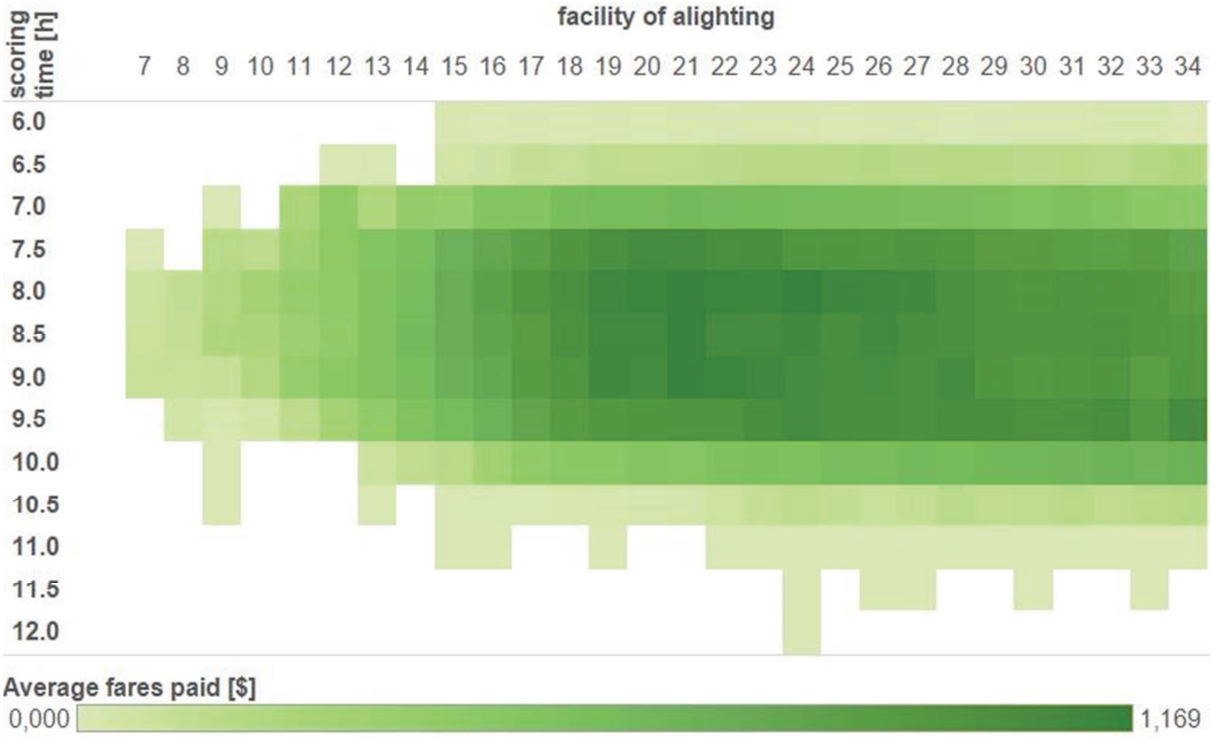

Evaluation of Dynamic Public Transport Pricing with MATSim

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Evaluation of Dynamic Public Transport Pricing with MATSim

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Abstract

With emergence of digital fare payment systems, the resolution of problems such as growing amount of air pollution or concentration of congestion around peak hour becomes feasible by the implementation of dynamic pricing schemes. But, because of the complexity and the difficult acceptance of these strategies by the populations, research need to be accomplished beforehand in order to show clearly the benefits brought. In this thesis, the agent based simulator MATSim is used to study effects of First-Best pricing strategy and to develop feasible Second-Best scheme in the case of a rather simple corridor scenario. In addition to that, effects of crowdedness in public transport vehicles and friction effects at boarding are implemented in MATSim and their consequences on the trip distribution of evaluated.

Firstly, the implementation of the new dwell time model shows that the dwell time may be strongly increased and the trip distribution spread if boarding occurs in a rather to high filled bus. Secondly, the addition of crowding effects leads up to results such as peak spreading, diminution of the travel times at peak and increasing of the percentage of PT users. The last point even suggests that the implementation of a crowding effect may ameliorate the congestion state of the roads. Thirdly, the implementation of externalities increases the benefits cited above and reproduces real behaviors: PT users with higher flexibility make changes in their plans in order to avoid the periods where the fares are higher. Finally, a Second-Best pricing strategy using the opportunities given by Smart-Card based fare payment systems has been designed. These results confirm that MATSim may be appropriate in order to develop pricing strategies.

In further steps, tests of the new implementations in more realistic networks and comparison with real situations shall be done.

1 Introduction

ETH and NRF furthered their collaboration by establishing the Singapore-ETH Centre for Global Environmental Sustainability (SEC) in Singapore. One aim of the collaboration is to advance research into the complexity of land transport, which derives from the demands of managing, planning and optimizing the flow of people and goods at different time scales and in its interaction with all elements of the future city.

At the core of the research module on Mobility and Transportation Planning is the implementation of a MATSim Singapore and expansion of MATSim's scope and functionalities in order to allow transport policy evaluation in Singaporean context. Most notably in the context of this thesis, MATSim will be used to study and evaluate dynamic pricing schemes for public transportation. As Singapore's public transport operators already introduced discounted public transport journeys during off-peak hours, development of tools for simulation and evaluation of such policies is of major relevance for policy makers and represent a challenge for transportation researchers. With emergence of digital, often smart-card based fare payment systems, implementation of dynamic pricing schemes became feasible and affordable. What are the effects of such schemes and how to design them in an efficient manner in order to achieve the desired changes in travel behavior and associated socioeconomic benefit are questions, which have still to be answered.

In this thesis, effects such as friction effects when boarding (L. Sun, 2013) or crowdedness effects (A. Tirachini, 2013) will be implemented and simulated using an agent-based simulation approach. Then, the consequences of first-best pricing strategies, where prices are set to be equal to marginal cost, will be estimated by internalizing in each agent externalities of crowdedness and delays imposed to other travelers (A. Tirachin, 2013, I. Kaddoura, 2013). Finally, a more realistic Second-Best pricing strategy will be designed, evaluated and compared with First-Best pricing schemes. Furthermore, additional constraints such as maximum vehicle occupancy will allow for realistic modelling of public transport, with ability to simulate dynamic phenomena as e.g. bus bunching.

2 Literature Review

This project is based on two important concepts that divide this chapter into two sections: the concepts of “crowding” and “pricing”. In the first section (chapter 2.1), the different kinds of crowding, their effects on passengers and some methods to estimate their impact are described. In the second section, the concepts of pricing are explained and overviewed.

2.1 Crowding effect

The notion of crowding in public transportation is connected with the density of passengers standing or sitting on vehicles, accessways and stations. If the density (or occupancy) is a physical phenomenon that can be easily calculated (number of passengers standing pro m^2, proportion of occupied seats …), crowdedness is rather a subjective interpretation that depends on many parameters (the kind of vehicle, the distance of the trip …).

Together with travel time, cost, trip time reliability and service frequency, the effects of crowding are now considered as having a significant influence on modal choice (Tirachini, Henser, & Rose, 2013). If some studies have already estimated the effects of crowding on public transportation, there are actually no values that can perfectly describe the consequences on the demand. In the first part of his research, A.Tirachini (2013) listed the different effects of crowding in several groups.

2.1.1 Effect on in-vehicle time

As the number of passengers in a public transport increase, a threshold where no more seats are available is reached: from this point on, the new passengers boarding have to stand, that mean that they travel with a higher discomfort like the sitters. Moreover, the standing passengers slow the movements of the passengers boarding or alighting and thus it increase the time needed by the PT vehicle to stop at a station (dwell time): this phenomenon is called the “friction” effect.

Using a smart card data set from buses traveling in the city of Singapore, L. Sun (2013) proposed a new dwell time model which incorporates the friction effect. Moreover, he showed that the type of vehicle, in particular the standee capacity, the number of doors and the presence of steps play an important role for both boarding and

alighting and that the variability of dwell time increases with the number of boarding/alighting passengers.

Furthermore, the design of the bus (Katz & Garrow, 2012) and the platform congestion at stations with many bus services are other elements that can increase the dwell time (TRB, 2003) (Jaiswal, Bunker, & Ferreira, 2010).

2.1.2 Effects on waiting time

High demand along a public transport line may provide some capacity constraint problems and may increase waiting time: if a bus is full, some passengers cannot board and may have to stay at the bus station until the next bus comes, increasing waiting time and discomfort of travel.

Moreover, another effect of high occupancy, the bus bunching, may rise waiting times (Abkowitz & Tozzi, 1987). When a full bus doesn't pick up all the passengers at a station because of capacity constraint, a larger number of passengers as expected will try to board the next bus. If this bus has the boarding capacity, it will have to stop longer to pick up all the passengers and thus will be delayed. Its headway between the bus ahead will be increased and it will be decreased between the bus behind. This phenomenon is amplified as bus move forward along the route. In short, bus bunching leads to headways variability, which increases average waiting time (Welding, 1957).

2.1.3 Effects on travel time reliability

When the occupancy rate is high, public transport users waiting at stations cannot be certain that the capacity of the next train/bus will be sufficient to allow them to board (see above). Moreover, the bus bunching effect can strongly change the arrival times written in a bus line schedule. These effects are sources of unpredictability, which are negatively valued by the users.

Secondly, there is a likely relation between high occupancy level and the occurrence of incidents (e.g. at station), which is a source of unexpected delays affecting the service performance and reliability.

2.1.4 Effect on wellbeing

There are multiple physical and psychological factors that can affect the passenger health and wellbeing. The list below makes a summary of the main effects studied (Tirachini, Henser, & Rose, 2013) :

- *Anxiety*
- *Stress and feeling of exhaustion*
- *Perception of risk to personal safety and security*
- *Feelings of invasion of privacy*
- *Propensity to arrival late at work*
- *Possible loss in productivity for passengers that work while sitting*

These effects depend mainly on the own perception of each passenger during a period of crowdedness. A few studies search for instruments able to make use of the different psychological components of crowding.

For example, N. D. Mohd Mahudin (2012) collected data from a sample of 525 commuters on rail lines serving Kuala Lumpur, Malaysia. A self-rating questionnaire asked the users about their measurement of three psychological effects of the crowded situation: (i) the psychological aspects of the crowding situation (dense, disorderly, confining…); (ii) the ambient environment of the crowded situation (stuffy, smelly, noisy or hot); (iii) the affective reactions to the crowded situation (stressful, irritable, uncomfortable…). The results demonstrated that neither the psychological aspects (i) nor the ambient environment (ii) nor the rated passenger density were directly related to the experience of stress and feelings of exhaustion, but they showed that the affective reactions (iii) were related. This suggests that the more unpleasantly crowded the commuters feel, the more stress and feeling of exhaustion they experience. However, passengers could still experience stress and exhaustion even under what appears to be a low-density condition.

Another survey was conducted by B. Theler and K. W. Axhausen (2013) in the city of Zürich. Using a sample of 215 returned questionnaires, they demonstrated that the perception of crowding, in particular the perception of the words “full”, “crowded” or “overcrowded”, changes according to the type of user: frequent and experienced users develop a higher tolerance to the conditions of their journey than the older and younger passengers, even if frequent users.

2.1.5 Effect on the valuation of travel time savings

The valuation of travel time savings (VTTS) can be described as the traveler's willingness to pay for change his traveling conditions, in particular to decrease his travel time. This value is often used as quantifiable factor in economic analysis of transport schemes.

In the second part of his research, A. Tirachini (2013) used agent-based simulations applying multinomial logit models to estimate VTTS. Then, he compared the VTTS given by a model without crowdedness effect with models comprising different kinds of crowdedness (depending on the proportion of standees and sitters, on the load factor, etc.) He showed that the model without crowdedness overestimates VTTS for low load factors (below a threshold that is between 1.0 and 1.25, depending on the model) and underestimates VTTS for high load factors (over 1.25). That means that the willingness to pay varies according to the crowdedness condition in the public transport: the willingness to save time is higher for a passenger in a crowded state than for someone who can seats in an almost empty bus. Moreover, A. Tirachini calculated in his research a "crowding multiplier", a factor that multiplies the value of in-vehicle time savings found in uncrowded conditions. A part of his results is showed below:

Figure 1: Value of in-vehicle time savings, MNL Model, A.Tirachini, 2013

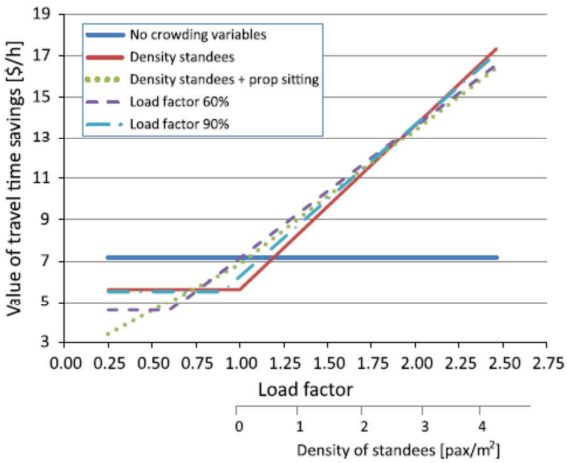
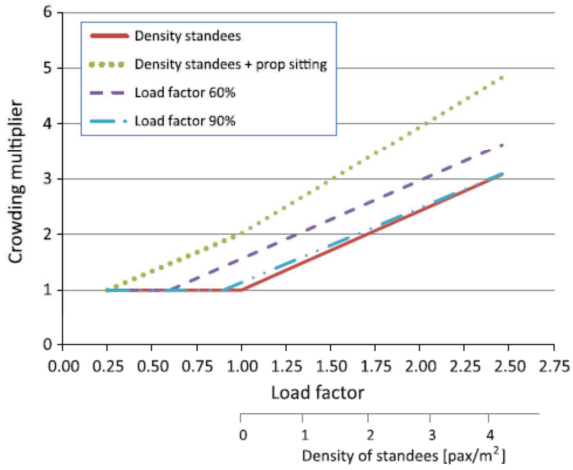


Figure 2: Crowding multiplier, MNL Model, A. Tirachini, 2013



As a supplementary result, A. Tirachini found that a model that is insensitive to crowding levels underestimates demand if vehicles are uncrowded and overestimates demand if vehicles are crowded (the generalizability of these findings is not proven). I.e., a bus that is not crowded should have more passengers as calculated with a model that doesn't take crowdedness into account and the higher demand (at peak hour) should be smaller as estimated because of crowdedness effect.

Moreover, it has been showed in other studies that some effects such as the difference between stand or seat in vehicles or the accessways, transfer areas or platforms crowdedness may also have an effect on the VTTS.

2.1.6 Effect on bus and route choice

As explained by A. Tirachini (2013), recent studies showed that the disutility of standing in public transport vehicles may influence bus and route choice when passengers have multiple alternatives to complete a trip. Thus, the probability of getting a seat is a key attribute: some passengers would better wait or travel longer to have an (expected) higher chance of getting a seat on a less crowded bus.

2.2 Marginal cost pricing

Over the next decades, pricing is going to be a well discussed topic, for two reasons in particular: firstly, pricing theories have evolved from some theoretical or analytical

models to some realistic options that are already used in real cities (Singapore, London…). This is due to two main reasons: the possibilities given by new technologies to charge automatically the users and, more importantly the willingness to resolve the problem of growing amount of air pollution or congestion all around the world. Moreover, pricing is a sensitive political topic because such proposal rarely receives a great approval from the public.

The concept of pricing is explained in this divided into two parts section. In the first part, the external effects and the method to take them into consideration are explained and illustrated. The second part is based on the difference between First-Best and Second-Best pricing strategies and on their applications.

2.2.1 External effects

Like other economic matters, public transport system can be described as a system of supply and demand trying to reach an equilibrium: the operator's costs (supplier) have to be compensated by the fares paid by the users (demanders) to reach a monetary equilibrium. But to maximize the social welfare of both the operator and the users, money cannot be only parameter that must be taken into account.

Indeed, when a good or service is produced or consumed, "external costs" may occur. For example, people driving their car produce "private cost" that they have to face by themselves (cost of petrol, tax or buying car) and external costs that may be monetary (health related costs due to pollution, decrease of house price due to noise) or temporal (congestion delays). The sum of these external effects and the private costs leads up to the "social cost" of car driving.

Normally, the external costs are not faced by the user who produce them, but by society in general. The meaning of pricing strategies is thus to add, or "internalize", these supplementary costs to the private costs that each people has to pay when he travels. In other words, each user should pay for the external costs he causes. The new equilibrium reached is called the "social equilibrium". According to I. Kaddoura (2013), reaching this equilibrium may archive market efficiency and may maximize the social welfare of the whole community.

In order to consider the effects of a new user, a new trip or a new PT vehicle on the system, "marginal" costs are used. By definition, the marginal cost of an additional unit of output is the derivative of total production costs with respect to the level of output (Small, 2007). In other words, the marginal cost of a new unit of output is the

cost needed to produce only that supplementary input. Marginal cost can be greatly different from the average cost: e.g., if it costs at an operator $300 to offer a bus trip to 30 users and $305 to 31 users, the average cost is $10 per user but the marginal cost of the last one is only $5!

According to I. Kaddoura (2013), the external effects arise if marginal private user costs deviate from marginal social costs. Marginal social cost pricing means setting generalized prices equal to the sum of marginal producer costs, marginal private user costs and marginal external costs. For the public transport market, the marginal social cost equilibrium will be found if the fares that have to be paid by the users are equivalent to their marginal private and marginal external costs or, in other words, the user is confronted with both his private costs and (a tax equal to) the external costs of his decision. In this way, the external effects are internalized by the users who produce them.

2.2.2 First-best pricing strategies

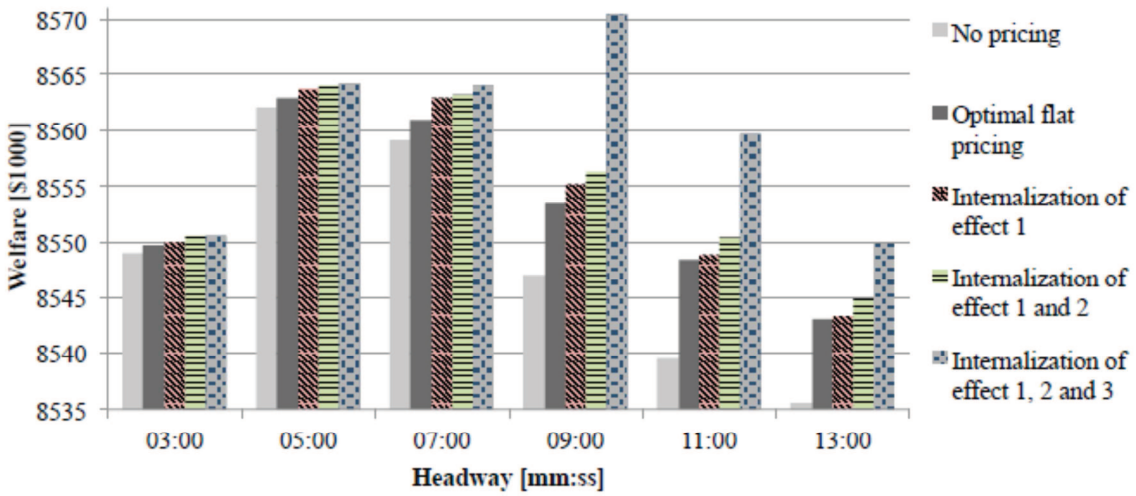
As said above, the internalization of the externalities caused by each user of a transport system allows charging each of these users by the exact amount he caused. If applied, this pricing strategy is known as first-best pricing strategy. In his research, E. T. Verhoef (2002) summarizes the principal motivations of using this kind of strategy:

- When individuals are confronted with prices that reflect the marginal social cost of their choice, they may exhibit behaviors that maximize their own benefit. At the same time, the resulting social equilibrium may be the one that maximize the social objective.
- Marginal cost pricing may not only make sure that the short run optimum for market (with given demand and cost functions) is archived, but in addition, in the long run (long term), these functions themselves may be automatically pushed to their optimal “shape and position”, each user making a socially optimal trade-off between his available possibilities.
- The variable costs of a public transport system cannot often be covered by the revenues generated by the users alone. That is why a part of these costs must be covered by the associated government (state, town). Therefore, pricing can be chosen because of a need of revenues for the financing of infrastructures capacity that falls only on the concerned part of the population.

A good illustration of First-Best pricing strategy is given by the research accomplished by I. Kaddoura (2013). Using an agent-based approach, he internalized the delays imposed by public transport users to each other, such as boarding/alighting effects on the inside passengers, boarding/alighting effects on the waiting time at station or delays of passengers denied to board a full bus. In the simulations, the agents were able to switch their transportation mode (between public transport and car) and their departure time.

The results showed that the social welfare (here: the sum of operator profit and user benefits) was always higher if a kind of pricing was used. In addition to that, an analysis of the distribution of bus trips over time revealed that peaks was flattened in the pricing schemes compared to the other schemes: since user-specific fares were higher during peak periods, some agents switched their departure times or change their transportation mode in order to avoid these periods. Therefore, the in-vehicle and waiting times were shorter and the social welfare increased.

Figure 3: Welfare for each headway and pricing rule, I. Kaddoura, 2013



2.2.3 Second-best pricing strategies

Unfortunately, first-best pricing strategies are really difficult to apply in a real world situation, due to the fact that the parameters cannot be fully controlled and that several sorts of barriers and constraints may prevent to charge the ideal amount of fare. Most of the informations cited below arise from a research of E. T. Verhoef (2002).

A first problem is the complexity of application of a First-Best pricing strategy. For instance, in the case of a public First-Best pricing scheme in public transportation, the fares used for pricing may vary continually, they may depend on the exact amount of passengers, on the congestion state, on the time of the day, etc. The monitoring technology needed may be too sophisticated than the currently available technology or the pricing scheme too complex to be understood by the users. In addition to that, some laws may prevent adjustments of the pricing scheme, e.g. quick adjustments to avoid congestions during an unpredicted change on the system (construction work, weather conditions, etc.).

Secondly, a pricing strategy can have not only an effect on the road system itself, but, because of the market interactions, on other economic activities. Changes in transport prices may affect the equilibria on other markets, especially the labor market: high marginal tax rates may lead to a serious under-supply of labor, because of the increase of transportation costs. It may tend to a downward adjustment in transport taxes when the revenues are used to lower labor supply decision or an upward adjustment when the revenues are used to lower labor taxes.

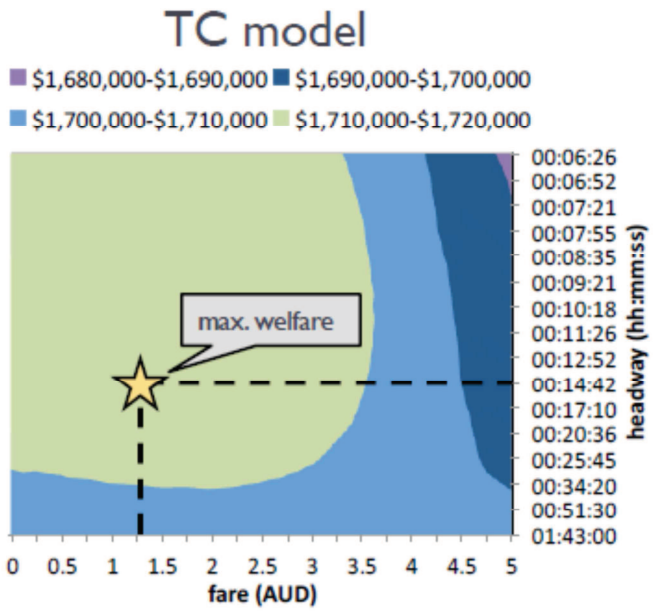
Finally, the acceptance of a pricing scheme is difficult to obtain because of the uncertainty of the results and the supplementary charges that appears to the users. Moreover, in some democracies, the quantity of charges becomes an important political issue, maybe more than an economic question. The agreements needed between political parties may create limitations on the type of charges and the flexibility that can be implemented.

Due to the several constraints listed above, the first-best pricing strategy has often to be replaced by a so called “second-best pricing strategy”, more adapted to a realistic situation, but more complicated. Indeed, the informational requirements are considerably higher: in addition to the level of marginal costs found with the first-best pricing scheme, other parameters such as demand and cost elasticity within public transport or estimation of the effects on the other markets are needed.

Taking into account all these new parameters, the welfare gains that can be achieved with second-best pricing may be substantially lower than those arising from theoretical first-best pricing. The researches accomplished by I. Kaddoura on optimized supply (fares and headway) of a public transport schedule showed that pricing leads to a larger welfare (the optimal fare wasn’t $0) (Kaddoura, Kickhöfer, Neumann, & Tirachini, 2012), but that the welfare obtained with this optimal fare was always smaller than with use of an agent-based pricing strategy (see *Figure 3: Welfare*

for each headway and pricing rule, I. Kaddoura, 2013) (Kaddoura, Kickhöfer, Neumann, & Tirachini, 2013).

Figure 4: Social welfare level dependent on bus headway and fare, I. Kaddoura, 2013



Worst still, if some parameters are not taken into account or their consequences wrong estimated, or if the wrong prices are set, a risk of failure is possible, causing a reduction in overall social welfare.

Fortunately, the body of research on this topic is growing fast and many models are currently available with which the detailed effects of various types of second-best pricing instruments can be studied in detail.

For instance, the use of “policy packaging” allows to reduce the risk of failure. The method consists on a combination of second-best pricing instruments, such as parking fees, toll booths or fuel taxes in a case of road pricing that may not give satisfactory results if implemented alone, but that can replicate the full set of incentive given by a First-Best pricing scheme if combined.

In addition to that, the emergence of new fares payment systems offers more opportunities to the transport system designer to implement pricing strategies. For example, the Smart Card used in Singapore records the boarding and alighting stations of passengers and calculates the trip fare according to these data. Moreover, the times when boarding or alighting occur or the number of agents in the vehicle can be recorded.

3 MATSim

MATSim is an open-source software that provides a framework to implement large-scale agent-based transport simulations. It has been initially developed by the Transport Systems Planning and Transport Telematics group at the Technische Universität Berlin, the Transport Planning group at the Swiss Federal Institut of Technology Zurich and the Senozon company. In addition, other research groups are using and extending MATSim around the world (www.matsim.org)

This section gives a general overview of how works MATSim, including the special characteristics of public transport. Furthermore, the modifications of the MATSim's code accomplished in the framework of this project are explained.

3.1 MATSim Overview

In MATSim, private and public transport users are modelled as individual agents that have a mental and physical behavior. These agents can move in a chosen network and they have to follow the rules given by the latter (free flow speed, maximum capacity, etc.). They interact with each other and, following the rules of the fundamental diagrams, and they can create congestion effects that reduce the traveling speed of all agents on the affected link.

In addition, the facilities of the network ("Home", "Work", "Shopping", etc.) are modelled. They represent the origins and the destinations of each agent trip. As the MATSim simulations are time-dependent, it is possible to implement the opening and the closing time of the facilities.

Basically, the goal of each agent during a simulation is increasing his own benefit, or "utility". The utility increases when the agent is performing an activity (when "working" in particular) and decreases when the agent is traveling (see section 4.2.1 for more explanations).

A simulation with MATSim can be summarized in the following steps:

1. **Plans generation (initial demand)**

All agents independently generate daily plans that contain the planned activities, the departure times and transport modes for incoming trips. For the simulations describing a real network (a city, a quarter, etc.), these first plans can derivate from survey and real data analyses.

2. **Traffic flow simulation (execution)**

All agents simultaneously execute their selected plans, interacting with each other in the physical layer.

3. **Plan evaluation (scoring)**

The benefits (or utility) of each executed plans are calculated taking into account both activities and trips. Thus, a score is given to each of these executed plans.

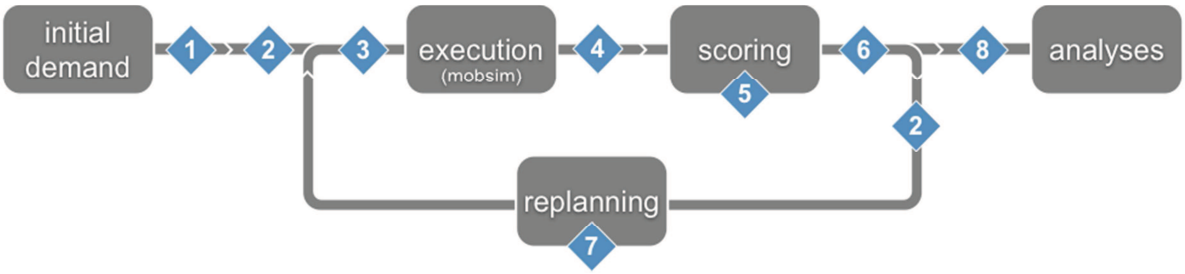
4. **Learning (replanning)**

To allow an increase of their score during the next execution of the simulation (next iteration), some agents generate a new plan or modify copies of existing plans. The type of allowed plan modification must be given at the beginning of the simulation: mode change (e.g. car => public transport), departure time, visited facilities, etc. The other agents chose among their existing plans according to a multinomial logit model.

The amount of plans saved by each agent can be limited: when a new plan is created, only the best plans are kept and the worst is erased.

Then, an iterative process is engaged, each agent trying to improve his own plans. The simulation is stopped when the average utility of all agents is maximized. The outcome is normally stable, the demand is relaxed and, assuming that the travel alternatives form valid choice sets, the system state is in an approximate stochastic user equilibrium (Nagel & Flötteröd, 2011). For simulations describing a real network, simulation data are compared with real data in order to validate the obtained results.

Figure 5: MATSim Overview, www.matsim.org



3.2 Public transport in MATSim

In addition to the flexible trips planned by the agents, MATSim allows to create a transit schedule for the public transportation, containing all the transit lines, the routes, the stations and the departure times. Each vehicle is separately simulated in the traffic flow simulation. Depending on the vehicle type and the number of boarding or alighting agents, a vehicle can be delayed or be too full to allow the boarding of new passengers. If the transit vehicles are using the same lane as the cars, they may be delayed by the congestions occurring along this way.

Regarding boarding and alighting, two kinds of doors operation type are available: “parallel” or “serial”. A parallel door operation mode allows simultaneous boarding and alighting, whereas a serial mode gives priority to alighting passengers. In this project, the buses of the Singaporean public transport system are studied: the front door is normally used to board and the rear door(s) to alight. It means that these operations are done simultaneously and thus the door operation mode that must be chosen is “parallel”.

The “dwell time” is the time during which a bus has to stop at a bus station to allow passengers to board or alight. In MATSim, the dwell time for a parallel door operation mode is calculated as follow:

$$Dw = max\{a \times A, a \times B\} + t_d \tag{3.1}$$

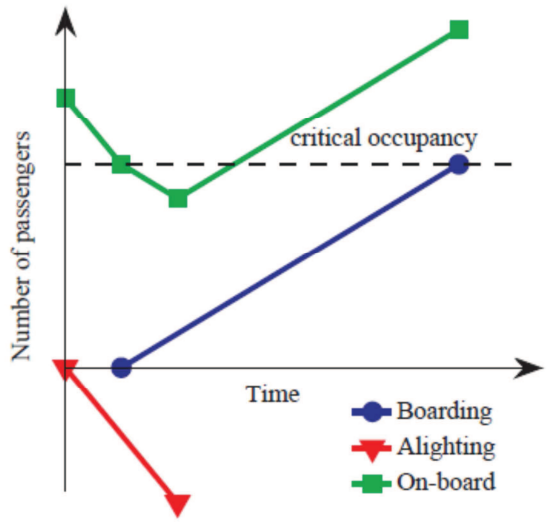
where A and B are number of boarding and alighting passengers, respectively. Correspondingly, a and b represent the marginal time for boarding and alighting per passenger. Finally, t_d is the dead time spent on opening and closing the doors.

In this project, it has been decided to take into account the research of L. Sun (Sun, Tirachini, Axhausen, Erath, & Lee, 2013), in which the amount of on-board passengers has an effect on the dwell time (see 2.1.1). The combined dwell time model found in the research is showed thereafter:

$$Dw = max\{b \times (B-1) + a \times (\max\{On - c, 0\}), a \times (A-1)\} \tag{3.2}$$

where On is the number of on-board passengers, c is the critical occupancy and the other notations are the same as in Equ.(3.1). The recorded dwell time is here the interval between the first and the last-*nth* activities, so only $(n-1)$ intervals are taken into accounts.

Figure 6: Explanation of dwell time for 2-doors bus, L. Sun, 2013



The doors operation time was not taken into account in Sun's research, but it is required in this study. A supplementary waiting time t_d is thus added, representing the door operations (opening = 1 sec, closing = 1 sec) and the deceleration and acceleration times of the bus (acc. + dec. = 8 sec). Therefore, the dwell time is as follows:

$$Dw = max\{b \times (B-1) + a \times (\max\{On - c, 0\}), a \times (A-1)\} + t_d \qquad (3.3)$$

In addition, L. Sun observed a linear relation between the standard deviation of observed dwell time over all the types of buses studies. Thus, the standard deviation formula is used in this study:

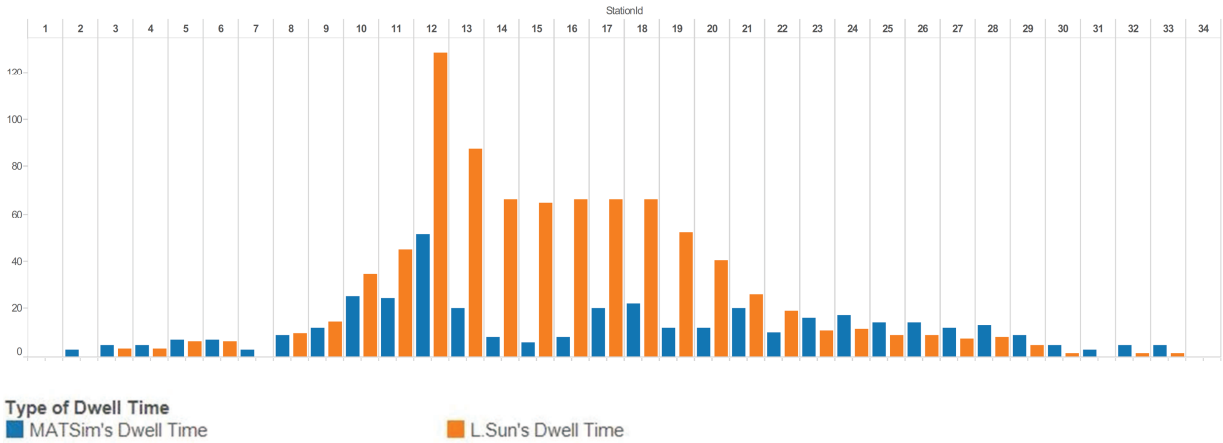
$$Std(Dw_o) = 2.22 + 0.12 \times Dw_p \qquad (3.4)$$

where Dw_p is the predicted dwell time (the dwell time calculated with Equ.(3.3)) and Dw_o the observed dwell time. It allows calculating the dwell time following a normal distribution. To keep only consistent results (and to not consider boarding or alighting times of e.g. 0.1 sec), a minimum is set to $Dw_p/2$. The dwell time is calculated as follow:

$$Dw = max\{NormalDistribution(Equ(3.3), Equ(3.4)), Equ(3.3)/2\} \qquad (3.5)$$

The next figure gives an overview of the differences that can occur between this new model and the normal implementation of MATSim. The occupancy of the bus represented below is high. The number of agents boarding and alighting is equal in the two cases.

Figure 7: Dwell time according to the model used



Finally, a last point concerning the boarding and alighting operations in MATSim can be noticed: when a bus arrives at a station, all the agents waiting get on this bus. If the following bus arrives at the station before the end of the boarding in the first bus, the agents who haven't been boarding yet are going to continue to board the first bus and are not going to get on the second one, which is less full, as it is the case in the reality. If this situation occurs, the following bus is going to overtake the first one and continue to the next station.

4 Scenario

In this section, the data used for the simulations of this project (supply and demand) are summarized and the method used for the simulations is explained.

4.1 Setup

4.1.1 Supply

For the simulation experiments, a corridor with a total length of 20km is considered. From 6 a.m. the corridor is constantly served in one direction by a constant number of buses with headway of 2 minutes. Transit stops are placed each 600m along the corridor.

The chosen bus type is Mercedes-Benz OC500LE: it has a maximal capacity of 90 passengers including 34 seats. Its length is 12.5m and its width is 2.5m. There are two doors, the front door using for boarding and the rear door for alighting. According to the L. Sun's results (2013), the boarding time for this kind of bus is set to 1.49 sec per person, the alighting time to 1.29 sec per person and the critical occupancy is 55.98 passengers.

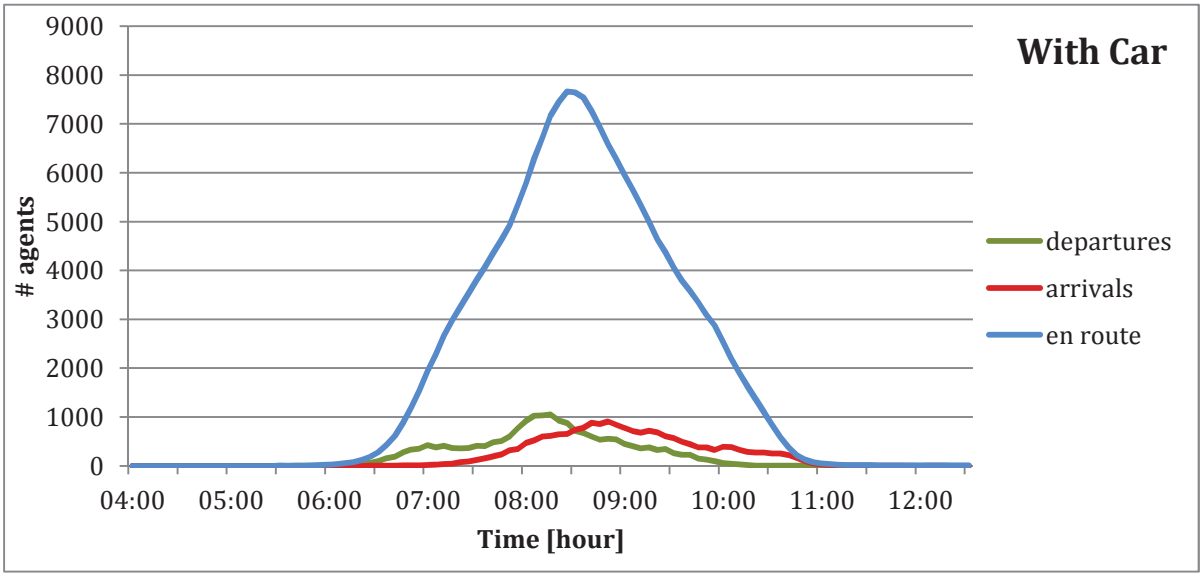
The free flow speed is the same for the buses and for the cars and it is set to 50 km/h. As the two kinds of vehicles use the same lane, they can interact with each other and may be both affected by congestion.

Finally, the walking speed is set to 3 km/h. The facilities ("Home" and "Work") are located along the corridor at a maximum distance of 2 km from them. The walking distance is calculated multiplying the beeline distance to the "Home" location by 1.3.

4.1.2 Demand

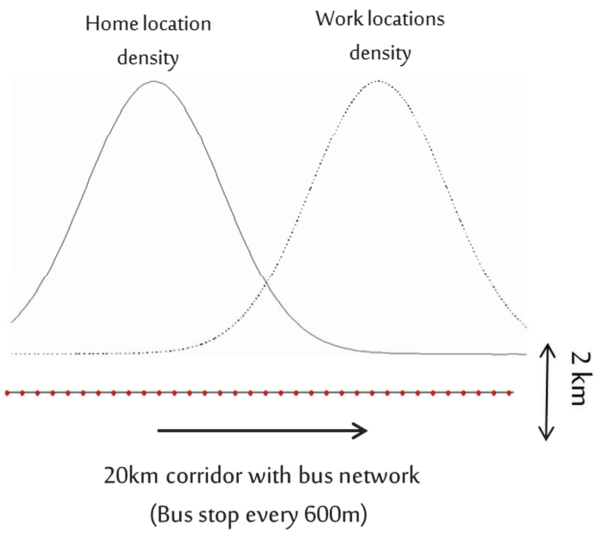
On the demand side, 20'000 travelers are considered. The data set results from a relaxed demand after 2'000 iterations on the corridor. Three modes are available for each agent ("Car", "Bus" and "Walk") without restrictions. At this point, 11'214 agents use the public transport system as main mode (56.1%), 7'365 agents drive a car (36.8%) and 1'421 agents walk (7.1%).

Figure 8: Trip distribution - Original state - With Car



On the one hand, the “Home” locations are situated along the first half of the corridor, following a normal distribution. On the other hand, the “Work” facilities are situated along the second half of the corridor, following a normal distribution, too. Therefore, there is only one activity pattern type: “Home” => “Work”.

Figure 9: Corridor Scenario, Supply and Demand, A. Chakirov, 2013

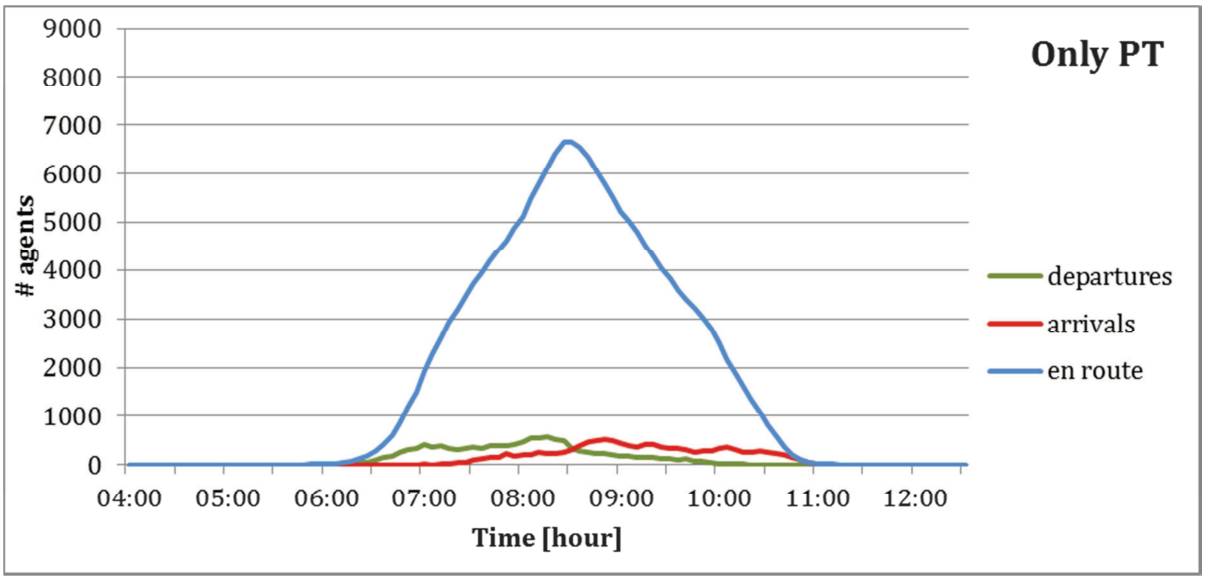


The typical working duration is 8 hours, but a minimal duration of 7 hours is allowed. The opening time is set at 8 a.m., the closing time at 17 a.m., whereas for the

agents, the latest start time is at 10 a.m. and the earliest end time is at 17 a.m. If some agents work out of this period of time, they will receive a penalty.

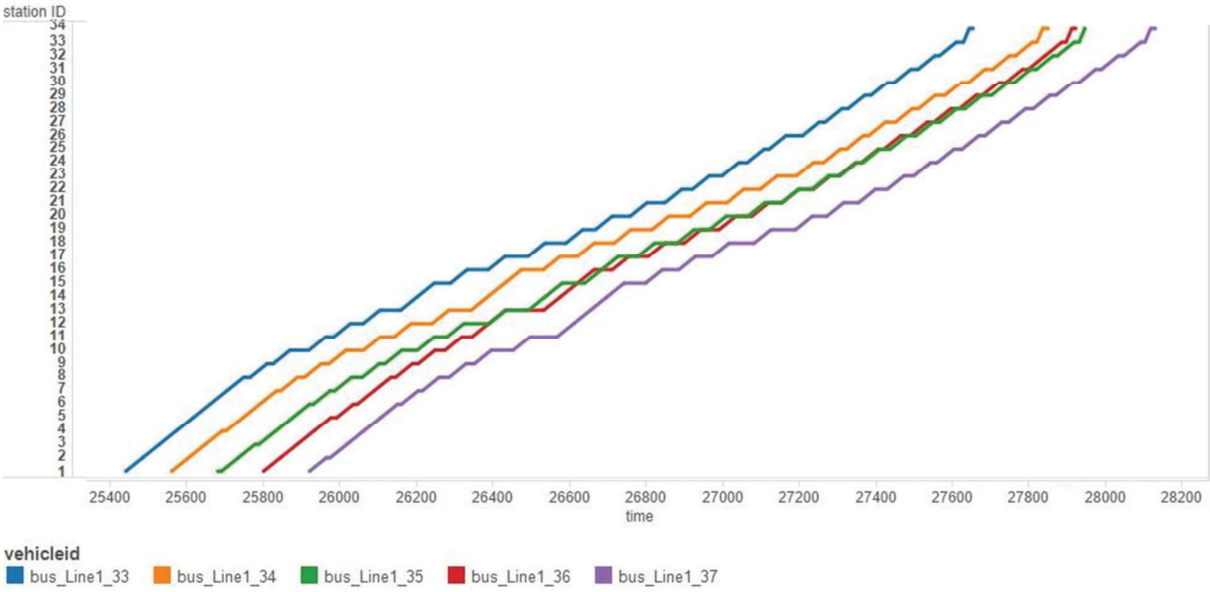
Another set of agents, containing 12'331 agents, was created from the initial set. It is composed only by the agents using the public transports (11'214 agents, 90.9%) or walking (1'117 agents, 9.1%)). Due to the lack of other vehicles on the lanes, this set avoids the congestion effects created by the cars and only focuses on the public transport behavior.

Figure 10: Trip distribution - Original State - Only PT



It is important to precise that the number of agents using the public transport system along the corridor is high in comparison with the supply, despite the fact that the headway is really small (2 minutes). Thus, phenomena of full buses or even bus bunching may occur during the peak period. An example of the data used in this project is given in the next figure:

Figure 11: Effects of full buses and bus bunching



In this time-space diagram, it can be observed that some buses are full and don't stop at facilities. It is the case for the bus number 37 which doesn't stop at stations 12, 13 and 14. In addition to that, the bus bunching effect is observable: since the beginning of its schedule, many passengers get on the bus 35. The next bus, bus 36, has fewer passengers who need to board. Therefore, this bus is faster and comes closer to bus 35. And the closer are the two buses, the shorter is the period of time that passengers have to come at station between the departure of bus 35 and the arrival of bus 36. At station 12, the bus 36 is already behind bus 35. After that, they stay together, overtaking each other.

4.2 Simulation Approach

4.2.1 Utility Functions

As written before, the iterative learning mechanism of MATsim uses an utility-based approach. Each iteration, agents choses one daily plan from their own set. At the end of the simulation's day, executed daily plans are evaluated by summing the activity and trip related part of the utility:

$$V_{plan} = \sum_{i=1}^{n}(V_{act,i} + V_{trip,i}) \tag{4.1}$$

where V_{plan} is the total utility of a daily plan, n is the total number of activities or trips, $V_{act,i}$ is the utility to performing an activity i and $V_{trip,i}$ is the utility of the trip to activity i. Normally, the utility to perform an activity has a positive value and the utility to travel is negative. Negative utility can be called "disutility".

The utility to travel is calculated using parameters β_i. They represent the utility costs per unit of time (t_i) or distance (d_i). In this project, the trip related utility is calculated as follow:

- **For a trip with public transport:**

$$V_{pt,i,j} = \beta_{v,pt} \times t_{i,v,pt} + \beta_{w,pt} \times t_{i,w,pt} + \beta_{walk} \times \left(t_{i,a} + t_{i,e}\right) + \beta_{d,pt} \times d_{i,pt} + \alpha_{pt} \quad (4.2)$$

where $V_{pt,i,j}$ is the utility for a person j on his trip to activity i. $t_{i,v,pt}$, $t_{i,w,pt}$ and $\left(t_{i,a} + t_{i,e}\right)$ represent the durations spent in the vehicle, waiting at facility and walking to/from the station respectively with their corresponding parameters β_i. $\beta_{d,pt}$ is the cost per distance to travel with a public transport, $d_{i,pt}$ is the covered distance and α_{pt} is a fixed cost.

- **For a trip with car:**

$$V_{car,i,j} = \beta_{tr,car} \times t_{i,tr,car} + \beta_{d,car} \times d_{i,car} + \alpha_{car} \quad (4.3)$$

where $V_{car,i,j}$ is the utility for a person j on his trip to activity i, $t_{i,tr,car}$ is the travel time, $\beta_{d,car}$ is the cost per distance for traveling with a car, $d_{i,car}$ is the covered distance and α_{car} is a fixed cost.

- **For a walk trip:**

$$V_{walk,i,j} = \beta_{walk} \times t_{i,walk} \quad (4.4)$$

where $V_{walk,i,j}$ is the utility for person j on his trip to activity i and $t_{i,walk}$ is the duration of the trip.

Then, the performing utility is calculated following the so-called "Charypar-Nagel scoring function" using a logarithmic form:

$$V_{act,i}(t_{act,i}) = \beta_{act} \times t_{*,i} \times \ln(\frac{t_{act,i}}{t_{0,i}}) \quad (4.5)$$

where $t_{act,i}$ is the actual duration of performing an activity i, $t_{*,i}$ is the activity "typical" duration (here, "Work" is 8 hours) and $t_{0,i}$ is a calculated duration. According to K. Nagel (www.matsim.org), this last duration is largely irrelevant and aims to shift the

function up and down, i.e., it determines how much you lose if you drop an activity completely. $t_{0,i}$ is set to $t_{*,i} \times \exp(-10h/t_{*,i})$.

β_{perf} is normally positive: it sets the gain of performing an activity. But if the activity is performed outside the opening time of the facility (from 8 a.m. to 5 p.m., see section 4.1.2), the agents are penalized by the opportunity costs of time $-\beta_{perf}$.

4.2.2 Crowding effects

The effects of crowdedness are actually not implemented in MATSim: if a public transport vehicle has some free places, the agents waiting at the stations are going to board without taking into account the disutilities caused by crowdedness (see section 2.1).

In this project, the crowdedness effect is implemented as a penalty and calculated in the scoring phase: if an agent suffers from crowding during a trip, a disutility depending firstly on the trip duration is added to the traveling disutility.

Two utility models used by A. Tirachini (2013) in his research about the crowding in public transport systems were chosen. The model notation used by A. Tirachini is kept:

M3: Standee density and proportion of occupied seats as source of disutility

$$V_{M3,i,j} = V_{pt,i,j} + \beta_{den} \times n_{den} \times t_{i,v,pt} + \beta_{seat} \times \max(p_{seat} - 0.25, 0) \times t_{i,v,pt} \quad (4.6)$$

where $V_{pt,i,j}$ is the public transport utility (Equ. 4.2), n_{den} is the density of standees per square meter, p_{seat} is the proportion of occupied seats and $t_{i,v,pt}$ the traveling time in these crowding conditions. β_{den} and β_{seat} are parameters of the multinomial logit model and were determined using a set of real data collected in Sydney, Australia.

This function results from a crowding disutility estimation made by Henser and al. (2011), used in order to estimate the willingness to pay to get a seat as a function of the number of people seating and standing. A. Tirachini (2013) showed that the density of standees alone wasn't enough to properly account for the disutility of crowding and that the availability of seats also plays a role in the choice made by respondents. The first crowding penalties appear when the proportion of seat is higher than 25%.

M4: Load factor as source of disutility

$$V_{M4,i,j} = V_{pt,i,j} + \beta_{lf} \times \max(lf_{pt} - 0.6, 0) \times t_{i,v,pt} \quad (4.7)$$

where $V_{pt,i,j}$ is the public transport utility (Equ. 4.2), lf_{pt} is the load factor (number of passengers over the number of seats) and $t_{i,v,pt}$ the traveling time in these crowding conditions. β_{lf} is a parameter of a multinomial logit model and were determined using a set of real data collected in Sydney, Australia.

This function was chosen by A. Tirachini (2013) because of the more common appearance of the load factor in the literature. Another Tirachini's model added penalty when the seat occupancy reachs 90% (Model M5), but the model M4 was chosen because of its proximity with to model M3: a crowdedness disutility is added when the occupied seat proportion (or load factor, if < 100%) reaches 25% for the model M3 and 60% for the model M4.

To observe the effects of crowdedness, both these models are compared with a "No Crowding" Model, $V_{NoCrowd,i,j} = V_{pt,i,j}$ (Equ. (4.2)).

4.2.3 Parameters

The parameters used in the simulations were estimated by A. Tirachini (2013) following the multinomial logit models described above. The data set (n = 4152 observations) was a part of a feasibility study of a new metro system proposed in Sydney, conducted in 2009 by the Institute of Transport and Logistics Studies at Sydney University.

In this study, three sets of Tirachini's parameters are required, according to the used model: parameters for model M3, for model M4 and for a model without crowding costs. However, the parameters are recalibrated: the value of the parameter corresponding to the public transport trips ($\beta_{v,pt}$) is set to 0 and the initial value is added to the others parameters, to keep the concordance between them. Thus, the performing value is +$\beta_{v,pt}$ and it is the only positive parameter. Moreover, the waiting time parameter ($\beta_{w,pt}$) is set to 0.

As far as the fixed costs for traveling by public transport (α_{pt}) is concerned, a $1.5 fare is taken to each agent boarding a bus. This cost is converted into utility by the marginal utility of money parameter (β_c) given in Tirachini's sets. The traveling costs per distance ($\beta_{d,pt}$) is assumed to be 0.

The cost to travel by car amounts to \$10 (α_{car}) for the car park and \$0.15 per km ($\beta_{d,pt}$) for the travel. These costs are converted into utility by the marginal utility of money parameter (β_c) given in Tirachini's sets.

Finally, if an agent arrives at work later than the latest starting time or finish working earlier than the earliest ending time, a negative utility equivalent to the performing utility ($-\beta_{perf}$) is accounted.

The same kind of parameters classification was used by A. Tirachini (2013) and I. Kaddoura (2013) in their study using an agent-based simulator. The following table summarized all parameters:

Table 1: Multinomial logit model parameters

			No Crowding	Model M3	Model M4
$\boldsymbol{\beta_{perf}}$	*Performing*	*[utils/h]*	1.14	0.48	0.66
$\boldsymbol{\beta_c}$	*UtilityOfMoney*	*[utils/\$]*	0.153	0.148	0.148
$\boldsymbol{\beta_{v,pt}}$	*TravelingPT*	*[utils/h]*	0.0	0.0	0.0
$\boldsymbol{\beta_{w,pt}}$	*WaitingPT*	*[utils/h]*	0.0	0.0	0.0
$\boldsymbol{\beta_{d,pt}}$	*UtililityDistancePT*	*[utils/m]*	0.0	0.0	0.0
$\boldsymbol{\alpha_{pt}}$	*ConstantPT*	*[utils]*	- 0.2295	- 0.222	- 0.222
$\boldsymbol{\beta_{tr,car}}$	*TravelingCar*	*[utils/h]*	- 0.24	- 0.96	- 0.78
$\boldsymbol{\beta_{d,car}}$	*UtilityDistanceCar*	*[utils/m]*	- 0.002295	- 0.00222	- 0.00222
$\boldsymbol{\alpha_{car}}$	*ConstantCar*	*[utils]*	- 1.53	- 1.48	- 1.48
$\boldsymbol{\beta_{walk}}$	*TravelingWalk*	*[utils/h]*	- 1.5	- 2.22	- 2.04
$\boldsymbol{\beta_{den}}$	*DensityStandees*	*[utils/h]*	*	0.0000333	*
$\boldsymbol{\beta_{seat}}$	*ProportionSeating*	*[utils/h]*	*	0.0002	*
$\boldsymbol{\beta_{lf}}$	*LoadFactorParameter*	*[utils/h]*	*	*	- 0.0001

4.2.4 Replanning strategies

The simulations conducted with MATSim are divided into two groups, depending on the population that is used: “WithCar” for the population with all agents and “OnlyPT” for the population without car. Each population follows different replanning strategies:

- For 80% of both populations, the “ExpBetaPlanSelector” replanning module is used, which changes to another plan if that plan is better. The probability to change depends on score differences (www.matsim.org).
- For 2% of both populations, the “TimeAllocationMutator” replanning module is used, which mutates randomly the duration of activities within a specified range (www.matsim.org). The value of the mutation range is set at 3600 seconds, i.e., the departure time or the end of work may be moved of one hour for 2% of the agents.
- For 2% of the “With Car” population, “ChangeLegMode” replanning module is used, which changes the transportation mode of all legs in a plan to a randomly chosen different mode (“PT”, Car” or “Walk”) (www.matsim.org). This module is not used with the “Only PT” population in order to keep only the public transport and walking modes.

5 Agent based Marginal Cost pricing for PT

As explained in section 2.2, to execute a first-best pricing strategy with MATSim, the external effects caused by an agent can be internalized charging him the equivalent monetary amount he caused. In MATSim, this internalization is accomplished by transforming the amount of money to pay in disutily, i.e., the externality is multiplied by the utility of money (parameter β_c).

This study focuses on crowdedness and delay effects within the public transport mode through three kinds of externalities: the crowdedness in public transport vehicles, the delay due to passengers boarding or alighting (in vehicle time delay) and the increased waiting time for passengers who cannot board a full bus (capacity constraint).

5.1 Crowdedness externalities

If the occupancy of a bus is already high, a passenger boarding it can create or increase the crowdedness effect, which will be felt by all the passengers already onboard. This effect is internalized converting it into a monetary cost: the crowding disutility calculated with the multinomial logit model is divided by the marginal utility of money (β_c) and the found cost is added to the public transport fare that the agent has to pay. The externalities induced by the crowding models M3 and M4 are calculated as follow:

$$Ext_{crowdingM3} = (\beta_{den} \times n_{den} \times t_{i,v,pt} + \beta_{seat} \times \max(p_{seat} - 0.25, 0) \times t_{i,v,pt})/\beta_c \quad (5.1)$$

$$Ext_{crowdingM4} = (\beta_{lf} \times \max(lf_{pt} - 0.6, 0) \times t_{i,v,pt})/\beta_c \quad (5.2)$$

5.2 In vehicle time delay

Each time an agent boards or alights a public transport vehicle, a delay corresponding to the access or the egress time is added to the transit schedule and imposed on each on-board passengers. Therefore, the travel time, i.e. the in-vehicle time, increases with the number of agents who gets on and off the bus.

This effect is internalized calculating the delay caused by an agent during his boarding/alighting and multiplying this time by the number of passengers in the bus and by

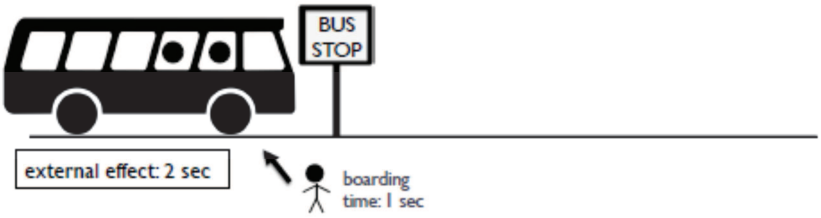
the value of travel time savings ($VTTS_{v,pt}$). For example, the externalities induced by an agent boarding are calculated as follow:

$$Ext_{inVehTimeDelay} = t_{access} \times On \times VTTS_{v,pt} = t_{access} \times On \times \frac{\beta_{v,pt} - \beta_{perf}}{\beta_c} \quad (5.3)$$

where t_{access} is the access time (in hours), On the amount of onboard passengers and $VTTS_{v,pt}$ the value of travel time savings to travel by public transport.

The codes used by I. Kaddoura in his studies (2012-2013) and available in the MATSIM playground are modified and reused in this project.

Figure 12: In vehicle time delay, I. Kaddoura, 2013



5.3 Capacity constraints

If a transit vehicle arrives at a station and the amount of available places (seating and standing places) is not enough to let all agents waiting board, there is a so called "capacity constraint" problem. The denied passengers have to wait until a vehicle with free places arrives, increasing their waiting time.

Assuming the onboard passengers are the cause of this disagreement (they occupy the bus places), they have to pay for the externalities (increasing waiting time) caused. The amount of time lost, i.e., the waiting time until the next vehicle arrives times the number of agents waiting, is divided by the number of onboard passengers and its monetary cost is internalized in each of them using the $VTTS$:

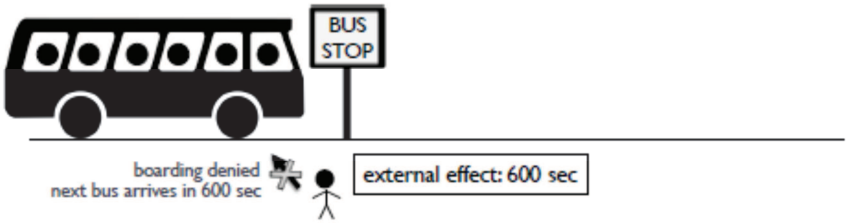
$$Ext_{capacityConstraint} = \frac{t_{w,sup} \times n_w}{On} \times VTTS_{w,pt} = \frac{t_{w,sup} \times n_w}{On} \times \frac{\beta_{w,pt} - \beta_{perf}}{\beta_c} \quad (5.4)$$

where $t_{w,sup}$ is the waiting time until the next vehicle arrives (in hours), n_w is the number of agent that are forced to wait, On is the number of onboard passengers and $VTTS_{v,pt}$ the value of travel time savings to wait for public transport.

In case boarding is denied a second time, the agents in the second bus pay for the interval until the third bus arrives at the transit stop, and so forth.

The codes used by I. Kaddoura in his studies (2012-2013) and available on the MATSIM playground are modified and reused in this project.

Figure 13: Capacity constraints externality, I. Kaddoura, 2013



6 Overview Simulations

The diversity of available populations, crowding effects and externalities allows executing several simulations with MATSim in order to measure and compare the effects on the agent choices. The possibilities are listed below:

Table 2: Overview Simulations

		No Crowding	***Model M3***	***Model M4***
With Car	*No Externalities*	X	X	X
	Crowding Externalities	O	X	X
	In Vehicle Time Delay	X	X	X
	Capacity Constraints	X	X	X
	All Externalities	X	X	X
Only PT	*No Externalities*	X	X	X
	Crowding Externalities	O	X	X
	In Vehicle Time Delay	X	X	X
	Capacity Constraints	X	X	X
	All Externalities	X	X	X

"X" = Simulation executed; "O" = Simulation not executed

In order to obtain a stable state, it was decided to run 600 iterations before stopping the simulations. After 500 iterations, the "TimeAllocationMutator" and the "ChangeLegMode" strategies are switched off. It allows to stabilize faster the simulation, the agent using for the last 100 iterations only the best plans they created during the first iterations.

7 Results

At the end of each simulation, data concerning the vehicles (load factor, number of boarding/alighting at station, externalities produced, etc.), the agents (mode choice, score, money paid, etc.) and the behavior of the simulation along the iterations are written in PostgreSQL tables.

In this section, the simulation results are showed and analyzed. The first part concerns the behavior of the simulations along the iterations, the second part shows the effect of the new dwell time model, the third part describes the agents and vehicles behavior depending on the crowding model or the externality type and the last part is about the monetary differences between each type of externalities.

A unique notation describing the different kind of models is used:

Table 3: Model notations

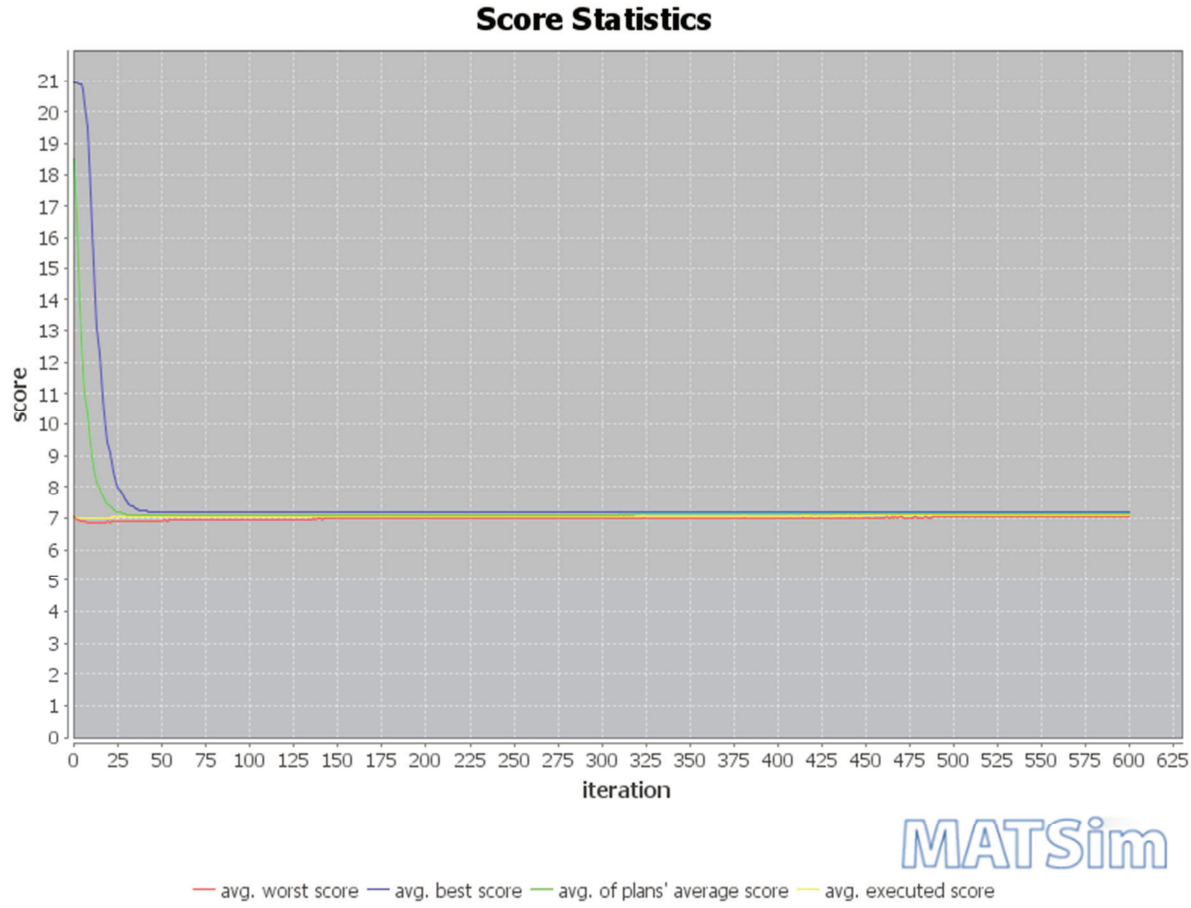
Source of disutility	Any crowdedness effect	Density of standees and proportion of occupied seats	Load factor
Section in project	4.2.1	4.2.2	4.2.2
Notation	*NoCrowding*	*ModelM3*	*ModelM4*

7.1 Behavior along the iterations

The simulations accomplished in the framework of this project showed significant differences depending on the type of crowding model used.

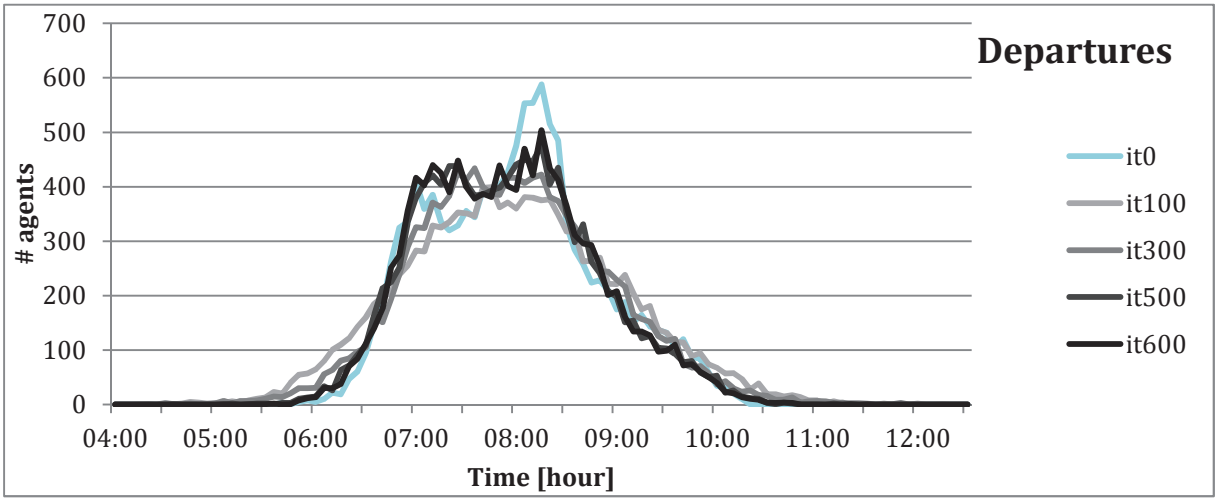
Firstly, the average score is highly dependent on the model used, i.e. the multinomial parameters of the logit model. Indeed, average scores of circa 20.5 for the *NoCrowding* model, circa 7.0 for the *ModelM3* and circa 10.5 for *ModelM4* have been found on simulations without externalities as well as on simulations with externalities (±0.2). These values are set after a few iterations and stay constant along the rest of the simulation. The small score variation between the different types of externalities suggests that their use hasn't a real impact on the score.

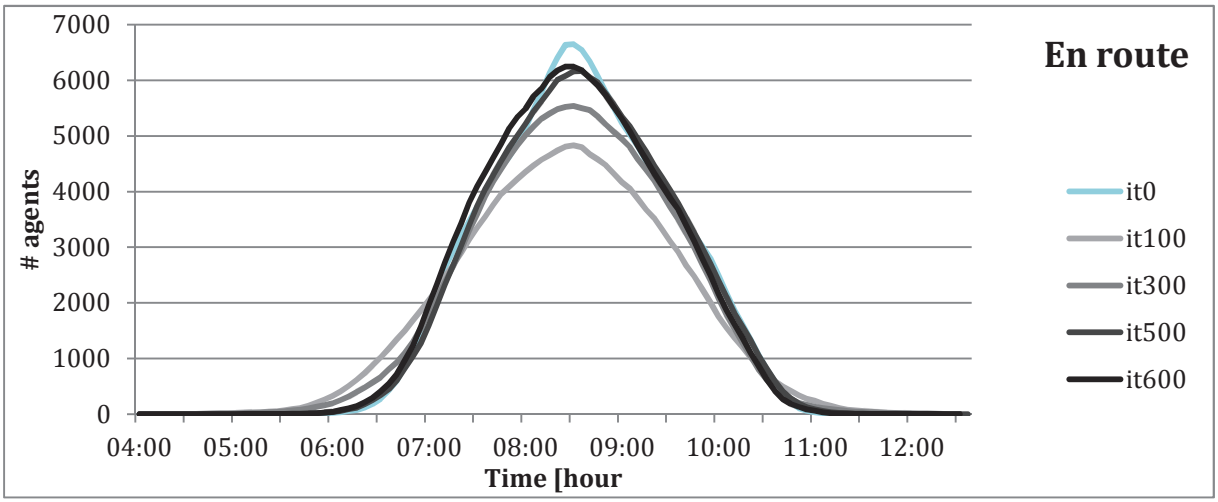
Figure 14: Score along iterations, CrowdingM3 - No externalities - With Car



Although the score is stable, the trip distribution varies strongly along the iteration. The following figures show the reparation of the departure times and of the en-route agents for the simulations using the “OnlyPT” population (no trips with cars, no mode choice).

Figure 15: Trip distribution along iterations, Only PT - CrowdingM3 - No Externalities





It appears than an important spreading of the trip distribution occurs between the iterations 0 and 150: some agents change their departure time and set it earlier or later (see “Departure”). Thus, the amount of agents traveling at the same time is clearly decreased (see “En route”).

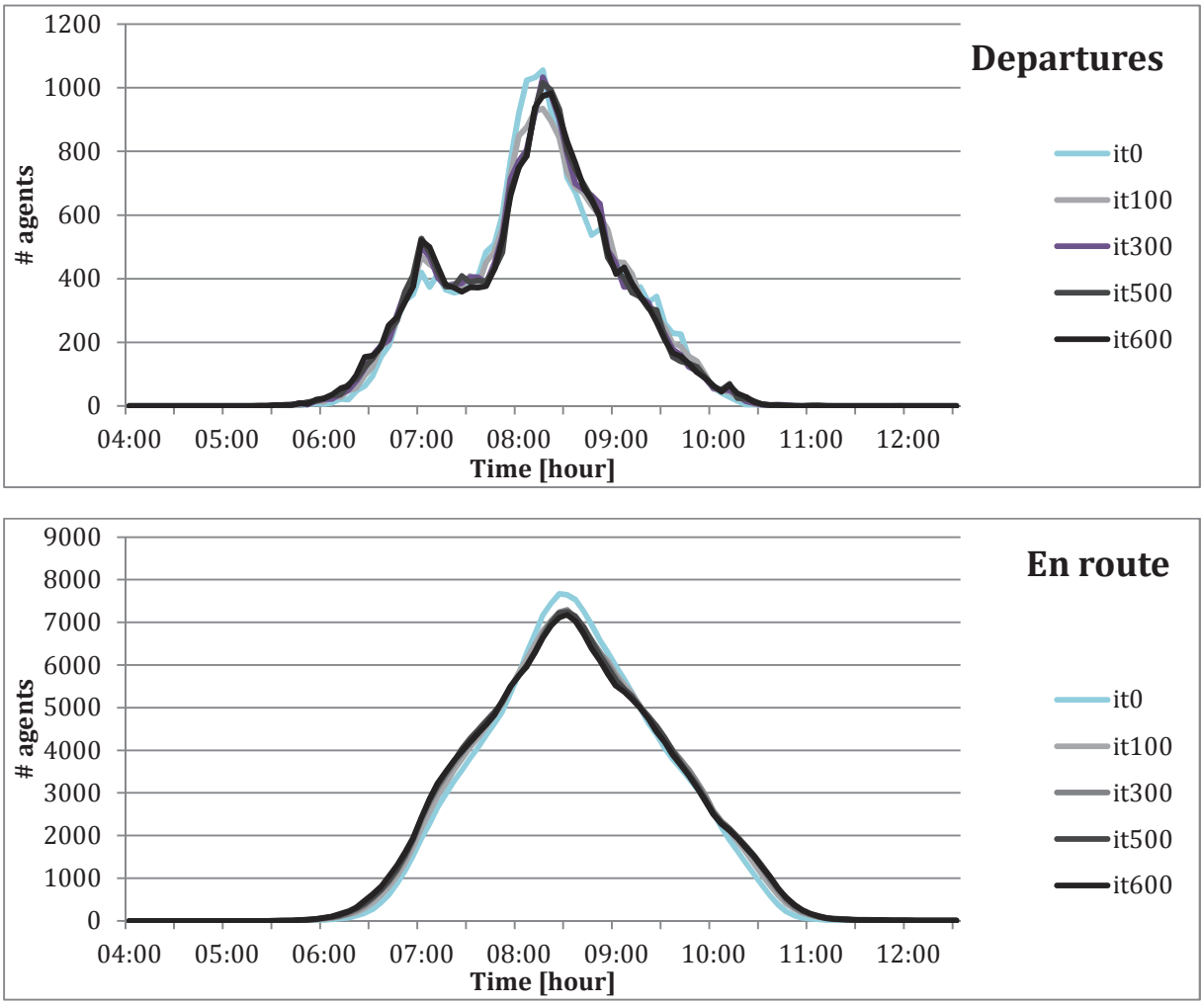
After this state, the agents continue to adapt their journey: the early and late departure times decreased till a state close to the initial situation. However, the initial peak, localized between 08:00 and 08:30, is spread over a longer period, from 07:00 to 08:30. Logically, the amount of en-route agents is also decreased.

These great changes in the trip distribution show that the new implementations added in MATSim (here only the Sun’s dwell time) produce an effect on the agents: firstly, some of them move their departure times in order to avoid the peak hour. Then,

they come close to the peak again, certainly to increase their performing time. In addition to that, there is no congestion on the driving lanes due to the remove of car driver population. These kinds of results along the iterations are observable in each simulation using the “OnlyPT” population, with variation of the number of agents.

The next figures provide the repartition of departure times and of en-route agents for the simulations using the “WithCar” population (car trips allowed, mode choice available).

Figure 16: Trip distribution along iterations, With Car - CrowdingM3 - No Externalities



First of all, the biggest differences with the trip distribution of the “OnlyPT” population are the real peaks situated at 08:30 in the departure distribution and at circa 09:00 in the arrival distribution. They represent the journeys accomplished by the car drivers: as they don’t have to walk to the nearest station and to wait for a bus, they can depart later and arrive earlier.

Concerning the behavior of the trip distribution along the iterations, the biggest changes appear during the circa 100 first iterations: the amount of agents traveling during the peak hour drops and a new “peak” is created around 07:00. Then, the two peaks continue to increase slowly until they reach a stable state. Moreover, peak spreading is slightly observable between 06:30 and 08:00, showing the increasing amount of agents that departs earlier.

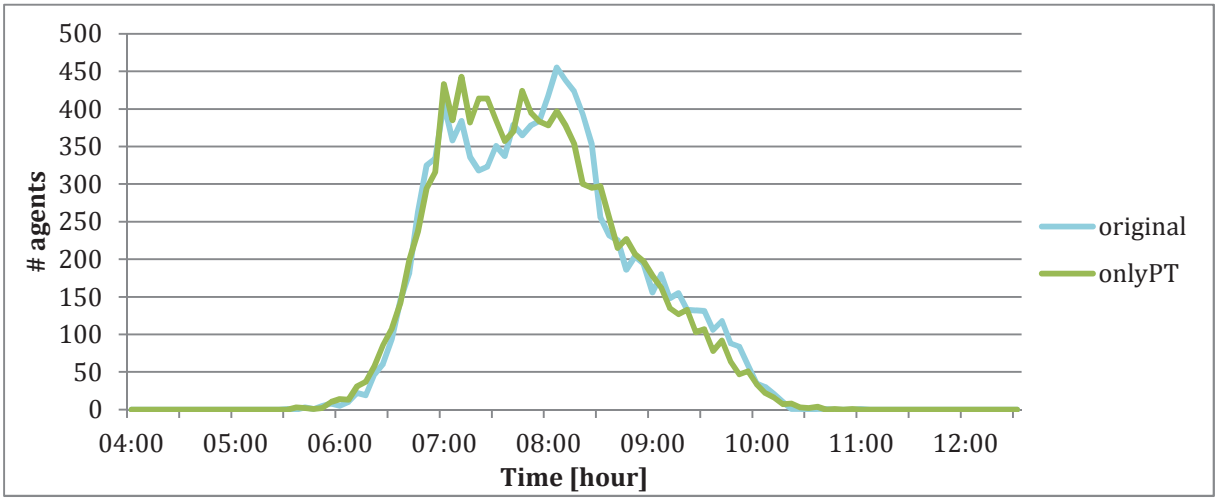
The changes occurring in this simulation are smaller in comparison them of the simulations using the “OnlyPT”. The “ChangeLegMode” replanning strategy may be the main reason of this difference: agents who undergo too many disutilities can here also change their traveling mode in order to avoid disutilities of traveling by PT. Thus, the departure time spreading is smaller. However, the growing of the 07:00 peak shows that this spreading exists. The results showed on *Figure 16* are the result of only one kind of simulation (CrowdingM3 – No Externalities), but the behavior of the trip distribution along the iterations is similar for the other simulations.

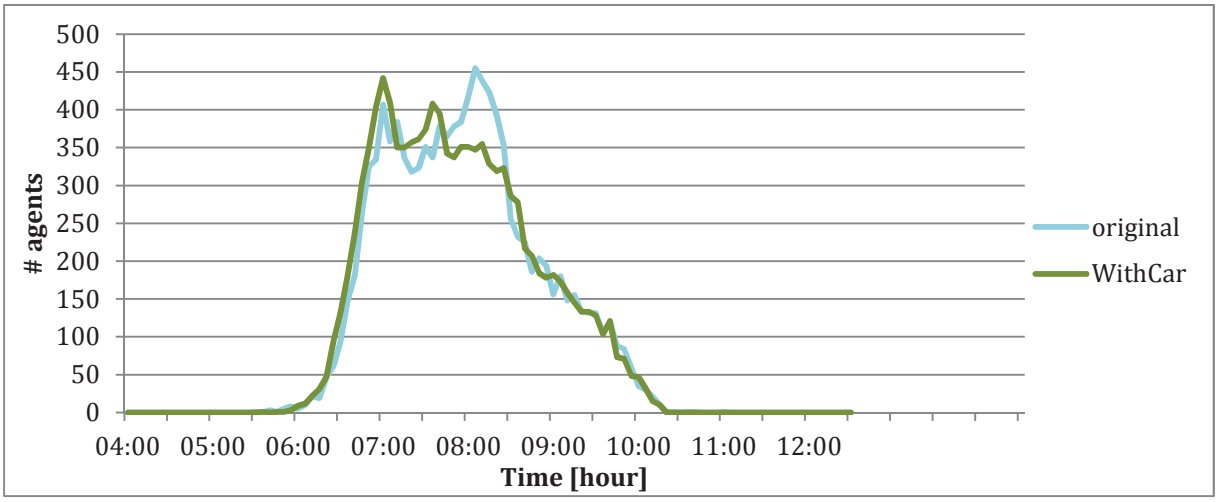
7.2 Effects of the new dwell time function

The new function that calculates the dwell time at station and that were implemented in MATSim (L. Sun, 2013 – section 3.2) increase strongly the dwell time if the occupancy of the vehicle is high, that is the case in this project.

The figures below show the changes on the public transport trip distribution between the initial situation (iteration 0) and the 600th iteration of a simulation without crowding effect and without externalities (for populations “OnlyPT” and WithCar”). A trip is called “public transport trip” if the main mode is public transport. The departure time is thus the time when the agent quits home and not when he gets on the bus.

Figure 17: Trip distribution, effects of the L. Sun's dwell time – No Crowding – No Extern.





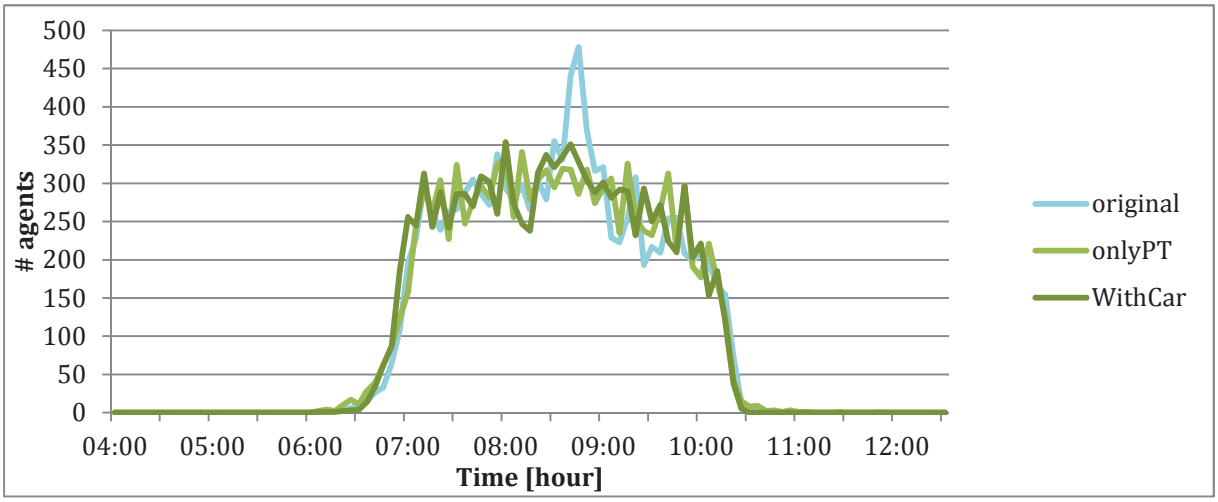
The two figures above show clearly that the agents adapted their departure time to avoid the peak hour and, at the same time, the too full buses. The travel time may be longer as when the original dwell time function was used, but an earlier depart allows some agents to not come too late at work.

In the first figure ("OnlyPT"), the trips are better distributed between 07:00 and 09:00 than in the original distribution. At the original peak hour (08:30), the amount of trips is really smaller.

In the second figure, it appears that the original peak (08:30) is totally spread and that a second peak grows around 07:00. It confirms that this peak, already observed in section 7.1 is caused by PT users in order to avoid the effects of the new dwell time model.

Moreover, an analysis of the boarding time distribution show that the peak that appeared in the initial distribution is totally spread after 600 iterations using the L. Sun's dwell time model:

Figure 18: Boarding times distribution, NO Crowding – No Externalities



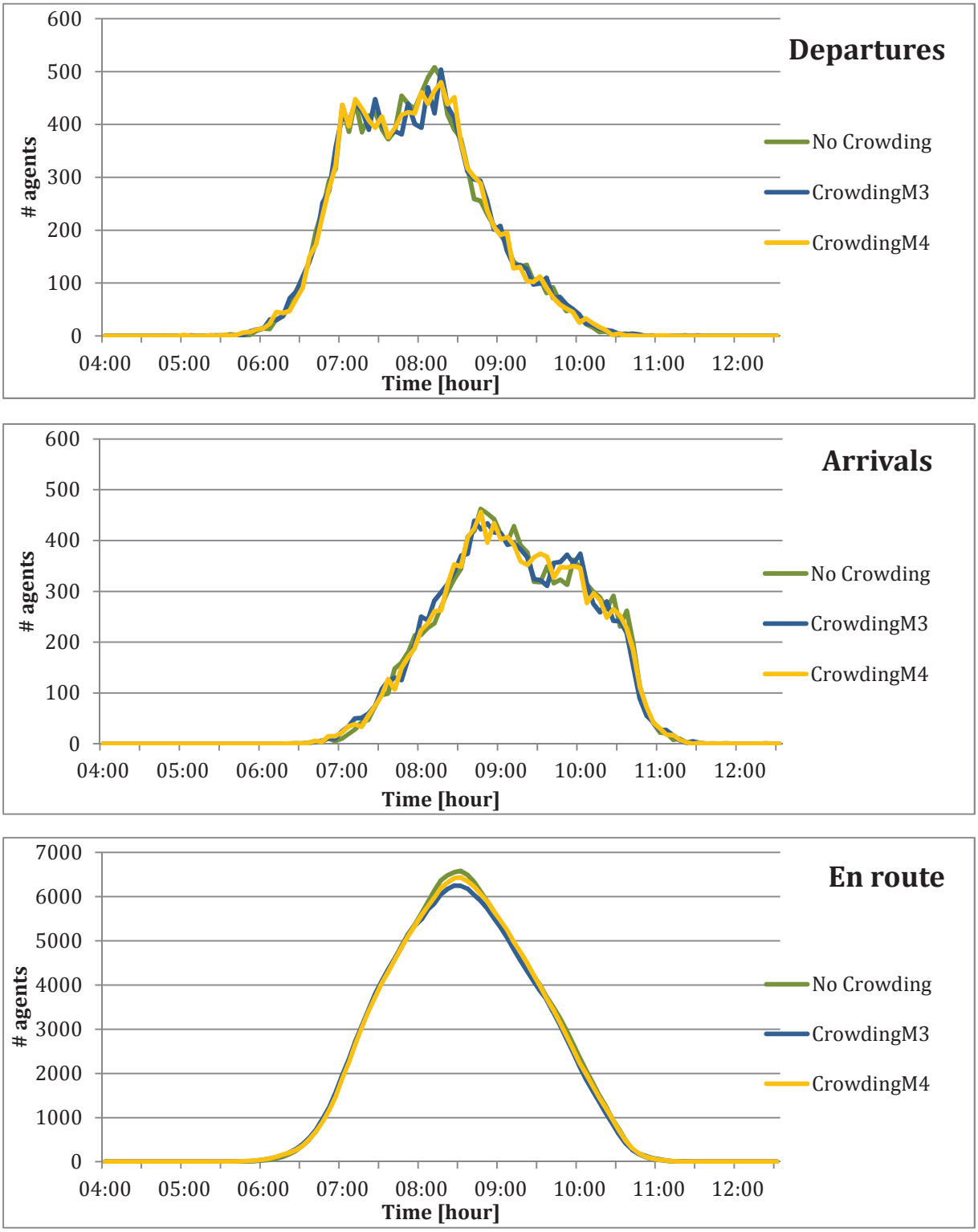
7.3 Behavior according to the simulation type

The several simulations executed have producted a large amount of data. To keep clear the analyze of the results, the data obtained using the "OnlyPT" population are separated from the data from the "WithCar" population in most of the cases

7.3.1 "OnlyPT" population

The figures below show the trip distributions of the simulations using the population "OnlyPT" and containing no externalities. The goal is to obtain a comparison focused on the different kinds of crowdedness.

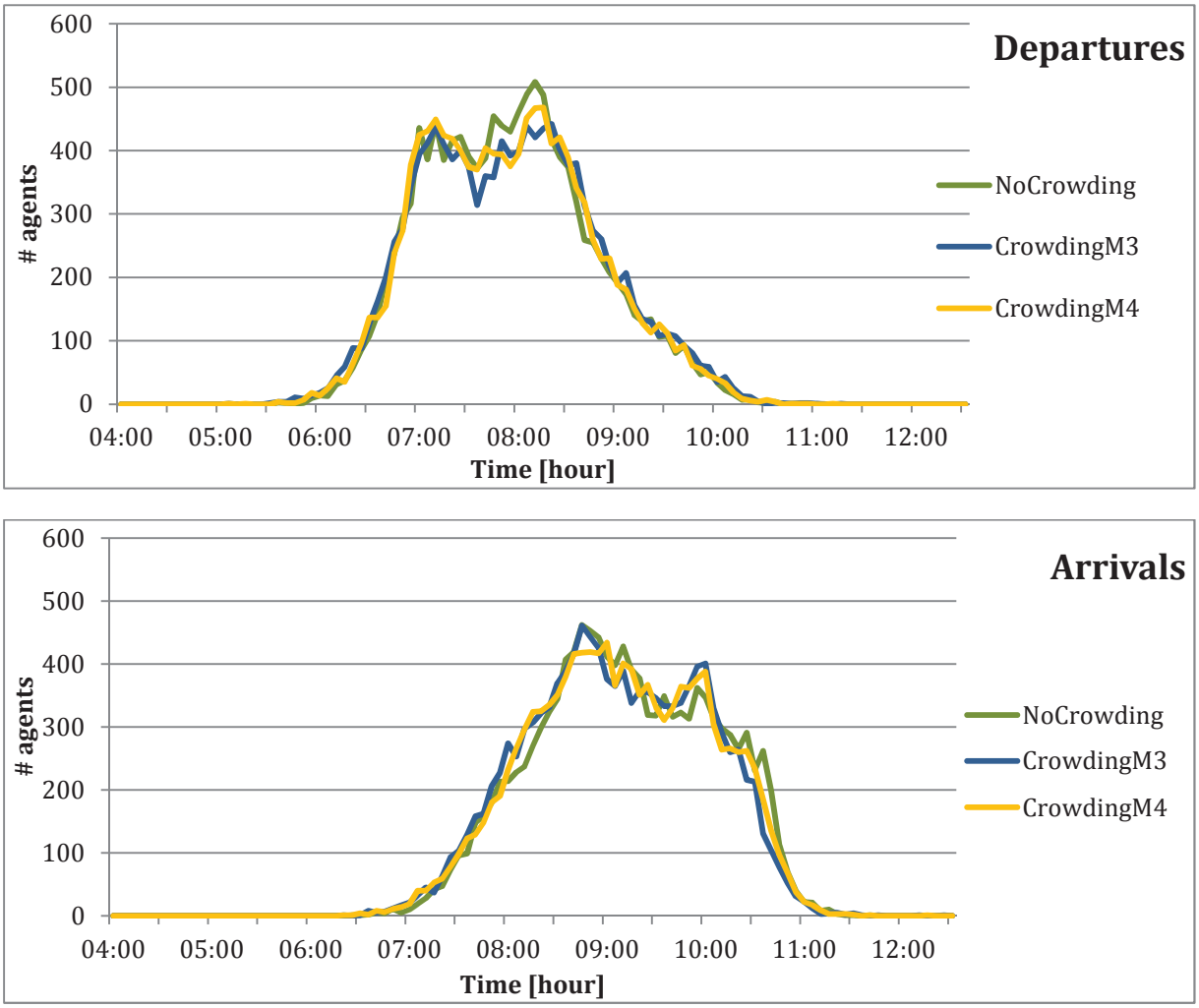
Figure 19: Trip distribution per crowding model, Only PT - No Externalities

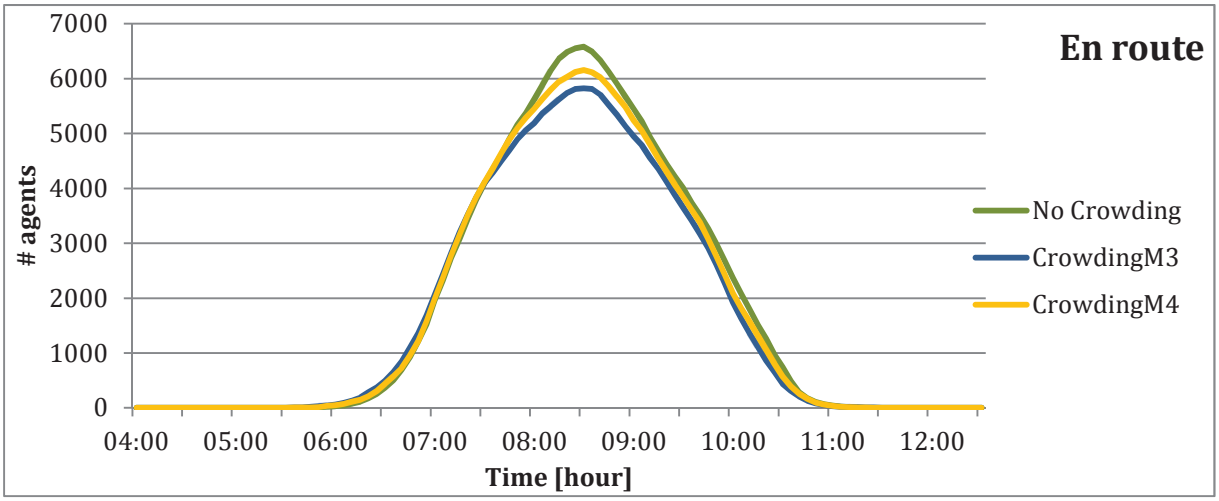


The differences between the models observable in the tables may be small, but they confirm that the implementation of a crowdedness effect produces an effect on the agents behavior: With use of a crowding model, the 08:30-peak is slightly reduced (see “Departures”) and the maximal amount of agents en-route is smaller (circa 130 less agents for model M4 and circa 300 less for model M3).

In the next step, the effects of the externality internalization on the trip distribution are analyzed. The figures below show the trip distributions for simulations internalizing Crowding externalities.

Figure 20: Trip distribution per crowding model, Only PT - Crowding Externalities





Differences between models are in this case clearly observable, showing the impact of the externalities on the trip distribution: for departure times, the 08:30-peak is strongly decreased and a small spreading of the departures earlier and later takes place. Concerning the arrivals, it can be show that more agents arrive early (08:00) or late (10:00) at activity if crowding externalities are implemented. The sum of these effects has for consequence a decrease of the amount of en-route agents at peak hour.

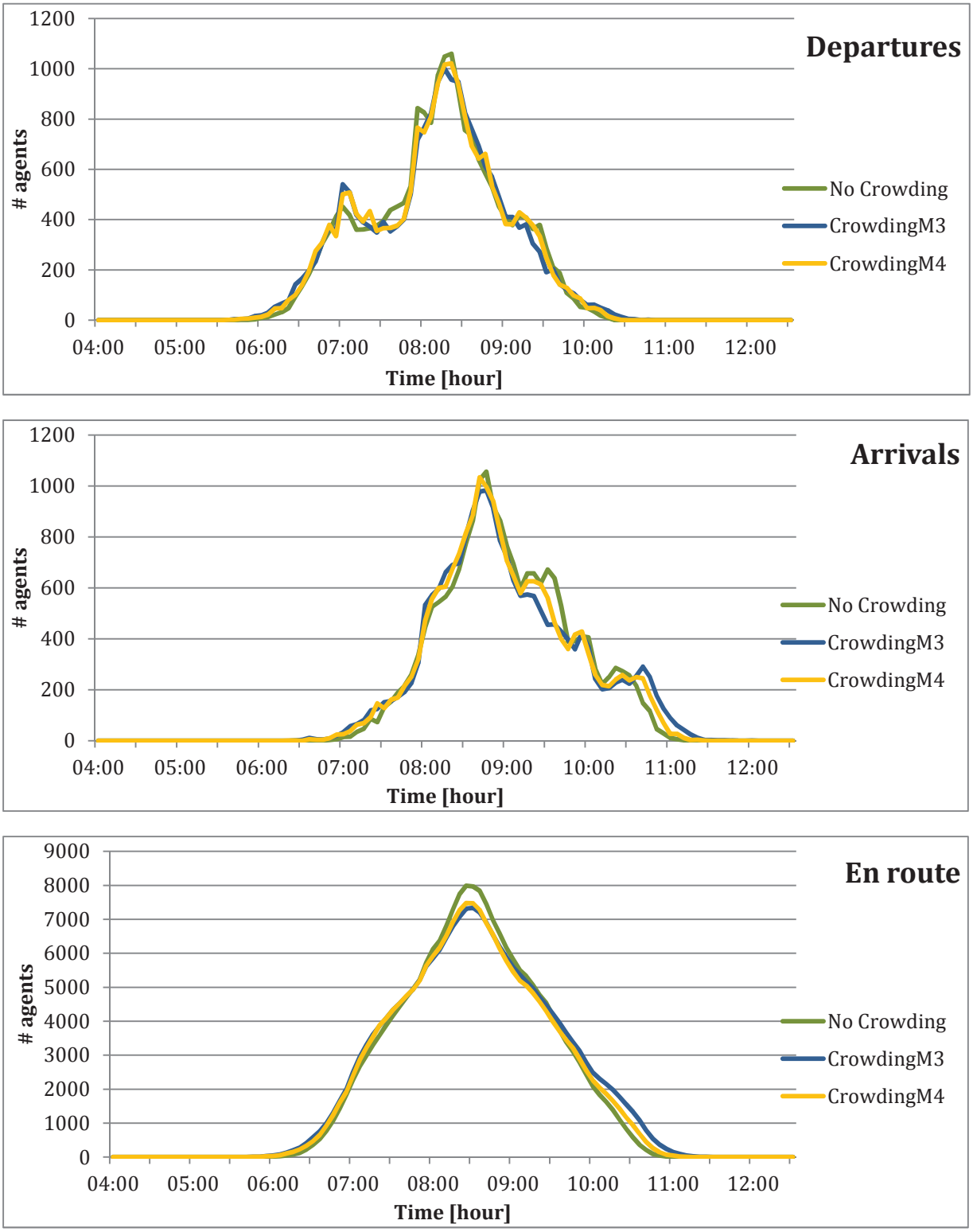
In addition to that, these figures show clearly that the impact of the model M3 on the trip distribution is higher as the impact of the model M4.

The trip distributions resulting from the internalization of the In Vehicle Time Delay and Capacity Constraint externalities follow the same model as the figures above, but in a smaller range: the same increases/decreases of the peaks occurs a spreading is observable and the order between the model effects is kept (CrowdingM3 > CrowdingM4). Thus, the figures are not drawn in this section but they are available in the annexes of the project (Annexes A1 – A5).

7.3.2 “WithCar” population

As a reminder, the “WithCar” population contains car drivers that interact with the PT system and the agents are allowed to change their mode in a new created plan. The next figures show the trip distributions of the simulations using this population and containing no externalities, in order to observe the differences between the crowding models.

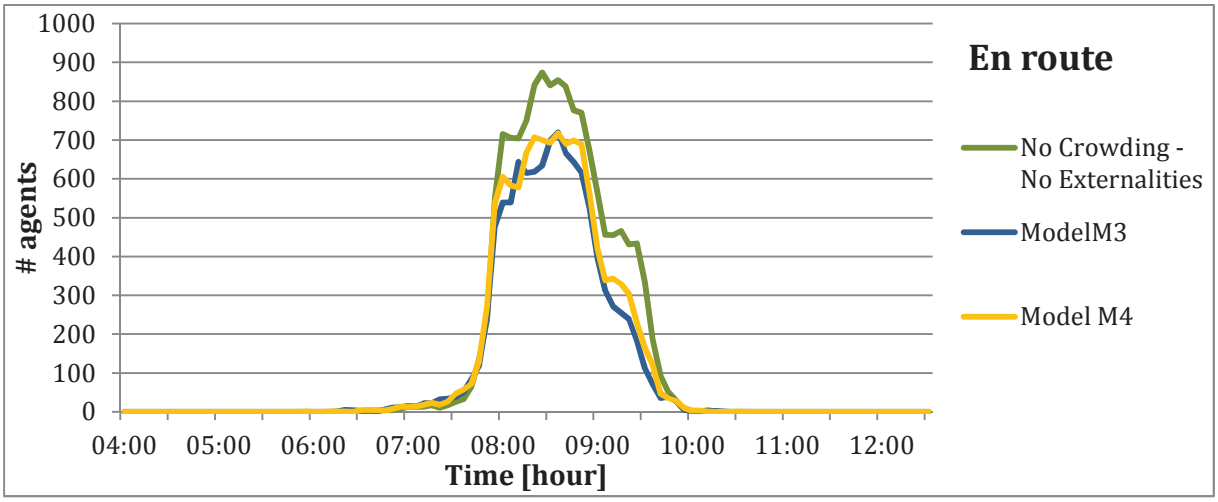
Figure 21: Trip distribution per crowding model, With Car - No Externalities



Concerning the crowdedness, its effects on the trip distribution is clearly observable in these models: the amount of agents departing at first peak (07:00) increases strongly and the amount at second peak (08:30) decreases. Knowing that this second peak is created by the earlier departure of the PT user (see section 7.1 and 7.2), this result shows that crowding effects increase this spreading.

Furthermore, the arrival distribution is modified from 08:00 to 08:30 (earlier arrival) and from 09:00 to 11:00 (later arrival). This two last changes cause a spreading of the en-route distribution. The impact of the CrowdingM3 model on the trip distribution is slightly higher as the impact of CrowdingM4. In addition to that, a better analysis of the car trip distribution shows that a spreading occurs also at 08:30 peak within this mode. Thus, the implementation of crowding effects has not only an effect on the PT distribution, but also on the car mode, as showed in the figure below:

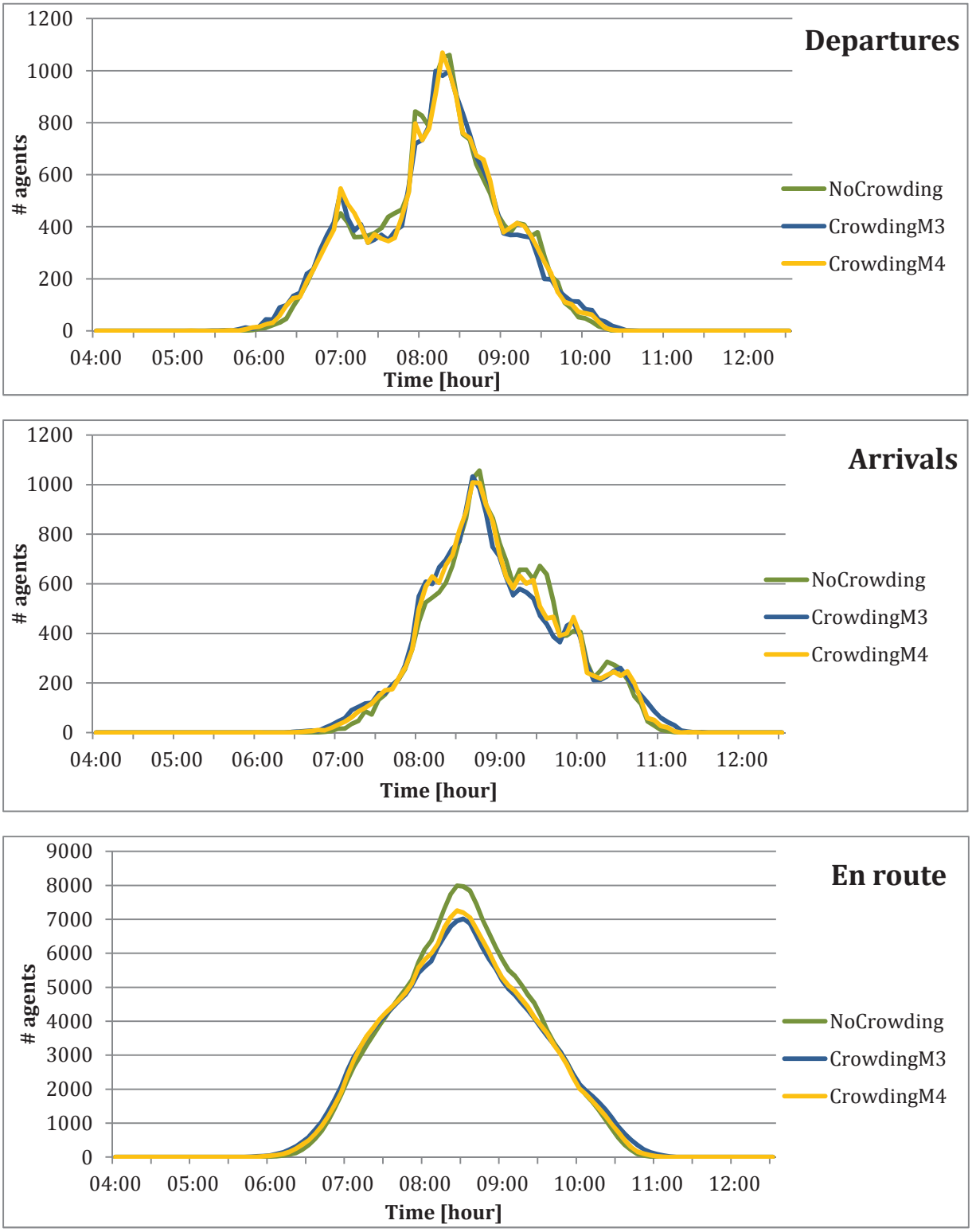
Figure 22: Car driver trip distribution, With Car - Crowding externalities



With regards to mode choice, the percentage of agents using public transport increases for the models with crowding effect: +1.5% (315 agents) for model M4 and +3.6% (720 agents) for model M3. Taking account of the figure above, it is probable that some of these agents change from car to PT mode to avoid the congestion effects at peak hour. But these agents aren't only car drivers: for the model M3 34% (245 agents) and for model M4 61% (193 agents) of the mode changing agents are going to "Work" by walk.

Secondly, the figures below show the trip distributions of the simulations using the population "WithCar" and internalizing Crowding externalities.

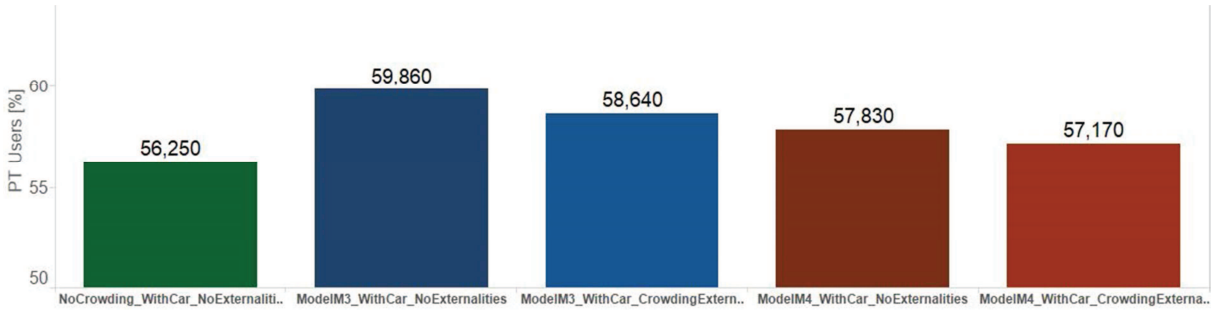
Figure 23: Trip distribution per crowding model, With Car - Crowding Externalities



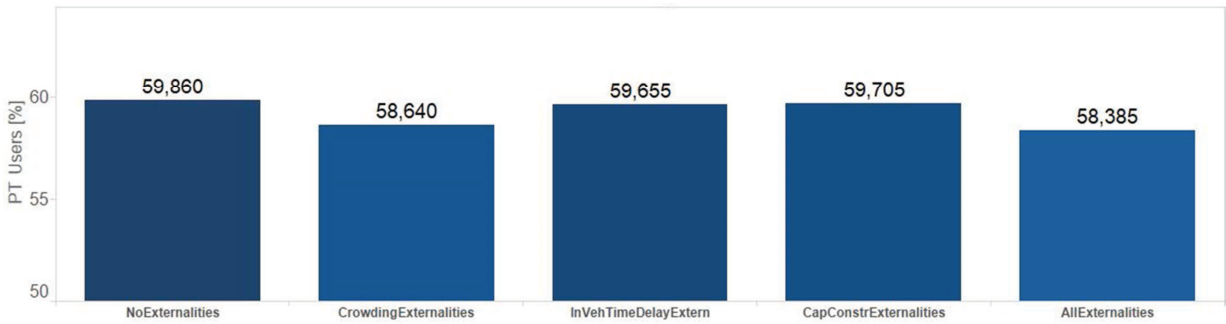
The same changes as these occurring in the simulations without externalities can be observed, but in a bigger way: the increase of the first peak (07:00) is higher and the spreading of the en-route distribution is larger due to the increasing amount of agents arriving earlier and later. Thus, the maximum number of agents traveling at the same time decreased in comparison with the simulations without crowding effect (from circa 7400 agents to circa 7000 agents at peak).

Concerning the mode choice, the percentage of users traveling by PT is again higher as for the NoCrowding model (58.6% for model M3 and 57.2% for model M4, versus 56.3% for NoCrowding model). But the implementation of Crowding externalities reduce the number of agents traveling by PT. The next figure summarizes these results:

Figure 24: Percentage of PT users within simulations



The trip distributions resulting from the internalization of the In Vehicle Time Delay and Capacity Constraint externalities follow the same model as the figures above (*Figures 22 and 23*), but in a smaller range. They are not inserted in this section, but are available in the annexes of the project (Annexes A6 – A10). However, the percentage of PT users according to the externality type for model M3 is drawn below:



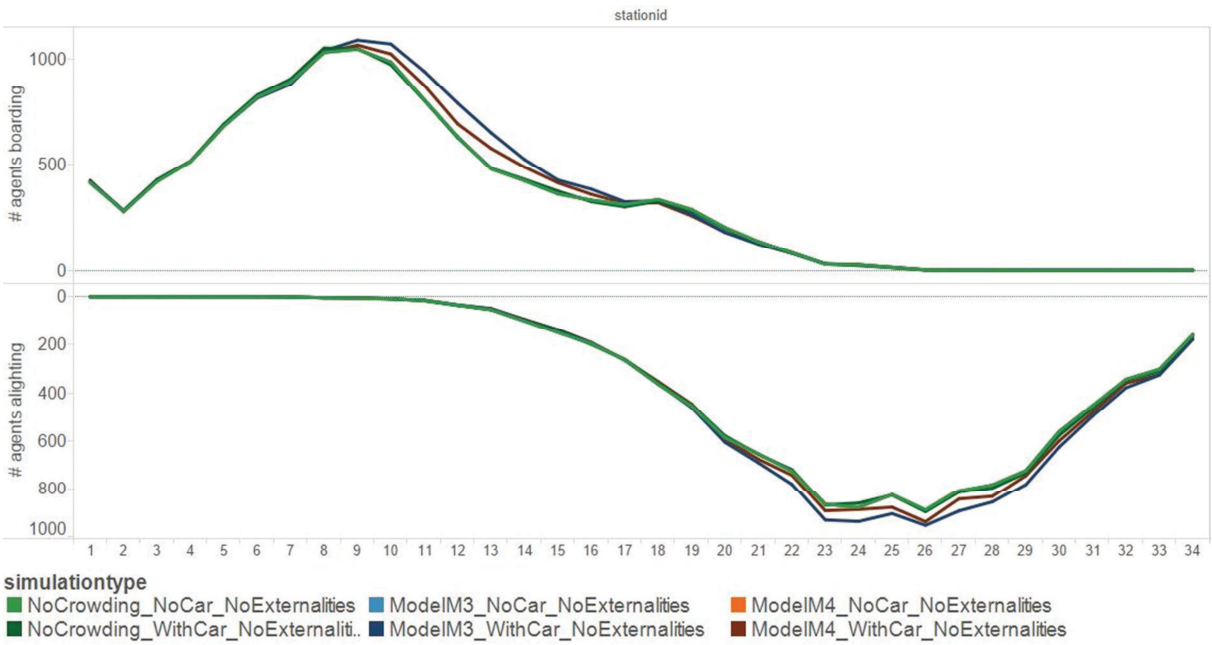
It can be observed that the percentage of PT user decreases if externalities are internalized, in particular the Crowding externalities. The In Vehicle Time Delay and Capacity Constraint externalities obtain a percentage almost similar. These results are observable with the three kinds of models (model M3, model M4 and NoCrowding model). A summary of the mode repartitions is available in the annexe of this project (A15).

The reduction of the PT user number after implementation of externalities is an effect that can (and sometimes that has to) occurs when a pricing strategy is implemented: the PT users who have a bigger flexibility (e.g. other traveling modes available, more flexible working times) are pushed to change their plans, which benefit the agents who cannot modify their plans.

7.4 Behavior per station

The next figure summarizes the amount of agents boarding and alighting at each station along the whole day of simulation. No externalities are implemented.

Figure 25: # agents boarding and alighting pro station along the whole day - No externalities



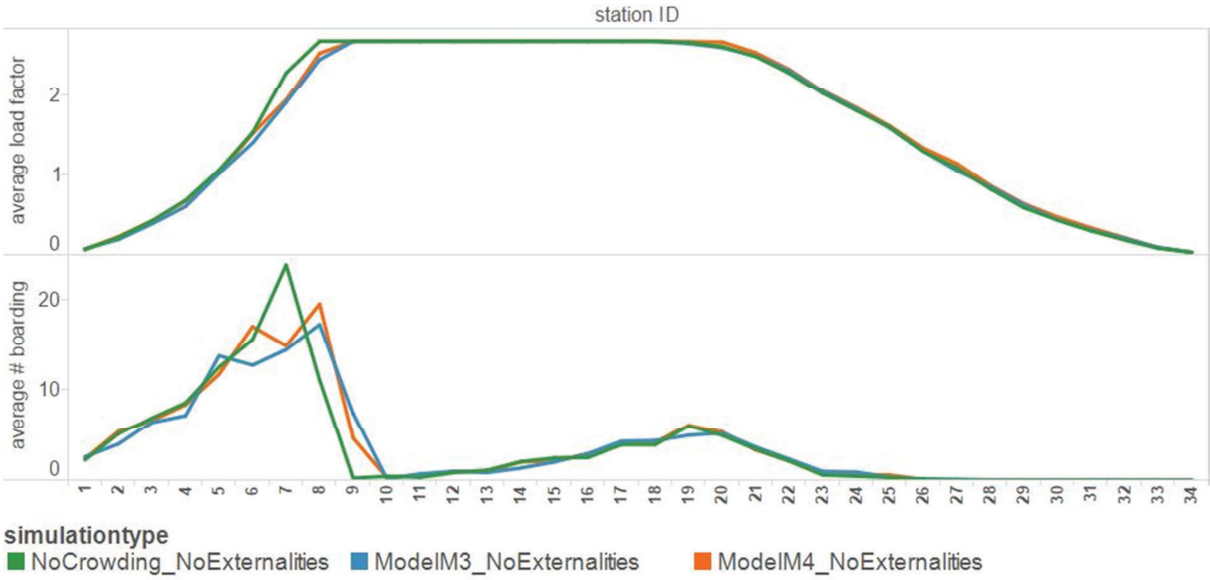
Some observations can be done according to this figure. Firstly, the results obtained by the three simulations using the “OnlyPT” population are exactly the same. The main reason is the impossibility for the agent to change their mode, i.e. they have to

travel by public transport. Secondly, for the simulations using the “WithCar” population and containing crowding effect, the number of agents increases for the stations 9-17 (boarding) and 19-33 (alighting). These additional agents are certainly the agents who change their traveling mode to PT (see section 7.3.2). Furthermore, the high number of agents boarding at the first station is only due to the “boarding” of the bus driver at the beginning of a bus schedule. This information has then not to be taken into account in the analysis.

But the most important information may be the “hollow” observable in the boarding distribution. Since the “Home” location density follows a normal distribution, the boarding distribution should also follow this distribution. On the contrary, the distribution found suggests that agents situated along the stations 9 to 18 rather use the car than the public transport vehicles. To explain this behavior, the occupancy at different periods of the day must be studied.

The next figure represents the average load factor in the buses that travel between 08:15 to 08:45, that mean during the peak seen in the trip distribution analyzis.

Figure 26: Load factor and boarding pro station around 08:30, Only PT - No Externalities

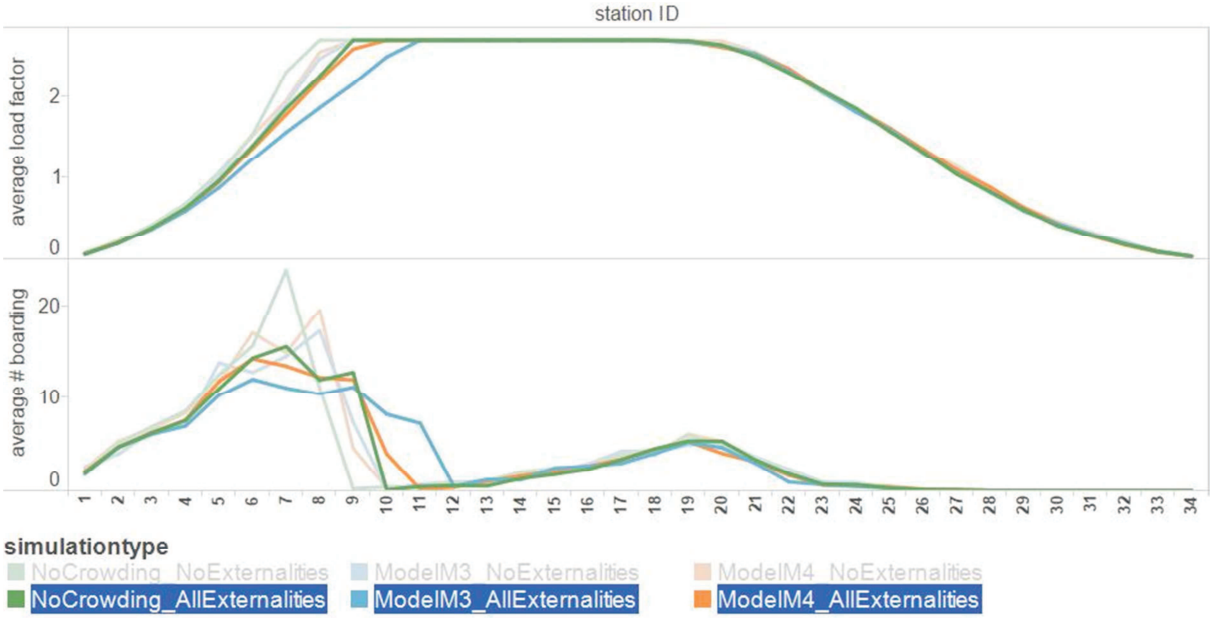


This figure shows that the average load factor is maximal between the 10th and the 20th station. That means that all the vehicles that arrive at these stations during this period of time are full (load factor = 90 users / 34 seats = 2.65). The average number of agents boarding confirms this fact: there are almost no boarding between the stations 10 and 14 and then the number increases slowly. Thus, for agents situated

along these stations, it is worthwhile to to depart earlier or later (or to change their traveling mode if this replanning strategy is allowed) if they want to board a bus.

Secondly, the figure 27 show that the implementation of crowding effects in simulation ameliorate slightly the situation: the load factor is smaller at stations 6, 7 and 8 for the crowding model M3 and M4. Moreover, if externalities are implemented, the situation is even better. The next figure represents the same situation as above, but with the simulation in which the three kinds of externalities are implemented. It is clearly observable that the average number of agents boarding during this period is smaller and that the buses are full along a smaller part of the corridor. The increased spreading of the trip departure distribution has certainly allowed this better state.

Figure 27: Load factor and boarding pro station around 8:30, Only PT - All Externalities



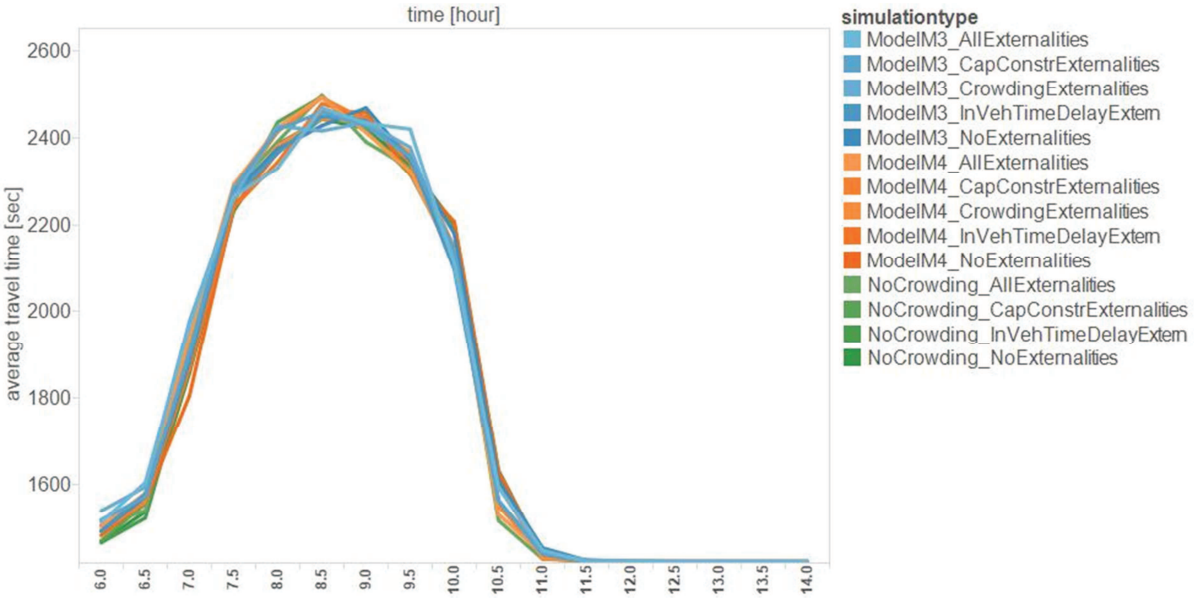
Moreover, an analysis of the load factor before the peak shows that more agents are boarding earlier if externalities are implemented.

7.5 Analyses of the vehicles travel times

The travel time of the public transport vehicles varies according to congestion state of the corridor and the dwell times at stations. A vehicle undergoing no congestion effect and with nobody getting on need 1440 seconds (24 minutes) to accomplish the whole trip along the corridor.

The next figure shows the average travel times depending on the period of the day for all the kinds of simulations done with the “OnlyPT” population

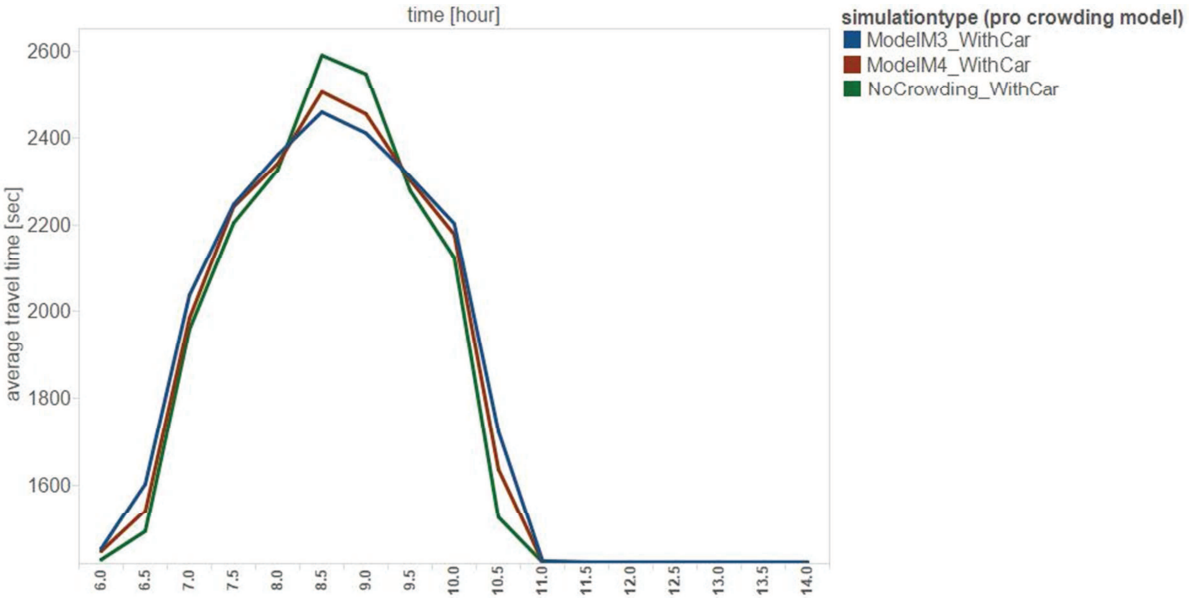
Figure 28: Travel times – Only PT



It is observable on this figure that the travel time increases a lot between 06:00 and 11:00. It is totally normal, knowing that most of the trips occur during this period. The variation at peak within the types of simulations is small, but the travel times of the simulations using the crowding model M3 and, in a smaller rate, the crowding model M4 are shorter at the peak and are longer out of it. This is a consequence of the trip distribution spreading caused by the crowdedness effects and the externalities.

Then, the next figure illustrates the travel times obtained with the simulations using the “Withcar” population. To make it more understandable, an average travel time pro crowding model is drawn. Indeed, the variation between the simulations of a same model (different kinds of externalities) is small enough to group all the data together and average them.

Figure 29: Average travel time along the simulation day



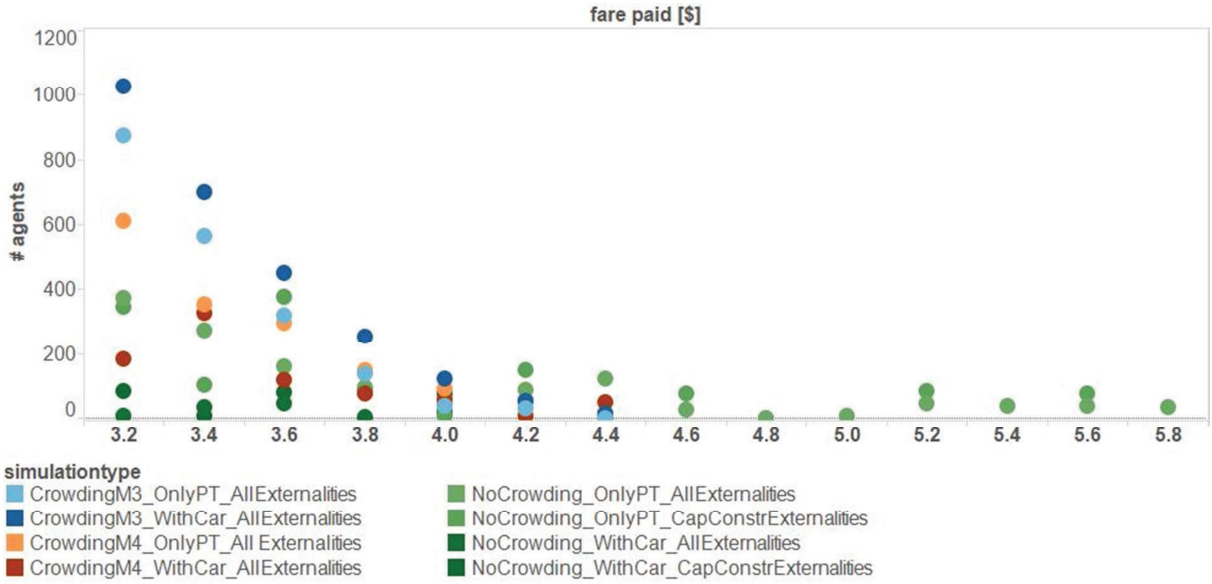
Here, bigger differences are observable: the travel times resulting from model containing crowdedness effects are smaller at peak and higher before and after. This result confirms that the adaptation of the agents plan to avoid the crowding effects has an effect not only on the public transport system itself, but also on the congestion states along the corridor. The implementation of crowdedness effects may reduce the congestion.

7.6 Analyses of the externalities

The externalities internalized by each agent, i.e. the money each agent has to pay, change a lot depending on the kind of simulation or on the period of the day. Most of the monetary charges are situated between $0.5 and $2.0, which is conceivable, knowing that the price of a PT ticket is $1.5. The maximum external fare is $5.6 and was internalized during the simulation *OnlyPT_NoCrowding_AllExternalities*. All the fares higher than $4.4 come from this simulation and the other one containing the Capacity Constraint externalities (*OnlyPT_NoCrowding_CapConstrExternalities)*. For the simulations that use crowding models, the higher fare is found when all the externalities are internalized and its maximum is $4.4 for model M3 and $4.2 for model M4. Finally, it is interesting to see that the maximum fares for models using the population “WithCar” are lower than these using the population “OnlyPT. It can be ex-

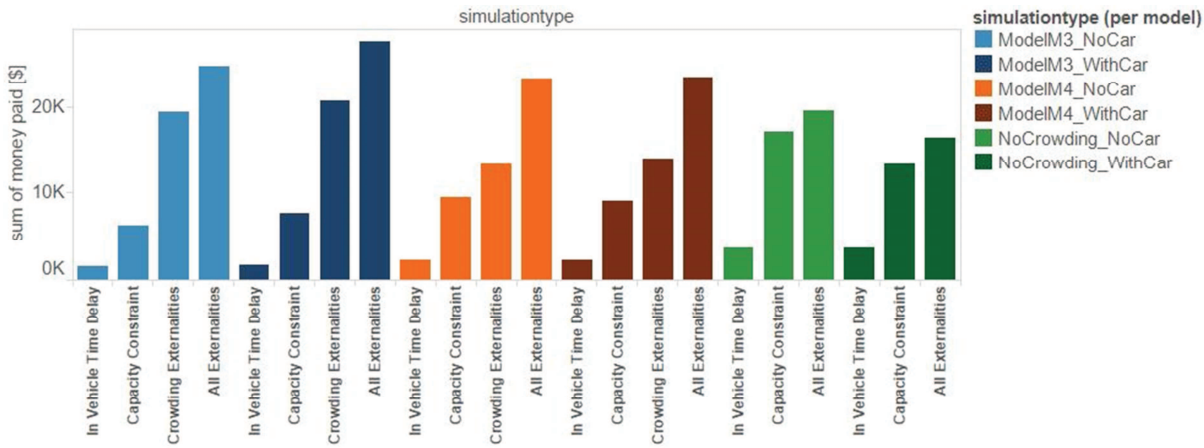
plained by the fact that the agents of simulations “WithCar” undergo congestion disutility at peak hour (longer travel time = more traveling disutility) and that this disutility is added to the externality disutility. In the simulations “OnlyPT”, this supplementary congestion disutility doesn’t exist and thus agents can internalize more externality disutility and obtain the same score as agent from the “WithCar” population.

Figure 30: Maximal fares paid



Furthermore, it is interesting to check the sum of all fares produces by each simulation. The next model summarizes these results:

Figure 31: Sum of fares pro simulation



Firstly, it is observable that the fares paid because of the In Vehicle Time Delay externalities are small in comparison with the others. There is little increase between the simulations with crowding models and without crowding model and between the “OnlyPT” and the “WithCar” simulations. This last result seems to be in contradiction with the fact that the higher fares are greater for the “OnlyPT” simulation than for the “WithCar” simulations. An explanation may be that because of the congestion effects along the corridor, the time in crowded bus and the waiting time at facility are higher and increase the Crowding and Capacity Constraint externalities respectively.

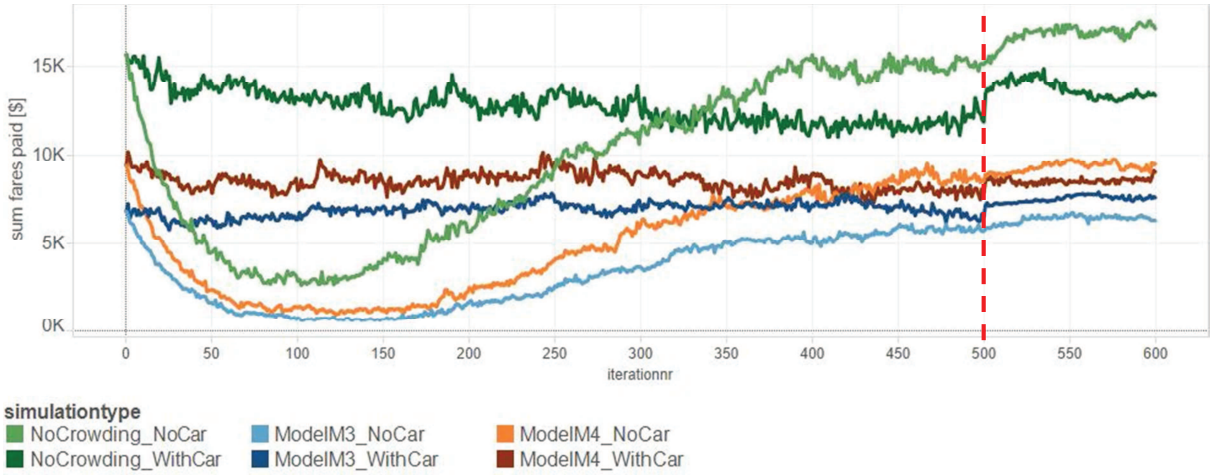
Moreover, it is normal to see that the sum of fares is higher for the simulations containing all externalities. It is important to remark that the Crowding externalities cannot be implemented in the simulations using NoCrowding model. This is certainly why this sum is smaller for these simulations.

Finally, the sum of fares resulting from the Crowding externalities is higher for the model M3 as for the model M4. The reason come certainly from the formula implemented, knowing that the fares to pay for the same time is higher with model M3 as with model M4.

But the most interesting point is the behavior of the simulations using the Capacity Constraint externalities: the sum of these externalities is smaller if a crowding model is used. As this externality is strongly dependent on the amount of full buses during the simulation (more full buses = more waiting at station = more externalities), it suggests that the use of the crowding model reduce strongly the problem of full buses.

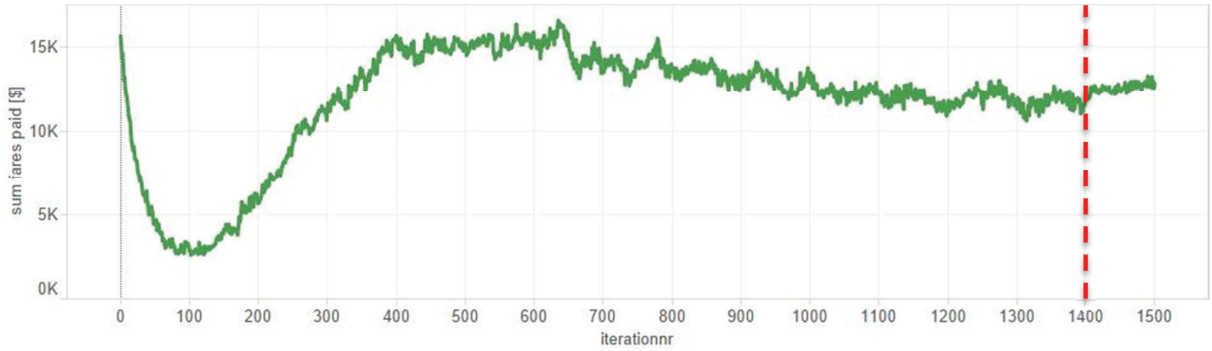
However, this result must be taken carefully. Indeed, an analysis of the fare sum along iterations shows that this sum “jump” after the 500th iteration, especially for the NoCrowding simulations. It means that the switch off of the replanning functions (“TimeAllocationMutator” and “ChangeLegMode”) has an important effect. The next figure depicts this situation:

Figure 32: Capacity Constraint externalities, sum of fares paid along iterations



To evaluate if this "jump" has a real impact on the function or if this behavior is normal after 500 iterations, the same simulation was ran again with 1500 iterations. The behavior along the iterations is showed below.

Figure 33: Capacity Constraint externalities, 1500 iterations



The figure above shows clearly that the sum of fares paid should normally continue to go down after 500 iterations (particularly between the iterations 650 and 700) and stabilize after circa 1100 iterations. A smaller "jump" is visible after the switch off of the replaning methods (after 1400th iteration), but in a smaller scale as after the 500th iteration.

These results suggest that the simulation *NoCrowding_OnlyPT* and *NoCrowding_WithCar* wasn't stable enough to be stopped. This situation could lead up to a renewal of each simulation, but, knowing that the sum of fares paid with this model is

always higher after 1500 iterations than the sum of fares resulting from the model M4, it has been decided to keep the data used until now.

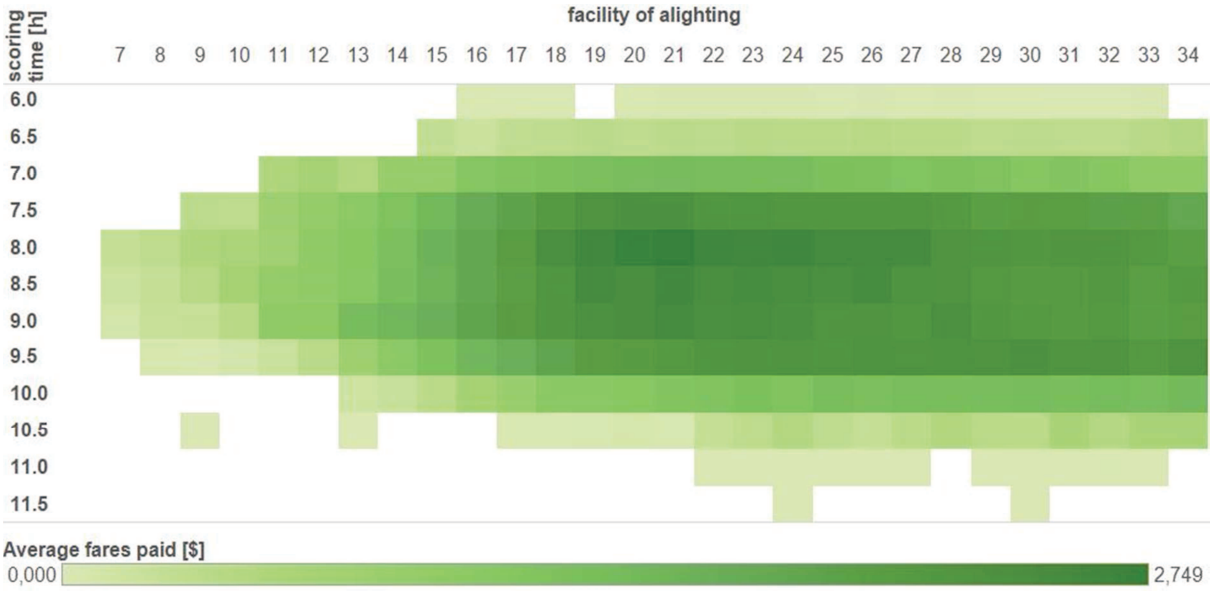
In addition to the effects described above, it is observable in the *Figure 32* that the simulation behavior is completely different depending on the population used ("OnlyPT" or "WithCar"). If the population contains only public transport, the sum of fares paid decreases till the 100th – 150th iteration and increase again to reach a level close to the model using the population "WithCar". This behavior results from the trip distribution spreading analyzed in section 7.1 and is observable for all the simulations using "OnlyPT" at different scales. Concerning the "jump" after 500 iterations, it is especially observable in the simulations taking into account the Capacity Constraints externalities, but in a smaller scale than the example described above.

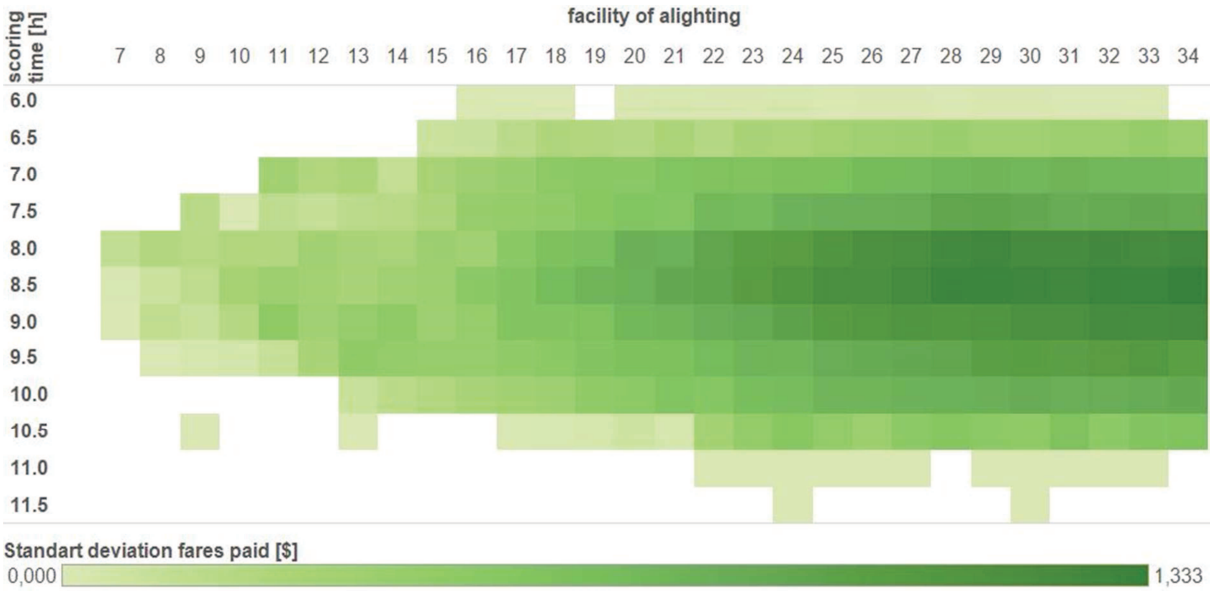
7.7 Fares relations

In order to understand the behavior of externalities distribution and to allow the development of a Second-Best pricing strategy, relations between the fares paid by each agent and some of the parameters of the simulation have to be found.

Firstly, the next figure gives the average fares paid according to the facility of alighting and the period of the day for the simulations that include all externalities. In addition, to that, the standard deviation of the fares paid according to these two parameters is represented.

Figure 34: Fares paid, Average and Standard deviation – All Externalities



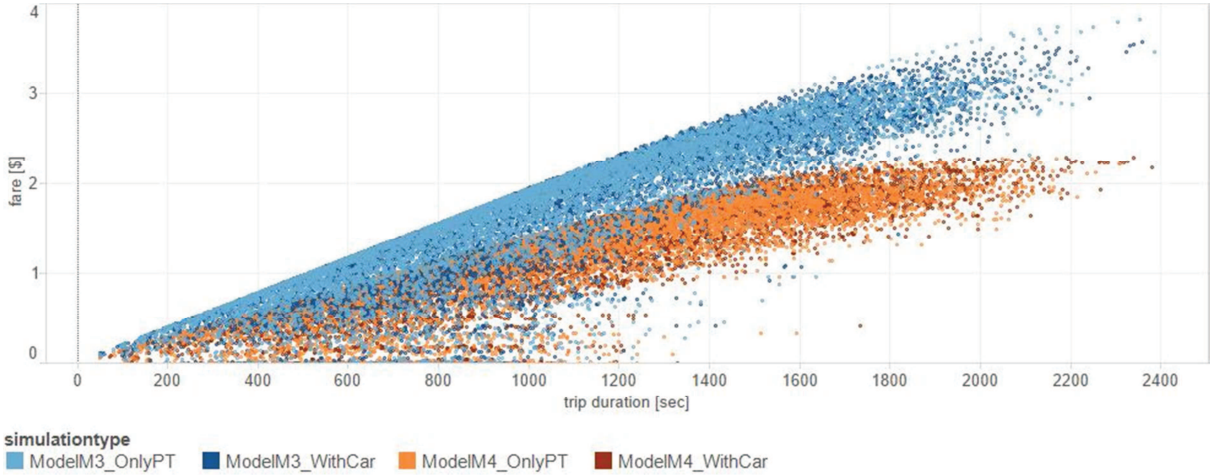


The first figure shows clearly that the higher average fares occur from 07:30 and 09:30. That's in relation with the trip distribution and the fact that most of the working facilities are located along the last bus stations of the corridor. Then, observation of the second figure shows that the higher average fares are distributed with a greater standard deviation as the lower. However, a focus on the facilities 18 to 21 from 07:30 to 09:00 shows that although the average fares are the higher of the simulation

day, the standard deviation keep average value in comparison with the last facilities. Thus, it suggests that the fares keep a high but stable value at this period.

Secondly, the analysis of the results allows finding a relation between externalities and trip duration. For example, the next figure represents this relation for the Crowding externalities within the two models M3 and M4.

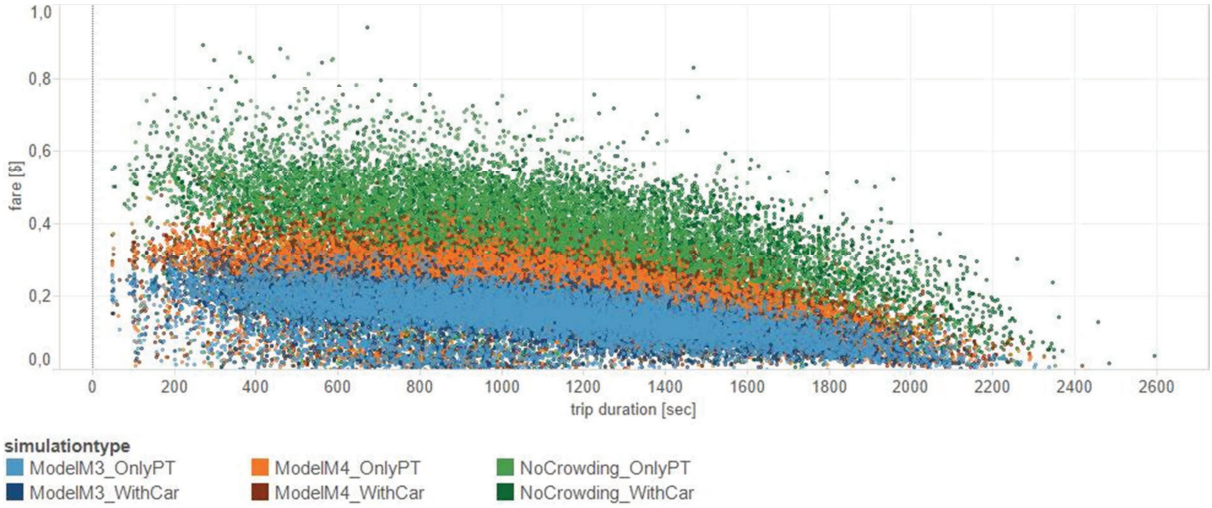
Figure 35: Relation Fares - Trip duration, Crowding externalities



For this kind of externalities, the relation is clear: a polynomial function and even a linear function can be used to describe the behavior of the models M4 and M3 respectively. The behavior of the function can be described as “longer the trip, higher the fare”, that is not surprising knowing that the initial functions depends strongly on the travel time (see Equ.(5.1) and Equ.(5.2)). But if the fares of model M3 seems to always increase with the trip duration, the fares of the model M4 stop to grow after reaching a maximum of around $2.3 and a trip duration of circa 1800 seconds.

As regards to the In Vehicle Time Delay externalities, another clear relation has been found:

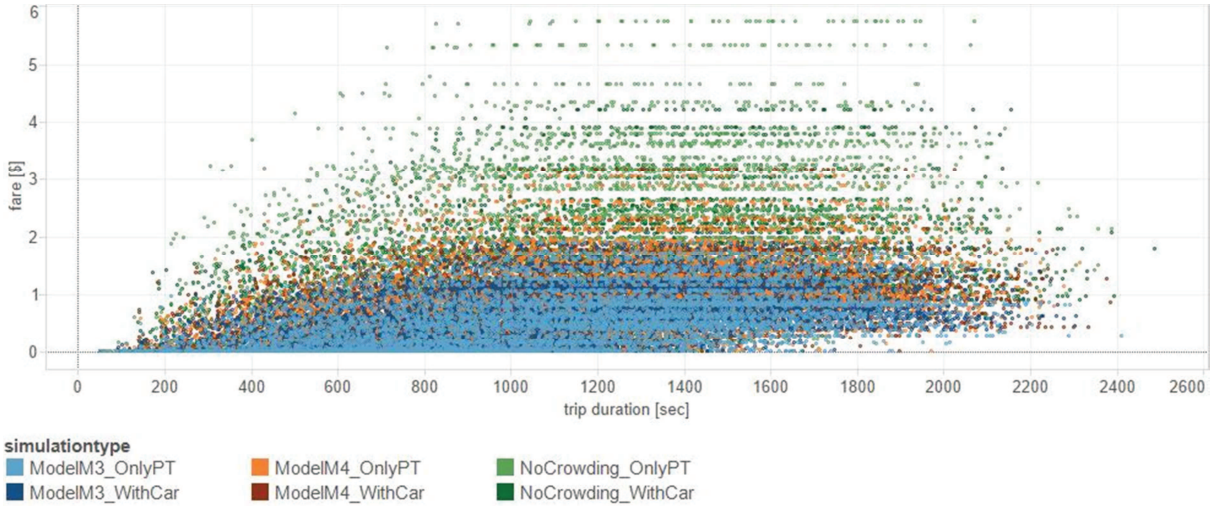
Figure 36: Relation Fares - Trip duration, In Vehicle Time Delay externalities



The variation of the results seems to be greater than in the *Figure 35*, but the range of results is here smaller (from $0.0 to $0.9). Thus, linear relations can well describe the fare behavior over the trip duration. It suggests that the agents traveling during a smaller period cause more externalities than the agents traveling during a longer period. That can be explained by the fact that agents traveling fewer board at stations situated farther on the corridor, and that the buses arriving at these stations are already highly occupied. As the In Vehicle Time Delay externalities depend on the number of passengers onboard when a new one get on, it is normal than the users boarding later pay more externalities.

Finally, the relation between the fares produced by the Capacity Constraints externalities and the trip durations is represented:

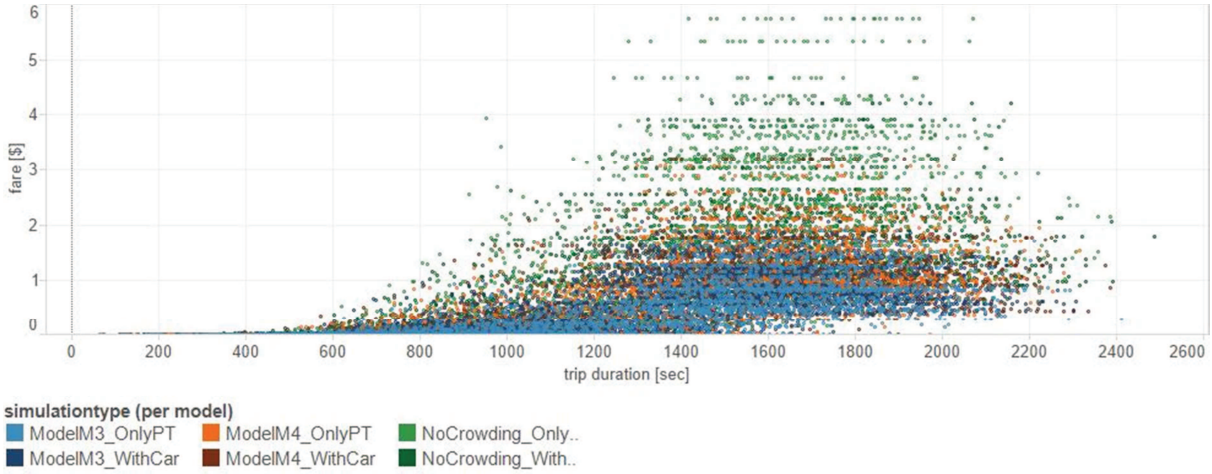
Figure 37: Relation Fares - Trip duration, Capacity Constraint externalities



Here on the contrary, there is no clear relation observable. On the one hand, the results deriving from the simulations using the model M3 seem to be more grouped (they stay below $2), but on the other hand, the variation of the results from No-Crowding models is high. The possible non-stable state of these last simulations (see section 7.6) may be the reason of this high variance.

However, it is possible to find better relations by focusing on the facility of alighting. Indeed, if an agent alights early, his Capacity Constraint externality is smaller. That's explainable by the fact that most of the buses become full in the middle stations because of the higher demand around these facilities. In addition, it can be observed that the Capacity Constraint externalities are almost zero if small trips are accomplished to the facilities situated far away on the corridor. The explanation may be that the agents that board late are not the cause of the externalities, but the agents that board early are because they stay longer in the bus and prevent many other agents to get on.

Figure 38: Relation Fares - Trip duration, Capacity Constraint externalities, stations 26-34



8 Second-best pricing

The methodology followed in section 7 can be qualified as First-Best pricing strategy: the externalities depend on several parameters that vary over time (bus occupancy, number of agents waiting at station, etc.) and are thus different for each agent. This kind of pricing may be inapplicable in a real situation. That's why a Second-Best pricing strategy has to be developed.

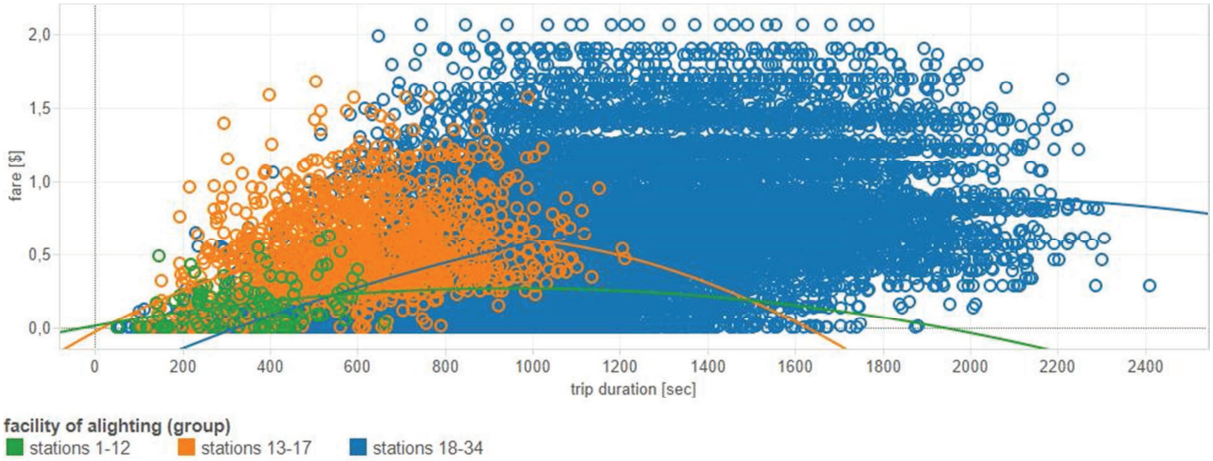
In this project, the opportunities given by the Smart Card system used in Singapore can be exploited. Knowing that the boarding and alighting times are recorded and because of the good relations found in section 7.7, a pricing strategy using the trip duration is developed. It uses several functions given by the relation between the externalities (or fares) to pay and the trip duration. The functions are polynomial (second degree) and are designed using trend lines models available on the software Tableau. It was decided to use only the data of the model M3, because the results of the precedent sections show their effect on the trip distribution is higher than these of model M4.

Concerning the externalities resulting from the Crowding and the In Vehicle Time Delay externalities, it has been showed in section 7.7 that the relation between trip duration and money paid was strong. It has thus been decided to use this relation in the pricing strategy by make depend on the trip duration the fares that passengers have to pay. In addition to that, to increase the accuracy of the strategy, the functions "fare/trip duration" vary according to the alighting time. The day has been divided in six parts: on the one hand, if a passenger alights from the beginning of the simulation to 06:30 or from 10:30 to the end of the simulation, no externalities are added. On the other hand, the period of time situates between 06:30 and 10:30 is divided in four equal periods of one hour each. For each of these periods, a polynomial function of the fare paid over the trip duration is implemented. The coefficient of determination R^2 has a value situated around 0.8 – 0.9 for the Crowding externalities functions and around 0.4 – 0.5 for the In Vehicle Time Delay externalities function. This worse result is compensated by the fact that the standard error of the function is situated around $0.04, which makes it accurate, too. The parameters of the polynomial functions can be found in the annexes (A16).

Concerning the Capacity Constraint externalities, the results developed in section 7.7 show that their relation with the trip duration isn't so great that the other kinds of externalities. To solve this problem, it is decided to divide the alighting facilities in three groups (from station 1 to 12, 13 to 17 and 18 to 34). The groups have been chosen

because of the similarities of behavior of the trend lines, as represented in the next figure:

Figure 39: Fares pro trip duration, groups of stations

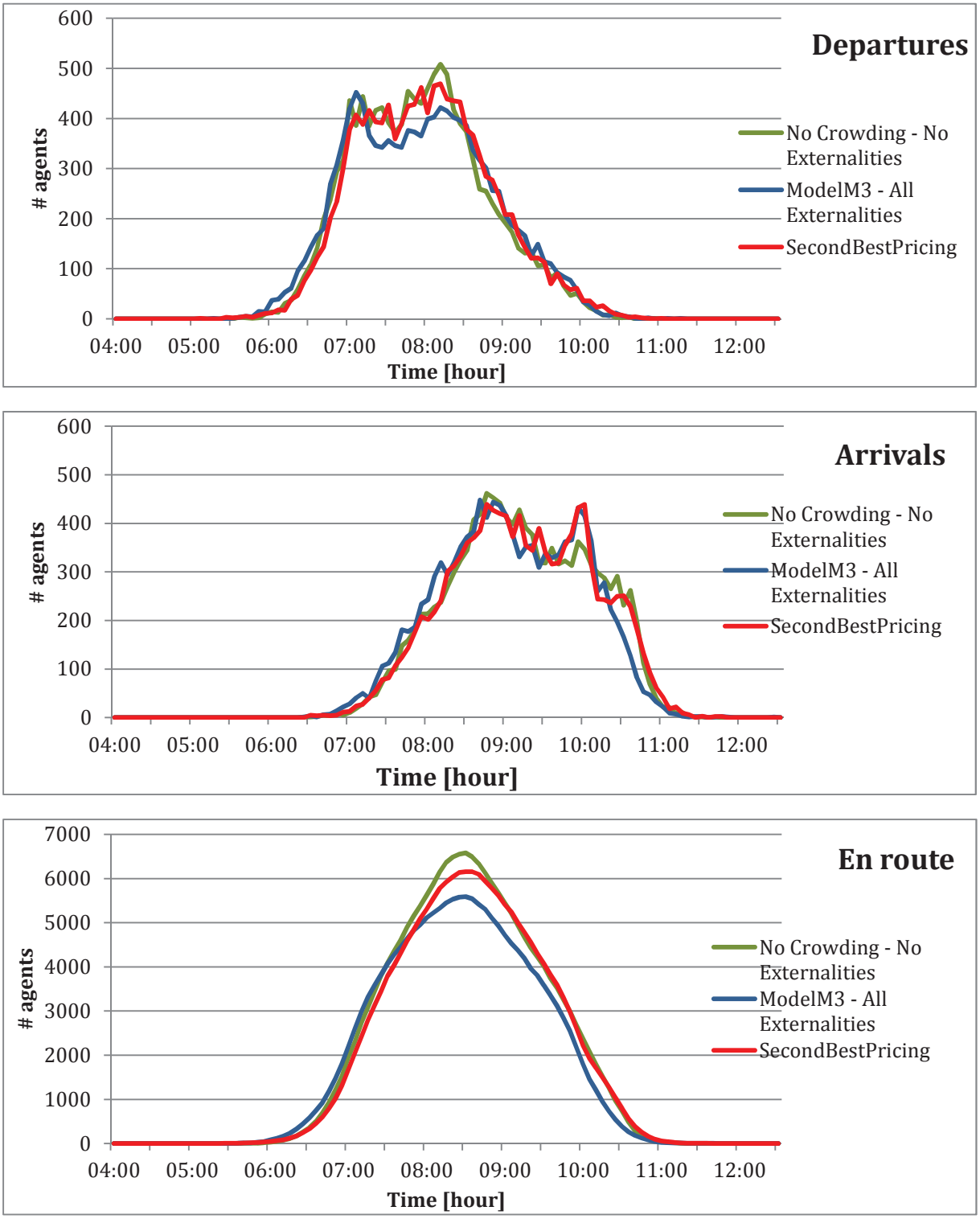


As the externalities caused by the group containing the stations 1-12 and the amount of data are smaller, it has been decided to not add Capacity Constraint fares if passengers are alighting at these stations. The parameters of the polynomial functions used can be found in the annexes (A16).

Using these functions, two simulations are conducted: the first one using the "OnlyPT" population, the second one the "WithCar" population. The parameters from the multinomial logit model remain the same as these used for the simulations using the crowding model M3. The replanning strategies are also the same (2% ChangeLegMode, 2% TimeAllocationMutator), as well as the number of iterations (600 iterations) and the time at which the strategies are switched off (after 500 iterations).

The results of the trip distribution for the population "OnlyPT" are showed below. The distribution found with the second-best pricing strategy is compared with the results of the simulation without externalities and without crowding (*OnlyPT_NoCrowding_NoExternalities*) and with the simulation using the crowding M3 model and internalizing the three kinds of externalities (*OnlyPT_ModelM3_AllExternalities*). Later in this section, to increase the clarity of the text, this last model is called "reference simulation" or "reference model".

Figure 40: Second-Best pricing, Only PT

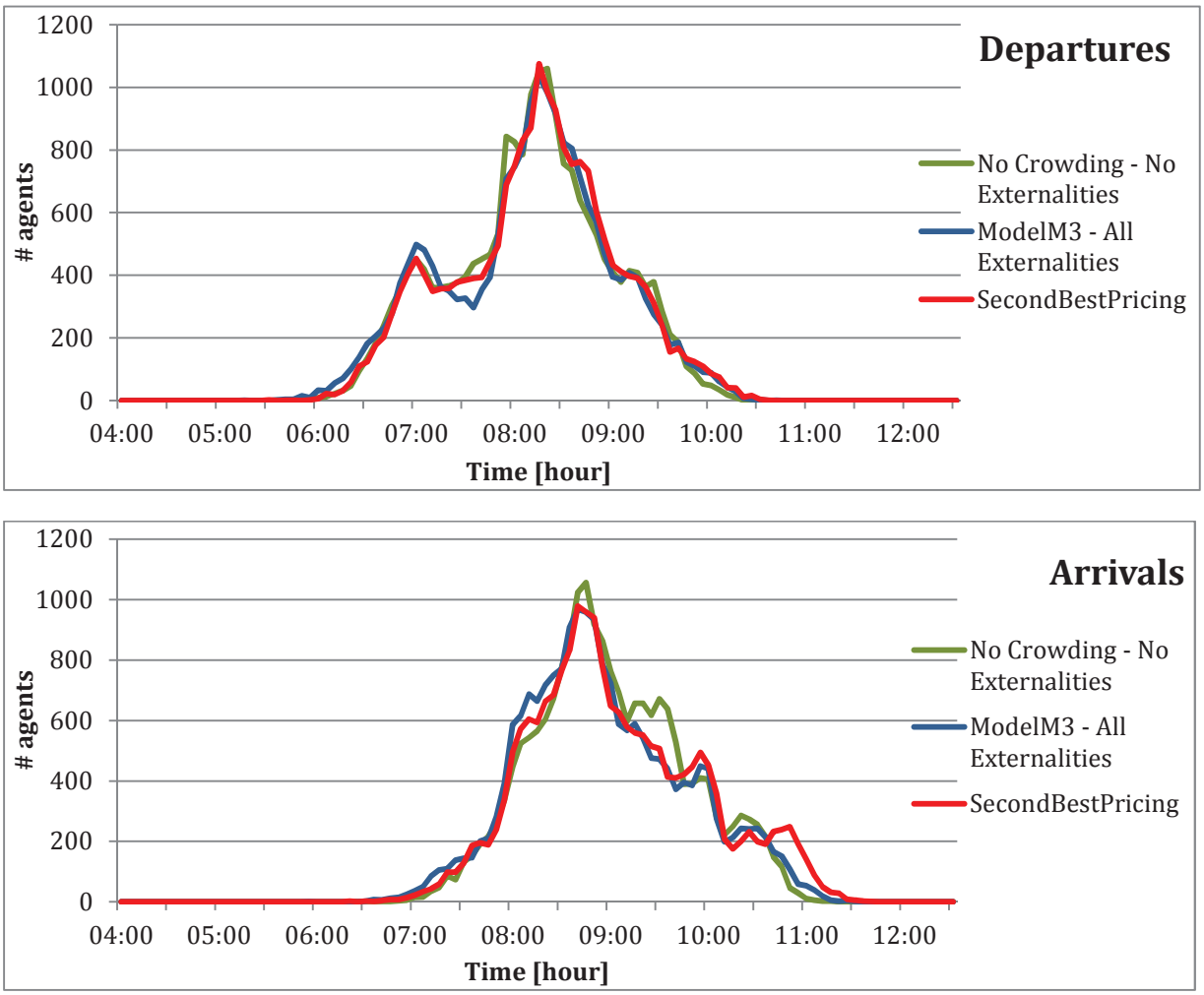


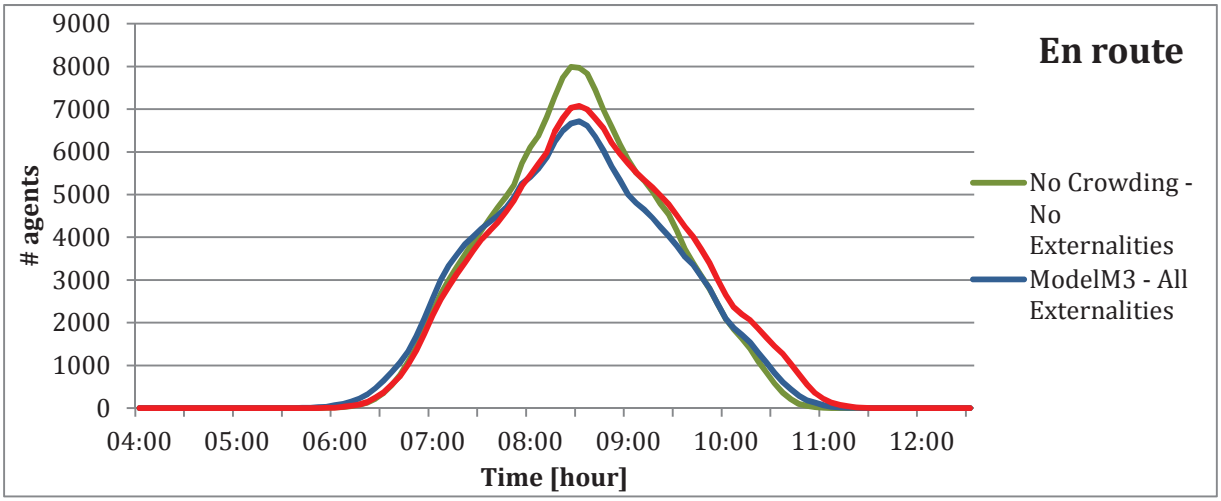
Firstly, it can be observed that the second-best pricing strategy has a positive effect on the trip distribution: the amount of agents traveling at peak hour is smaller than

without crowding or externalities and the peaks at 07:00 and 08:30 are slightly spread. However, greater differences with the trip distribution of the reference model are observable: the number of agents departing from 07:00 to 08:30 is higher, the number of agents arriving late also and it results to a trip distribution closer to the model without crowding effect than to the "goal" model.

For the simulation using the population "WithCar", the trip distribution of the Second-best pricing strategy is compared with the same models as in figure 40. The results are showed below.

Figure 41: Second-Best pricing, WithCar

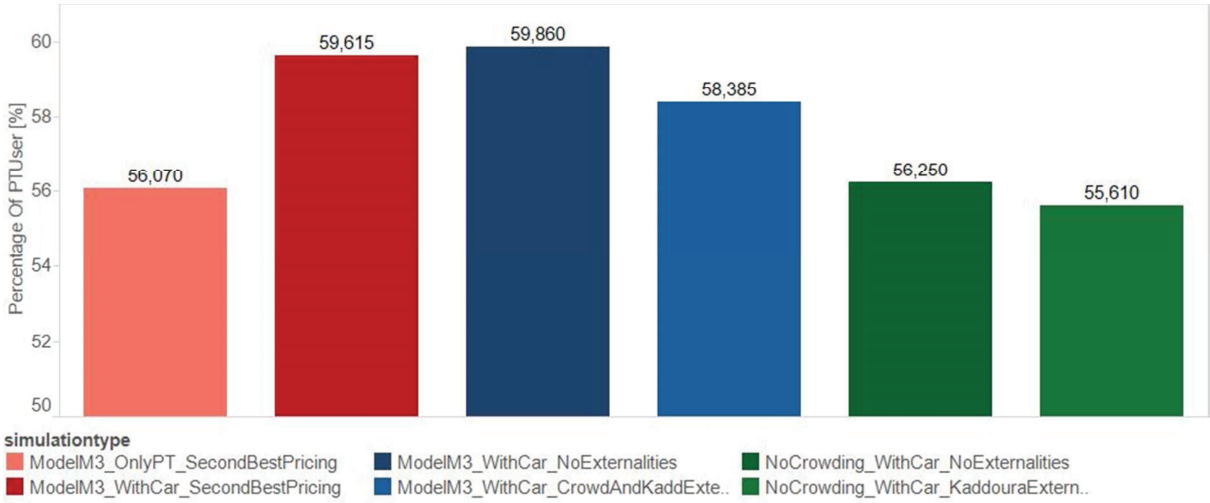




Here again, the implementation of the Second-Best pricing model ameliorates slightly the trip distribution along the day (the amount of en-route passengers is lower than the model without crowding/externalities). But a great spreading of the agents traveling can be observed on the left side of the en-route trip distribution. This result is due to the high amount of agents arriving later than in the reference simulation.

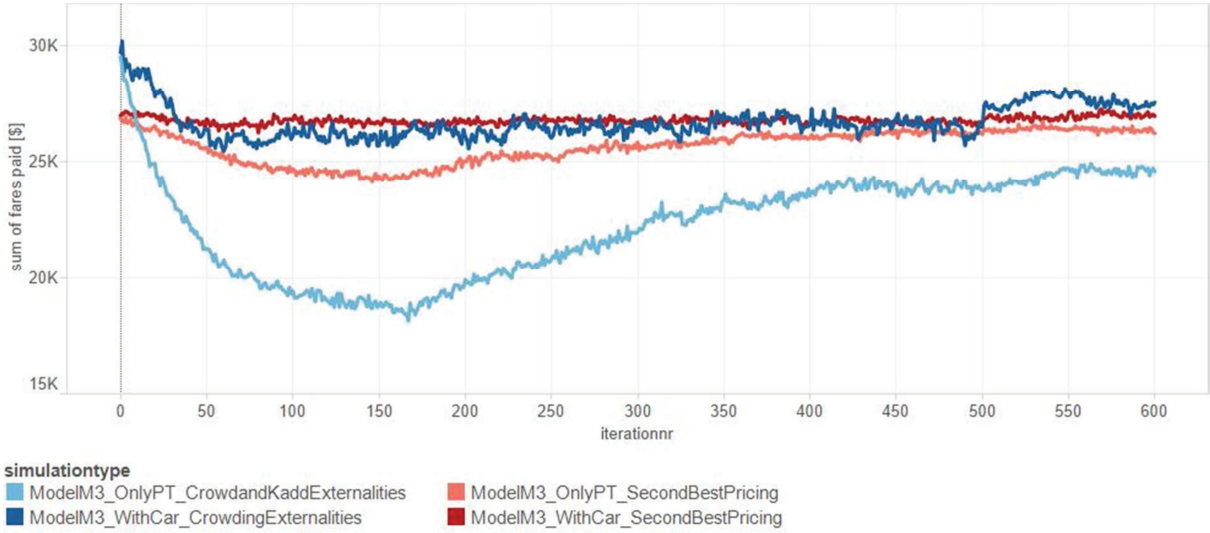
Concerning the mode repartition, the public transport mode contains 59.6% of the agents for the Second-Best pricing simulation. This percentage is situated in the same range as the results obtained with implementation of the reference model (see figure below). Thus, it may confirm that this second-best pricing strategy is working well, because of the proximity of this result with the first-best pricing strategy. However, the percentage of PT user is slightly too high in comparison with the result of the reference model for population “WithCar”.

Figure 42: Percentage of agents using PT



Finally, a view on the final sum of fares paid by agents shows that this sum is really close to the sum of externalities found with the reference model.

Figure 43: Behavior of the Second-Best pricing simulation along the iterations



In addition to that, it can be observed that the behaviors of the simulation using “OnlyPT” are similar between the first-best and second-best models, but in a smaller range for the second-best strategy. Knowing that this behavior comes from the spreading of the trip distribution along the first iterations (see section 7.1), it may be suggested that this spreading effect is smaller for the second-best pricing strategy.

In summary, these results shows that this implementation of a Second-Best pricing provides an amelioration of the situation, but in a smaller scale as with the use of a First-Best pricing strategy depending on the same parameters. In particular, the trip distributions are rather different: while the agents of the reference simulation seem to rather depart early to avoid the disutilities of peak hour, the agents of the Second-Best pricing simulation rather arrive later. An optimization of the parameters may bring closer the two results.

Finally, it is important to talk about the feasibility of this kind of pricing strategy. On the one hand, knowing that the boarding and alighting times of each agent are recorded, the technical constraints of implementing a Second-Best pricing strategy may be solved with small adjustments of the Smart Card system. On the other hand, the informations that need to be given to the users before the introduction of the pricing scheme must be clear and well explained. Indeed, a pricing strategy can only bring to the expected results if the repartition of the fares is totally understood by the users of the system. If not, the users cannot have the appropriate behavior that should permit them to optimize their trip.

9 Conclusion

The recent researches accomplished on friction effect at boarding and alighting (L. Sun, 2013), on crowdedness effects within the public transport vehicles (A. Tirachini, 2013) and on delay externalities occurring along a bus line (A. Kaddoura, 2013) have been for the first time grouped, implemented and simulated within the agent-based simulator MATSim. The main conclusions found by analyzing the simulation results can be summarize in four considerations.

Firstly, the implementation of the new dwell time model developed by L. Sun (2013) and describing the friction effect at facility has showed that the dwell time may be strongly increased if boarding occurs in a rather to high filled bus. Therefore, the dwell time increases lead up to a prolongation of the travel time and force the agents to adapt their plans to this new parameter. It is showed in this project that the peak of boarding agents that exists in the original trip distribution (i.e. using the normal MATSim dwell time model) has been totally spread, the number of agents boarding during the 5-minutes peak time decreasing from circa 475 to circa 350 agents. According to these results, it may be necessary to implement definitively this model in the MATSim code. However, the special state of the corridor used for the simulation (Demand >> Supply, many full buses) may have accentuated an effect that occurs in a smaller scale in real PT system.

Secondly, the addition of crowding effects on the travel disutility has lead up to the desired results: peak spreading, earlier departures of PT users, diminution of the travel times at peak and increasing of the percentage of PT users. The last point even suggests that the implementation of a crowding effect may ameliorate the congestion state of the roads along the corridor, because the number of private user is reduced by the mode change of some of them to the PT mode. But these results must be taken carefully: in this project, the implementation of crowding effects in MATSim hadn't for goal to modify the trip distributions to obtain a better state (that's the role of the externalities, see below), but to recreate the passenger behavior which can be observed in a real network. Thus, the next step would be to simulate a real network and to compare data obtained from the two crowding models (e.g. trip duration) with the real data, in order to determine which model is closer to the reality.

Thirdly, the implementation of different kinds of externalities (Crowding, In Vehicle Time Delay and Capacity Constraint externalities) has produced the desired effects on the agent populations, increasing the benefits obtained by the implementation of the new dwell time model and the two crowding models (better distribution of the de-

parture, diminution of the travel time, etc.). In addition to that, the decrease of the number of agents using PT when the amount of implemented externalities increases has showed that the agents in MATSim reproduced also behaviors observable in the reality: PT users who have a bigger flexibility (e.g. other traveling modes available, more flexible working times) make some changes in their plans in order to avoid the periods where the fares are higher. Therefore, these changes reduce the number of people traveling at the most critical times, which benefit the agents who cannot modify their plans. The effects of First-Best pricing strategies are thus completely designable with MATSIM.

Fourthly, the almost linear relations found between the fares paid and the trip duration was reused to develop a Second-Best pricing strategy that can be implemented in Singapore. Indeed, the Smart Card system actually in use within the public transport system records the boarding and alighting times of each user. After simulation, a comparison with the First-Best pricing strategies gives some contrasted results: on the one hand, the trip distribution is better spread in comparison with “empty” pricing model (without crowding models and externalities); on the other hand, although some results such as the amount of fares paid or the mode repartition are similar, the Second-Best pricing model has created a trip distribution strongly different as the First-Best Pricing scheme (with crowding model and all externalities) with which it was compared.

If an optimization of the actual model could be appropriate, it must be discussed. In order to increase the accuracy of the Second-Best strategy, fares have been set not only depending on the trip duration, but also on the time of the day and, for the Capacity Constraint externalities, on the facility of alighting. A supplementary refinement of the model, with e.g. fares depending on smaller span of times, may increase its complexity and make it incomprehensible for the PT users. In addition to that, it may be difficult that a so good relation between fares and trip duration is found if the network contains more than one straight way (corridor). In a next step, the use of a more complex network may lead up to the design of other type of Second-Best pricing strategies, such as fares per time/facility of alighting.

In summary, if this project gives a good overview of the consequences of implementation of new dwell time models, crowding effects or externalities within MATSim and offers some ways to design a Second-Best pricing stategy, the use of scenarios closer to real cases is a need for the further steps.

10 Aknowledgement

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