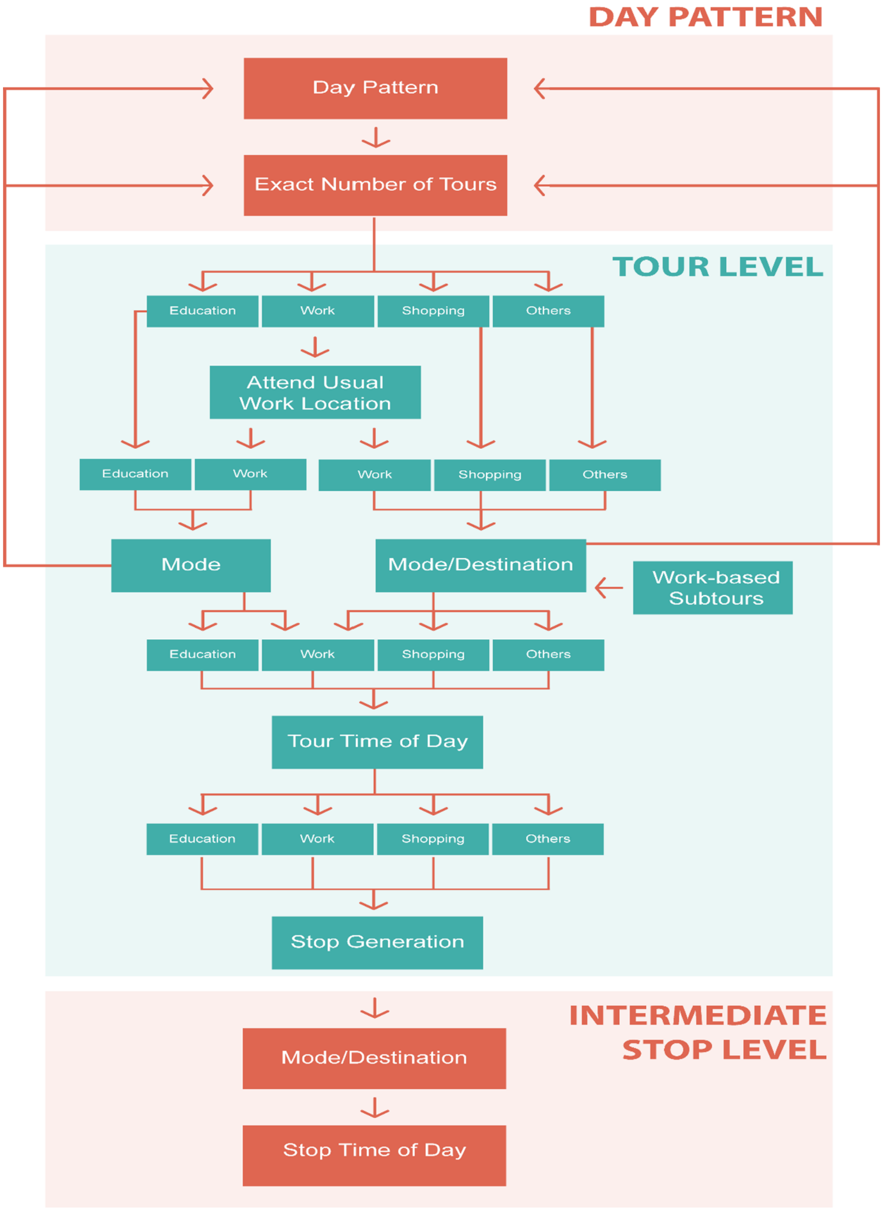

Fig. 2. SimMobility Mid-term: Preday Modeling Framework.

of-day models are based on the 30-minute time slots. Pre-day models have been estimated primarily using data from the HITS-2008 and HITS-2012 data, along with land-use and network skim data (for private and public vehicles) for different time periods during the day. Readers are directed to(Siyu (2015) for more information on the Pre-day models, including. an explanation of utility specifications and the variables used in model estimation results, in-sampled verification and also validation from 2012-HITS data.

3.1.2. Within-day model

The within-day simulator uses information from the Pre-day output to extract trips from the schedules and predict route choice in public and private networks. The within-day simulator also has the flexibility to re-schedule travel decisions using an event-driven publish/subscribe mechanism (more details available in Adnan et al. (2016). To estimate the route choice model, taxi GPS data is used for the private network and E-z link smart card data is used for the public network, including bus, MRT and LRT networks. A variety of algorithms are used to ensure the generated alternatives have maximum coverage from the observed routes for all trips in the data. Coverage is greather than 98% for both public and private networks. Please refer to Tan et al. (2015) and Lu et al. (2015) for more details on both models. We used taxi GPS data due to limited availability of other datasets. We considered only those trips in which taxi was occupied as this information was available in the taxi GPS dataset. The validity of taxi data for the private network was shown by comparing the value of time obtained from the mode choice model (estimated using HITS data) and this route choice model. The values closely match. Additionally, during the overall calibration of the SimMobility Mid-term simulator, route choice model parameters were adjusted to ensure that outputs from the Mid-term model were consistent with traffic counts. A public transport route choice model was developed to integrate the network of buses, MRT and LRT as an origin stop to destination stop model. Walking is considered an access and egress mode for the final destination (smart card data observations are based on origin stop to destination stop, and data from HITS indicated that 95% of public transport trips use walking as access and egress mode). Both the private and public route choice models contain level-of-service variables (such as in-vehicle travel time, waiting time, transfers, fare, tolls, access and egress times) to better describe the behavior of route choice among the individuals. The within-day simulator uses the information from the Pre-day output to extract trips from the schedules and predict the route choice in public and private networks.

3.1.3. Supply simulator

The mid-term supply simulator is a mesoscopic traffic simulator that shares many common features with the DynaMIT supply module (Ben-Akiva et al., 2010). The objective of the simulator is to estimate the actual movement trajectory of each vehicle; the path of each traveler can be a sequence of road segments or public transport route segments depending on the type of network. Several enhancements have been made to the supply model: it treats bus stops, MRT and LRT stations explicitly and it considers dwell time, bus queuing at stops, movement of buses and trains at stops/stations (i.e. acceleration and deceleration), train movement and control procedure adopted in Singapore. Different parameters used in the movement models were also applied in the simulator calibration in order to give accurate estimates of trips and vehicle travel times. The simulator provides various output statistics:. number of persons boarding or alighting at specific MRT stations and bus stops (for specific service), denied boardings, occupancy of bus/MRT/LRT at each stop/station, dwell time, waiting time for a specific person, etc.

The SimMobility Mid-term simulator is calibrated using the Weighted Simultaneous Perturbation Stochastic Approximation (W-SPSA) algorithm (Antoniou et al., 2015) for an objective function that contains multiple-parts. The parameters being calibrated include estimated coefficients of day-pattern, time-of-day, mode, destination choice, private and public route choice, speed-density parameters, capacities of mid-block sections, capacities of segments near intersections, and parameters that describe the movement of buses and trains at specific points. The data for the calibration process came from GPS floating car data from taxis and 29 screenlines that contain 403 classified counting locations. The processed classified counts and zone-to-zone travel times are aggregated by 30 min. For aggregate counts, on the basis of screenlines, we obtained a root mean squared error normalized (RMSN) of 0.19. Standard recommendations do no exist for such large-scale simulator goodness-of-fit values, although lower error values are preferable. Other studies reported similar results of goodness-of-fit statistics (ranging from 0.13 − 0.45) in cases where large-scale dynamic traffic simulation models (e.g. MATSIM) were calibrated that involved a large number of calibration parameters (Azevedo et al., 2017; Zhang et al., 2017; Moyo, 2014; Tavassoli et al., 2019). Based on these studies, a RMSN value of 0.19 seems reasonable. Table 1 describes some key aggregate measures obtained after the calibration of the simulator.

3.2. Experimental design

We provide a wide range of metrics to explain the outcomes of pricing strategies and evaluate their impact. Some metrics are similar to those used in previous studies such as ridership and mode share. However, we offer other metrics, including operator revenue and number of denied boardings, to obtain detailed outputs from the simulator. The number of denied boardings is a useful metric to represent crowding conditions of public transportation, and can be used to model commuters' mode and route choice preference. Operator's revenue is an important metric to show the burden of a discount policy. Metrics include:

- Peak and off-peak PT ridership: represented by transit network loadings. The morning peak time window is 7:30 AM to 9:30 AM. The afternoon peak time window is 5:30 PM to 7:30 PM. All other time is considered off-peak.
- PT mode share: the percentage of trips made using transit modes (public bus, MRT or LRT).
- Operator's revenue: calculated as the sum of trip fares collected from all passengers during one simulated day. This is a simplified calculation of revenue that assumes the same policy applies to all passengers and that passengers pay transit charges using their smart card electronic purse (which also assumes no other forms of public transport travel passes exist).
- Number of denied boardings: a supply-side output for bus stops, MRT and LRT stations. A denied boarding happens when bus/train capacity is reached and a passenger cannot enter (if N passengers are denied boarding to a bus, we count N, the number of persons affected). We calculate this metric for peak periods and off-peak period.
- Number of public transportation trips: the number of single transit trips made by all passengers during one simulated day.

Table 1
Summary of Aggregated Measures.

Measures	Observed data	Simulated data
Average daily Passenger Journeys in Public Transportation: (Using LTA 2013 transport statistics)	4.35 Million	4.39 Million
Average MRT Ridership: (Using LTA 2013 transport statistics)	2.51 Million	2.48 Million
Average travel time by car (entire day): (Using Singapore statistics website)	25 mins	23 mins
Average travel time by Public Transport (entire day): (Using Singapore statistics website)	45 mins	43.6 mins

The following pricing strategies are implemented and simulated:

3.2.1. Base case using nominal pricing

This policy with no fare reduction serves as the base case, against which the changes in key performance indicators are calculated for other pricing strategies. Upon analysis of the base case, we confirmed the results in terms of daily MRT/LRT and bus ridership and average travel times of the user while traveling in public transport. Our simulation results are reasonably close to the numbers mentioned in LTA statistics. Please see table 1.

3.2.2. Free pre-peak travel on MRT

This policy was implemented by LTA in June 2013 on weekdays. It enables free travel using MRT service for 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 (the number of stations has since increased to 18). A discount of up to 50 cents is offered to passengers who miss the cut-off time but manage to exit these stations between 7:45 AM and 8:00 AM. As the 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.

3.2.3. Off-peak discount in public transportation (bus + MRT + LRT)

This is a time-based policy that applies to the integrated transit system across Singapore. The trips for tap-ins during one of the off-peak periods (before 6:30 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 public transportation concession card called the Off-Peak Monthly Travel Pass. This pass provides unlimited free travel that begins in one of the three off-peak periods, and it costs 2/3 of the regular concession card. It is not clear whether the price (offered discounts) of this scheme will stablize over a certain period. Therefore, four discount levels are considered arbitrarily: 25%, 50%, 75% and free (100%). The effects of policy at some other intermediate discount levels can be reasonably estimated by interpolation.

We also combined the above two pricing strategies. Altogether, we examine nine different strategies using SimMobility Mid-term. The configuration of these strategies is shown in Table 2. It should be noted that if we combine the two types of policies, the peak times may conflict as free pre-peak MRT policy is considered when peak starts from 8:00 am and provides free-travel before this time but only at a few specific MRT stations (inside CBD). On the other hand, off-peak discount policy considers morning peak from 6:30 to 9:00 am, and, therefore, provides discounts before or after this time window. In simulation scenarios where these policies are analyzed together (i.e. 6,7,8,9), at those specific MRT stations, trips are considered free until 8:00 am, as free pre-peak MRT policy will govern there before 8:00 am.

3.3. Adaptations of Models

Three main sets of models in SimMobility Mid-term are adapted to reflect the effect of pricing strategies.

- *Time of Day choice models (Pre-day):* Cost variable in the utility specification is changed with respect to the time-of-day settings of different pricing strategies in time-of-day choice models for work, education, shopping and other purposes. Same is applied to time-of-day choice models at levels of work-based sub-tour and intermediate stops.
- *Tour Mode and Destination choice models (Pre-day):* These are a set of five models. For usual work location and education purposes, the destination is known. Therefore only mode choice is modeled. For unusual work location, shopping and other purposes, mode and destination are jointly modeled. Based on the hierarchical structure of the Pre-day framework (see Fig. 2), it is evident that

Table 2
Pricing Strategies.

Pricing strategy	Pre-AM Peak Free MRT	(BUS+MRT) off-peak Discounts			
		25%	50%	75%	100%
1	X				
2		X			
3			X		
4				X	
5					X
6	X	X			
7	X		X		
8	X			X	
9	X				X

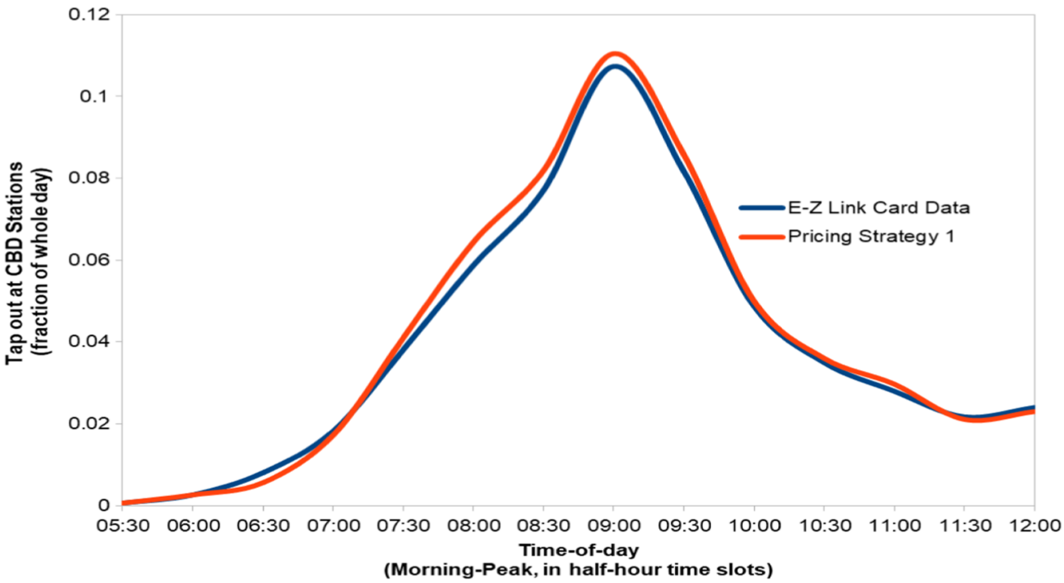

Fig. 3. Tap-outs at 18 CBD MRT Stations after Free Pre-peak MRT Policy (E-Z link card data and Model predictions).

tour level mode and mode-destination decisions are simulated before the time-of-day decisions. Thus, time-of-day is not known at that stage. Within the utility specification of these models, public transport cost and travel times for work and education purposes are assumed as applicable for the morning peak. For shopping and other purposes, the cost and travel time of public transport are assumed as applicable for the off-peak period. These assumptions are made to build the hierarchical structure of the Pre-day model for various travel decisions. The validation of the Pre-day model outcomes with the HITS 2012 dataset indicated that these assumptions were reasonable, as reported in Ben-Akiva and Abou-Zeid (2013). Furthermore, in the Pre-day modeling framework, there are no logsums used from tour time-of-day models to the mode and mode-destination choice models. To reflect the effect of policy in mode share changes, the following is adopted: for pre-peak free MRT, fare reduction was introduced for morning MRT trips from outside CBD into CBD by using a factor. This factor is based on the proportion of the population affected by the free pre-peak MRT (calculated from SMART card data available before and after implementation of this policy). This is an adjustment factor for calibrating mode choice models to reflect the changes in mode choices as a proxy for compensating the absence of logsums from the time-of-day model to mode choice model. The results of the Pre-day model after the introduction of this factor are then compared with the SMART card data (after policy implementation), which are shown in Fig. 3 as tap-out profiles. Both profiles closely align, which indicates that the adjustment of the mode choice model in this manner was plausible. Therefore, for off-peak discount policies where no data is available, we followed a similar notion, i.e. the factor is scaled based on the amount of fare reduction and also the proportion of demand that falls within the discounted periods. For combined strategies, both policy fare reduction factors were combined..

- *Public Transport Route Choice Model (Within-day):* For pre-peak free MRT, fare reduction was introduced for morning MRT trips from outside CBD into CBD, based on the identification of alighting MRT stations within CBD and estimated time of arrival for a particular public transport path. For off-peak discounts, the fare of the PT path is reduced with estimated trip start and end time in the PT network. Three main sets of models in SimMobility Mid-term are adapted to reflect the effect of pricing strategies.

4. Results and discussion

This section presents results of the nine different pricing strategies tested in this study using SimMobility Mid-term, including analysis of results in terms of changes in public transport ridership in different time periods (i.e. A.M., P.M. and off-Peak), changes in mode shares, revenue and level of service indicators, such as denied boarding. More detailed analysis includes changes in the above measures with respect to gender, income level and person type to ascertain which segment of the population is more responsive to these strategies. For simulation of each strategy, we start the simulation at 3:00 am of the same day and end it at 2:59 am of the next day. On average, simulations took 5 h, on a 30 core High Performance Computer (HPC). This simulation time is the total time required to run SimMobility Mid-term in two different modes, such as Pre-day mode with logsum computations (1.5 h) and within-day with supply mode (3.5 h). Simulation time does not include the time required to generate public and private path set generation processes, as these are stored in the database tables for every node in public and private type networks for Singapore. During each simulation run, we used the entire population generated by the SimMobility Long-term model containing around 5.25 million inhabitants. Table 3 presents mode shares for the total number of trips (i.e. 12.118 million trips) as outputs of the base case from the mid-term model to facilitate realization of the extent of changes predicted in policy simulation runs.

Table 3
Baseline Outputs: Mode Shares and Trips.

Modes	Mode Shares (%)
Public Bus	29
MRT/LRT	23
Car (Drive Alone)	11
Car Sharing (2 passengers)	4
Car Sharing (3 passengers)	3
Private Bus/Company Bus	10
Motorcycle	1
Taxi	3
Walk	16

4.1. Free Pre-Peak MRT (Pricing strategy 1)

Here we present results on the first pricing strategy, which includes Free MRT rides before 8:00 am to 18 CBD MRT stations. Simulation results suggest approximately 6% reduction in MRT ridership for the 18 CBD stations during morning peak period. LTA results indicated a reduction of around 7% trips in A.M. peak period for designated MRT stations using smart card data (Land Transport Authority, Singapore, 2018). Additionally, tap-out profiles (i.e. number of individuals leaving the CBD MRT Stations in the morning time) in half-hour time slots is shown in Fig. 3 for comparison. Both profiles closely align and indicate that the simulator is reasonably accurate in relation to prediction of changes that are caused by different policies. However, the actual policy is slightly different than the one tested here, as in the implemented policy free travel is provided till 7:45 a.m. and a discount of 0.5 SGD is provided if passengers finish their trip between 7:45 am and 8:00 am. Some differences (shown in Fig. 3) can be attributed to these conditions. The reason we are not able to test the exact implemented policy is because of the limitations of the Pre-day model, which works on a 30-minute time slot. Fig. 4 shows taps-outs on those 18 CBD MRT stations in two half-hour time windows for the base case and with pricing strategy 1. An interesting behavior of commuters in relation to the free pre-peak MRT policy may be observed, in which individuals travel further into MRT to get the benefits from this policy. The SimMobility MT simulator partially observes such behavior, as the Pre-day model assigns location on the zone level (for this policy MRT stations are mapped to the zones). However, at the within-day level, these locations are further disaggregated at the postcode level. The public transport route choice model implemented in SimMobility is flexible and can allow change of MRT station based on fare reduction which can be traded-off for a longer egress walk to the final destination. However, we noted no notable increase in the number of total tap-outs at CBD stations in comparison with the base case.

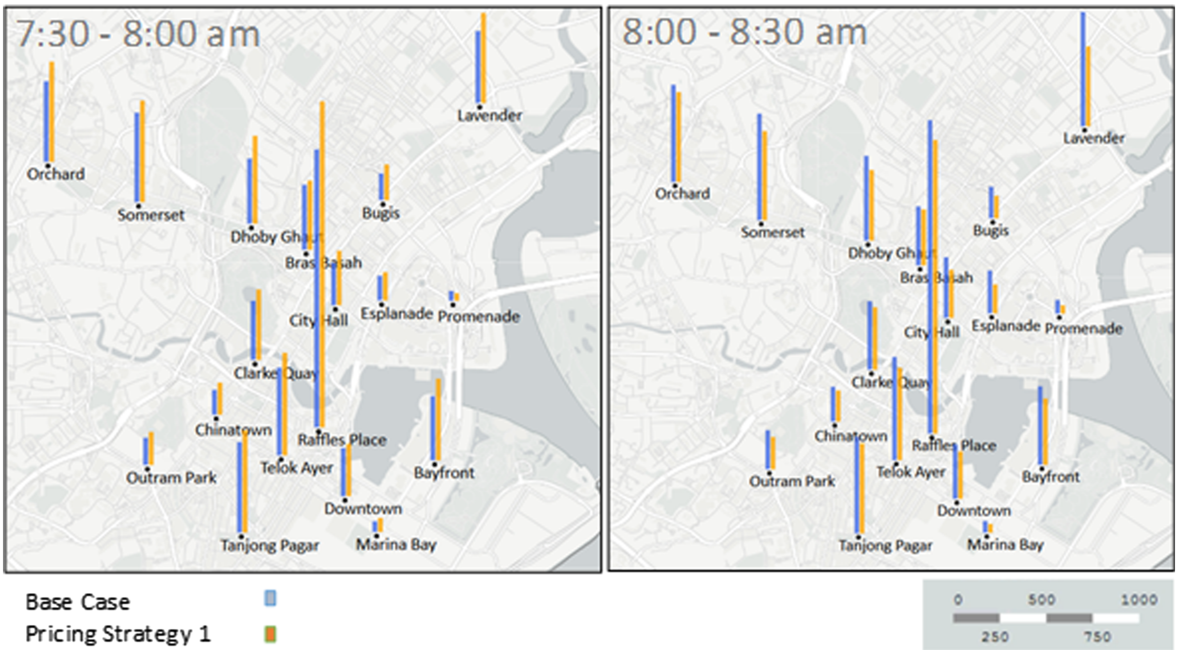

Fig. 4. Number of Tap-outs (i.e. Alightings) at 18 CBD MRT stations.

Table 4
Mode Shares, changes in Ridership and Revenue.

Pricing Strategy	Policy		Mode Shares in % and (mode share change in % points from base case)						Change in PT Ridership (%)	Change in Revenue (%)
	Pre-A.M. Peak Free MRT	Off-Peak Fare Discounts (%)	PT	Car (Drive Alone)	Car Sharing 2 and 3	Taxi	Walk	Others*		
1	Yes	0	52.0 (0.02)	10.9 (-0.011)	6.9 (−0.001)	2.9 (−0.007)	16.0	11.0	0.04	−2
2	No	25	52.3 (0.31)	10.8 (−0.18)	6.9 (−0.004)	2.93 (−0.07)	16.0	11.0	0.61	−15
3	No	50	53.2 (1.2)	10.4 (−0.58)	6.8 (−0.16)	2.7 (−0.29)	15.9	11.0	2.35	−29
4	No	75	53.8 (1.88)	10.1 (−0.89)	6.7 (−0.23)	2.5 (−0.44)	15.8	10.9	3.71	−43
5	No	100	54.3 (2.35)	9.8 (−1.19)	6.7 (−0.42)	2.4 (−0.61)	15.8	10.9	4.68	−58
6	Yes	25	52.4 (0.47)	10.7 (−0.24)	6.9 (−0.078)	2.8 (−0.15)	16.0	11.0	0.92	−14
7	Yes	50	53.8 (1.84)	10.0 (−0.95)	6.7 (−0.23)	2.3 (−0.63)	16.0	11.0	3.61	−28
8	Yes	75	54.5 (2.55)	9.6 (−1.32)	6.1 (−0.81)	2.6 (−0.38)	16.0	11.0	5.01	−42
9	Yes	100	55.4 (3.42)	9.3 (−1.64)	5.9 (−1.1)	2.4 (−0.55)	15.9	11.0	6.80	−56

*Others include *Motorcyle* and *Private/Company bus* travel modes.

4.2. Overall results from all nine pricing strategies

Table 4 presents the overall changes (Singapore wide) in mode shares, public transport (MRT + LRT + Bus) ridership and daily revenue for all nine strategies. 'Yes' or 'No' in column 2 of table 4 indicates whether the policy of free ride in MRT at pre-peak was incorporated. Column 3 in table 4 presents the rate of fare discount applicable at off-peak periods. For example, (Yes, 0%) corresponds to strategy 1, where the policy of free ride in MRT at pre-peak period is applicable and the fare discount rate at off-peak periods is 0. Changes in daily operator's revenue decreased significantly from −2% (strategy 1) to −58% (strategy 5). However, PT ridership increased along with the mode shifts. This suggests that off-peak discounts attract individuals from other transport modes. Further analysis showed that the majority of mode shifts towards PT occurred from Car (Drive Alone), Car sharing 2 and 3, and Taxi alternatives. The highest shift for Car and Car sharing 2 and 3 is associated with strategy 9, which is approximately −1.64% and −1.10%, respectively. Furthermore, for strategies 5 and 9 (i.e. free PT in off-peak periods), 0.21% and 0.09% mode shift occurred from the Walk alternative, respectively. The pricing strategies, therefore, have some effect in terms of reducing car-based alternatives. However, it does not result in noteworthy decrease in traffic congestion from roads, especially during peak hours. Earlier studies also found similar results (Paulley et al., 2006; Cats et al., 2014). In these studies, effects of subsidizing public transport by reducing its fares or making it completely free to reduce car use are studied, and it was found that such policies did not result in car use reduction. However, the major purpose of the time-based pricing studied here is to shift PT demand to optimize PT system capacity. The numbers for strategy 1, however, show that it is effective in changing the departure times of commuters. However, when combined with strategies that offer discounts in off-peak periods (i.e. strategies 6–9), more individuals are attracted to the PT mode.

The Pre-day model has the capability to incorporate induced trip as a result of logsums incorporated in the top level (day pattern) models from the lower level mode choice models. These induced trips are the result of increase in the accessibility measure of each individual. The results presented in table 4 should not be confused with the induced trips, as these trips are already accounted for. We carried out an analysis to quantify induced trips in each policy scenario and noted a systematic increase in the number of trips (that can be called induced trips) in the range of 0.005% − 0.05% of trips in the base case as compared to the pricing scenarios. In absolute terms, the induced trips are in the range of 600 to 6,000 trips per day, while the total number of trips per day is over 12 million trips. In addition, some of the percentage increase may be due to simulation error. The larger value of induced trips is noted for the pricing strategies 5 and 9, 4.68% and 6.80%, respectively, where PT is free during off-peak periods. For the sake of simplicity, if we assume that these additional trips are made using PT and in each policy scenario the respective number of these additional PT trips are subtracted, then any further increase in PT trips in each scenario can be easily attributed to the mode switch. Table 4, therefore, provides numbers without the inclusion of these induced trips.

For the first strategy, the PT ridership is inelastic (i.e. the values is almost 0). However, in relation to other strategies, elasticity of overall PT ridership with respect to fare price changes is measured in the range of (−0.02 to −0.07). These values are only slightly different than the perfectly inelastic case. Similar results are reported in other studies (Cats et al., 2014; Jacob, 2018). This situation also resulted in inelastic behavior in relation to mode switch from car-based alternatives (i.e. cross elasticity values of all strategies are around 0). Tirachini et al. (2016) reported a fare elasticity value of around −0.2 to −0.3 for metropolitan areas in the UK. Other studies (Litman, 2017) have shown cross elasticities in the range of 0.1 to 0.3. One reason fare elasticity is inelastic for strategies 1 to 9 is due to availability of fare discounts to only the segment of the population that is flexible in switching their departure times. The direct elasiticty value approaches the relative elastic range if discounts in fare are offered at all times of day. It is thus interesting to see changes in ridership with respect to different time periods and socio-economic characteristics.

4.3. Results disaggregated in time and socio-economic characteristics

Table 5 shows the change in PT ridership and denied boardings for all 9 strategies in A.M., P.M., and off-peak periods. Ridership changes in P.M, with peak and off-peak periods is plausible. However, individuals shifted from other modes to PT (especially the effect of strategies 2 to 9) tend to travel in the A.M. Hence, peak ridership in this period is increased up to 1.86%. As the off-peak discounts are available in all off-peak periods during the day, individuals tend to acquire benefits by shifting their evening trip departure times rather than shifting morning commute departure times. Thus, a reduction of up to 3.06% in ridership was observed.

Table 5
Overall changes in PT ridership and denied boardings during peak and off-peak.

Pricing Strategy	Policy	A.M. Peak Changes (%)		P.M. Peak Changes (%)		Off-Peak Changes (%)	
		Ridership	Denied boardings	Ridership	Denied boardings	Ridership	Denied boardings
1	Yes, 0	−1.03	−8.06	−0.26	−2.5	0.8	0.01
2	No, 25	0.22	1.01	−0.59	−4.12	1.40	0.05
3	No, 50	0.93	6.13	−1.05	−7.05	2.71	0.10
4	No, 75	1.32	10	−2.15	−12.31	4.43	0.52
5	No, 100	1.86	13.10	−2.78	−20.30	5.94	2.01
6	Yes, 25	−0.41	−3.12	−0.81	−8.23	2.08	0.11
7	Yes, 50	0.28	4.12	−1.28	−9.20	3.81	0.49
8	Yes, 75	0.79	8.23	−2.37	−14.19	5.36	1.86
9	Yes, 100	1.39	11.02	−3.06	−25.31	7.15	2.51

Table 5 further confirms that increase in PT ridership in the A.M. peak period brings more crowds as denied boarding changes are noted to follow a similar trend for all nine strategies. It is also noted that increase in ridership occurred in the peak direction of travel within PT (i.e. more individuals traveling towards business districts). Table 5 further elucidates that, in general, shifts from other travel modes in the peak direction occur during the morning work commute. The trend noted for strategies (2 to 9) of an increase in PT ridership in the A.M. peak period is largely due to off-peak discounts available in the early morning (i.e. till 6:30 am), even though A.M. peak period is defined from 7:30 to 9:30 am. This may be the reason why free MRT policy (strategy 1) is more effective in shifting A.M. peak period demand, as the discount is available till 8:00 am. Commuters may prefer to reach their work location a bit earlier, although, if too early (due to availability of discounts before 6:30 am), its benefit may not outweigh compromising sleep and other morning home tasks. Of course, departing late to enjoy off-peak discounts available after 9:30 am may entail other implications, especially for commuters. Indeed, in Singapore, few institutions offer such flexible work hour schemes. The findings from Theseira and Qiyan (2018) also support a similar notion as they concluded that cost of waking up early to take advantage of off-peak discounts is higher among Singapore commuters. Bianchi et al. (1998) reported similar findings for Santiago Metro travellers when they were given off-peak period fare discounts. Additionally, similar experiences were noted in Melbourne, where passengers were offered free rail travel trips during the off-peak period (Volinski, 2012).

We narrowed our focus by analzying ridership changes based on individual socio-demographic characteristics (e.g. gender, income and person type), shown in Fig. 5. It can be seen that income earning individuals have a tendency to shift towards PT mode, especially those belonging to lower income classes (e.g. increase in PT ridership is noted to be in the range of 2–5% for pricing strategies 2 to 9). Note that no income class represents children (mainly students) and unemployed individuals. According to HITS data as well as from other regions (such as Vancouver, Canada) (Tawfik, 2014), lower-income individuals tend to be characterized by even distribution of travel in relation to time-of-day compared to high-income individuals, who mostly travel during the peak hours. Therefore, off-peak discounts are generally considered to eliminate the cost burden for travel in PT for low-income individuals (Lipscombe, 2016). The results from Fig. 5b also point to a shifting of lower income individuals towards PT, although this shift resulted from the Walk mode, especially for strategies 5 and 9. This is not a desirable effect for such strategies.

In addition, retired individuals and homemakers shifted to PT mode. More interestingly, some workers also shifted their mode of travel, which may explain the increase in A.M. peak PT ridership, as seen in Table 5. The student population is found to be more rigid in their behavior, mainly due to their strict schedules and the fact that they already use another form of public transport such as school buses. Furthermore, females are more responsive to off-peak discounts than male, a difference only noted when off-peak discounts are greater than 50%. The highest difference noted in relation to increased PT ridership is 1 and 1.5% for pricing strategies 5 and 9, attributable to greater flexibility of women's work schedules. Data from HITS 2008 and HITS 2012 also suggested a similar flexibility in women's work schedules (Siyu, 2015).

Fig. 6 sheds further light on changes noted in PT ridership in the A.M. peak. It can be seen that worker class commuters are mainly responsible for the overall increase in A.M. peak PT ridership. Other demographics such as students, homemaker, and retiree all shifted in off-peak periods (by departing before or after the A.M. peak). In conjunction with Fig. 5b and 6, it can be concluded that workers (i.e. income-earning individuals) have shifted from other modes. This population tends to travel in the A.M. peak and simultaneously capitalizes on benefits offered in off-peak periods for their return journey.

Overall, the higher off-peak fare discounts (i.e. more than 50%) provided in strategies 4,5,8 and 9 result in adverse consequences, especially for A.M. peak. Therefore, they are not recommended. It is necessary to explore more effective pricing strategies: e.g. provision of discounts in the time windows surrounding the A.M peak period only, which may translate into more positive results compared to discounts in all off-peak periods of the day. Additionally, the free pre-peak MRT policy concentrated only on the 18 CBD MRT stations may need to be extended for the whole MRT/LRT network as it serves the main objective of peak spreading. This may result in more equality and target the working class, who represent the major commuter group of in the peak direction. Authorities in Singapore already announced the extension of the policy to all MRT/LRT stations, although travel is discounted to only 0.50 cents and is not free due to significant revenue losses (Choo, 2017). Christina (2015) noted the effectiveness of pre-AM peak discounts, but at the same time also advocated for use of a smartphone application to convey real-time information about crowding levels in the PT system to optimize results for peak spreading. Our models consider flexible working hours, although inflexibility in school and work scheduling mitigates the effects of fare reductions. Therefore, it is necessary to give this aspect due consideration along with the application of time-based pricing strategies. Even so, the results obtained from the simulator seem plausible, with similar reproducible effects of pricing strategies, as noted in earlier empirical data and studies. However, there are several aspects that require improvements. Further work is needed to improve the demand simulator (Pre-day) structure and relevant sub-models in order to address the following limitations. In the simulation, the time-of-day decision is conditional on the mode choice decision, which is similar to many other ABM models in the literature (Castiglione et al., 2015). This results in a situation that, at a mode choice decision level assumption, is made about the use of off-peak travel times and costs to determine alternatives utilities for "shop" and "other" activities because time-of-day choice is not known. To address this limitation, a link between the time-of-day model and mode choice model through logsums should be established. In addition, the preday model incorporates fewer activity types (work, education, shop and other). This is due to the lower number of observations available (for activities grouped as "other") in the household travel data. This limitation can be overcome, if a similar dataset can be collected using GPS-based smartphone apps, which require accurate annotation of individual activity-travel patterns. Recently, the LTA has coupled their traditional periodic household travel survey with an activity-diary survey from a smartphone app. A variety of submodels within the pre-day structure can be further fine-tuned with the availability of such rich datasets. Additionally, our ability to model crowding conditions is also limited. Improving the models by adding crowding condition variables in vehicles and platforms will also make our simulation more realistic as indicated in Batarce et al. (2016). Their empirical study concluded that inclusion of crowing (passenger density) in a mode choice

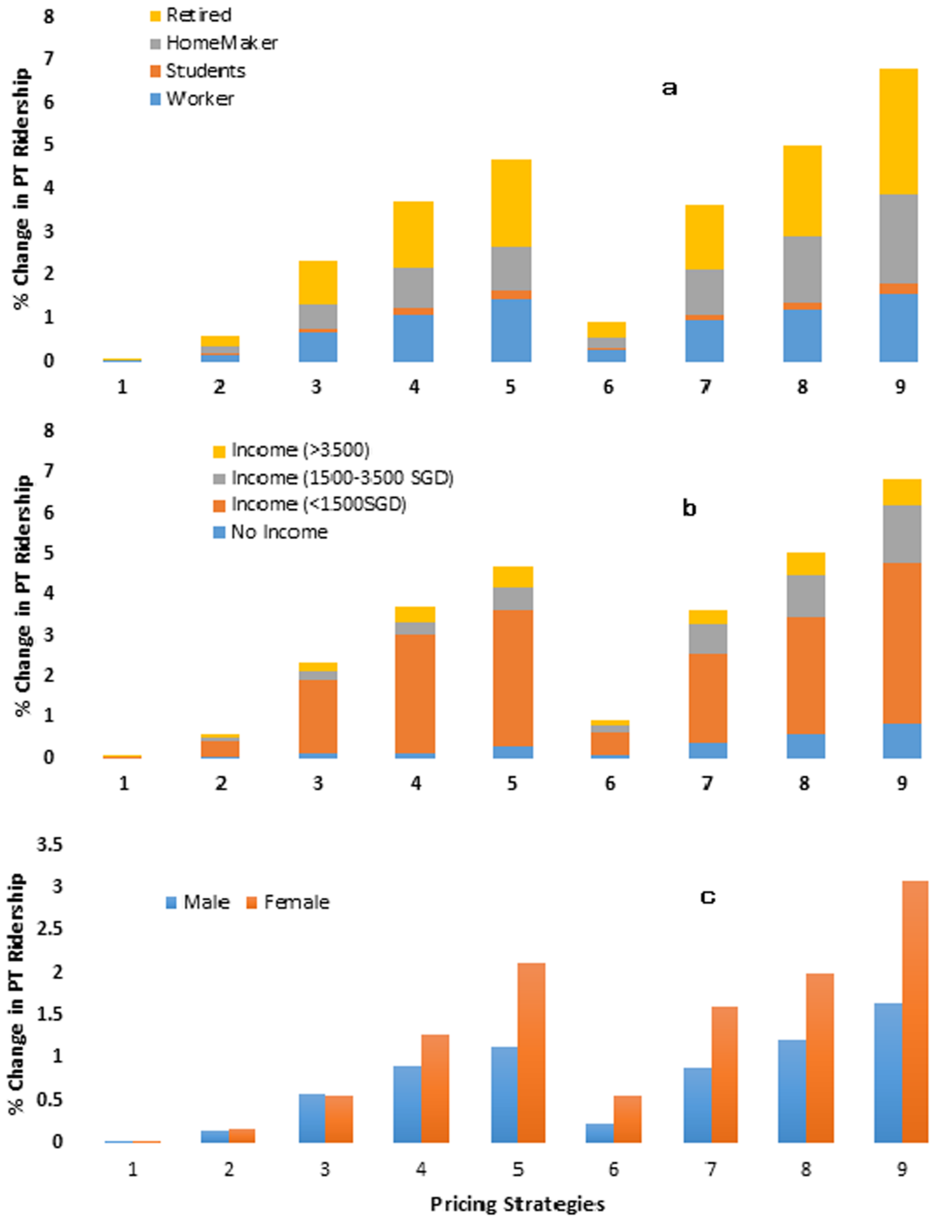

Fig. 5. Changes in Overall PT ridership (%) for Nine Pricing Strategies with Different Socio-Demographic Characteristics (a) Person types (b) Income levels (c) Gender.

model is vital, as a minute of travelling in a high density condition produce a discomfort that is 2.5 times greater than obtained at lowest density condition.

5. Conclusions and recommendations

This paper analyses the impact of free pre-peak MRT rides combined with off-peak public transport fare discounts stemming from nine (09) pricing strategies applied in the state-of-the-art simulator, SimMobility Mid-term. For the examination of the different time-based pricing strategies, various key indicators such as peak PT ridership, mode shares, operator's revenue and denied boarding were used. Additionally, impacts on different population segments by income class, employment status, and gender were analyzed.

The results suggest that free pre-peak MRT travel shifts commuters in off-peak periods. However, off-peak fare discount strategies tend to shift travel demand only in the P.M. peak. At the same time, they are able to increase the number of public transportation trips and attract individuals from other transport modes. The increment in PT ridership in the A.M. peak period is largely due to off-peak discounts, which attract more crowds, similarly for all nine strategies. Thus, providing discounts in all off-peak periods can increase

Fig. 6. Changes in PT ridership (%) in A.M. Peak with Worker Class and Overall Population.

demand in the A.M. peak. Our analysis showed that the majority of mode shift towards PT occurred from Car (Drive Alone), Car sharing 2 and 3, and Taxi alternatives. The pricing strategies, therefore, have plausible effects in terms of reducing car-based alternatives. However, they have a minor effect in terms of road congestion reduction, especially during peak hours. Furthermore, for free PT in off-peak periods, an undesired shift occurred from the Walk alternative. It was found that workers were primarily responsible for the overall increase in A.M. peak PT ridership, and they tended to benefit by shifting their evening trip departure time rather than shifting their morning departure times. Our results suggested that higher off-peak discount strategies should be avoided, with a focus on strategies providing discounts in surrounding time windows of AM peak. Extension of free Pre-peak MRT/LRT to all stations may also contribute to achieving the peak spreading objective. Both policies should target the worker class. Thus, an examination of both strategies is of interest in future work.

Furthermore, future reseach may evaluate time-based pricing policies in private transportation, and especially the mutual effects that private transportation has on public transportation and vice versa under different strategies. The impact of price in relation to the quality of both public and private transport and other competing transport modes is also highly relevant since a worldwide lack of flexible work hours seems to be blocking the impact of pricing strategies aimed at reducing peak travel. Examination of flexible work hours in different sectors along with pricing strategies may give new insights. Finally, developing models which will be based on incentives in the form of trade-able tokens in order to spread peak demand in public and private transportation is also a desirable future research direction.

Credit authorship contribution statement

Muhammad Adnan: Conceptualization, Methodology, Investigation, Formal analysis, Writing - original draft. **Bat-hen Nahmias Biran:** Methodology, Formal analysis, Writing - review & editing. **Vishnu Baburajan:** Data curation, Formal analysis, Writing - review & editing. **Kakali Basak:** Software, Visualization, Resources. **Moshe Ben-Akiva:** Supervision, Conceptualization, Resources, Project administration.

Acknowledgement

The research is supported by the National Research Foundation, Prime Minister's Office, Singapore, under its CREATE programme, Singapore-MIT Alliance for Research and Technology (SMART) Future Urban Mobility (FM) IRG.

We would also like to thank the Singapore Land Transport Authority (LTA) for providing guidance with the case study, and the data used in this research.

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