Agent based micro-simulation of a passenger rail system using customer survey data and an activity based approach

Agent Based Micro-Simulation of a Passenger Rail System Using Customer Survey Data and an Activity Based Approach

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Abstract. Passenger rail overcrowding is fast becoming a problem in major cities worldwide. This problem therefore calls for efficient, cheap and prompt solutions and policies, which would in turn require accurate modelling tools to effectively forecast the impact of transit demand management policies. To do this, we developed an agent-based model of a particular passenger rail system using an activity based simulation approach to predict the impact of public transport demand management pricing strategies. Our agent population was created using a customer/passenger mobility survey dataset. We modelled the temporal flexibility of passengers, based on patterns observed in the departure and arrival behavior of real travelers. Our model was validated using real life passenger count data from the passenger rail transit company, after which we evaluated the use of peak demand management instruments such as ticketing fares strategies, to influence peak demand of a passenger rail transport system. Our results suggest that agent-based simulation is effective in predicting passenger behavior for a transportation system, and can be used in predicting the impact of demand management policies.

Keywords: Agent Based Simulation, Customer Survey Data, Passenger Rail System

1 Introduction

Due to consistent increase in urbanization and societal changes in economic status, tremendous pressure has been mounted on transportation infrastructure, leading to the rise in research on travel demand models (i.e. models created to reflect the travel behavior of a population), as opposed to continuously building new infrastructure to meet growing demand.

The first generation of travel demand models were developed in the 1960's and are popularly called four step models[1]. These models fast became obsolete as their limitations became obvious. Firstly they consider individual trips separately, ignoring the fact that people make travel plans while considering entire trip chains. Also, submodules within the step sequences were inconsistent, and in the heart of the model itself lay aggregation based procedures[2]. These limitations, made these models inefficient in testing policies. This led to the development of two new approaches –disaggregate choice and activity based travel demand models[3]. Although, disaggregate choice travel demand models were accepted for a while, they maintained a fundamental error of their predecessor which analyzed each trip independent of another trip made by the same individual, thereby limiting its policy testing ability. Activity based travel demand models have gradually gained popularity since the 1990's.

Activity based approach to travel demand views travel as a derived demand, derived from the need to pursue activities distributed in time and space[1]. Its approach allows the creation of travel models in which represented individuals from the complex system can be trace throughout the simulation. Therefore by implementing the activity based approach using agent based methods, micro simulations can be created with generated activities and trips for every person in the study area. This and in addition to the fact that computing capabilities have soured over the years have led to the increased development of large scale agent based traffic demand microsimulations for large metropolis such as Netherlands[4], Germany[5], Buffalo-Niagara[6], Zurich[7], Toronto[8], and south Africa[9].

One of the early activity based models created is the AMOS model[10] which was implemented in Washington Dc's traffic flow prediction, in which six policies were considered, including congestion pricing. The model input is a customized stated survey in which the respondents answered questions on how they would respond to the application of a control measure in context of their activity and travel behavior a day before. Fourie et. al.[11] created a fictitious model of the transportation demand of the city of Sioux-fall, focusing on its public and private transportation with the aim of using the model as a general test bed for different transportation policies. They used real world household survey data in creating an agent population and land-use data in extracting spatial locations of activities of individuals travelling within the area of focus which was then mapped to a physical model of the relevant transportation infrastructure. The model also took into cognizance the socio demographic characteristics of each represented individual, such as age, sex and income. Many others such as Kickhofer et.al[12], and Rolando et. al.[13] , used similar data and methods in creating their models, with some of them validating their models using traffic signal data. These models were created as test beds for testing various policies and scenarios which revealed travel demand impact on environment[14], energy usage[15], evacuation and many more. Managing peak congestions have also become popular over the years. Lovric et al. [14] created an agent based traffic demand model using smart card dataset from a Dutch public transit company in which he analyzed passenger behavior while applying three different pricing strategies. This growing research in demand modeling has encouraged the development of different simulation toolkits such as: MATSim[16], DynaMIT[17], TRANSIM[18], and AIMSUN[19]

As much as progress has been made in this area, agent based demand models using the activity based approach have mostly used travel data from national census, of which are never available at spatial micro level. Not as much research has been done in creating agent based models from PTO's (public transport organization's) passenger survey dataset [20, 21]. Therefore, our contribution is as follows: we propose a truly agent based micro simulation model created using a PTO's passenger survey datasets. This model is then used as a test bed to simulate the travel demand impact of seven common strategies used by PTOs.

The unique daily travel behavior of each rail passenger is modelled in individual agents so as to form an agent population that would reflect the demand on the rail system. A model of the physical rail system consisting of the links and coordinates of the real life rail tracks, stops, characteristics of individual trains (such as speed, capacity

and engine size), and the different schedules (train time table) of the various routes is used in simulating a game-like interplay between supply and demand such that agents try to find the best times to leave their destinations and the best route to apply in getting to their destination without being late. An evolutionary algorithm is applied to this problem such that day plans created for each agent are optimized on each simulation iteration till it gets to an equilibrium were no better change to its day plans can be made.

The remainder of this paper is as follows: section 2 gives an overview of the simulation discussing its basic modules. Section 3 explains how the demand model is created using an agent population created from the customer survey dataset. Section 4 details how the score of an agent's day plan is calculated. Section 5 compares the simulated data with real life passenger count data, in an attempt to validate the model. Section 6 uses the model as a test bed to simulate common fare pricing policies to see their effect in influencing passenger peak demand and Section 7 concludes.

2 Simulation Overview

Our simulation is constructed around the notion of agents that make independent decisions about their actions. Each passenger of the rail system is modelled as an individual agent (NB the simulation has been scaled down to 10% of the actual system), traveling from one activity (e.g. "Home") to another (e.g. "Work"). There are three important pieces of this simulation:

1) Each agent generates his initial day plan, encoded with information of his activities (i.e. duration, route and end times within a day). An example of an initial day plan for 20 agents can be found in [22]

2) All agents execute a plan simultaneously in a virtual model of the physical rail system. This is known as the traffic flow or mobility simulation. (NB a model of the physical rail system consisting of the links and coordinates of the real life rail tracks, stops, the different schedules of the various routes, and characteristics of individual trains - such as speed, capacity and engine size.). Therefore agents can miss the train, be late for an activity or not be able to get in the vehicle if it is already filled to capacity.

3) Agents learn from experience by performing an evolutionary process on their day plans. An iteration is completed by evaluating the agents' experiences with the selected day plans (scoring). The scoring of the plans is described in detail in section 4. So for every iteration the agent could either chose the plan with the highest score, re-evaluate plans with bad scores (with an option of discarding them) or create new plans by modifying existing ones (modification can be done by changing time or route). The iterative process is repeated until the average population score stabilizes.

A basic assumption of this simulation is the assumption that customers have no alternative mode aside from this public transport train line.

The simulation is built using the MATSim (Multi Agent Transportation Simulation) java library, developed to provide a structure for implementing large-scale agent-based transport simulations. Currently, MATSim offers a framework for demand-modelling, agent-based mobility-simulation (traffic flow simulation), re-planning, a controller to iteratively run simulations as well as methods to visualize some outputs generated by the modules. A thorough description of MATSim can be found in Horni et. al.[16].

2.1 The four core modules

The simulation is organized into 4 core modules as shown in Fig. 1 below.

Data source. To create the day plan for each agent we use a travel survey dataset made openly available by Metro-North Commuter Railroad (MNR) [20]. The survey was conducted on board of every inbound train operated on the Harlem, Hudson and new Haven routes in 2007, and customers filled forms detailing their trip boarding and alighting times, traveling purpose, and how often they use the rail system. The survey dataset contains 92,726 rows and 99 columns all stored in a Microsoft access database. Each column represents the survey questions asked in a passenger survey executed on board the trains in the Harlem, Hudson and new Haven routes of the MNR, while each row represents each passenger's data who filled the survey. After pre-processing, we were able to capture each passenger's travel purpose, station check-in, station check-out and activity durations and purpose. The stations geographical location and the rail network map was extracted from OpenStreetMap, while train schedules and capacities were gotten from the PTO's website.

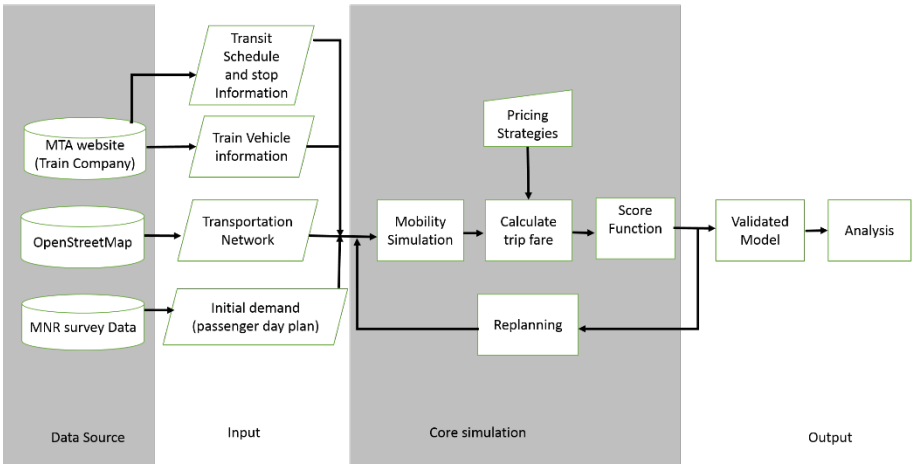

Fig. 1. Simulation overview

Input. Input files used in this simulation refer to the post-processed data in machine readable format, from which the major simulation input parameters are extracted from. These files include the initial demand file which contains the individual day plan of each agent, an XML representation of the rail network of Metro Northern Commuter Rail, describing the physical layout of the network and the coordinates of its stations and links between them. Two GTFS files containing the transit system's latest daily schedule and physical characteristics of all train vehicles on chosen active transit lines were also used. Train's physical properties such as: capacity, was given a constant of 100 seats for each carriage (this was extracted from the GTFS files). Each link free-flow speed was set to 18m/s, which allows a realistic time for the vehicle to reach the next stop according to the schedule. An early arrival vehicle will wait till the next departure time before leaving the station. The inputs has been deposited in a GitHub account [22].

Core simulation. This module is where the mobility simulation is executed such that virtual transit vehicles are simulated according to their schedules. A queue model is used to simulate the traffic flow such that when the agents enter into the train the train travels through a link (i.e. the rail) in free flow speed and only comes out (gets to its

next station) at the time required to travel through the link. Therefore agent transition is possible if capacity of the link and the train allows for agent to enter it. Agents board these train vehicles in order to get to their activities within their daily plans. When this is over, the Agent's daily plans are scored (explained in section 4) by incorporating people's preference such as price sensitivity, route and late/early arrival to an activity. Passenger agent interaction within this environment can lead to consequences such as lateness. To avoid this, agents may modify copies of their plans after each simulation iteration, in order to avoid situations that lead to bad scores. Such changes could include: change in departure time or change in route. Not all plan copies are discarded after each run, each agent has a maximum of 5 plans within the working memory. This aspect of the simulation is handled by the re-planning submodule of the core simulation module. These ultimately allows the agents to mimic real life passenger's adaptation to changes made by PTOs, such as fare pricing changes.

Output. In this module, the validation and analysis are done**.** Our simulation was validated by comparing passenger arrival and departure volume to real life passenger count data. The validated model was then used in predicting passenger behavior when different pricing strategies were applied.

The next section discusses how we use the PTO's travel survey dataset to extract an O-D matric (origin destination matric) of each passenger activity, to create an overall agent plan for the day, centered on the passenger's day activities. This will serve as the initial demand that will be passed into the core simulation module.

3 Demand Modelling

Traffic demand is generated based on the concept of daily activity demand from which the need for transportation is derived. Such activity could be activities that require you to be at home (Home activity), work (Work activity), leisure activity or shopping activity.

We segmented customers based on their travel patterns:

Trip based passengers. Customers that were only taking a single journey but were not coming back through the train system.

Tour-based passengers. Customers that were departing and arriving using the same stations, and were either leaving from home or would finally arrive at home at the end of the day.

Pattern-based passengers. These are tour-based passengers that use the system at least twice a week.

3.1 Activity profile

Based on the information available in the survey we can derive an activity profile for a passenger which would be represented as a tuple (l, b, e, Δb, Δe). The profile is then recreated in an xml format to represent a day plan.

- the closest station to the activity location is represented as l in x-y coordinates. This could either be extracted from the Begstationidr, endstationidr, ob1stationidr or ob2stationidr columns in the survey dataset.
- the scheduled start time of the activity is represented as b. Extracted from the depmam_r column of the survey dataset.
- the scheduled end time is represented as e. Extracted from outdepmam_r column.

- train boarding time on the day of survey at beginning of the activity is represented as Δb, extracted from depmam column.
- train boarding time at the end of the activity represented as Δe, extracted from outdepmam column.
- the actual duration $t_{dur,q}$ of preferred activity q is b – e (the difference of e and b).

It should be noted that an activity is assumed to start at the time the passenger boards the train. (NB during the evolutionary/learning process, the start time and the route to an activity can be altered, but the duration cannot. Therefore plans with activities whose duration ends up surpassing its preferred end time due to chosen routes or start times will be scored as bad plans and would be likely discarded as superior plans are generated)

3.2 Creating the initial demand for the simulation

The initial demand for the simulation is the combined initial individual day plan of all agents. This is represented in an xml format.

For our simulation we decided to use only pattern based passengers in creating our agent population as this is the group that places the most consistent demand on the rail system, and the group from which plans can also be generated, that start and end at home (this is a crucial condition in activity based demand generation). This will give frequent journey patterns of: home….outing….home. Where outing represents the major journey purposes extracted from the customer survey data, which are work, recreation, school, personal business and other. For our simulation we only used passengers going to/from "work", "recreation" and "school", in an aim to extract more consistent passengers.

Using the tuples generated for each day activities of each agent, MATSim Java library is used in generating each plan file. We assume the agent's activity takes place at the final station from which the agent alight to indulge in the activity.

In the next section we discuss how an agent's day plan is scored

4 Scoring an agent's day plan

An agent's day plan is scored after an iteration, in an attempt to weed out bad plans so that only viable day plans evolve to further iteration steps in the simulation [16]. The value of score S of an agent's plan is represented in equation 1

$$S = \sum_{q=0}^{N-1}(s_{act,q} + s_{act.q}^{late}) + \sum_{q=1}^{N-1} S_{trav,Rail\_PT(q)} + U_{mon} \quad (1)$$

Where: N is number of activities, which is 2 (e.g. home and work or home and school), $\boldsymbol{s_{act,q}}$ is the utility for performing activity q, and $\boldsymbol{S_{trav,Rail\_PT(q)}}$ is the (dis)utility (i.e. negative utility or penalty) for traveling to activity q from the location of an activity q-1 using the rail public transport mode. This implies that routes with longer distance will be less attractive as this will reduce the overall score. U_{mon} Is the (dis)utility based on the total monetary cost of the combined day trip (therefore higher transport cost will reduce the overall cost of the plan). The penalty for performing activity q late is given as:

$$S_{act.q}^{late} = \beta_{late} * t_{late} \quad (2)$$

Where t_{late} is the duration of lateness and β_{late} is a negative slope (we use the MATSim default of -18$/h). The utility earned from performing an activity is given by:

$$s_{act,q} = \beta_{dur} * t_{typ,q} * \ln(t_{dur,q} / t_{0,q}) \quad (3)$$

Where: $t_{dur,q}$ and $t_{typ,q}$ are the actual and typical duration of activity q respectively. The actual duration for activity q was extracted from each passenger's survey and mapped to the corresponding agent while the typical duration was the highest occurring duration of the activity q among the surveyed passengers. β_{dur} is the marginal utility of the activity duration or time as a resource (we use the MATSim default of 6$/h). $t_{0,q}$ Is the minimal duration. The mode-specific utility from traveling is described by equation 4

$$s_{trav,mode(q)} = C_{mode(q)} + \beta_{trav,mode(q)} * t_{trav.q} \quad (4)$$

Where: $C_{mode(q)}$ is the alternative specific constant represented as 1, $t_{trav.q}$ is the travel time, $\beta_{trav,mode(q)}$ is the direct marginal utility of time spent traveling. This value is 0 since we are only concerned about the rail mode.

After the plan has been scored for each agent, it is then stored in the agent's memory. Plans selected for the next iteration are either previous plans whose scores have been improved either by changing the agent's route or adjusting its activity departure time, or plans picked from the agent memory randomly.

The proof for the equations stated above is beyond the scope of this paper. It can be found in Horni et al. [16].

5 Running the simulation

We ran our experiment on a desktop PC with an Intel i7 3.6GHz processor and 8 GB RAM. We ran 200 iterations to bring the simulation to equilibrium. The simulation was scaled down to 10% of the original passenger daily volume for MNR (this was because, after pre-processing the survey data, only about 12,000 records were usable). In response to this, the physical system model was also scaled down so that one agent will represent 10 individuals within the system. This will have minimal impact on the simulation results[16]. Fig. 2 gives a graphical view of the simulation as it approaches equilibrium, as all the agents optimizes their plans in each iteration.

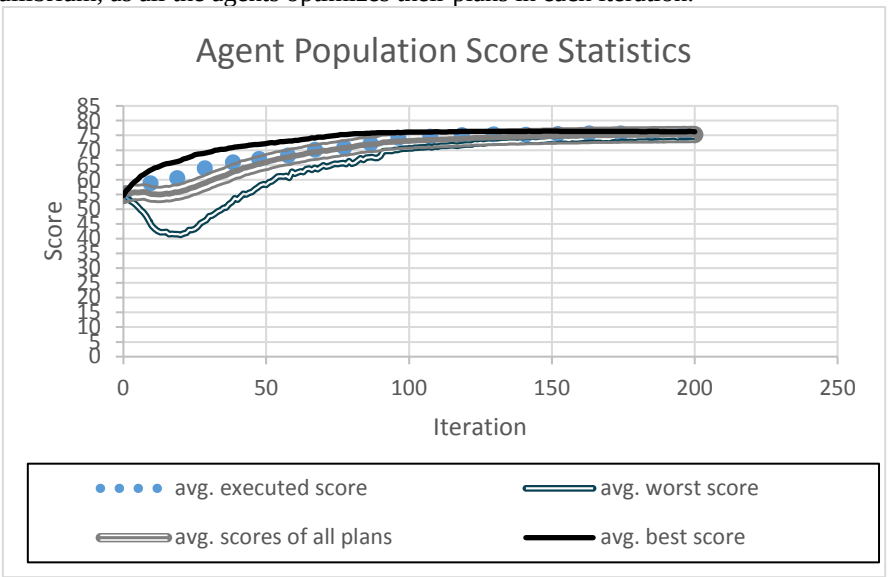

Fig. 2. The score statistics gives a graphical view of the scores of the agent population daily plans. This gives a picture of the evolution of the plans, as they get better and better till they reach an equilibrium phase where each agent seems to have reached its best plan which cannot be improved.

5.1 Validation

In addition to the surveys distributed, MNR field workers created a count dataset from counting the total number of passengers getting on, and the number of passengers getting off. We compared the simulated volume percentages of agent's arriving and departing at peak hours bins to that of real passengers getting off and on the trains. The bar chart for this can be seen in Fig. 3 and 5. Also, in an attempt to measure the accuracy of the model we analyzed the correlation of the simulated data to the count data in fig. 4 and 6. Both arrival and departure data from the simulation seem to have high associations with the count data equivalents, giving correlation co-efficiencies of 0.88 and 0.95 respectively.

The simulated data is not expected to correspond perfectly with the count dataset, due to the fact that not all the counted passengers volunteered to fill the survey form. But it can be deduced that the volume of simulated agents getting off the train (simulated arrival), peak in the evening at about 6pm while the volume of simulated agents getting on the train (simulated departure) peak in the morning at about 8am. This corresponds to the real passenger count conducted.

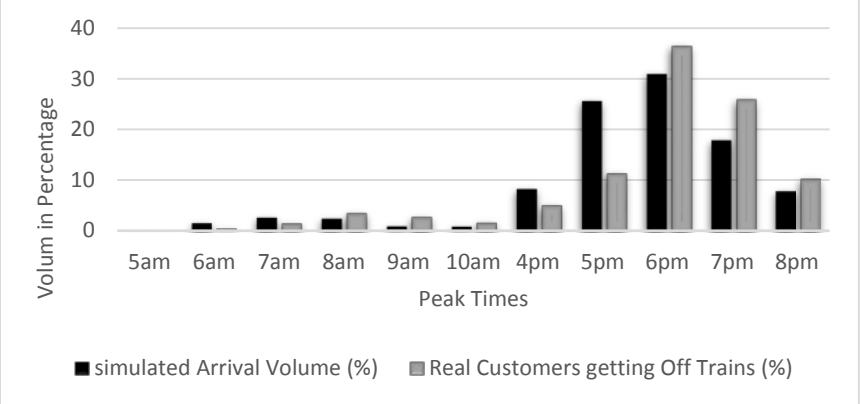

Fig. 3. Comparing agent volumes arriving at all virtual station links at peak time to the count data volumes of customers getting off the trains at the same time.

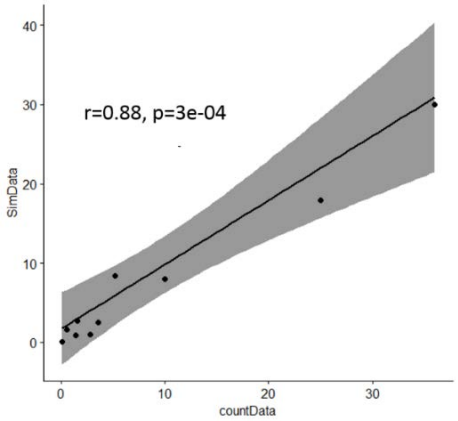

Fig. 4. Correlation test between the volume of agent arriving at virtual train stops per time and the number of passengers getting off the trains in the count data

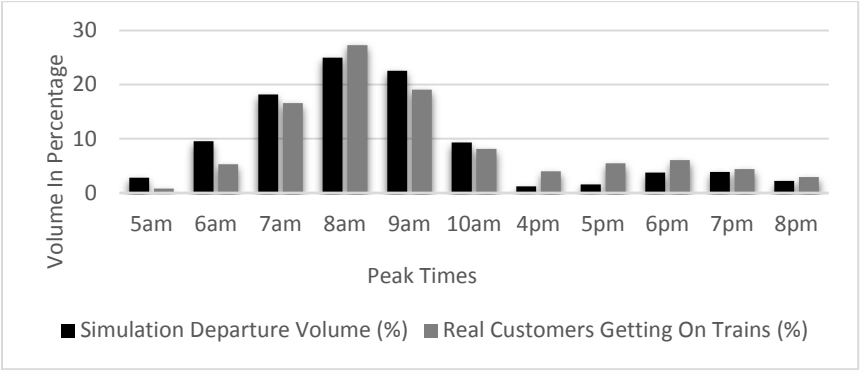

Fig. 5. Comparing agent volumes departing from all virtual train station links at peak time to the count data volumes of customers getting on the trains at the same time.

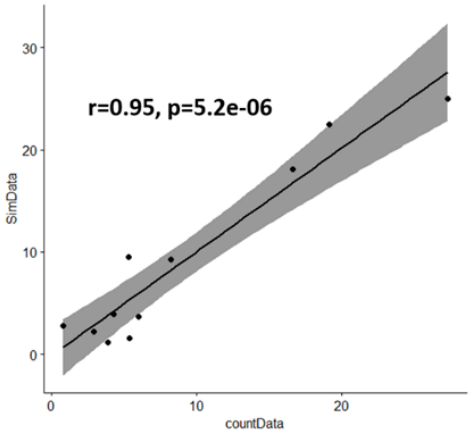

Fig. 6. Correlation test between the volume of agent departing from virtual train stop links per time and the number of passengers getting on the trains in the count data.

The highest level of difference can be seen in the evening peaks of Fig. 3 (especially at 5pm). There seems to be a sharp arrival change between the 5pm bin and the 6pm bin in the passenger count dataset. This is not reflected in the simulation results as the simulation predicted such sharp change an hour too early i.e. between 4pm and 5pm.

In the next section, we use this model to analyze the impact of different pricing policies on customer behavior.

6 Peak Pricing Policy Analysis

We intend to see how some basic pricing policies used by PTO's will influence customer behaviour. We will be considering seven different fare pricing policies shown in Fig. 7 below.

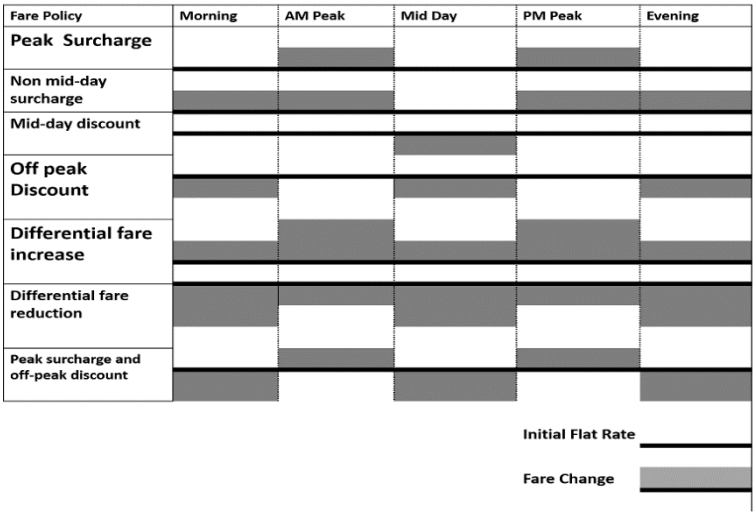

Fig. 7. Common daily fare policy used by many PTOs

Peak Surcharge. Fares at AM peaks and PM peak times.

Non mid-day surcharge. Charging base fares only at mid-day.

Mid-day discount. Fares are discounted at mid-day only.

Off peak Discount. Fare discount at early mornings, midday and evenings.

Differential fare increase. General increase in fares, especially during peak period.

Differential fare reduction. General reduction in fare, especially at off-peak times.

Peak surcharge and off-peak discount. Fare discount at off-peak times and fare increase at peak times

Morning fares for the MNR rails starts from 12 am to 4:59, AM peak (morning peak) starts from 5am to 9:59am, mid-day starts is from 10:00am to 3:59pm, PM peak (evening peak) is from 4pm to 8:59pm while evenings starts from 9:00pm to 11:59pm. For the sake of analysis, we would assume that a flat price was in place at all hours of the day and that each customer bought a boarding ticket at point of entry.

By changing the fare price of each agent, different price strategies are simulated. For example, the peak surcharge policy is simulated by increasing the flat price by 40% during the AM and PM peak.

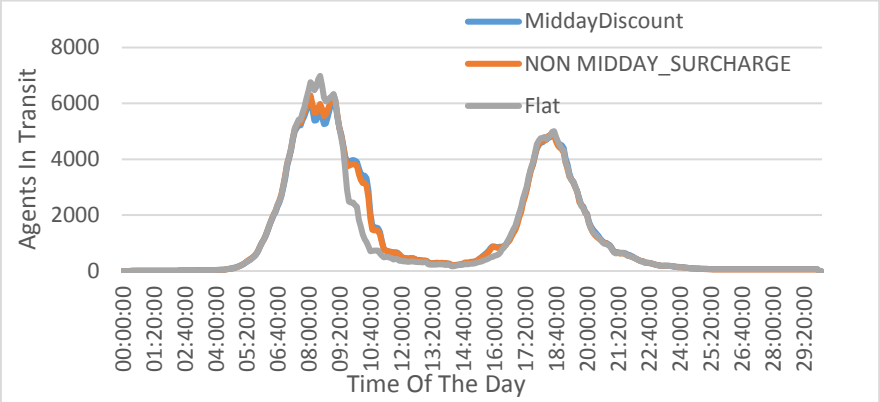

Fig. 8. Mid-day Discount Vs Non Midday Surcharge Vs Flat

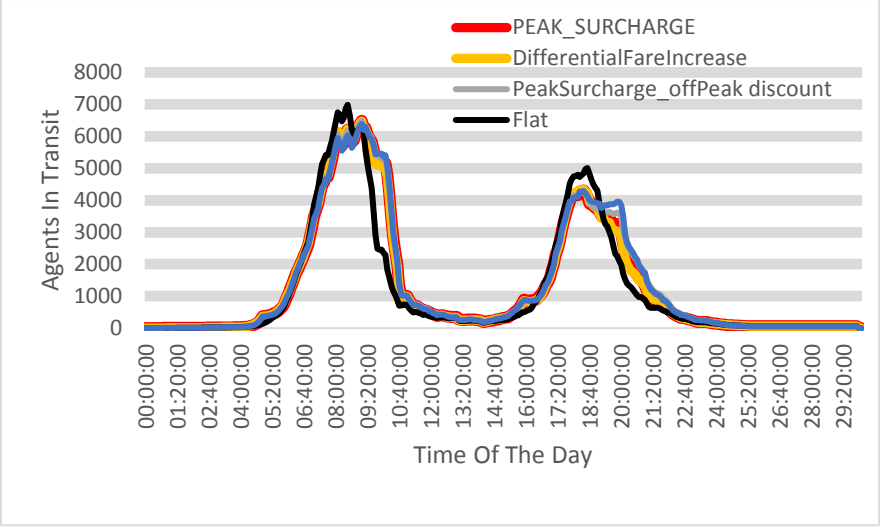

Fig. 9. Peak Surcharge Vs Differential Fare Increase Vs Peak surcharge_offpeak discount Vs off_peak Discount Vs Flat

Reducing demand peak. All the policies applied reduce the AM peak by at least 9%. The midday discount policy and the non-midday surcharge seem to produce the same effect, and reduce the am peak by up to 14%, with a slight widening of agents in the morning. This is common with other policies also. This could be the effect of agents with “recreation” and “school” travel purposes leaving a little later (or earlier) than normal to take advantage of price changes. The policies in Fig. 9 produce similar effects, reducing the evening peaks by about 16%.

Shifting Peak time. The policies in Fig. 9 seem to have the ability to shift the peak times. The AM peak shifted by more than 30 minutes while the evening peak was widened. Therefore a PTO that seeks such effect in demand might consider any of these.

7 Conclusion and Future works

This paper has majorly discussed simulating a commuter rail network using an agent based simulation. We used customer survey data to create agent profiles which was used in creating an agent population whose daily plans were optimized as they utilized a simulated commuter rail system. The purpose of all this is to create a model that can serve as a test bed for testing policies. This test bed was validated in section 5.1, and policy testing was demonstrated by running a simulation to forecast passenger demand behavior on commuter rail system as pricing policies are applied in order to manage peak demand. We were able to determine policies that will likely generate similar behaviors (as shown in Fig. 8 and 9), and how different pricing policies have different effect on peak demand. All the data used in creating this simulation have come from open data sources easily accessible on-line, and our biggest challenge in creating this simulation has been in the accumulation of data.

In general, 70% of the commuters of MNR are going to or coming from “work”. This explains why the flexibility of their behavior due to price change is not as pronounced, as it is difficult for such commuters to change their schedule or their route. By adding more municipality data, such as the spatial locations of businesses within the metropolitan area, we would be able to test the impact of adding other train lines, allowing the agents more choices in terms of route change. If we are also able to add the data of other modes such as buses, then mode shift impact analysis would also be a possibility, as accurate microscopic data of other optional transportation modes can be used in bridging the assumption made that customers will remain loyal after a price changes. With more data, a holistic view of the impact of a policy change such as price change, to the rail system can be estimated. Also the GTFS files used in the simulation is for recent years as compared to the customer survey data. This is more of a data challenge as we were unable to obtain GTFS files as far back as 2007. But there have been minimal changes to the schedule of the PTO over the years.

Finally, as at the time the survey dataset was created, the PTO already had a pricing strategy in motion, therefore in our future works we aim to improve the model such that a predicted flat price can be simulated which will be the basis for predicting and comparing the other pricing strategies.

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