Towards an Agent-Based Artificial Transportation System as a Test-Bed for Policy Making and Incentive Design

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Master Thesis in Modelling, Data Analysis and Information Support Systems

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September 2014

Short Bio

Nuno joined the School of Economics and Management, University of Porto in 2006 and he holds a Bachelor in Management, concluded in 2011. Currently he is in the last year of the Master in Modelling, Data Analysis and Information Support Systems at the same University.

He has been interested in studying urban planning for a while and this work reflects this interest. Meanwhile he joined Optimus for one year, in 2011, SONAE Telecommunication Company where he worked as a Sales Analyst in the mobile broadband department.

Acknowledgments

I would like to thank my family for all the support they gave me throughout this year. I would like to thank also Alice and her support, ideas and critics throughout this year.

I would like to thank Professor Pedro Campos and Professor Rosaldo Rossetti for all the support and understanding during all this year.

Finally, I would like to thank Zafeiris Kokkinogenis. I think without your support and friendship this dissertation would not be possible. I would also like to thank to all LIACC team for their receiving me in their lab for the duration of my research work..

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Abstract

The major problem with the increase in transportation volume is that it generates traffic congestion. The consequences are well known: delays, air pollution, and user un-satisfaction, which may lead to risk manoeuvres thus reducing safety for pedestrians as well as for other drivers. Therefore, public transportation policies and incentives must be generated in order to solve this problem.

In transportation analysis and policy-making, the way individuals make choices and their behaviour plays a paramount role, as they will affect the general efficiency with which people can travel. Introduction of modifications in the environment affects the commuter's perspective and these impacts on the performance of the network and on the society's welfare. The emergence of system's behaviour as result of decisions at individual level provides the traffic manager the opportunity to evaluate the modifications that have been done in the system.

The main contribution of this dissertation is the proposal and discussion of a social-oriented simulation framework for ATS, which accounts for the different social dimensions of the system in the evaluation and application of policies interventions. To illustrate the framework, we implemented an agent-based model of an artificial society of commuters on a bimodal transportation network and tested the possible effect of different policies on the network and commuter performance. We illustrate how a social agent-based model can be a useful tool to test the appropriateness and efficiency of transportation policies.

Keywords: Multimodal Transportation, Agent-Based Models, Intelligent Transportation Systems, Four Step Model, Transport Analysis, ODD protocol, Incentives, Policy Making, Cooperative Games

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Acronyms table

Acronym	Full Name
ATS	Artificial Transportation Systems
ITS	Intelligent Transportation Systems
FSM	Four Step Model
MAS	Multi Agent Systems
ABM	Agent Based Model
ODD	Overview, Design Concepts, Details
TSA	Transportation Systems Analysis
OD	Origin-Destination
MMNDP	Multimodal Transportation Design Network Problem
AON	All-or-Nothing Algorithm
UE	User Equilibrium
BPR	Bureu of Public Roads Function
CA	Cellular Automata
SO	Self-Organization
MD	Classic Mechanism Design
ABDG	Activity-Based Demand Generation
STST	Social-Transportation Simulation Tool
PT	Public Transport Mode
PR	Private Tranportation Mode
DA	Desired Arrival Time
DD	Desired Departure Time
ETT	Expected Travel Time
EC	Expected Crowding
OTT	Observed Travel Time
TAP	Traffic Assignment Problem
MG	Minority Games
ATT	Average Travel Time
FFtt	Free-Flow Travel Time
Ca	Link Capacity
PTT	Previous Travel Time
PF	Pollution Factor
BC	Bus Capacity
EBC	Expected Bus Capacity
EW	Expected Waiting PT Time
DW	Desired Waiting PT Time

Chapter 1 - Introduction

This chapter begins by presenting the context of the proposed work; introduces the vision, the theme and the kind of problems that will be discussed in the following chapters. In addition, it summarizes the document's structure.

1.1. Overview

Our view of cities is changing. Until the last century, cities were seen and planned with a key concern in architecture. The objective of urban planning was to improve economic functioning and the quality of live. As the 20th century move on, this view weakened and the attention started to turn for the economic city structure and the efficiency of localization (Henderson, 1986).

Efficient transportation systems are crucial to an industrialized society being its main communication infrastructure. One important characteristic to bear in mind is that the domain of mobility presents an inherent complexity. It involves diverse heterogeneous entities either in structure or in behaviour, e.g. vehicles, pedestrians, traffic system, among others, which can interact reflecting social behaviours that go from coordination and collaboration to competition (Batty, 2009).

To address the rising issues of these new trends a new generation of mobility systems emerged. The advent of what has been coined Intelligent Transportation Systems (ITSs). ITS are advanced applications which aim to provide innovative services relating to different modes of transport and traffic management and enable various users to be better informed and make safer, more coordinated and 'smarter' use of transport networks (Official Journal of the European Union, 2010). This process forces architectures to become adaptable and accessible by different means. Therefore, it can meet different requirements and a wide range of purposes (Passos, Rossetti, & Kokkinogenis, 2011).

The explosion of the computing technology in terms of applications experimented in the last couple of decades brought together expertise from different scientific and technical disciplines giving birth to new computing and communication paradigms. This explosion began with the concept of self-organization in the early years of cybernetics with its modern form related to several physics basic theories (Portugali, 1997). Self-organization is not a theory but rather an umbrella for several theories, which rely on the concept but differ on the approach. In the area of urbanism, some models were developed and explained in the past thirty years (Bretagnolle, 2003).

A new concept has been developed to deal with this revolution, the so-called future urban transportation (FUT) systems (The Volvo Research and Educational Foundations, 2011). This concept, instead of focusing only on the simple processes of transporting goods and persons they become self-conscious in terms of environment, accessibility, equality, and sustainability of resources. People are placed as a central aspect, as well as are their preferences, of the urban systems, forcing architectures to become rather adaptable and accessible to their needs. Therefore, new technologies and methodologies are necessary to support these new models.

1.2. Motivation

The major problem with the increase in transportation volume is that it generates traffic congestion (Goodwin, 1996). The consequences are well known: delays, air pollution, and user dissatisfaction, which may lead to risk manoeuvres thus reducing safety for pedestrians as well as for other drivers. To solve the traffic congestion problems there are two feasible strategies. On one side, a traditional control strategy and on the other side is to influence user behaviours.

A traditional control strategy can be seen as way to increase the supply (roads). However, this is not either economically or socially attainable or feasible. Thus, traffic engineering seeks to improve the existing infrastructure, without increasing the overall nominal capacity, by means of an optimal utilization of the available capacity (Bazzan & Klügl, Introduction to Intelligent Systems in Traffic and Transportation, 2014).

To measure a control strategy, the traditional approach is to use the FSM (Four Step Model) (McNally, 2000). The FSM tries to analyse the transportation network as a whole. The idea is that the FSM is a framework model developed that functions like an iteration model with four steps.

However, the FSM by its own does not account for information about user preferences and tend to deal with “management and control” policies. Therefore, it does not take into account the effect of selfish behaviour from self-interested agents that have reasons to improve their individual utilities rather than the collective social welfare. The strategic interactions of such self-interested agents lead systems to a Nash equilibria (Rosenthal, 1973), Wardrop equilibria (Wardrop, 1952) in the case of transportation network domain (Stier-Moses, 2011) that can be highly inefficient from a social point of view (Dubey, 1986).

An example of such situation is reported in the Braess paradox (Braess, 2005), where the addition of a new road leads the network in Nash equilibrium with an increase in the social cost.

To solve this problem, traditional methods, as a control strategy, are not sufficient by themselves, so complementary approaches need to be searched and implemented to surrogate traditional traffic control. One possible suggestion proposed in the literature is by influencing user behaviour.

A strategy to change user behaviour can be based on road pricing (Levinson, 2010). This tends to optimize the traffic network and reduce traffic congestion. However, this approach penalizes the user and creates social inequalities as it imposes a tax to be paid and only who is insensitive to the price will benefit (Metz, 2008).

An approach that has gain transportation community’s attention is based on the implementation and design of policies based on incentive schemes. Incentives are seen as those external measures that try to motivate a behaviour change toward the objective of the system. It appears to be a more “fair” vision, as it does not discriminate the user rather tries to bring the community into an equal level, see (Ettema, Knockaert, & Verhoef, 2010) and (Holleis, et al., 2012).

The main problem emerging in the traffic and transportation systems is that not always individual objectives of commuters align to system global objective. To study this kind of problems of coordinating actions, allocating resources, and making decisions in environments with multiple rational agents each seeking to maximize individual utility, Multi-Agent Systems community has used concepts such as self-organization, roles, and norms to favour a fluid functioning of the system. In this sense, there is a strong evidence of cross-fertilization between transportation engineering and multi-agent community (Portugali, 1994).

1.3. Aim and Proposed Solution

This dissertation addresses the policy making process in ITS. As said before the policy making process can favour the emergence of social-aware behaviour in agents that have selfish tendencies for a global optimal evolution of a society, particularly speaking Intelligent Transportation Systems.

To solve the problem statement, a simulation model of the FSM with the help of an agent artificial society using an Agent Based Model (ABM) is proposed. This approach can be seen as a way to combine the different transportation models used to analyse the transportation system. Although combined models integrating any or all of the four stages have been developed, they have rarely been applied in practice. Therefore, this model can be used as a tool for simulation and prediction interactions between infrastructure changes, public transportation investments, endogenous traffic effects in a daily basis, and a test-bed for policy making in urban transportation.

The expected results driving the goals of this research and model are the following:

1. More realistic behavioural models of commuters to analyse simulation of artificial societies in a transportation point-of-view,
2. Specification and implementation of an incentive-based design approach suitable for the domain of intelligent transportation systems. Study the possibility to turn the effect of incentive mechanism being persistent.
3. Study incentives as mechanism for social coordination in the transportation domain

We want to extend the approaches proposed by the Multi-Agent Systems (MAS) community existing in the literature and apply them to the ITS domain.

1.4. Methodological Approach

The methodological approach to solve the problem is divided in two phases.

The first phase is to develop a methodological framework for ABMs regarding the FSM and the artificial society. This framework must be underlined with the Overview, Design concepts and Details protocol (ODD protocol) (Grimm V. , et al., 2010). The ODD protocol is a generic format and a standard structure by which all ABMs could be documented. This framework is used as a test-bed for a simple simulation. Moreover, this first step can be seen as adapting the first three steps of the FSM.

In the second phase, we will introduce and present a more robust simulation based in the framework discussed in the first step. A robust and larger network demands a bigger setup in which several origins and several destinations must exist. Therefore, a proper traffic assignment model is necessary. In section 4.1. we will discuss which methodology should be used to perform. This last step is conducted in order to conclude the implementation of the FSM, the traffic assignment model.

In Figure 1 is presented the roadmap that leads this work.

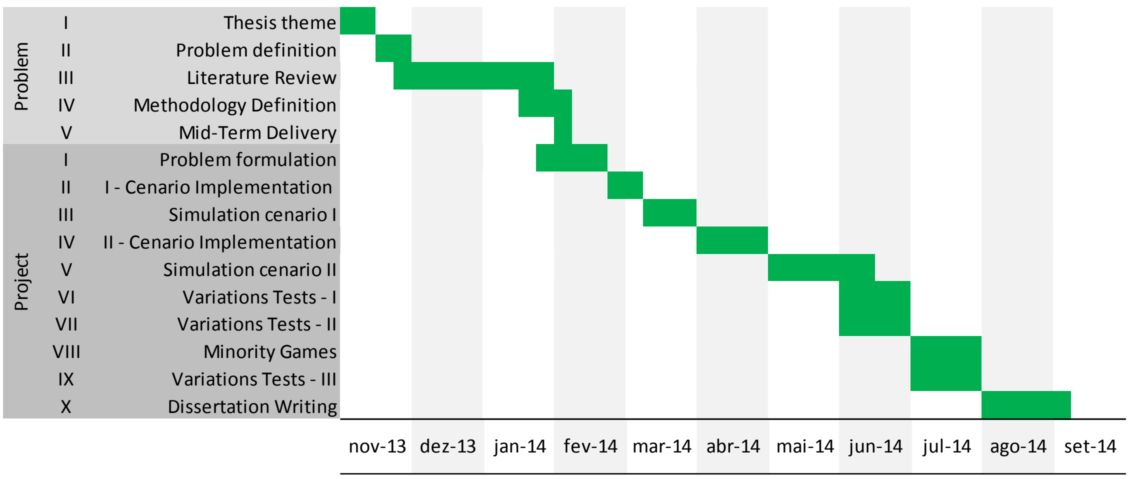


Figure 1 – Project Roadmap

As one can see in Figure 1 the project lasted almost one year. Almost 2 months we dedicated to literature review, were knowledge about topics in transportation, programming in ABM environment and policy making were collected. From the project steps III until V, we can find the outcome at chapter 3. From steps VII until IX the results are found at chapter 4. The implementation, programming and model fine-tuning were long lasting and time wasting as we can observe at figure 1 (from January 2014 until end July 2014).

1.5. Expected Implications

This work can contribute for the advance in transports by presenting a different approach to simplify the transport measures and analysis. This model is going to be developed with two main ideas: the first is that this model must be used as a decision support tool with real application data and must be developed for other cities with a simple input/output for data analysis; the second is that the present investments in the Futures Cities and Smart Cities projects is huge, and this work can be seen as a contribution in these areas.

1.6. Document Structure

This work is organized as follows. In chapter 1, an introduction is given with the motivation, problem statement, aim and goals, methodological approach, and contributions. In Chapter 2, a literature review with the background in ABMs, Transport Networks Analysis, and Policy Making. Moreover, a definition of the ODD protocol is referred. In Chapter 3, methodological framework for the ABITSM is given and a first implementation. In Chapter 4, the implementation of a traffic assignment model in the STST framework is given. Moreover, we will present the first results and discuss them. In Chapter 5, we draw some conclusion and refer future work on those topics.

Chapter 2 - Reviewing concepts and related work

2.1. Overview

In the following paragraphs, some topics related to the proposed research will be presented. Firstly, we will overview some concepts related to Transportation Topics. Then we will discuss the topics about MAS systems, Incentives in Transports and related works about MAS, Transportation Systems, Incentives, and Evolutionary Games in Transportation Optimisation.

2.2. Transportation Theory Topics

New performance measures brought about by an extensive future urban transport agenda and the implementation of the concept of smart cities pose additional requirements, which the user is, the central piece. In that sense, Fei-Yue Wang introduced the concept of Artificial Transportation Systems (ATS) in a series of papers (Wang, 2003), (Tang & Wang, 2004). ATS goes beyond traditional simulation methodologies and integrates the transportation system with other socio-economical urban systems with real-time information resulting in a powerful tool for transportation analysis, evaluation, decision-making and training. Rossetti et al. in (Rossetti, Oliveira, & Bazzan) discuss the specifications and design of an ATS framework. In (Ferreira, Esteves, Rossetti, & Oliveira, 2008) an agent-based simulation framework is discussed following the ATS concepts, where policy intervention are negotiated among various stakeholders in a cooperative manner. Rossetti et al. (Rossetti, Ferreira, Braga, & Oliveira, 2008), (Macedo, Soares, Timóteo, & Rossetti, 2012) discuss the implementation of an AI-based traffic control and management test-bed in ATS settings.

Due to the high complexity and uncertainty of contemporary transportation systems, traditional traffic simulation fails to capture in detail all the dynamics that characterize them. However, traditional tools of Transport Analysis are still valid as a part of study of the traffic problem. In the next section, we will present the FSM and Steffi's Traffic Network Representation.

2.2.1. Urban Transportation Network

The Four Step Model (FSM) is the primary tool for forecasting future demand and performance of a transportation system (McNally, 2000). Nonetheless, the FSM is a particular application of a framework, Transportation Systems Analysis (TSA), developed in 80s (McNally, 2000). A brief presentation of this TSA framework introduces the FSM context.

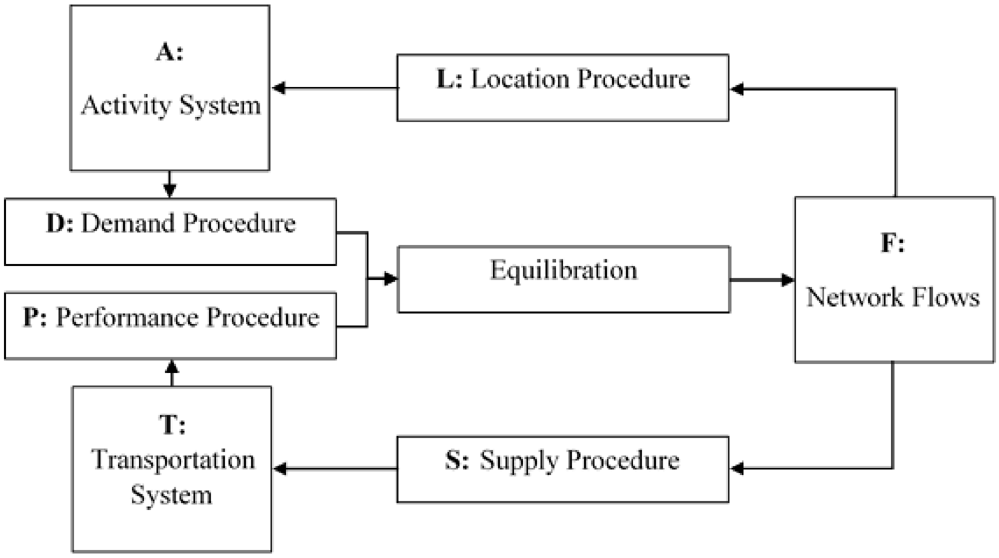


Figure 2 - The Manheim/Florian Transportation Systems Analysis Framework

The basic structure of TSA provides a comprehensive paradigm in which to examine the FSM, which is represented in Figure 2. The transportation system *T* is defined as the transportation infrastructure and services elements, and the activity system *A*, defined as everything else (e.g. economic activity that occurs in the location) serve as inputs to performance procedures *P* and demand procedures *D*, respectively. It is here, that the basic FSM arises. While some form of location procedure *L* is required, it has typically been executed independent of the FSM and similarly formal supply procedures *S* are non-existent.

A key point of this framework is the correct understanding of the units of analysis for these procedures, defined spatially and temporally. Demand procedure *D* manages person trips, defined as the travel required from an origin location to access a destination and those trips reflects units of time and space, e.g. daily person trips per household. Performance procedure *P* reflects mode-specific trips (person or vehicle) defined as a link volume, e.g., freeway vehicle trips per hour. The equilibration process must deal demand and performance procedures defined at two separate spatial levels. Demand procedures defined at zone level and performance procedures defined at the link level are interconnected by what connects Origin-Destination pairs.

2.2.2. Four Step Model

The FSM provides a mechanism to determine equilibrium flows, as seen in figure 2. The FSM was developed to deal with this complexity by formulating the process as a sequential four-step model. This section is based in the work of McNally (McNally, 2000) and Ortuzar (Ortuzar, 2001).

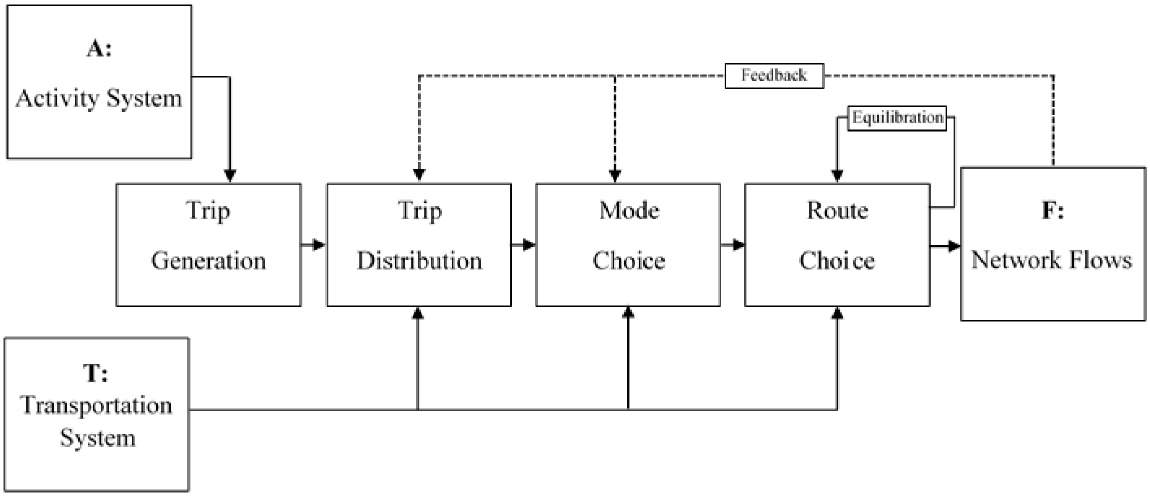


Figure 3 - The Four-Step Model

In Figure 3 a representation of the Four Step Model is given. First, in trip generation, a trip frequency is developed that provides the will to travel. Trips are presented as trip ends, productions and attractions, which are estimated differently. Next, in trip distribution, trip productions are distributed to match the trip attraction distribution and to reflect travel impedance, time and cost are the usually the most studied, building trip tables of person-trip demands. Next, in mode choice, trip tables are divided to reflect the proportions of trips by alternative modes. Finally, in route choice, modal trip tables are assigned to mode-specific networks (McNally, 2000).

The FSM has several requests regarding data demand in addition to those that define the activity and transportation systems. The first use of the data is model calibration. Household travel surveys with travel-activity data provide it. This survey data is utilized to validate the representativeness of the sample, to develop and estimate trip generation, trip distribution, and mode choice models, and to conduct time-in-motion studies (McNally, 2000).

a. Trip Generation

The first stage of the FSM is defined by one objective and it is the total daily travel in the model system, at the household, for various trip purposes. The first stage also deals with the transformation of activity-based to trip-based, and simultaneously divides each trip into a production and an attraction, to prevent network performance measures from influencing the frequency of travel. Thus, this defines total travel in the region and the following steps are just modelling the share models.

The model that defines this separation is estimated for productions $f_P^p(A)$ and attractions $f_A^p(A)$ for each trip type (purpose) p:

$$P_i^P(A) = f_P^p(\boldsymbol{A}\ activity\ system\ characteristics) \tag{1}$$

$$A_j^P(A) = f_A^p(\boldsymbol{A}\ activity\ system\ characteristics) \tag{2}$$

Where: P_i^P are the total number of trip production generated for trip type p for analysis unit *i* and A_j^P are the total trip attractions for trip type *p* for analysis unit *j*.

Essentially, those models provide a measure of attractiveness for various trips because of socio-economic and demographic variables. However, the estimation of these models is problematic. First, because regional travel surveys are made at the household level and not for non- residential land uses and second because the explanatory power of attraction variables is usually not as good (Ortuzar, 2001).

b. Trip Distribution

The objective of the second stage of the process is to recombine trip ends from trip generation into trips, typically defined as production-attraction pairs (*P*-*A* pairs). The trip distribution model is essentially a destination choice model and generates a trip matrix, represented at typical represented as Table 1. The notation T_{ij} is used for each trip purpose utilized in the trip generation model as a function of activity system attributes, through the generated productions P_i and attractionsA_j, and network attributes. The general form of the trip distribution model as the second step of the FSM is:

$$T_{ij} = f_{TD}(P_i, A_j, t_{ij}) \tag{1}$$

Where t_{ij} represents or the travel time or generalized cost between the two zones. For internal trips, perhaps the most common model is the gravity model:

$$T_{ij} = a_i, b_j P_i, A_j, f(t_{ij}) \quad (2)$$

Where:

$$a_i = \left[\sum_j b_j P_i, A_j, f(t_{ij})\right]^{-1} \quad (3)$$

$$b_i = \left[\sum_j a_j P_i, f(t_{ij})\right]^{-1} \quad (4)$$

The parameter $f(t_{ij})$ represents the function of the network level of service.

The production-constrained gravity model sets all b_j equal to one and defines W_j in place of A_j as a measure of relative attractiveness. The term $f(t_{ij})$ essentially provides a structure for the model with the balancing terms scaling the resulting matrix to reflect the input productions and attractions. The estimation of gravity models involves the estimation of this function.

Table 1 - Notation of an origin-destination trip matrix (McNally, 2000)

Zones	1	2	...	j	...	n	Productions
1	T_{11}	T_{12}	...	T_{1j}	...	T_{1n}	P_1
2	T_{21}	T_{22}	...	T_{2j}	...	T_{2n}	P_2
...	...	...	...	...	...	...	...
i	T_{i1}	T_{i2}	...	T_{ij}	...	T_{in}	P_i
...	...	...	...	...	...	...	...
n	T_{n1}	T_{n2}	...	T_{nj}	...	T_{nn}	P_n
Attractions	A_1	A_2	...	A_j	...	A_n	T

The calibration process is driven by the trip length frequency distribution. The relative distribution of trip interchanges is not directly considered. On one hand, it is difficult to relate any policy to these factors, thus, it is difficult to assess their validity in the future. On the other hand, the resultant base trip matrix will more closely reflect observed behaviour.

The trip matrices are at this stage defined as *P-A* flows. Depending on the treatment of mode choice, these matrices may be converted from *P-A* format to *O-D* (Origin-

Destination) format, which is required in the route choice step. *P-A* to *O-D* conversion typically reflects the observed travel data. In (Cascetta & Nguyen, 1988), (Zhou & Mahmassani, 2006), (Filgueiras, et al., 2014), (Freitas, Coelho, & Rossetti, 2009) are discussed methodological and technological approaches to be used for the estimation of origin-destination trip matrices.

c. Mode Choice

Mode choice factors the trip tables from trip distribution to produce mode-specific trip tables. These methods are exclusively disaggregated models often estimated on separate choice-based samples and reflect the choice probabilities of individual trip makers. Due to space limitation, the mode choice model utilizes a simplified person trip tables to allow the development of vehicle trip tables. Thus, vehicle trips are used to produce the trip table while ignoring trips by other modes.

Multimodal transportation design network problem (MMNDP) problem appeared because many types of vehicle modes must be combined in a network (e.g. Cars, bus, bicycles). The problem focuses on the distribution of transportation network and the coordination of different modes of multimodal network. Travellers need improved information of alternative transport modes and with this they can solve problems affecting their journeys.

The multi-modality in urban transportation networks is captured in several forms in the literature, as follows.

(i) No interactions between flows of different modes: In this case, the networks of different modes are not related to each other, and thus the flows of one mode do not have any effect on the flows of the other modes (Mesbah, Sarvi, & Currie, 2008);

(ii) Interactions between flows of different modes: When buses share the same roads with automobiles, the flows of buses and automobiles affect each other (Gallo, 2011);

(iii) Interrelations in flows and in decisions: Most multi-modal problems only consider flow interactions, while in problems with mode related topographic decisions, the effects of decisions of one mode on the other are addressed (Szeto, 2010).

MMNDPs usually consider multi-level networks (Farahani, 2013). In the high-level problem, the road network and different public transit networks are sub-networks of the urban transportation networks. In the lower, level the number of modes involved in travelling between two points. There are two cases in this dimension: first, travellers can only choose one mode; and second, travellers can choose a combination of modes to finish their trips and the number of modes involved is two or more. This mode is the so-called multimodal trips.

Demand for each mode between each O-D is often a problem. When the demand for travel is dependent on various factors such as travel time of the mode considered or other system performance attributes, it is called elastic demand. Elastic demand can be found in two forms; or travellers decide to give up their travel when the travel costs are too high or the travellers only change their mode of travel (Farahani, 2013).

At the high level simulation, there are only a few studies using heuristics to estimate the optimal solutions. The most important one is the work of Mesbach (Mesbah, Sarvi, & Currie, 2008). They use exact enumeration for the exclusive lane allocation problem. However, it is not a true multi-modal network because it only handles lane allocation and so it do not take into account interactions between flows of different modes. Another work in this area of abstraction includes the work of Miandoabchi et al. (Miandoabchi, Farahani, Dullaert, & Szeto, 2012), which uses heuristics to find new solutions for a multi modal network.

Techniques to lower-level problems have been applied to solve the modal-split and trip assignment problem using various approaches. Here there are several differences. Some worked the lower-level problem as one problem, so they aggregate modal-split and trip assignment in one and used simulation packages like NETSIM (Seo, 2005) and VISSIM (Elshafei, 2006). Other authors went for dividing the analysis in steps. Some went used fixed travel times for the transit network to find the equilibrium traffic assignment (Cantarella, 2006), others used iterative steps until convergence met (Mesbah, Sarvi, & Currie, 2008), and finally a two-iterations solution was proposed (Eltran, 2009). The last proposal methods used a combined view of mode split and traffic assignment problem, and to resolve it a heuristic algorithm (Li, 2009) was proposed and a diagonalization algorithm (Miandoabchi E. F., 2012b) were presented.

d. Route Choice

A distribution of cars in proportion to the capacities of the roads can be regarded as equilibrium, which is fair on all participating drivers. This is a simple equilibration of demand and performance where the driver/agent choses the road to follow.

Previous approaches involves Frank-Wolfe algorithm obtains the basic user-equilibrium solution (Ortuzar, 2001). This algorithm works in computing the minimum path and all-or-nothing (AON) assignments to these paths. AON assignments are weighted to determine link volumes and then link travel times for the next iteration. The estimated trip tables are fixed, that is, they do not vary due to congestion. Hence, these approaches are not entirely realistic. Chen and Ben-Akiva attempted to reach the system-optimal distribution as well as the minimum total travel time for all drivers by applying their game theoretic formulation (Chen & Ben-Akiva, 1998).

Several works using an equilibrium based on market-based methods have been presented. Vasirani and Ossowski introduce the concept reservation-based approach in a series of papers (Vasirani & Ossowski, 2009) and (Vasirani & Ossowski, 2011). Their aim is to introduce the equilibrium in an intersection. The market-based system works when the agents trade in a virtual marketplace, buying reservations to cross intersections and the infrastructure owners selling them. The market goes to equilibrium when the global profit and the social welfare intersect. This creates a situation where an increase in the infrastructures monetary benefits implies a decrease of the drivers average travel times.

Schepperle and Böhm presented also a system for an optimal single intersection in (Schepperle, 2007) and (Schepperle, 2009). It is presented a four-step model. In the first step, the vehicle contacts the intersection; vehicle acquires an initial time slot to cross the intersection; if not satisfied, a vehicle can try to acquire a better time slot, this time from another vehicle; vehicles cross the intersection. In the second step, an auction is run among the vehicles that do not yet possess a time slot. The third step, vehicles arriving late can acquire time slots that have already been auctioned off. In the last step, the final one, the vehicle crosses the intersection.

Another work based on intersections but in this case based on the traffic signals (Balan, 2006). Here the work base is to allow communication between traffic signals and vehicles. Through this communication, a historical data series is kept and thus a scheme of credits is developed. Each time the vehicle stops in a traffic signals receives points. Each time the vehicle stops, it gives points away. This creates equilibrium throughout the metropolitan area.

However, those works rely on providing real-time information to the drivers. These systems have some drawbacks. If the drivers do not have perfect information, their travel time may increase compared to those having perfect information (Arnott, Palma, & Lindsay, 1991). The quality of the information provided to the drivers affects the choice of the drivers (Kitamura & Nakayama, 2007). Rossetti et al. (Rossetti & Liu, 2005) present an agent-based approach using deliberative agent architecture to assess the effect of information systems with pre-trip information on the route choice.

This topic will be discussed in an implementation view in chapter 4.

2.2.3. Mathematical Implementation for Network Representation

This section is based on the work of Sheffi (Sheffi, 1985). Sheffi describes in detail how to implement a mathematical urban transport network in (Sheffi, 1985).

a. Network Representation

The mathematical definition of a network is a set of nodes, vertices or points and a set of links connecting those nodes (Sheffi, 1985).

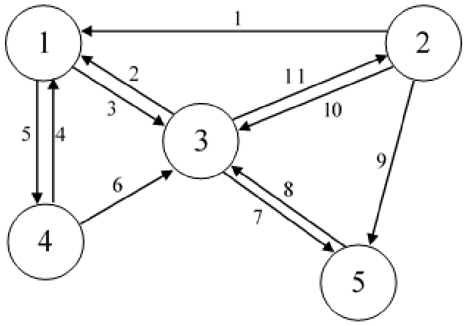


Figure 4 - Network with five nodes connected by 11 links

Figure 4 shows a network including five nodes connected by 11 links. Each link in this network is associated with a direction of flow. For example, link 11 represents flow from node 3 to node 2, while link 10 represents the reverse flow, 2 to 3.

The transportation planning process for urban areas uses a partition of an area into traffic zones. A node represents each traffic zone. After, the desired movements over an urban network expresses in terms of an Origin-Destination matrix.

Travel time on urban context is an increasing function of flow. Each network link is typically associated with some impedance. The delay of a travelling vehicle is null when the impedance is also null. As the flow increases, the travel time increases since the number of cars along the link increases (Sheffi, 1985).

A stable condition reached only when no traveller can improve his travel time by unilaterally changing routes. This is the characterization of the user-equilibrium (UE) condition (Beckmann, 1956).

The approach for solving large problems uses the equivalent minimization method. The solutions bases on the behavioural assumption that each motorist travels on the path that minimizes the travel time t from origin to destination.

b. Network Functions

Each O-D pair $r - s$ is connected by a set of paths (routes) through the network $\mathcal{K}_{rs}$ where $r \in \mathcal{R}$ and $s \in \mathcal{P}$, so the O-D matrix is denoted by q with q_{rs}.

Let x, and t, represent the flow and travel time, respectively, on link a (where $a \in \mathcal{A}$). Therefore, the link performance function is $t_a(x_a)$. Let f_k^{rs} and c_k^{rs} represent the flow and travel time, respectively, on path k connecting origin r and destination s ($k \in \mathcal{K}_{rs}$).

$$c_k^{rs} = \sum_a t_a . \delta_{a,k}^{rs} \qquad \forall\, k \in \mathcal{K}_{rs}, \quad \forall\, r \in \mathcal{R}, \quad \forall\, s \in \mathcal{A} \tag{5}$$

Where $\delta_{a,k}^{rs} = 1$ if link a is part of path k, connecting the O-D pair r-s, and $\delta_{a,k}^{rs} = 0$ otherwise. Link flow expresses as follows.

$$x_a = \sum_r \sum_s \sum_k f_k^{rs} . \delta_{a,k}^{rs} \qquad \forall\, a \in \mathcal{A} \tag{6}$$

Equations 8 and 9 define the path-arc incidence relationships.

The equilibrium assignment problem is to find the link flows x_a, that satisfy the user-equilibrium criterion when all the Origin-Destination entries q_{rs}, have been appropriately assigned. Solving the following mathematical program obtains link-flow pattern:

$$\min z(x) = \sum_a \int_0^{x_a} t_a(\omega) d\omega \tag{7}$$

Subject to

$$\sum_k f_k^{rs} = q_{rs} \qquad \forall\, r, s \tag{8}$$

$$f_k^{rs} \geq 0 \qquad \forall k, r, s \tag{9}$$

The definitional constraints are also part of the program.

$$x_a = \sum_r \sum_s \sum_k \; f_k^{rs} . \delta_{a,k}^{rs} \qquad \forall \; a \; \in \; \mathcal{A} \tag{10}$$

Equation 10 represents a set of flow conservation constraints that the flow on all paths connecting each O-D pair has to equal the O-D trip rate and equation 11 is required to ensure that the solution of the program will be physically meaningful with no negativity path flow.

The link relationship with the capacity and the volume expresses in a function called the BPR function (Bureau of Public Roads, 1964). This function works as follows

$$\mathrm{S}_a(\mathrm{v}_a) = \; t_a^0 \left[1 + \alpha (\tfrac{x_a}{c'_a})^\beta \right] \tag{11}$$

At equation 14, $\mathrm{S}_a(\mathrm{v}_a)$ is the average travel time for a vehicicle on link a, t_a^0 is the free-flow time, and c'_a is the practical capacity of the link a. This practical capacity means that the links never reach their maximum capacity, but rather they have a maximum possible flow through.

2.3. Urban Models and Agent Based Models

The increasing interest in the agent paradigm results from the possibility of decomposing a complex system into multiple individual agents. The traffic domain is composed of various complex systems, where agent-based solutions can be used since the elements of each system can be naturally identified using the agent metaphor, e.g., air traffic control, transportation planning and scheduling or road traffic control.

In this context, Parunak suggests an ideal setting for application of MAS having the following characteristics: modular, decentralized, dynamic, not completely structured and complex (Parunak, 1999). In particular, one may identify a number of main motivations for using agents and multi-agent system technologies in traffic and transportation:

1. Natural and intuitive problem solving by active entities with a (potential) local perspective.
2. Autonomous agents provide an appropriate basis for modelling heterogeneous systems. Every entity may possess its individual architecture, state representation, and behaviour.

3. Agents and their interaction can be described using high-level abstractions. Thus, they provide an intuitive level of interaction between human users or modellers and the agent-based system.
4. Agents or multi-agent systems technologies allow coping with variable structure of the system in an efficient way.
5. The agent metaphor used for modelling a traffic participant or decision-maker enables us to capture complex constraints connecting all problem-solving phases.

An extensive review on agent-based technology in transportation domain can be found in (Cheng, 2010) and (Bazzan & Klügl, 2014), where the reviewed works are grouped into two categories: modelling and simulation, and control and management.

2.3.1. Concepts in Models and Urban Theory

Models are simplifications of reality, theoretical abstractions that represent systems in a way that essential features crucial to the theory and its application are identified and highlighted. Therefore, urban models are essentially computer simulations of cities functions, which translate theory into a form that is testable and applicable without experimentation on a real world (Batty, 2009).

What connects the theory and models as a vehicle to test hypotheses has weakness with the traditional models because they have loosened their link to theory (Portugali, 1997). This trend appears because, theories of the city system in the 1970s and 1980s did not reflect the diversity and heterogeneity that was very evident in modern cities, nor did they reflect the comparative volatility of urban dynamics. Thus, the aggregate static approach to theory and modelling began to switch around to more bottom-up decentralized dynamics, somehow how ABMs now works. Urban models are more likely to be frameworks for structure information where they are essential tools of decision support tools. In Rossetti et al. (Rossetti R. J., Liu, Cybis, & Bampi, 2002) and (Rossetti & Liu, 2005a) is presented a framework that considers demand models following the multi-agent system metaphor for generating simulation scenarios for *"what-if"* analysis.

2.3.2. Concepts of Self-Organization and Cities as Self-organization Entities

Cities models will be discussed in following paragraph because they ultimately lead to the use of ABM in self-organization, urban planning and transport theory.

The explosion of the computing technology in terms of applications experimented in the last couple of decades brought together expertise from different scientific and technical disciplines giving birth to new computing and communication paradigms. A new type of systems coined as socio-technical arose from such mutual conjunctions where people and technology live in mutual symbiosis

The first models were mainly conceived as systems of nonlinear differential equations describing the evolution of state variables at a macro-level, the lower level interactions summarized in relations or in parameters (Bretagnolle, 2003). The most relevant and important work on the domain of cities and urbanism are models, such as, *Dissipative cities* (Prigogine, 1980), *Synergetic theory* (Haken H. , 1984) and (Haken H. , 1995), *Chaotic Cities* (Portugali, 1994), and *Fractal geometry* (Mandelbrot, 1983).

CA (Cellular automata) (Batty, 1997) models can be described as models where contiguous or adjacent cells change their states, their attributes or characteristics. An iterative process generates the dynamics of the model. During iteration, the state of each cell is determined by some transformation rule. The origin of CA models goes back to Alan Turing and his ideas concerning self-reproducing machines and then to John Conway's *game of life*, which is an explicit CA, game (Gardner, 1971). In this context, cities modulation, which are built under the CA approach, city-blocks can be seen as cells, and the local spatial units, like land value or inhabitants, are determined in relation to their immediate neighbours. This is one of the main proprieties of the cells in CA models (White & Engelen, 1993). Furthermore, the fact that CA models deal with self-organization just increase the realism and sophistication to the simulation (Batty, 1997).

Self-organization here is essentially a new way of seeing cities and their planning. One can realized that cities are essentially unstable, chaotic, far-from-equilibrium, and unpredictable, so therefore we have to find ways to live with their complexity (Portugali, 1997). From this perspective follows a new type of city planning where the aim is not to control, but rather to participate and to learn with it.

2.3.3. Agent-Based Models

Agent-Based Models (ABM) are the evolution of CA models. One reason for the popularity of agents and Multi-Agent Systems (MAS) are the advances in computers, which are more distributed, open, large, and heterogeneous (Bazzan & Klügl, 2014).

Managing interactions among autonomous entities with increasing interdependencies has been one of the biggest motivations for distributed artificial intelligence and for MAS. These aim to develop and analyse models derived from social interactions in human societies.

Agent-Based Simulation uses the metaphor of autonomous agents and Multi-Agent Systems as the basic model conceptualization. This means that a model consists of interacting agents situated in a simulated environment thus; agents may correspond to cities, blocks, platoons, households, individual travellers (drivers), pedestrian, vehicles, sensors, traffic signals, etc. In addition, elements of the environment may be conceived as agents (Rossetti & Liu, 2005b), (Soares, Kokkinogenis, Macedo, & Rossetti, 2014), (Passos, Kokkinogenis, Rossetti, & Gabriel, 2013).

However, there is not a general definition on an *agent*. So it is important to describe some typical proprieties an agent can have (Wooldridge & Jennings, 1995) and (Jennings, 2000):

1. Location: Every agent has a place in an environment; there is an ongoing interaction between the agent and its surroundings.
2. Autonomy: There is no global control that dictates what actions the agent must take; it dos whatever it is programmed to do based on its current internal state.
3. Social ability: agents are able interact with other agents.
4. Reactivity: agents sense their environment and they are able to react appropriately to stimuli coming from it.
5. Pro-activeness: agents do not simply act in response to their environment; they are able to have goal(s) that they pursue on their own initiative.

Additional characteristics that agents might have:

1. Rationality: The notion of agent rationality means that an agent is working towards its personal goals. Moreover, an agent always selects the action with maximum expected outcome with respect to its goals.
2. Flexibility: this for an agent means to mediate between reactive behaviour, being able to react to changes in its environment, and deliberativeness to pursue its goals.

3. An agent may be adaptive, by having rules or more abstract mechanisms that modify its behaviours. An agent may have the ability to learn and adapt its behaviours based on its accumulated experiences. Learning requires some form of memory.

As said before, model consists of interacting agents situated in a simulated environment. In that sense, Axelrod is credited with founding ABM with his evolutionary simulations of cooperative behaviour (Axelrod R. , 1985) and he is still one of the area's main advocates. In a recent text about ABM (Axelrod & Tesfatsion, 2006) Axelrod rises four research questions/goals for the ABM.

1. Empirical; "Why have large-scale regularities evolved and persisted, even when there is little top-down control?"
2. Normative understanding: "How can agent-based models be used as laboratories for the discovery of good designs?"
3. Heuristic: "How can greater insight be attained about the fundamental causal mechanisms in social systems?"
4. Methodological advancement: "How can one best provide ABM researchers with the methods and tools they need to undertake the rigorous study of social systems and to examine the compatibility of experimentally generated theories with real-world data?"

Section 2.3.1, shown that, modelling is a process of simplification. This reflects the difficulties in abstraction where there is always a doubt between how much to leave in and how much to leave out of any theory and its model. Therefore, one should study the levels of abstraction a model should have.

a) Environment

The first issue involves simplifying the spatial system in a dynamic sequence of change, the issue of time. Cities can be seen as largely unchanging in terms of their land uses and transport structures with marginal change far less important to that, which exists in totality. Statics versus dynamics is a central and an often issue (Lowry, 1965).

This issue of time also relates to aggregation and scale. Generally speaking, the finer the spatial scale and shorter the period, the greater the dynamic in that the activities are aggregated from their elemental form. The degree to which the model should reflect heterogeneous activity depends on what is being modelled at what scale with this trade-off part of the process of simplification (Batty, 2009).

Representation of the key elements of an urban structure, either they are individuals comprising various populations or aggregates need proper definitions and classification (Batty, 2009). When urban models were first developed in the 1960s, almost all were highly aggregated, as it was shown at section 2.3.2, in terms of their representation whereas now a new class of individual or agent-based models have appeared which seek to represent the urban system in much more open terms. All these issues involve trade-offs involving scale, which in turn are determined by more pragmatic concerns such as available resources of data and computation.

Given the increasing complexity of transportation and traffic systems, which arises from the modern way of life and new means and organization of transportation, not only new techniques must be deployed, but also the individual choices must be better understood if the whole system is to become more efficient (Rossetti, et al., 2002), (Rossetti, Almeida, Kokkinogenis, & Gonçalves, 2013)

Traffic simulation represents a prominent application for modelling and simulation. It supports complex urban and transport planning, as well as management tasks on different levels of analysis in space and time (Rossetti & Bampi, 1999).

b) The model building process

Modelling and simulation are useful approaches to exploring urban modelling, but their utility depends on adequate calibration, verification, and validation. A model must be validated before it can be used for making prediction.

Calibration provides values for unknown parameters. In fact, most models are first calibrated to simply ensure that they meet certain dimensional constraints in the problem domain (Batty, 2009). Sometimes these are also chosen to optimize some goodness of fit criterion such as how close predictions are to observed data and in this sense, calibration merges into validation. Even if calibration is considered a separate process, validation takes place immediately after, the difference being that parameter values are often chosen using criteria different from those used to validate the model.

Verification and validation means the correctness of model construction and the truthfulness of a model with respect to its problem domain, respectively. Parker et al, in an extensive review in multi-agent systems for simulation states that "*verification means building the system right, and validation means building the right system*" (Parker, et al., 2003).

In one hand, verification reduces the problematic nature of flexibility by closing the model structure and the rules employed. This means that, the models are balance between theory and data and for that the Multi Agent Simulation have the ability to map the concepts and structures of real world onto the model in a way that preserves natural objects and connections (Batty, 2001) and (Kerridge, Hine, & Wigan, 2001).

The main part to verification is a sensitivity analysis of relationships between model parameters and the state or time path of endogenous variables to the urban model. Some techniques, that appear from closed analytical modelling, include the comparative static (Silberberg, 1990), comparative dynamic (Kaimowitz, 1998), use of error propagation and uncertainty (Robinson, 1994), errors of mathematical operations (Alonso, 1968), error classification (Riley, 1997) and, treatment of error and uncertainty in geographic information systems (Heuvelink, 2002).

Moreover, verification essentially involves attempts to break the model by varying model configurations. This is known as debugging, a careful assessment of model objects and linkages and a growing tradition of publishing software code along with manuscripts, however, exist now within the agent-based modelling community (Parker, et al., 2003). Therefore, as more models adopt common standards, verification will become easier, as is shown in the next section.

There are very few models that exist that can be tested on all their dimensions and the new class of agent-based models which are much richer in terms of the hypotheses they frame and the data required to calibrate and validate them. This suggests that the models are being developed more for their value to develop a robust process for knowledge and decision process facilitator rather than their ability to generate good theory (Batty, 2009).

2.3.4. The ODD Protocol

In the previous section, we focused in a ABMs model calibration, verification and validation, the building process. In the verification part, ABMs models are criticized because they are so poorly documented that the models could not be evaluated (Lorek & Sonnenschein, 1999). These criticisms motivated the *Overview, Design Concepts, Details* (ODD) protocol (Grimm V. , et al., 2006), which attempted to create a generic format and a standard structure by which all ABMs could be documented. The primary purpose of ODD is to make writing and reading model descriptions easier and more efficient.

In Table 2, the seven elements of the original and updated ODD protocol (Grimm V. , et al., 2010) are presented. The rest of this section is an overview of the seven elements of the ODD protocol. The aim here is to show why this protocol enables ABMs by defining and establish a protocol for the documentation of a purposed model. In the appendix A an ODD discussion is given.

Table 2 - The Seven Elements of the original and updated odd protocol

	Elements of the original ODD protocol	Elements of the updated ODD protocol
Overview	1. Purpose 2. State variables and scales 3. Process overview and scheduling	1. Purpose 2. Entities, state variables and scales 3. Process overview and scheduling
Design Concepts	4. Design Concepts a. Emergence b. Adaptation c. Fitness d. Prediction e. Sensing f. Interaction g. Stochasticity h. Collectives i. Observation	4. Design concepts a. Basic principles b. Emergence c. Adaptation d. Objectives e. Learning f. Prediction g. Sensing h. Interaction i. Stochasticity j. Collectives k. Observation
Details	5. Initialization 6. Input 7. Submodels	5. Initialization 6. Input data 7. Submodels

a. Overview

The first phase, *Purpose*, defines that every model has to start from a clear question, problem, or hypothesis. Therefore, ODD starts with a concise summary of the overall single or multiple objectives for which the model was developed.

The next one is the Entities, State Variables, and Scales. An entity is a distinct or separate object or actor that behaves as a unit, and thus is defined as a set of attributes that can contain numerical or references to behavioural strategies (Huse, Giske, & Salvanes, 2002). Most ABMs include entities such as agents, spatial units' environment and collectives. A *state variable* or *attribute* is a variable that distinguishes an entity from other entities of the same type or category, or traces how the entity changes over time. *Scales* can be described as spatial or temporal with mean the amount of space and time represented in the simulation.

The last process of the overview part is called *Process overview* and *Scheduling* and defines the names of the model's processes. Those names are then the titles of the sub-models that are described in the last ODD element, sub-models. ABMs platforms like NetLogo include the concept of the 'Observer', which acts as a controlled object that performs such processes (Wilensky, 1999). The relevance of the order of those processes is highlighted in the way that different process order can have a very large effect on model outputs (Bigbee, Cioffi-Revilla, & Luke, 2006) and (Caron-Lormier, Humphry, Bohan, Hawes, & Thorbek, 2008). Most ABMs represent time simply by using time steps but time can be represented in different aspects).

b. Design Concepts

The Design Concepts tend to be seen as what defines an ABM. They may also be crucial to interpreting the output of a model, and they are not well understood via the traditional model description techniques such as equations and flow charts. Therefore, they are included in ODD to make sure that important model design decisions are made and that readers are aware of these decisions (Railsback, 2001).

The Basic Principles are defined as the general concepts, theories, hypotheses, or modelling approaches that are under the model. The Emergence is what is expected to vary in complex of individuals or their environment change. The Adaptation rules what kind of decisions the agents must have in response to changes in their environment. Objectives are defined as success criteria previous to the model itself. Learning many agents change their trait over time as consequence of their experience, so the way but is explicit. The Prediction is how the agents can predict the future experience is they learn new things in the present. Sensing is what the state variables can feel and with the new information how they can communicate it to other agents. Interaction is what the agents encounter and affect other agents, and how they can deal with those encounters. Randomness, as the name implies, is that processes are calculated in a random way. If the individuals' agents can form aggregations or form Collectives they must be well explained and represented. For last, the Observation is how the data was collected to perform the model.

c. Details

The first part is the initialization. The initial state of the model must be defined and be well understood and the initial parameters as well. As we saw before model results cannot be well replicated unless the initial conditions are known and replicable.

The second part is the input data, which is different from initial data, or initial states. The source of the data must be highlighted as well if the data is dynamics, because in that case the dynamics part is or a time series or an environmental variable and so they are is treated in a different way as an external forcing. According to the ODD protocol even if this kind of that is not used one should refer the statement: "the model does not use input data to represent time-varying processes".

The last part of the ODD description is the Sub-models. Here all the sub-models used in the simulation must be described in detail. Because agent-based modelling is new and lacks a firm foundation of theory and established methods, the ODD protocol reinforces that descriptions must "include appropriate levels of explanation and justification for the design decisions they illustrate, though this should not interfere with the primary aim of giving a concise and readable account of the model."

2.4. Policies and Incentives in Transportation Systems

Policy generally speaking, is defined as course-of-actions, plans or strategies by which governments; organizations translate their vision into programmes and activities. Policy is conceived as a set of principles that orient decisions and actions of the agents that operate in a given context, especially in what concerns the uses of resources available in that context (Easton, 1965).

2.4.1. Policy-Making Process and Incentives

Hill (Hill, 2009) explains public policy as concerning the uses of resources that are considered public in that society. As policy making process is intended the way to conceive the structure and form of operation of public policies, and explains how public policies are created and put to operation.

A typical way to describe the sequential cycle of steps involved in a public policy goes as follows (Hill, 2009):

1. Identification and formulation of the issue to be solve through the issue and implementation of a public policy;
2. Formulation and comparative analysis of various possible alternative policies able to solve the problem;
3. Choice of one of the those policies for implementation;
4. Implementation of the chosen public policy;
5. Evaluation of the effects of the implementation of the public policy, and possible adjustment of the policy, to improve results and reduce negative effects (thus returning the process to step 1).

Van Engers et al. characterize policy-making into a policy field theory and a policy effects theory; one theory dedicated to a problem and the other to a solution space (van Engers, van Haaftena, & Snellenb, 2011). A policy field theory will answers on questions like, which actors and factors do create problems and possibilities in a certain policy field, which require the attention of the policy makers.

As such, a policy field theory has a causal component and a normative component. On the other side, policy effects theory describes the effects of possible actions that are assumed to provide a solution to the problem at hand. The connection between those actions and the problem is through factors that have a causal relationship to the problem. The policy-making process is aimed at finding and deliberating possible alternative solutions/ actions.

Van Wee distinguishes six general criteria for policy intervention to be taken onto account during the decision-making process (Wee, 2009):

1. Effectiveness: does the policy do what it supposed to do?
2. Efficiency: are assessed the cost-effectiveness and the cost-to-benefit ratio indicators
3. Equity: are there winners and losers because of the policy introduction?
4. Ease of implementation.
5. Flexibility in adapting the policy

6. Long-term robustness: policy is ‘no-regret’ under uncertain long-term developments that could have a major impact on society.

2.4.2. Theory of Incentives

Policy-makers have two broad types of instruments, borrowed from economics, available to achieve a desired outcome. They can use traditional regulatory approaches (sometimes referred to as command-and-control approaches) or they can use incentive-based (or market-based) policies that try to create a motivation to behaviour changes in individuals.

In a society, individuals have information about their resources, desires and preferences. Therefore, they choose actions for producing, redistributing, and consuming those resources. In markets and other institutions, individuals’ actions may depend on others’ information as it has been communicated in the market or institution. The institutions are to be used as mechanisms for communicating people’s information and coordinating people’s actions. A good social institution is decided upon how it performs in this communication and coordination role. If we do not like the performance of our current institutions, then we may want to reform them, to get an institution that implements some desired social plan, where a social plan is a description of how everyone’s actions should depend on everyone’s information (Myerson, 2008).

Classic Mechanism Design (MD) is the area of microeconomics and game theory concerned with how to design systems that involve multiple self-interested individuals each with private information about their preferences, using tools developed by game theory analysis, such that certain system-wide properties emerge from the interaction of the constituent components (Maskin, 2008).

A mechanism design considers a set of outcome rules and actions, and a set of players. The mechanism is designed so that the players’ preferred strategies obtain an outcome that it corresponds to the desired outcome of the system manager. This is interpreted as efficient use of the system (i.e. existing transport infrastructure). In a mechanism design problem, one can imagine that each agent holds one of the inputs to a well-formulated but incompletely specified optimization, and that the system’s wide goal is to solve the specific instantiation of the optimization problem specified by the those inputs (Nisan, 2007).

Incentives and incentive systems are fundamental to developing capacities and to translating developed capacities into better performance (Ratto, 2003). Incentives are external measures that are designed and established in order to influence motivation and behaviour of individuals, groups or organizations. Incentives can be classified according to the different ways in which they motivate agents to take a particular course of action. Janzik and Herstatt (Herstatt, 2008) classifies incentives divided into four categories (see Table 3):

1. Material incentives: financial, monetary-value-based
2. Immaterial incentives: Social, organizational related
3. Self-directed incentives
4. Indirect incentives

Table 3 - Classification of Incentives (Herstatt, 2008)

Material Incentives (Financial Incentives)		**Immaterial Incentives**		**Incentives from the Activity itself**
Direct Financial Incentives	Indirect Financial Incentives	Social Incentives	Organizational Incentives	• Enjoyment, pleasure, internal satisfaction (flow) • Internal impulse to solve a problem • Feeling of competence & autonomy (creativity) • Self-reward • Self-determination • Sense of belonging to the community • Altruism
• Monetary compensation (payment, premiums, financial rewards, licenses, etc.)	• Free products & free services (as give-away) • Bonus points with financial value • Coupons • Sweepstakes • Free usage of the developed product / solution (personal need, use need, problem pressure, dissatisfaction) • Low transaction costs for participation	• Peer recognition • Status, reputation • Power (e.g. to influence others) • Awards, visible member level • Get credits as a co-developer (Pride) • Skill enhancement, collect knowledge & experience • Recognition by the community carrier • Trust • Strengthen social ties • Social exchange (form of reciprocity) • Identification	• Additional rights & functions inside the community, access to extra information (form of reciprocity) • Professional status enhancement, career progression, recruitment by companies (self-marketing)	**Indirect Incentives** • (uncontrolled) Feedback

2.4.3. Policy & Incentives in Transportation Domain

Policy-making is of particularly interesting in transportation domain, as it constitutes an important area in socio-economic and technical systems. Some transport policies aim at decreasing transport resistance factors (money, time, and effort); other policies try to influence the needs and location of activities or try to improve the environmental performance of vehicles, and so forth.

Externalities in the transportation domain develop to generate inefficiencies and social-welfare losses are generated. The most important dimensions of external costs are usually found to be congestion, air pollution, accidents, and noise. Santos et al. (Santos, Behrendt, Maconi, Shirvani, & Teytelboym, 2010) and (Santos, Behrendt, & Teytelboym, 2010) extensively review the main road transport externalities and economic policies in transportation. Throughout their study authors has examined the most important negative externalities and a number of command-and-control and incentive-based policies.

Among the policies that have been proposed to attenuate these negative externalities, road or congestion pricing is the major strategy considered. In this case road pricing aims to internalize the external costs of car traffic. This will increase the welfare of all road users, assuming that the charges will be return to car-users in terms of investments that will improve his/her comfort (Santos, Behrendt, Maconi, Shirvani, & Teytelboym, 2010) and (Verhoef, 2006). In that sense, road pricing has become a central point in the transportation economic literature (Levinson, 2010), (Blythe, 2005), (Elvik, 2010), (Rentziou, et al., 2010), and (Voβ, 2009).

Those behavioural responses in the road pricing application lead to an increased efficiency of the transportation system (Bonsall, Shires, Maule, Matthews, & Beale, 2007). Pricing, however, is a negative incentive and commuters' public acceptability of such a measure is typically low. One of the first approaches to circumvent this unwillingness is proposed by Kveiborg (Kveiborg & Lohmann-Hansen, 2001) where it is discussed the possibility of using MD in transportation for implementing social optimal congestion levels in an urban region. Kveiborg proposes a theoretic compensation-based mechanism to substitute the fixed road pricing schemes (Pigou taxes). In this mechanism, drivers need to announce what how much transport he will demand, and how much he will pay for this to the other, and how much he should be paid to accept the other individuals' choice of transport.

Ettema et al. (Ettema, Knockaert, & Verhoef, 2010) suggest the use of positive incentives (monetary and credits) to stimulate changes in travel behaviour of commuters on a congested highway in the Netherlands. Among the finding of the experiment is that commuters adjust their behaviour when they have flexible work hours, have public transport alternatives and regularly use traffic information. Finally authors observed that when no reward was offered commuters avoiding traffic decreased significantly.

Merugu et al. (Merugu, Prabhakar, & Rama, 2009) describe the INSTANT an incentive based mechanism to encourage commuters to commute at less congested times. Authors sustain that for achieving an improvement in congestion management only a part of the overall population it is necessary to be induced to change its travel behaviour. Commuters who modify their behaviour unilaterally will benefit from reduced commute times and have a more comfortable commuting experience.

Goodwin (Goodwin P. , 2008) extensively reviews available evidence on the nature and size of demand responses in passenger transport, which would be relevant to setting and achieving carbon reduction targets. The review reveals the variety of travel choices people make. The modal choice is between not only cars and public transport, including the volume and location of travel, but also walking and cycling, driving styles, levels of car ownership, where to live and work and shop, and the type of activities they participate. A common characteristic of those interventions (evidence based on experience is available) is that they often are cost-benefit solutions.

Incentives it is not only related to pricing schemes and traffic congestion but embraces all the dimensions reported previously in Table 3 in order to deliver a sustainable mobility services. This is for example the objective of the SUNSET[1] (Sustainable Social Network Services for Transport) project. The direction followed in SUNSET lies within four types of incentives:

1. Real-time travel information (i.e. system provision and peer-to peer exchange);
2. Feedback and self-monitoring;
3. Rewards and points;
4. Social networks.

It is worthy to notice how transportation community started to embrace the influence and potentialities of the social networks to align individual and system objectives.

In this directions are moved the works proposed in (Hoh, 2012) and (Holleis, et al., 2012) that leverage on the use of socials networks and social participation to motivate or to give pressure to people to behave in certain ways. An incentive-centred design based on self-monitoring and feedback is proposed in (Agerholm, Waagepetersen, Tradisauskas, &

[1] http://sunset-project.eu/

Lahrmann, 2008) and (Agerholm N. , 2011) where it is proposed a mechanism for intelligent speed adaptation. Similar applications, focus on fuel consumption this time, is currently pursue by the automotive industry. Rossetti et al. in (Rossetti, Almeida, Kokkinogenis, & Gonçalves, 2013) and (Gonçalves, Rossetti, & Olaverri-Monreal, 2012) discuss gamification as an important instrument toward behaviour persuasion. Authors support the use of serious games in ITS as a way to implement incentive-based schemes to promote social awareness toward future smarter and sustainable transportation systems.

2.5. MAS for Incentive-Based Mechanisms and Policy Evaluation

Policy-making is an extremely complex problem. It implicates the interactions among many diverse autonomous entities such as individuals, households, businesses and government organizations, as well as the physical world

Each of these entities comprises interdependent economic, environmental, political and social behaviours. Since autonomous entities produce the effects of regulatory policy, the multi-agent approach to explain expectations about the effects of alternative policies, makes obvious sense. Agent-based models provide a powerful and scalable approach to analysing vital aspects of policy design and forecasting that traditional econometric models cannot (Moss, 2002), (Moss, 2008), and (Boer, Engers, & Sileno, 2011).

2.5.1. Agents in Policy-Making Process

Policies are conceived in a way to drive individuals to change their behaviour. However, the way people adapt their behaviour might not be the one intended by the policy. People interpret the policies in the context of their own state and influenced by their social surrounding. Thus, agents can be used to model individual behaviour.

Dos Santos and da Rocha (Costa, 2012) introduce the concepts of *agent-based model of public policy process* and of *policy artefacts*. The former emphasizes the need of direct modelling and simulation of the main policy actors in terms of cognitive agents and their interactions, while the latter abstracts public policies that are addressed to the agents representing the authorities and other member of the society.

The benefit of agent-based motivation models in the policy-making and implementation processes is discussed in (Sterling & Pedell, 2012). They show that agent-oriented models are suitable for modelling the social domain because they represent the goals and motivations of roles and individuals, and the notion of quality goals can be used to discuss high-level outcomes relevant for policy making.

Wyner et al. (Wyner, Atkinson, & Bench-Capon, 2012) and (Wyner, Wardeh, Atkinson, & Bench-Capon, 2012) discuss the use of agent-based argumentation techniques taken from to provide intelligent support for intelligent support for opinion gathering and eliciting a structured critique of the policy-making process. Dignum et al. (Dignum, Dignum, & Jonker, 2009) argue about the necessity to combine micro and macro-level models to simulation-based support for policy-making. (Almeida, Kokkinogenis, & Rossetti, 2012) uses agent-based simulation to evaluate different policy setting in evacuation scenarios.

The design and the optimization of pricing policy in the transportation domain is a complex task. For example in the context of road pricing schemes Fosgerau (Dender, 2013) considers that congestion charging should not be account in isolation of the travellers. There are important implications spanning from traffic dynamics and the endogenous nature of trip timing, to the heterogeneity of travellers and the travel time variability. Yet, the design of pricing schemes needs cohesive assessment, considering the interactions between congestion and traffic network dynamics with heterogeneous behavioural as well as socio- and spatial-economic factors.

Nagel et al. (Nagel, et al., 2008) present the first version of MATSim traffic simulator to show, how multi-agent simulations approach with full daily plan for each agent can be applied for economic policy evaluation on a large-scale scenario. Thereby, Kickhöfer et al. (Nagel, et al., 2008), (Grether, Kickhöfer, & Nagel, 2010), (Kickhöfer, Zilske, & Nagel, 2010), (Kickhöfer, Grether, & Nagel, Income-contingent user preferences in policy evaluation: application and discussion based on multi-agent transport simulations, 2011) and (Nagel B. K., 2012) expand Nagel's approach and present a number of papers where it is discussed the econometric evaluation of different transportation policies using the multi-agent paradigm. Authors describe the new MATSim[1] framework for large-scale agent-based transport simulations. In MATSim, each traveller of the real system is modelled as an individual agent. For each, an Activity-based demand generation (ABDG) models generate daily activities in sequence and trips connecting these activities for every

[1] http://www.matsim.org/

"agent" in the network. Demand generation thus is embedded in a concept of daily activity demand from which the need for transport is derived. Random utility theory is used to generate plans of daily activities.

MATSim model has been widely applied for transport and land-use studies; it is the only model so far that consider economic activities and their interaction with other behavioural processes. Indeed several authors that studies public policy in the transportation domain have adopted it (Zheng, Waraich, Axhausen, & Geroliminis, 2012) and (Erath, 2012).

In (Macedo, Kokkinogenis, Soares, Perrotta, & Rossetti, 2013) is discussed an integrated traffic simulation framework to be used for policy evaluation of electric road mobility. Pereira introduces a simulation tool to evaluate policies in fully autonomous vehicle scenarios (Pereira & Rossetti).

In Kokkinogenis et al. (Kokkinogenis, Monteiro, Rossetti, Bazzan, & Campos, 2014) is discussed a conceptual framework for evaluating transportation policies in multimodal scenarios from a social-simulation perspective. It is suggested the use of an agent-based platform for modelling & simulation of social systems in order to complement the study of social factors on the performance of transportation systems.

2.6. Summary

Along this section, we have review some fundamental concept interlaced in this dissertation. We have started by considering the transportation domain and in particular way the Intelligent Transportation system area. Then we proceed by considering the agent technology. These are the two areas this dissertation aspires to contribute.

An agent-based approache can contribute around the design and control of intelligent transportation systems (ITS) and ultimately to make our cities smart. The Four Step Model (FSM) is the primary tool for forecasting future demand and performance of a transportation system but it as problem with the complexity of the mode choice. As discussed, the FSM lacks information in a social perspective, and rather deal on a transportation model.

This is where our framework and methodology will focus on the following chapter. We will discuss on how to build a social-transportation simulation tool in an ATS context. Then use this framework and test policies. We believe incentive-based mechanism to influence the behaviour both of users and of the providers can be helpful for the system to reach the so-called social fairness equilibrium.

Chapter 3 - Framework for STST and an illustrative scenario

3.1. Overview

In (Wang & Tang, A framework for artificial transportation systems: From computer simulations to computational experiments., 2005) the concept of artificial transportation system (ATS) is discussed as a framework to appropriately represent, test, and analyse transportation control policies and solutions.

In this chapter, the intention is to go beyond traditional simulation methodologies by integrating the transportation system with other socioeconomic urban systems and real-time information. In (Rossetti, Liu, & Tang, 2011), authors provide a brief overview of contributions in ATS development along three dimensions: modelling issues and metaphors for ATS models, architectures for ATSs, and practical applications of ATSs. Although the achievements made by the transportation community are promising, there has been a slow advance in appropriately representing users and their behaviour in the social dimensions of the intelligent transportation systems.

3.2. Framework Description

In this section, we present the conceptualisation and implementation of a methodological framework based in an ABM and deliver a platform to serve as social-transportation simulation tool (STST) in ATS (see Figure 5).

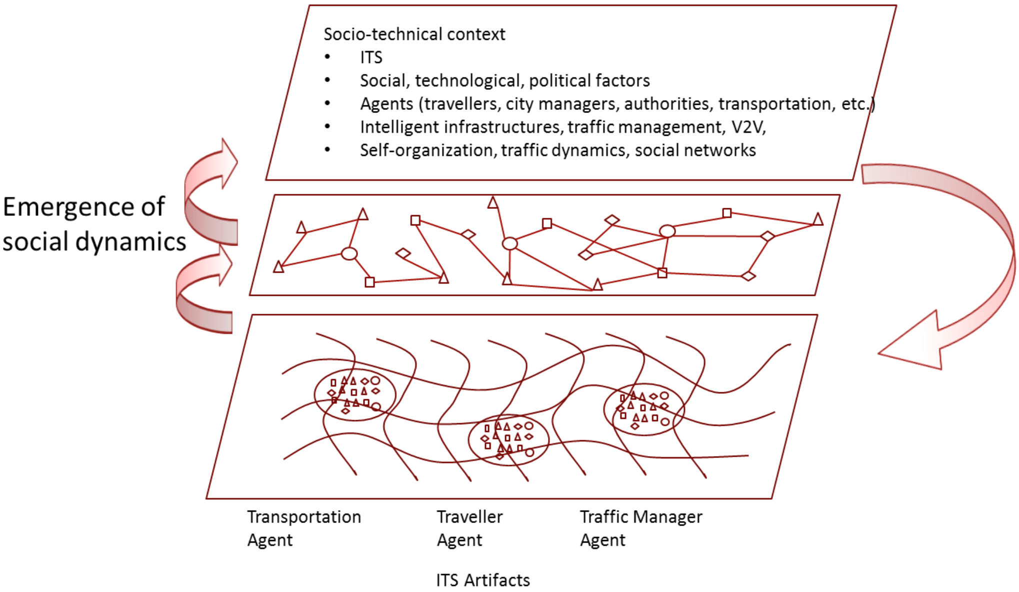


Figure 5 - A social-transportation simulation tool in ATS

The bottom layer represents the environment and the various types of agents that reside on it. The middle layer considers the social dynamics and their implications that can emerge as result of interactions and learning among heterogeneous agents. The upper layer represents the context that we consider to our analysis.

a) Purpose

The purpose of the framework is to support traffic planners and managers in designing and evaluating ITS solutions. Modifications in the environment (i.e. multimodal transportation network), introduced either as direct or indirect actuation by the system authorities, can influence the travelling behaviour of the commuters in order to align their objectives and preferences with the ones of the system

In the conceptual model of the social ATS framework, we consider the transportation system as integration of a macroscopic representation of a road transportation network and the microscopic representation of an artificial society of agents, as commuters, each one having its own decision-making process and perception of the environment.

b) The Structure

The structure must follow the updated version of the ODD protocol. This acts as an underlying code structure being easier for new models to be built-in or to be expanded.

c) The General Framework

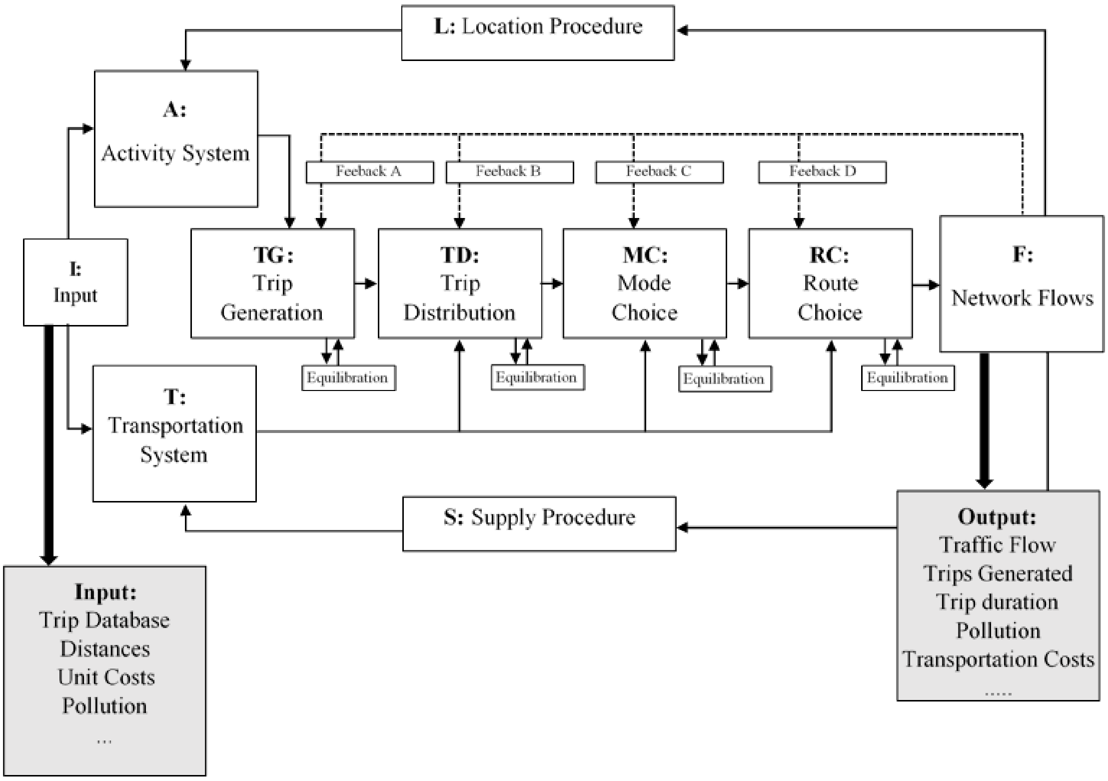


Figure 6 – The updated methodology

The major framework must start in the work of Manheim/Florian Transportation System Analysis Framework. The combined STST (Socio-Transportation Simulation Tool) methodology can be found in Figure 6. To help resolving the problem this approach can be used to combine the different transportation models used to analyse the transportation metropolitan transportation system. Therefore, this model can be used as a tool for simulation and prediction interactions between infrastructure changes, public transportation investments, and endogenous traffic effects in a daily basis.

The supply procedure will be based on a given artificial population.

d) Models

Commuters in the real system are described as an artificial society of agents, each of them characterised by a set of attributes regarding its travel preferences in terms of costs and time, and a set of socio-economic features (e.g., income).

The agents make daily travel decisions based on their personal expectations and their past travelling experiences. This acts as a memory where each commuter stores his travel experience. A generation module creates the demand to be assigned on the transportation network. Here, each agent creates an activity-based schedule, based on its own preferences and constraints, for a given period of the day. The schedule defines the set of origins and destinations with the respective desired departure and arrival times to and from each node. The agents' decision is based on the evaluation of their travel experience by means of a utility-based approach.

Kenneth A. Small (Small, 1979) introduced the concept of utilities based in scheduling of consumer activities. Small tries to find a solution for time-based utilities, and how those utilities weight in a decision-making process, based on the information they have. Latter in, Feil et al (Feil, Balmer, & Axhausen, 2009) developed a utility function in order to deal with all-day activity-travel schedules. This utility function is an evolution of the one introduced and goes as follows:

$$\max U_{total,i} = \max\left[\sum_{j=1}^{n} U_{perf,ij} + \sum_{j=1}^{n} U_{late,ij} + \sum_{j=1}^{n} U_{travel,ij}\right] \tag{12}$$

Where $U_{total,i}$ is the total utility of the given schedule i; n is the number of activities/trips; $U_{perf,ij}$ is the utility gained from performing activity j; $U_{late,ij}$ is the utility gained from arriving late at activity j; and $U_{travel,ij}$ is the (negative) utility gained from travelling trip j. $U_{perf,ij}$ is a positive utility that we win in performing an activity, $U_{late,ij}$ is a negative utility of arriving late to that utility and $U_{travel,ij}$ is a negative utility of traveling to perform that activity. This utility is used in the social transportation MATSim software (Feil, Balmer, & Axhausen, 2009).

In this work we decided to add a social factor to the later utility function. In that sense, each agent evaluates the available choices (e.g. mode, route departure time) over a set of individual contributions (see Equation 15).

$$U_{total} = U_{time} + U_{cost} + U_{social} \quad (13)$$

The two main components of the utility U_{total}, $U_{time}$and U_{cost} reflect the cost of travel that is incurred by the agents: time and monetary costs.

1. Time costs

The measurement of the travel time needs to quantify the agent's perception of time in different components such as access, waiting, and in-vehicle travelling.

1. Access time U_{acess} is a measure of accessibility, especially in public transportation, and accounts for the time necessary to access into a transportation system.
2. Waiting time, U_{wt} indicates the service frequency in public transportation.
3. In vehicle travel time (or travel time),U_{tt} is the effective travel time, necessary to travel from one origin to a destination node.

Therefore, the indirect utility function about the travel time costs, for agent j is:

$$U_{time}^{j} = \sum_{i=1}^{n}\left[a_1 U_{acess,i}^{j} + a_2 U_{wt,i}^{j} + a_3 U_{u,i}^{j}\right] \quad (14)$$

Where n is the number of activities in the agent's schedule, which equals the number of trips. The weightsa_1,a_2,a_3 can be consider as marginal utilities or preferences for the different components of the U_{time} with which commuters assess the value of time.

2. Monetary costs

The measurement of the costs is direct and additive as well as. The set of monetary costs can be defined as: fares, tolls, and other running costs (e.g. fuel costs). The (negative) utility earned for travelling during a trip can be seen as:

$$U_{cost}^{j} = \sum_{i=1}^{n}\left[b_1 U_{fares,i}^{j} + b_2 U_{tools,i}^{j} + a_3 U_{travel,i}^{j}\right] \quad (15)$$

where, U_{fares}, U_{tools}, and $U_{travel}$are the components of the utility regarding the paying of fares, tolls, and other travelling costs such as fuel consumption, and n is the number of activities in the agent's schedule. The weights b_1,b_2,b_3 can be consider as marginal utilities or preferences for the different components of the $U_{cost}$with which commuters assess their monetary efforts of travelling.

3. Social and personal benefits/costs

While the previous definition about time and monetary costs are typically used to describe the commuter's perspective of gain/loss about his/her travel activity, the social factors lie into a not well-defined dimension. This means that there are several issues that can be defined social factors and that must be accounted for an utility function. Therefore, we can consider not only typical social aspects found in the transportation literature as equity, accessibility, safety, but also the social interaction and influence the commuter receives during a trip. Indeed, an activity-travel patterns can emerge from the individuals social networks (Arentze & Timmermans, 2008), and it might be necessary to understand how social interactions (to be meant differently than the interactions among drivers) can influence the attraction or repulsion for travelling with a given mode or to a given location for example.

Typically, the modeller will account for the social interactions during a trip in a way that measures the strength of the links among an agent and his peers using a *homophile* principle of their common characteristics (McPherson, Smith-Lovin, & Cook, 2001). In this case, as it is suggested in (Natalini & Bravo, 2013), we could consider the commuter's social satisfaction as the ratio of commuters in commuter$j$'s neighbourhood that use the share the same mode m as the commuter j:

$$U^{j}_{sociability,m} = \frac{n_{jm}}{n_j} \tag{16}$$

Where $U^{m}_{sociability,m}$ is the satisfaction of commuter j choosing the mode m, n_{jm} is the number of commuters in j's network that have chosen the same transportation mode, and n_j is the number of j's peers in the network that use the same transportation mode. The peers may represent social relationships of many different kinds such as friends, relatives, colleagues, and neighbours.

In a social context, the attractiveness of a transport mode can be also appraised in terms of perceived comfort or crowding levels. This aspect can be an important factor for the mode choice as it has been studied in (Cantwell, Caulfield, & OMahony, 2009), (Beirão & Cabral, 2007). We can consider comfort to be linked with equity and accessibility from the traveller perspective.

Thereby we can consider the social component to include in equation 15 as the one shown in equation 19, where $U^j_{crowd,i}$ reflect the perceived comfort of agent j during the trip i, and $U^j_{awareness,i}$ can be considered the commuter's perception about the impact of his choices to the social welfare (e.g. pollution costs). The parameters c_1, c_2 and c_3 weight the importance commuters attribute to each component of the utility function.

$$U^j_{social} = \sum_{i=1}^{n}\Big[c_1 U^j_{crowd,i} + c_2\, U^j_{awareness,i} + c_3 U^j_{sociability,m}\Big] \tag{17}$$

e) Model Flow

Commuters in the real system are described as an artificial population of agents, each of them characterised by a set of attributes regarding its travel preferences in terms of costs and time, and a set of socio-economic features (e.g., income). The agents make daily travel decisions based on their personal expectations and their travelling experiences. A generation module creates the demand to be assigned on the transportation network. Here, each agent creates an activity-based schedule, based on its own preferences and constraints, for a given period of the day. The schedule defines the set of origins and destinations with the respective desired departure and arrival times to and from each node. The agents' decision is based on the evaluation of their travel experience by means of a utility-based approach. In that sense, each agent evaluates the available choices (e.g. mode, route departure time) over a set of individual contributions

f) Visualization

The model must be presented in such a way a not specialist must comprehend what is shown. This kind of models can almost only make sense if they are understandable and user-friendly. Furthermore, the model must be practical and must be thought as something useful for the community.

For example, macro visualization of city maps or graphs for analysing the output data model are good examples of visualization tools.

g) Tools

In **Table 4** we can find a comparison between some Agent Based Platforms.

Table 4 - Agent Based Modelling Toolkit Comparison

Platform	Primary Domain	Programming Language	User Support	Easy to Begginers	GIS Capabilities	3D Capabilities
MATSim	MATSim provides a framework to implement large-scale agent-based transport simulations.	Java	FAQ; mailing list; defect list; tutorials; API; documentation	No	Yes	Yes
NetLogo	Social and natural sciences; Help beginning users get started authoring models	NetLogo	Documentation; FAQ; selected references; tutorials; third party extensions; defect list; mailing lists	Yes	Yes	Yes
SUMO	SUMO is an open source, highly portable, microscopic and continuous road traffic simulation package designed to handle large road networks.	Python, C++	FAQ; mailing list; defect list; tutorials; API; documentation	No	Yes	Yes

SUMO (Krajzewicz, 2002) is intended to perform microscopic simulation whereas this project intends to focus on a macroscopic analysis. In this sense we decided to build this model in the NetLogo (Wilensky, 1999) environment. NetLogo is a social simulation tool. Here we try to merge transportation traditional tools with social interaction phenomena and so NetLogo with its easy to use software and open source software can make a good tool for a rapid prototyping tool.

3.3. First Implementation

3.3.1. Model Description

The goal of this section is to illustrate through a simple setup the plausibility of the conceptual framework as it was presented in section 3.1. We consider the evaluation of five changes in the network: three market-based and two incentive-based policies. In this setup we consider, time and monetary cost, whereas for as social costs are only considered the level of crowding and comfort, in the PT mode (Public Mode Transportation), and the level of emissions in the PR mode (Private Mode Transportation). We implemented the framework and simulation model using the NetLogo (Wilensky, 1999) agent-based simulation environment. One can find the source code at appendix B, part 1.

a) Network

The scenario consists (see **Figure 7**) of a bi-modal network with one origin O and one-destination D nodes, and two routes. For question of simplicity, each route is composed of one-way links of different capacities, and is dedicated to one mode; a PR and a PT road transport. Each link i is characterised by a length l_i km and a capacity c_i vehicles/h.

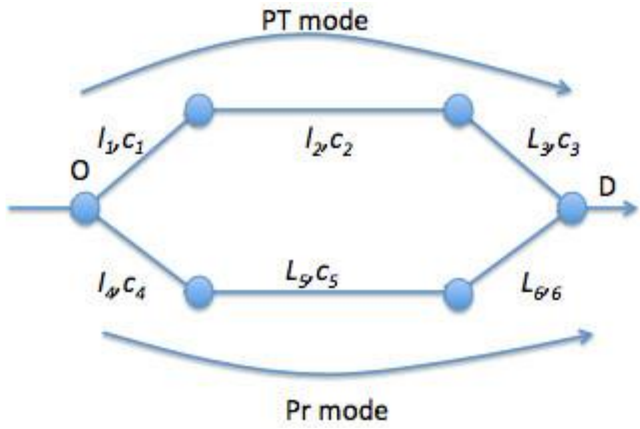


Figure 7 - Illustrative scenario of a bimodal network

Based on the BPR function described in section 2.2.3, we compute the free flow travel time for each link and thus its free-flow speed.

b) Entities and State Variables

The model comprises only one type of agent, the commuters. Each agent is defined by a number of state variables which are: (i) desired departure and arrival times, (ii) experienced travel time, (iii) the uncertainty they experienced during the trip with a given transportation mode, (vi) a daily income variable. While the agent experience its travel activities, the costs associated with the different transportation mode, the perceived satisfaction of travelling as it expressed in terms of travel times and comfort, and the magnitude of the applied policies will have a certain impact on his mode/time choice. Some other characteristics of the agents are:

1. Decision-making: The agents can choose to travel by PT or PR transportation mode. The decision making process of each agent is assumed to follow the principle of the expected utility maximisation.
2. Adaptation: Agents in the policy assessment scenarios have to adapt their decisions according to the modifications in the environment they are situated in. Such modification is the result of policy intervention and can be expressed as a variation on the perceived costs or benefits.

3. Objectives: Agents try to maximise their personal goals and satisfaction, accounting for the uncertainty of the environment, therefore based on this deliberative outcome the make their decision about the mode and departure time choice.
4. Sensing: Agents perceive the level of crowding in the public transportation and the levels of congestion in PR-mode.

c) Initial Setup

The scenario reflects a typical daily trip from a home to a work location. A typical three-hour morning peak is modelled from 7h30m until 10h30m. In this interval of time, one observes a high demand on the PR-mode, where the utilisation of the route reaches the highest occupation.

A synthetic population consisting of 2500 agents has been created, where each agent is characterised by a number of attributes denoting departure, arrival time and mode preferences, plus some other socio-economical features such as its monthly income. Each agent has an initial activity-travel schedule that considers expected departure and arrival travel times. The travel times are given by a normal distribution function, which give a rush hour peak between 8h30m and 9h30m in the morning.

The income is setup to represent an average monthly income of 1125 units, daily. The agent has two variables related to the mode choice capacity: car-ownership and flexibility. Car-ownership is a Boolean variable and indicates if the agent is private and/or public transportation user (we do not consider other type of modes, e.g. walking).

Flexibility reflects the willingness of a private mode user to change for the public transportation. Thus, all agents in the scenario start their trip at node O, between 07:30 am and 10h30 am. The routes between nodes OD have both a length of 19 km. The free-flow travel time from home (node O) to work (node D) is roughly 25 minutes by car in the PR-mode. For the public transportation, we consider a travel time from home to work is 33 minutes plus the waiting time at the bus stop. The bus frequency service is ten minutes before the rush hour and five minutes during the rush hours (for the test setup 8:30-9:30).

d) Behavioural Parameters

The behavioural parameters are set and can be interpreted as follows:

1. Marginal utility time: $U_{time} = 0.25$
2. Marginal utility of travelling by car: $U_{car} = 0.25$
3. Marginal utility of travelling by bus: $U_{bus} = 0.25$
4. Marginal utility of pollution: $U_{pollution} = 0.25$
5. Marginal utility of comfort in public transportation: $U_{comfort} = 0.25$
6. Marginal utility of capacity in public transportation: $U_{capacity} = 0.25$

The formal utility described early can be translated as follows.

$$U^{j}_{private} = \sum_{i=1}^{n} \left[U_{time} * \left(DA - (DD + ETT)\right) + \left(U_{car} * \left(\frac{private_{costs}}{income}\right)\right) + \left(U_{pollution} * (ETT * pollution)\right) \right] \quad (18)$$

Where:

- DA - Desired arrival time
- DD - Desired departure time
- ETT - Expected travel time

$$U^{j}_{public} = \sum_{i=1}^{n} \left[U_{time} * \left(DA - (DD + ETT)\right) + \left(U_{buc} * \left(\frac{public_{costs}}{income}\right)\right) + \left(U_{confort} * \left(\frac{EW}{DW}\right)\right) + \left(U_{capacity} * \left(\frac{EC}{bus_{capacity}}\right) * ETT\right) \right] \quad (19)$$

- DA - Desired arrival time
- DD - Desired departure time
- ETT - Expected travel time
- EW - Expected waiting time
- DW - Desired waiting time
- EC - Expected crowding

e) Scheduling

The demand is generated at the setup procedure. In the generation node, all the commuters are created and they are assigned a desired departure travel time. When desired departure is reached they move to the mode choice procedure where, accordingly to their utilities, they choose a mode to travel, PR-mode or PT-mode. After that procedure, they are assigned to the network, to the origin node. At the end of the travel, each agent stores the experienced travel time, costs, and level of crowding (public mode users only). These variables will be used to calculate next day utility. After that, each agent evaluates its own experience, comparing the expected utility to the effective utility. The network is also evaluated with the average travel speed and the average travel time being stored for future comparisons. In Figure 8, we can find a diagram depicting the scheduling.

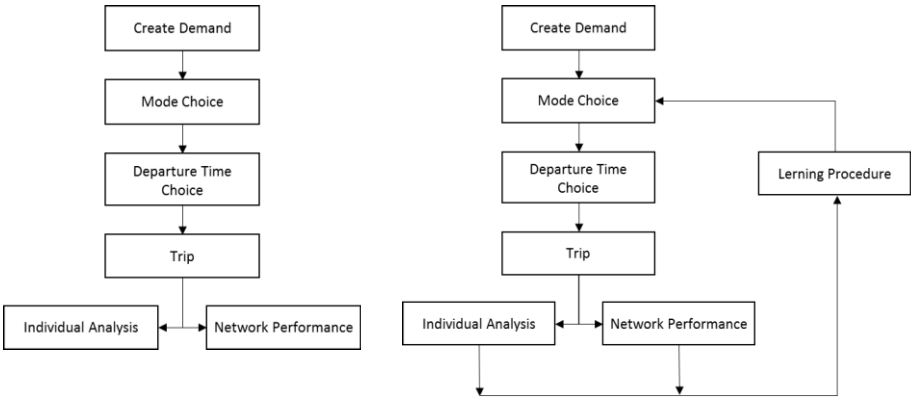


Figure 8 - Scheduling: left) Within-day Dynamics, right) Day-to-day

f) Market-Based and Incentive Based Policies

We consider five simple policies: three market-based and two incentive-based. Market-based policies actuate directly on the prices commuters need to support during their travel. Incentive-based policies aim to trigger shift in the traveller's behaviour regarding their travel choices. With the aforementioned utility functions, we try to analyse the different impacts of prices vs time choice incentives. The policies are defined as follows.

Market-based policies:

1. An increase in PR-mode transportation (*Policy-1*) - increase in private costs from 6 units to 20 units;
2. a decrease in PT-mode (Policy-2) - reduce of 20% fare, from 1 units to 0.8 units;

3. In addition, a policy mix (*Policy-3*) - a decrease of 0.2 units in PT-mode and an increase of 10 units in PR-mode costs.

We also implemented two departure time incentive-based policies:

4. A Departure Time Incentive for all the commuters (*Policy-4*) - Each commuters is rewarded with 2 euros before rush hour and 1 euro after rush hour;
5. A Departure Time Incentive only for commuters who travel at rush hour (*Policy-5*) - 2 euros before rush hour and 1 euro after rush hour.

These incentives tries to change the departure times of each commuter and this way flat the demand peak and curve.

g) Who is impacted by the policies

In the following table (table 5) a population description regarding the Boolean variables “owns a car” and “mode flexibility”.

Table 5 - Agent Based Modelling Toolkit Comparison

Owns a Car	Mode Flexibility	
No		1253
	Yes	609
	Yes	644
Yes		1247
	No	599
	Yes	648
Total		2500

From this table we can that from the 2500 agents artificial created 648 have a car and have flexibility. So this 648 agents are going to be the target of this policies.

3.4. Simulation Runs Results

We first consider a “baseline” scenario where no policy intervention is applied. We perform a preparatory run of the model for the corresponding of one-month simulation (30 iterations of the morning rush hours). This serves to establish the ratio of commuters distributed between the two modes along the departure time interval. We can consider that during this period the agents' ”adapt” to make the choice that maximizes their utility. During the execution of the scenario, we monitor the agents' utilities, travel times, the ratio of the expected travel time for the PR-mode and the observed travel time *TTExp/TTObs,* and the pollution/crowding level for the PR-mode and PT-mode respectively.

After, a policy is introduced and the model is executed for another 30 iterations, starting from the final iteration of the baseline scenario. In the market-based *Policy-1*, we can see, compared with the baseline scenario, an increase of commuters in 7.5% in the PT-mode (see **Table 6**) and a decrease of commuters of 9.34% in PR-mode (see **Table 7**). The social effects of a change in prices is that in one hand, when a rise in PR-mode transportation costs the commuters who have changed from PR-mode to PT-mode are the commuters who do not have the capacity to pay the new price. We can see that the effect in the average expected utility in PR-mode where it increases by 2.8%. The agents who stay in the PR-mode are not influenced by the prices. On the other hand, because the PT-mode transportation supply does not change, there is a 5% lost in expected utility in PT-mode that it is explained by a rise of the average crowding by 5%.

If we compare these results with *Policy-2,* we can see that the PT-mode expected utility drops by 1% and there is a rise in PT-mode ratio of 6.28%. Therefore, the PT-mode commuters are somehow rewarded with a ticket price reduction and their utility does not drop as much as in *Policy-1*. At the same time, there is a rise in PR-mode utility average because the networks become less crowded.

The results from the incentive-based policies need a different analysis, because there is not an increase effect on prices but rather the inverse effect, a subsidisation. At the same time, the incentive looks to approximate the PR-mode costs to the PT-mode costs by a two units subsidy before rush hour and one unit after rush hour. More, the objective of those incentives in theory is not to achieve mode shift but rather to flat the demand. However, the results show us a different perspective. In a modal shift perspective there is a rise of 7% (*Policy-4*) and 6.7% (*Policy-5*) in mode shift. This modal shift is not explained only by the effect of the subsidisation per se. It also occurs because, all the agents that have travelled before the rush hours, some have changed their mode from PR-mode to PT-mode as they can reach a higher utility.

Another point that emerges from the results is that the shift in departure time, obtained applying of the incentive-based policies, obtains a similar effect of the Braess's paradox

(Braess, 2005). Here we find the congestion effect not in a route choice but rather on a time choice basis (see **Figure 9**).

Table 6 - Public Transportation Insights

Public Transportation	Ratio	Average Travel Time [min]	Average Utility	Average Crowd
Baseline	55,4%	36,67	11,11	0,81
Policy 1	7,50%	-0,56%	-4,97%	5,06%
Policy 2	6,28%	-0,30%	-0,81%	3,20%
Policy 3	6,49%	-0,61%	-1,45%	3,97%
Policy 4	6,93%	-0,43%	-3,90%	2,24%
Policy 5	6,64%	-0,36%	-3,82%	2,70%

Table 7 - Private Transportation Insights

Private Transportation	Ratio	Average Travel Time [min]	Average Utility	*TT Exp/TTObs*	Average Pollution
Baseline	44,6%	25,24	17,60	1,05	5,05
Policy 1	-9,34%	-0,30%	2,76%	-18,89%	-0,30%
Policy 2	-7,81%	-0,26%	1,16%	0,39%	-0,26%
Policy 3	-8,08%	-0,29%	1,78%	-19,74%	-0,29%
Policy 4	-8,62%	0,38%	4,77%	0,22%	0,38%
Policy 5	-8,26%	0,90%	2,65%	-6,38%	0,90%

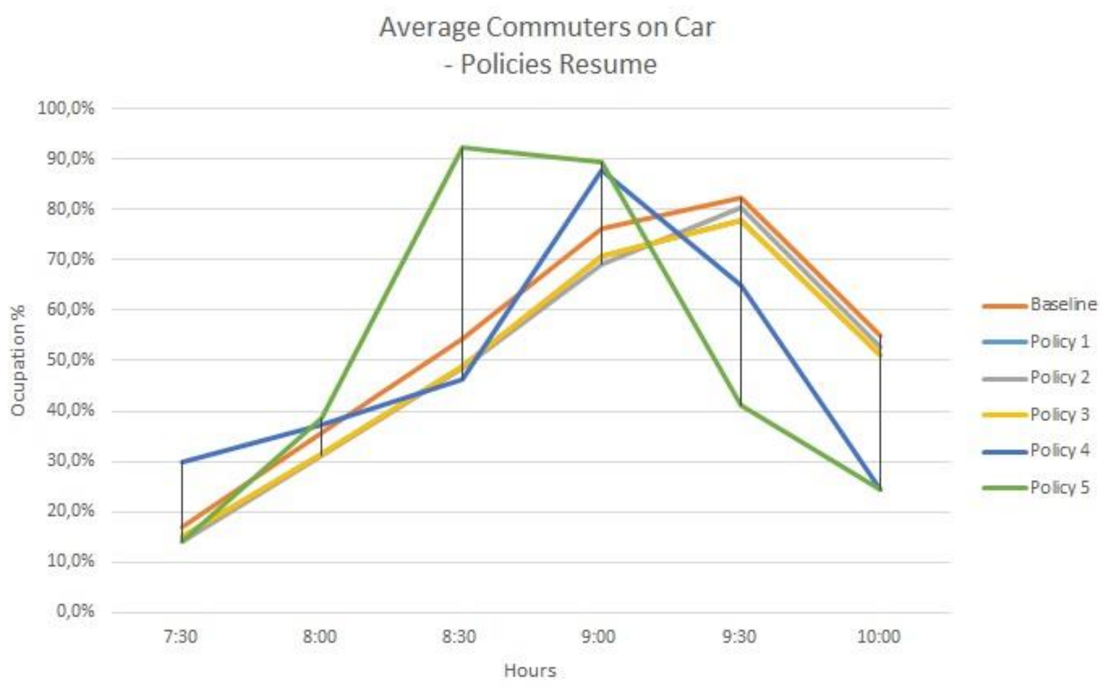


Figure 9 - Average commuters on car under different policies

3.5. Summary

In this chapter, we have discussed a conceptual framework for evaluating transportation policies in multimodal scenarios from a social simulation perspective. Hence, we suggest the use of an agent-based platform for modelling and simulation for social systems in order to complement the study of social factors on the performance of transportation systems.

To illustrate the viability of our approach in representing human behaviour, we built a synthetic population of adaptive commuters, where each of them implements a memory to store his travel experience and thus we can conduct the within-day and day-to-day transportation and traffic analysis considering behavioural and social aspects of the commuter based on his/her preferences. What we can conclude from this illustrative example is that the transportation planners should anticipate both positive and negative effects of a market-based or an incentive based policy. Trying to achieve a behavioural shift in mode choice needs to be followed by proper investments (i.e. encouraging the usage of public transportation can succeed only if it is followed by an improvement at infrastructure and service levels).

Chapter 4 - Policies Effectiveness - Iteration Games

4.1. Overview

In this chapter, we will introduce and present a more robust simulation based in the framework discussed in the previous chapter. A robust and larger network demands a bigger setup in which several origins and several destinations must exist. Therefore, a proper traffic assignment model is necessary.

A common assumption is that drivers choose the route between an OD pair according to the principle of minimum experience travel time (Chiu, et al., 2010). As there are other drivers on the routes, the travel time between an OD pair depends on the choices of these other drivers who also aim to minimise their travel time. When all drivers succeed in choosing the optimal route that minimises their travel times, this is referred to as Equilibrium or User Equilibrium or Wardrop's Equilibrium (Wardrop, 1952).

Bazzan and Klügl investigated the behaviour of agents under the effect of real-time information and thus how the agents change their route mid-way (Bazzan & Klügl, Re-routing Agents in an Abstract Traffic Scenario, 2008). Precise information about the travel time on the routes may improve the network flow negligibly if the drivers repeatedly make route choices from the same origin to the same destination on the same road network around the same time of the day (Kitamura & Nakayama, 2007). Providing real-time information to the drivers has some drawbacks. If the drivers do not have perfect information, their travel time may increase compared to those having perfect information (Arnott, Palma, & Lindsay, 1991). Moreover, the drivers tend to ignore the information if they are informed regularly or they tend to concentrate on certain roads if they are informed about congestion on other roads (Ben-Akiva, De Palma, & Isam, 1991). Providing information to the drivers is not an easy task and ensuring the quality of the information so that it is of use to the drivers is complicated.

The drivers on the road are independent entities who make decisions usually without communication with other drivers. Each driver's decision has an effect on the traffic flow and thus on others' decisions. Hence, the Traffic Assignment Problem (TAP) and route choice can be seen as a game-theoretic problem (Chen & Ben-Akiva, 1998) where individual choices affect other individuals. The drivers are independent; they share limited information and try to minimise their travel time and thus, inadvertently, to form the equilibrium.

Challet and Zhang's Minority Game (MG) model (Challet & Zhang, 1997)is one such approach where coordination among the agents occurs through self-organisation with minimal information and without communication among the agents. Challet and Zhang showed that their MG model could achieve equilibrium among agents by self-organisation (Challet & Zhang, 1997). TAP and Route choice can be seen as a problem of self-organization, and though iteration game agents can reach equilibrium. Therefore, the MG might be well suited for solving this problem.

MG was introduced to simplify Arthur's (Arthur, 1991) El-Farol bar problem. However, the original MG formulation is not sufficient to solve the TAP. Therefore, in this work an extension of MG and a variation of El-Farol bar problem is integrated and proposed as an approach to solve the TAP and route choice. This hybrid approach ensures a reasonable travel time for the travellers and a near-optimal distribution of cars on the road network. In the next section an introduction of the El-Farol bar and Minority Game is given.

4.2. The El-Farol Bar Model and Deducting the Minority Game into a TAP

The EFBP starts with a problem. The problem consists in a set of agents, without the possibility of communication, which have to self-organise themselves while they are in a competition for a limited resource, and there is no solution deductible *a priori*. In this problem, every agent has to choose *to go* or *not to go* to the 'El-Farol' bar each week, using a predictor of the next attendance. It is given that the agents try to avoid crowd however, since there is no single predictor that can work for everybody at the same time, there is no deductively rational solution. The consequence is a belief described by Arthur: "*if all believe few will go, all will go. But this would invalidate that belief. Similarly, if all believe most will go, nobody will go*" (Arthur, 1991).

Implementing the EFBP implies that each agent has predictors that map the history of past attendances. The agents rank their predictors by evaluating the predictions after each decision. If a predictor predicts correctly for an agent, that predictor scores a point regardless. To make a decision, an agent uses the predictor with the highest score.

To predict the exact number of attendants using the past *m* days' history, the length of each predictor would have to be N^m, which is a rather large number even for a moderate *N*. In order to simplify the EFBP, Challet and Zhang defines the MG as an odd number, *N*, agents repeatedly take an action, either +1 for going to the bar or -1 for staying at home. The agents on the minority side win.

The previous winning decisions form the history. If the agents taking decision +1 were in the minority last time, the history will be +1. Thus, the history can be denoted as a binary sequence. The agents are provided with the common history of last *m* winning sides. Each agent has a finite number of predictors which map the action +1 or -1 to the next time step based on the *m*-bit history.

The left side of the table contains all possible combinations of the history for m = 3 and the right side is the proposed action for that particular combination of the history. The predictors are initialised randomly and the agents cannot change their predictors in the traditional minority game. The length of the predictor is 2m which is significantly smaller than Nm.

4.2.1. Adaptation of MG in Traffic Assignment Problem

This section is based in the work of Galib and Moser (Galib & Moser, 2011). We adapted the model the authors developed and integrated it in our framework. In their study, Galib and Moser proposed a novel approach using the concept of Challet and Zhang MG model. We will describe their approach in the following paragraphs.

The authors assume that each driver has an OD pair and some previous experience of travelling to the destination. It is assumed that there are usually several routes to reach the destination and drivers decide at each intersection which outgoing link they will take from there. Each driver has predictors to anticipate the usage level of the links as a percentage of the link's capacity. A predictor maps a history of previous usage levels to a prediction of the current usage level and the driver will choose the link with the minimum predicted usage. At the end of the trip, the driver will compare the experienced travel time with the expectation and score the predictors accordingly. By scoring the predictors, drivers can select the best predictor with highest score to use for prediction of the link usage in the next iteration.

The algorithm of proposed by Galib and Moser (Galib & Moser, 2011) approach is given below which they called *Hybrid Traffic Assignment Approach* and can be seen bellow.

---

1) For each driver
    a) For each node i in the developing route
        i) For each link j in the driver's list for node i
            (1) Select best predictor for link j
            (2) Predict the percentage usage by mapping current link history to the best predictor
        ii) End For
        iii) Select link l with minimum weighted prediction
        iv) Set the current node i to the end node of link l
        v) End For
    b) End For
2) Update the link histories for each driver for the links they travelled
3) Update the score of the predictors used by each driver for each link
4) Calculate experienced/actual travel time for each driver along their OD pair
5) Calculate new weights for each link using the current experienced travel time.

---

a) Number of Agents

Challet and Zhang's original MG (Challet & Zhang, 1997) could only be applied to an odd number of agents. This was necessary to determine the minority side. However, in our traffic scenario, we are applying the concept of the MG without the limitation of odd numbers agents, as the success of a choice is not determined by minority allocations but according to the actual travel times experienced.

b) History

At the MG, the history shows the winning alternative. In TAP, we have more than two alternatives to choose. Therefore, the history is a percentage of road usage with respect to the capacity of the road. Authors show that the range of historic usage values is limited to a range of 60 to 140 because the values smaller than 60% or larger than 140% usage are of no consequence in the decision-making.

c) Predictors

The predictors were modified in order the historic values expresses the percentage of usage. In the El-Farol bar problem, the predictors predict the number of attendants. Here in order to deal with the exponential information in traffic context, the predictor predicts a percentage of road occupancy. **Table 8** shows two predictors for a history length of three. According to these predictors, if the history is 60-60-60 or 60-60-61, predictor 1 will predict 91% and predictor 2 will predict 120% road congestion.

Table 8 - The mapping of a Predictor (Galib & Moser, 2011)

Possible history				Predictor 1	Predictor 2
60	60	60		91	120
60	60	61			
. .					
. .				. . .	. . .
90	91	92			
90	92	91		107	93
. .					
. . .				.	.
				.	.
140	140	140		117	101

d) Decision-Making

In MG and El-Farol bar problem, the agents take the actions according to the prediction. Therefore, the drivers choose the link, which has the minimum weighted prediction. The weight is the ratio of the actual travel time for the route taken and the expected travel time and is calculated as.

$$W = \frac{ATT_R}{ETT_{R^*}} \tag{20}$$

Where ATT_R is the actual or experienced travel time on route R, and ETT_{R^*} is the expected travel time of a driver between the OD pair on the optimal route R^*. The optimal path is the path that includes the minimum number of nodes. The drivers assume an approximate impression of the current road usage based on their current observations as well as previous experience. The ATT_R and ETT_{R^*} are calculated as

$$ATT_R = \sum_{a \in R} tt_a \tag{21}$$

$$ETT_{R^*} = \sum_{a \in R^*} ff tt_a \left[1 + \left(\frac{eX_a}{C_a}\right)^2\right] \tag{22}$$

Where tt_a is the travel time on link a , which is calculated as:

$$tt_a = ff tt_a \left[1 + \alpha \left(\frac{X_a}{C_a}\right)^{\beta}\right] \tag{23}$$

Where $fftt_a$ is the free flow travel time, $C_a$is the road capacity, X_a is number of cars on the link a , α and β are two control parameters and, eX_a is the expected number of cars on the link a of the optimal route R^* (Sheffi, 1985). The equation 26 is the so-called BPR described in section 2.2.3.

e) Updating the Predictors' Scores

The score of the predictor is calculated as follows,

$$\theta_{a,t+1} = (1- \mu)\theta_{a,t} + \mu \left[\left(\frac{C_a}{X_a}\right) - 1\right] ATT_R \tag{24}$$

Where, $\theta_{a,t}$is the score of the predictor for link a at time t , and μ is a number in the range $\{0, 1\}$. Note that if the number of cars on the link exceeds the capacity, $\left[\left(\frac{C_a}{X_a}\right) - 1\right]$ will become negative, which decreases the score, otherwise it increases the score.

4.3. Implementation

4.3.1. Model Description

In this implementation, we will use the model description described at section 2.3.4, the ODD protocol. As we discussed the ODD protocol tries to achieve a common description and language to complex agent-based models, so they can be easily understood, replicable and scientific relevant (Grimm V. , et al., 2006).

4.3.1.1. Purpose

We will consider the evaluation of three different changes in the network: three market-based. In this setup we consider, time and monetary cost, whereas for as social costs are only considered the level of comfort, in the PT mode, and the level of emissions in the PR mode. We implemented the framework and simulation model using the NetLogo agent-based simulation environment (Wilensky, 1999). One can find the source code at appendix B, part 2.

4.3.1.2. Entities, state variables and scales

The model comprises only one type of agent, the commuters. Each agent is defined by a number of state variables which are: (i) desired departure and arrival times, (ii) experienced travel time, (iii) the uncertainty they experienced during the trip with a given transportation mode, (vi) a daily income variable. While the agent experience its travel activities, the costs associated with the different transportation mode, the perceived satisfaction of travelling as it expressed in terms of travel times and comfort, and the magnitude of the applied policies will have a certain impact on his mode/time choice.

4.3.1.3. Process overview and scheduling

The demand is generated at the setup procedure. In the generation node, all the commuters are created and they are assigned a desired departure travel time. When desired departure is reached they move to the mode choice procedure where, accordingly to their utilities, they choose a mode to travel, PR or PT. We run the model for 180 days, roughly 6 months.

In the first implementation seen in chapter 3, time was represented, as said before, by each step of the simulation representing one minute. However, in this implementation each simulation step represents a period. Each day consists of 5 period of time that comprises the morning peak from 7h 30m until 11h30m.

After that procedure, they are assigned to the network, to the designated origin node. At the end of the travel each agent stores the experienced travel time, costs, and level of crowding (public mode users only). Those variables will be used to calculate next day utility. After that, each agent evaluates its own experience, comparing the expected utility to the effective utility. The network is also evaluated with the average travel speed and the average travel time being stored for future comparisons.

In figure 8 at section 3.3.1 we find a diagram depicting the scheduling. However, in this implementation, we will not only have the last day history, but a set containing the set of history days we want.

4.3.1.4. Design concepts

Based on the ODD protocol presented at section 2.3.4 some other characteristics of the agents are:

1. Basic Principles: The agents can choose to travel by PT or PR transportation mode. The decision making process of each agent is assumed to follow the principle of the expected utility maximisation.

2. Adaptation: Agents in the policy assessment scenarios have to adapt their decisions according to the modifications in the environment they are situated in. Such modifications are the result of policy intervention and can be expressed as a variation on the perceived costs or benefits.
3. Objectives: Agents try to maximise their personal goals and satisfaction, accounting for the uncertainty of the environment, therefore based on this deliberative outcome the make their decision about the mode and departure time choice.
4. Learning – the agents learn how to travel in the network. This learning is based on the prediction they make to update the occupancy scores. Moreover, the agents store the information so they have a notion of what happened in the past.
5. Prediction - They will update their history in order to update the link occupancy prediction, so they can evaluate which is the best route to follow.
6. Sensing: Agents perceive the level of crowding in the public transportation and the levels of congestion on PR road transportation mode.
7. Randomness – each agent is setup with some random variables. Their origin and destination, the income and the accessibility to a PT road is a given randomly.

4.3.1.5. Initialization

The road network used in these experiments consists of the nodes and links shown in figure 10. The drivers have their OD pairs and thus they have several alternative routes/paths, which consist of sets of links. In the decision-making, we only consider unidirectional links. We can reasonably assume that drivers who commute are aware which links are options for a route to the destination.

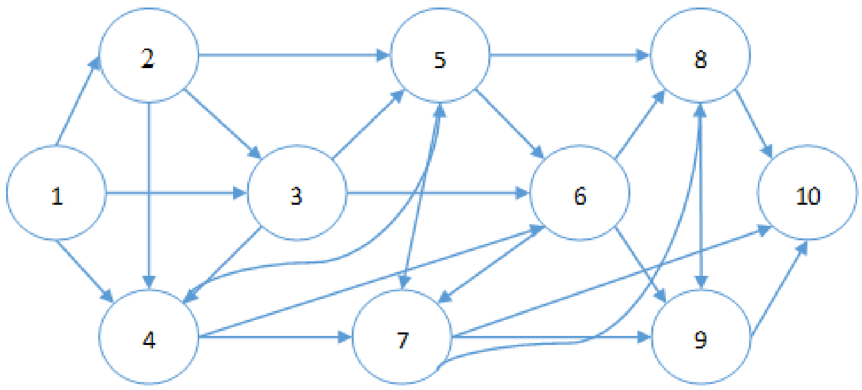


Figure 10 - Network representation

The network has 10 nodes, which represent intersections, and 24 links that represents the roads. Each link has a randomly capacity in the range of {550, 850} vehicles. There are three origins (Nodes 1, 2 and 3) and three destinations (Nodes 8, 9 and 10), resulting in nine combinations of OD pairs. At table 8, we find the OD pairs information, the system optimal routes and the expected travel time each commuter have for each optimal route.

Table 9 - OD Pairs, Optimal Routes and Expected TT

Origin	Destination	Optimal Route	Expected Travel Time
1	8	{ 1 -> 2 -> 5 -> 8 }	42,03
1	9	{ 1 -> 4 -> 7 -> 9 }	40,42
1	10	{ 1 -> 4 -> 10 }	42,68
2	8	{ 2 -> 5 -> 8 }	28,73
2	9	{ 2 -> 5 -> 6 -> 9 }	42,78
2	10	{ 2 -> 5 -> 8 -> 10 }	43,45
3	8	{ 3 -> 6 -> 8 }	26,94
3	9	{ 3 -> 6 -> 9 }	28,17
3	10	{ 3 -> 6 -> 9 -> 10 }	42,64

4.3.1.6. Input data

A synthetic population consisting of 4001 agents were created, where each agent is characterised by a number of attributes denoting departure, arrival time and mode preferences, plus some other socio-economical features such as its monthly income. Each agent has an initial activity-travel schedule that considers expected departure and arrival travel times. The travel times are given by a normal distribution function, which give a rush hour peak between 8h30m and 9h30m in the morning.

4.3.1.7. Submodels

In this implementation, we have several different sub models for the artificial society behaviour.

In the system behaviour, we have the functions to update the scores, to update the predictors, to measure travel time and to predict the road to use. Those models were describe and discussed in the section 4.2.1 of the current chapter. They act as the travel decision-making process.

However, this implementation, being a multi-modal transit network, has to deal the mode-choice decision-making process. As in the framework presented at chapter 3 here each agent/commuter has a utility function. Then they choose the mode maximizing their own utility. These utility functions are based on presented before, however with small changes. Being this a implementation where time is not seen as in microscopic way as the first implementation (where each step of the model represent a minute, here each step represent a period of time) the utility function had to be updated.

The PR-mode and PT-mode utility function goes as follows:

$$U_{private}^{j} = \sum_{i=1}^{n}\left[(\alpha_{time} * (ETT - PTT)) + \left(\alpha_{cost} * \left(\frac{private_{costs}}{income}\right)\right) + \left(\alpha_{time_{pollution}} * (ETT * PF)\right)\right] \tag{25}$$

$$U_{public}^{j} = \sum_{i=1}^{n}\left[(\alpha_{time} * (ETT - PTT)) + \left(\alpha_{cost} * \left(\frac{public_{costs}}{income}\right)\right) + \left(\alpha_{confort} * \left(\frac{BC}{EBC}\right)\right)\right] \tag{26}$$

Where, *ETT* is the expected travel time, *PTT* is the previous travel time, *PF* is the pollution factor, *BC* is the bus capacity and *EBC* is the expected bus capacity. With this utility function, we believe we define a set of utility based on travel time, costs and social interaction.

We decided to create a utility function that will account for the total system utility. This utility, *world-utility*, will be used to measure and compare the population satisfaction with the policies. The world-utility works as basic sum of both private and public utility.

$$U_{world} = \sum_{i=1}^{j}\left[U_{private}^{j} + U_{public}^{j}\right] \tag{27}$$

4.3.2. Initial Setup

In this section, we will go thought the setup we chose. Therefore, we decided to create an artificial society, we performed a sensitivity analysis in the network behavioural parameters (learning-factor, number of predictors and history-size) and the population behavioural parameters (utilities). Moreover, we explain in detail the policies we decided to implement in this setup.

4.3.2.1. Population

In **Table 10** we can find more social and location information about the population.

Table 10 - Population by Origin-Destination

OD Matrix - Income Distribution				
	8	9	10	Avg.
1	46,32	45,17	44,74	45,37
2	45,22	44,45	44,74	44,79
3	44,94	45,68	44,03	44,86
Avg.	45,48	45,09	44,50	45,01

OD Matrix - PT accessibility				
	8	9	10	Total
1	404	0	463	867
2	415	0	0	415
3	431	0	0	431
Total	1250	0	463	1713

OD Matrix - Trips				
	8	9	10	Total
1	404	460	463	1327
2	415	470	450	1335
3	431	435	473	1339
Total	1250	1365	1386	4001

OD Matrix - Desired Travel Time					
Origin	Time	8	9	10	Total
1	1	69	106	104	279
	2	80	95	85	260
	3	77	84	90	251
	4	67	80	103	250
	5	111	95	81	287
Total		404	460	463	1327
2	1	96	112	83	291
	2	71	86	93	250
	3	81	99	85	265
	4	83	100	82	265
	5	84	73	107	264
Total		415	470	450	1335
3	1	92	96	108	296
	2	93	80	79	252
	3	77	73	98	248
	4	87	95	99	281
	5	82	91	89	262
Total		431	435	473	1339
		1250	1365	1386	4001

As it can be noticed, the population is equality distributed by all origins and destinations nodes. The income, accessibility (when exists) is also distributed equality. We had a procedure in the model to ensure this homogeneity, so when we run the policies when do not have the problem of zoning in our analysis. It will have another complexity and "noise" to the results.

The time O-D matrix was also developed within the procedure, which distribute equally the commuters by desired time but has to be analysed in a different way. By assigning the commuters at time 2, 3 and 4, we simulate a peak demand. Because when agents that leave the origin node at time 2 will be influenced by the commuters that leave at time 1, and so on. However, when commuters leave at time 5 commuters that leave at time 1, 2 and 3 had already arrived at the destination node.

4.3.2.2. Behavioural Parameters

The control parameters α and β are set to 1 and 2, respectively. This is the standard parameters of the BPR function (Bureau of Public Roads, 1964).

We decided to make a sensitivity analysis in order to detect, if they exist, changes in travel time and mode choice. This is can be seen as a part of verification and validation discuss at section 2.3.3 part b.

In **Table 11**, the results for the system behavioural parameters are shown. The basic assumption is num-predictors = 2, history-size = 3 and learning-factor = 0.1, and then for each parameter we perform some variation.

Table 11 – System parameters analysis

Variables	Average Utility PR	Average Utility PT	Average Travel Time
History-Size 2	1,89	2,72	34,15
History-Size 5	2,14	2,95	33,72
History-Size 8	1,98	2,82	35,53
Learning 0.1	1,95	2,76	35,17
Learning 0.5	2,00	2,82	33,24
Learning 0.9	1,94	2,79	32,49
Num-Predictors 2	1,94	2,72	27,49
Num-Predictors 6	1,94	2,75	27,49
Num-Predictors 10	1,94	2,75	27,49
Average	1,97	2,78	31,86

This analysis shows different travel times for each variable. However, these changes are not relevant due to the decrease of computational performance. This is a relevant topic. The difference between running the model with history-size = 2 and history-size = 8 is enormous, because as shown before those parameters are computed in the N^m way, so for num-predictors = 10 and history-size = 3 the size of information will be 1000 (10^3) parameters instead of 8 (2^3) , when num-predictors = 2. We have the same conclusions as Galib and Moser in their implementation. Therefore, with these results we will use the set of parameters consisting of: history-size = 3, learning-factor = 0.1 and num-predictors = 2.

We decided to run the same test but this time in order to test the utilities parameters. Here the results are different and the observation but be deconstructed. **Table 12** shows the utilities sets to be analysed and **Table 13** shows the results for that analysis.

Table 12 – Set of Utilities to Run the Parameters Analysis

	PR utility			PT utility		
Set	α_time	α_cost	α_pollution	α_time	α_cost	α_confort
1	0,3	-0,3	-0,3	0,3	-0,3	-0,3
2	0,5	-0,5	-0,5	0,5	-0,5	-0,5
3	0,6	-0,4	-0,2	0,6	-0,4	-0,2
4	0,2	-0,4	-0,6	0,2	-0,4	-0,6
5	*random*	*random*	*random*	*random*	*random*	*random*

Table 13 - Utilities Parameters Analysis

		Number of Commuters	Average Utility PT	Average Utility PR	Average Travel Time
Set 1	PR	2288		2,54	33,86
	PT	1713	1,87		36,91
	Total	4001	2,76	1,95	35,17
Set 2	PR	2213		3,62	32,20
	PT	1788	3,56		35,05
	Total	4001	4,37	3,07	33,47
Set 3	PR	2213		5,86	32,25
	PT	1788	4,77		34,99
	Total	4001	5,69	5,16	33,47
Set 4	PR	2213		-0,13	32,25
	PT	1788	0,98		34,99
	Total	4001	1,28	-0,26	33,47
Set 5	PR	2815		3,91	32,77
	PT	1186	5,27		33,81
	Total	4001	4,60	3,15	33,08

We decided to create those sets of utilities to show that different margin utilities values can influence the model performance.

In the set 1 and 2, we select this combination in order to represent a homogenous society. In this range of values we define them as the standard, making the values to compare in future. We can see the average utilities are higher in set 2, PT 4.37 vs. 2.76 and PR 3.07

vs. 1.95 (see **Table 13**). We believe the difference is due to the parameters α_{time} and his weight in the utility function (α_{time}= 0.5 vs α_{time}= 0.3)

Set 3 and set 4 we created in order to simulate a utility function that reflects opposite preferences in the society. In set 3 a society of individuals with high preference time factor is confronted with a set 4 society with a lower preference time factor. We can see that this function works because the average utility PR is negative in set 4, which reflects the high weight of pollution factor.

In an opposite dimension to sets 1, 2, 3 and 4, in set 5 we created a heterogeneous society. Here, commuters have their own individual preference and so, this way makes it a more realist society as define in the theory. The results are in line with the best results, where the travel time is almost identical in PR vs PT mode.

To the first results, we decided to divide our approach in two different societies. One with a homogenous preferences population (section 4.4.1) is defined and another one with heterogeneous preferences population (section 4.4.2).

4.3.2.3. Market-Based and Incentive Based Policies

Three market-based policies where consider. An increase in the prices changes the prices of private transportation and public transportation and the third one being a mix of the previous. In this implementation, we not considered a time incentive policy because the results were not satisfying in the previous approach.

Market-based policies:

1. An increase in PR transportation (*Policy-1*) - increase in private costs in 4 units (e.g. tolls, fuel, etc.);
2. A decrease in public transportation (*Policy-2*) – reduce in fares in 1 unit;
3. Mixed policy (*Policy-3*) - a decrease in fares and an increase in PR costs at same time (*Policy-1* and *Policy-2*).

With these policies, we will test the effects in the individual utility, travel times, mode choice, and impacts in the world utility.

Impacts:

From the section in chapter 3, 3.3.1, we can recall that a split of 50% in the variable “owns a car” and another at “mode flexibility” is done. So in this implementation we decided to follow the same logic. So, in this results, the policies target will be roughly around 1000 agents.

4.4. Results

We first consider a “baseline” scenario where no policy intervention is applied. We perform a preparatory run of the model for the corresponding of six-month simulation (180 iterations of the morning rush hours).

This serves to establish the ratio of commuters distributed between the two modes along the departure time interval. We can consider that during this period the agents' ”adapt” to make the choice that maximizes their utility. During the execution of the scenario, we monitor the agents' utilities, travel times, and the pollution/crowding level for the PR and PT mode respectively.

4.4.1. First Run Results

In figures 11, 12, 13, 14, and 15 we can find the travel time distribution, the utility evolution, the travel time evolution and the world utility evolution, respectively.

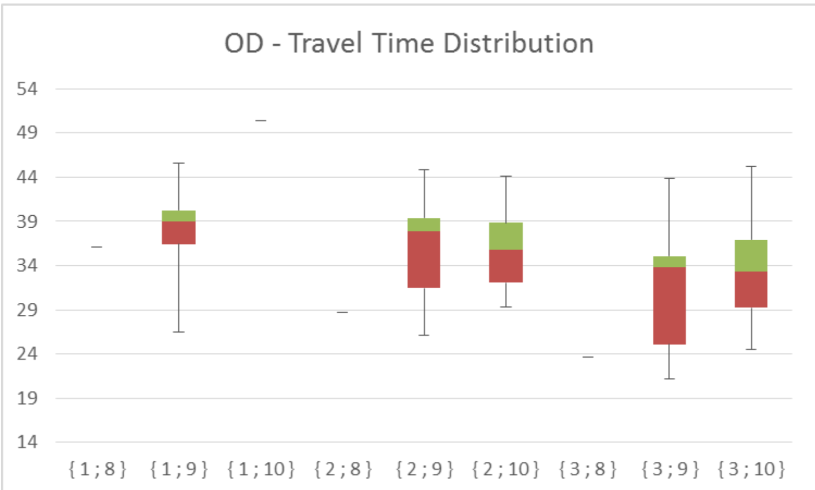


Figure 11 - Travel Time Distribution within OD pairs

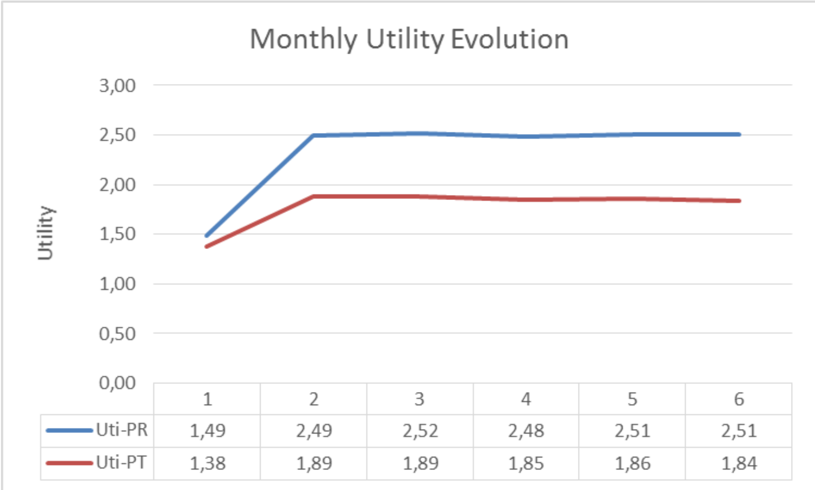


Figure 12 - Monthly utility Evolution

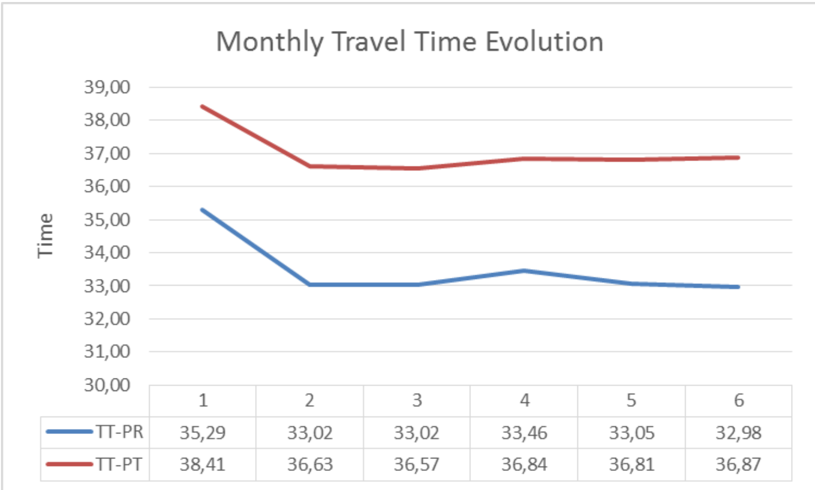


Figure 13 - Monthly Travel Time Evolution

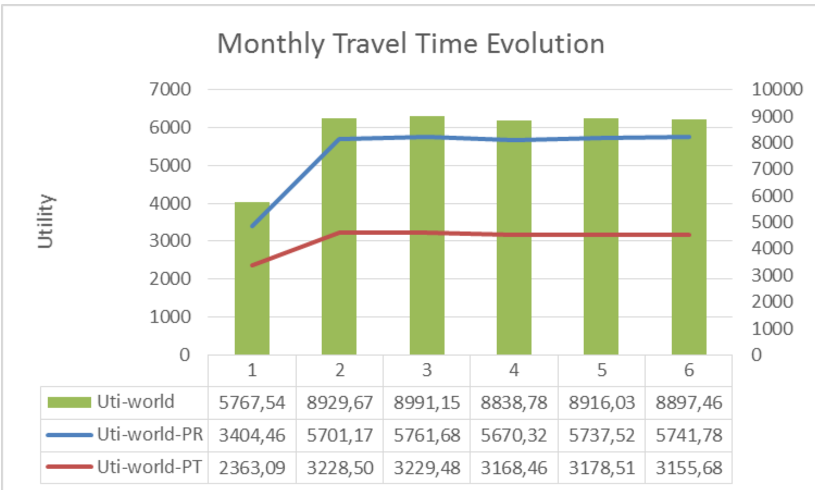
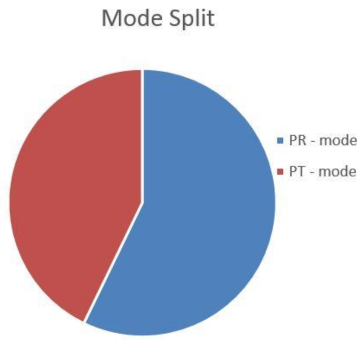


Figure 14 - Monthly Utility Evolution



PR - mode	2288	57%
PT - mode	1713	43%

Figure 15 - Mode Choice

In the first chart (**Figure 11**), the OD – Travel Time Distribution we conclude observe that in pairs 1, 3, 4 and 7, the population travel by bus therefore not having oscillation on their travel times because they travel on a fixed route. On the other hand, the commuters who travels on the others OD pairs are affected by the others commuters. Therefore, their travel times are variable. In the OD pair (3, 9), there is at least one commuter who takes almost 44 minutes to travel versus the minimum travel time registered, around 22 minutes.

In the utility graph (**Figure 12**), we noticed that during the first month the agents iterate until they reach a steady estate, where the utility is around 2.51 for the private transportation, and 1.84 for the utility transportation. The travel time (**Figure 13**) assume a slight descend curve until they stabilize at 32 minutes for PR mode and 36 minutes for PT mode. For the world utility, we observed an increase from an average of 5767 to an average of 8897. The world utility for PR mode and PT mode after first month are stable around an average of 5740 and 3166, respectively.

In **Figure 14** and **Figure 15**, we have a table and a pie chart reporting the mode split between the commuters. What we can conclude is that, and comparing to the initial population reported at section 4.3.2.1, all the commuters who have access to a public transportation line opted to enter this mode. This seems to point out that if all the agents have access to a public transportation line, all the agents will go. However, not all the commuters have access to a PT line.

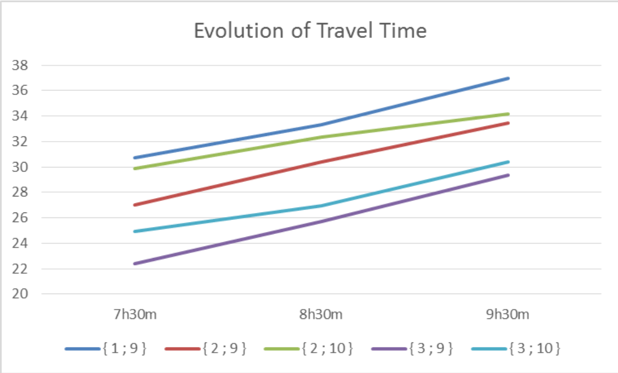


Figure 16 - Evolution of travel time – Series Example

In **Figure 16**, we can observe the rush hour forming at 8h30 until 9h30m. This is a simple example of a morning rush hour that emerges from the model. We opted to not show the all series to lack of space and it is not important to the future comparative examples.

After this, a policy is introduced and the model is executed for another 180 iterations, starting from the final iteration of the baseline scenario.

Table 14 - Policy Results

Policies	Number Commuters	Average Travel Time		Average Utility		World Utility	
PR mode	2288	34,44	100%	2,38	100%	5441,14	100%
PT mode	1713	35,06	100%	2,05	100%	3515,40	100%
Baseline	4001	34,70	100%	2,24	100%	8956,54	100%
PR mode	2288	33,19	-3,61%	2,36	-0,93%	5390,69	-0,93%
PT mode	1713	36,67	4,61%	1,86	-9,54%	3180,10	-9,54%
Policy 1	4001	34,68	-0,06%	2,14	-4,31%	8570,79	-4,31%
PR mode	2288	33,19	-3,61%	2,37	-0,29%	5425,42	-0,29%
PT mode	1713	36,67	4,61%	1,86	-9,36%	3186,47	-9,36%
Policy 2	4001	34,68	-0,06%	2,15	-3,85%	8611,88	-3,85%
PR mode	2288	33,04	-4,05%	2,51	5,61%	5746,58	5,61%
PT mode	1713	36,43	3,91%	2,64	28,71%	4524,64	28,71%
Policy 3	4001	34,49	-0,61%	2,57	14,68%	10271,22	14,68%

The consequence of the introduction of *Policy-1* vs Baseline is two-fold. On one side, the mode-split is the same. On the other hand, there is a change in travel times. We can see, at **Table 14** that a price increase in PR-Mode makes a reduction of 1% of the utility. However, we should notice that this decrease is slight inferior, as we should expect because there is the side effect of a reduction of 3.61% in travel time. This reduction of travel time can be seen as an effect of the social-utility. The commuters having their utilities reduced, by the increase of prices, started to look for better roads in order to maximize again their utilities. In this process, the average travel time is reduced. On this process they start to travel in roads were they negatively affect the PT-mode travel times (increase of 4.61%).

The consequence of the introduction of *Policy-2* vs Baseline follows the same behaviour as *Policy-1*. Nevertheless, as we can see at table 13 the impact is smaller vs *Policy-1*. In this case there is also a decrease in travel times, the roughly the same amount vs Baseline (-3.61%) but the utilities in PR-mode is the same, and in PT-mode is almost the same (-9.36% vs. -9.54% in *Policy-1*).

In the market-based *Policy-3,* we can see, compared with the baseline scenario, that there is a decrease in travel times in PR-mode, -4.05% and an increase in PT-mode, 3.91%. However, the utilities increase when compared to baseline, 5.61% PR-mode and 28.71% PT-mode. This can be explained be the changes in prices combined with the less travel time, in PR-mode, and by the decrease in prices that

In *Policy-1* and *Policy-2*, the results are equally bad, in terms of policy effectiveness. There is not a mode sift from PR-mode to PT-mode, as expected due to results in the previous implementation, presented at chapter 3, the utilities values stay almost the same and the utilities as well. Nevertheless, those results point out the need to analyse the routes/path the agents in PR-mode followed during the different policies.

In **Table 15**, we can see road usage under different policies scenarios. The roads usage 6, 9, 12, 15 and 20, can explain why under different scenarios, but same mode split and same utilities, the travel time changes. Under *Policy-1* and *Policy-2* the road, usage is the same vs. Baseline. However, under *Policy-3* we notice some agents travelling at higher density nodes changing to less density nodes. Those changes explain the values of table 13. Where at *Policy-3* the utility values are so different vs Baseline.

Table 15 - Resume of road usage in different policies scenario

Road	Capacity	Baseline			Policy 1		
		Avg. Commuters	vs. Capacity	vs.Baseline	Avg. Commuters	vs. Capacity	vs.Baseline
1	659	376,11	57,1%	-	375,16	56,9%	-0,3%
2	608	144,93	23,8%	-	145,52	23,9%	0,4%
3	723	565,00	78,1%	-	565,09	78,2%	0,0%
4	581	254,46	43,8%	-	253,37	43,6%	-0,4%
5	551	405,63	73,6%	-	405,87	73,7%	0,1%
6	638	770,56	120,8%	-	770,25	120,7%	0,0%
7	588	309,16	52,6%	-	309,67	52,7%	0,2%
8	588	382,96	65,1%	-	384,43	65,4%	0,4%
9	722	763,23	105,7%	-	760,46	105,3%	-0,4%
10	634	262,46	41,4%	-	262,37	41,4%	0,0%
11	753	399,36	53,0%	-	400,30	53,2%	0,2%
12	615	587,60	95,5%	-	587,80	95,6%	0,0%
13	792	263,70	33,3%	-	262,86	33,2%	-0,3%
14	769	311,66	40,5%	-	312,63	40,7%	0,3%
15	702	775,80	110,5%	-	776,53	110,6%	0,1%
16	786	221,66	28,2%	-	221,38	28,2%	-0,1%
17	675	559,74	82,9%	-	558,65	82,8%	-0,2%
18	699	540,00	77,3%	-	538,93	77,1%	-0,2%
19	559	270,19	48,3%	-	269,35	48,2%	-0,3%
20	559	581,73	104,1%	-	581,90	104,1%	0,0%
21	562	229,49	40,8%	-	231,10	41,1%	0,7%
22	775	324,63	41,9%	-	322,93	41,7%	-0,5%
23	617	266,39	43,2%	-	266,99	43,3%	0,2%
24	551	450,87	81,8%	-	448,97	81,5%	-0,4%

Road	Capacity	Policy 2			Policy 3			
		Avg. Commuters	vs. Capacity	vs.Baseline	Avg. Commuters	vs. Capacity	vs.Baseline	vs. Policy 1 and 2
1	659	375,16	56,9%	-0,3%	375,18	56,9%	-0,2%	0,01%
2	608	145,52	23,9%	0,4%	145,42	23,9%	0,3%	-0,07%
3	723	565,09	78,2%	0,0%	565,17	78,2%	0,0%	0,01%
4	581	253,37	43,6%	-0,4%	254,18	43,7%	-0,1%	0,32%
5	551	405,87	73,7%	0,1%	406,47	73,8%	0,2%	0,15%
6	638	770,25	120,7%	0,0%	768,85	120,5%	-0,2%	-0,18%
7	588	309,67	52,7%	0,2%	310,03	52,7%	0,3%	0,12%
8	588	384,43	65,4%	0,4%	384,18	65,3%	0,3%	-0,07%
9	722	760,46	105,3%	-0,4%	760,97	105,4%	-0,3%	0,07%
10	634	262,37	41,4%	0,0%	262,84	41,5%	0,1%	0,18%
11	753	400,30	53,2%	0,2%	400,65	53,2%	0,3%	0,09%
12	615	587,80	95,6%	0,0%	587,91	95,6%	0,1%	0,02%
13	792	262,86	33,2%	-0,3%	262,88	33,2%	-0,3%	0,01%
14	769	312,63	40,7%	0,3%	312,91	40,7%	0,4%	0,09%
15	702	776,53	110,6%	0,1%	775,16	110,4%	-0,1%	-0,18%
16	786	221,38	28,2%	-0,1%	221,75	28,2%	0,0%	0,17%
17	675	558,65	82,8%	-0,2%	558,86	82,8%	-0,2%	0,04%
18	699	538,93	77,1%	-0,2%	539,06	77,1%	-0,2%	0,03%
19	559	269,35	48,2%	-0,3%	270,28	48,4%	0,0%	0,34%
20	559	581,90	104,1%	0,0%	581,73	104,1%	0,0%	-0,03%
21	562	231,10	41,1%	0,7%	230,99	41,1%	0,7%	-0,05%
22	775	322,93	41,7%	-0,5%	322,91	41,7%	-0,5%	-0,01%
23	617	266,99	43,3%	0,2%	267,10	43,3%	0,3%	0,04%
24	551	448,97	81,5%	-0,4%	448,99	81,5%	-0,4%	0,00%

4.4.2. Experiments with a Heterogeneous Population

Since the results on the previous section were not good, we decided to run the model using the set of utilities *random*. This intends to create a heterogeneous population. Performing this analysis and then applying two simple policies we intend to understand the way a more realistic artificial population perceives and evaluate a public policy. We decided to simplify the policies to run in order to simply the output.

The basic population is the same described in section 4.3.2.1, however with the set of utilities set to *random*. The policies used are following:

1. *Policy-1* – increase in private transportation costs
2. *Policy-2* – decrease in private transportation costs.

We intended to simply the policies in order to understand it they an impact and which is the amount impact. We intended to create two public policies in a opposite way to see if that kind of policy reflects in the commuters mode-choice, travel times and utility evaluation.

Table 16 – Mode-Choice Results

Policies	PR-mode		PT-mode		Total
	Total	vs. Baseline	Total	vs. Baseline	
Baseline	2815	100%	1186	100%	4001
Policy 1	2813	-0,07%	1188	0,17%	4001
Policy 2	2840	0,89%	1161	-2,11%	4001

In **Table 16** we can find the output regarding the mode-choice. Those results are in line with the ones results found at chapter 3. An increase in private transportation costs lead to a reduction of -0.07% (2 commuters) in PR-mode. Those results are not significant in terms of quality but show that a heterogeneous population respond to a public policy. The evolution of the commuters' mode-choice can be seen at **Figure 17**.

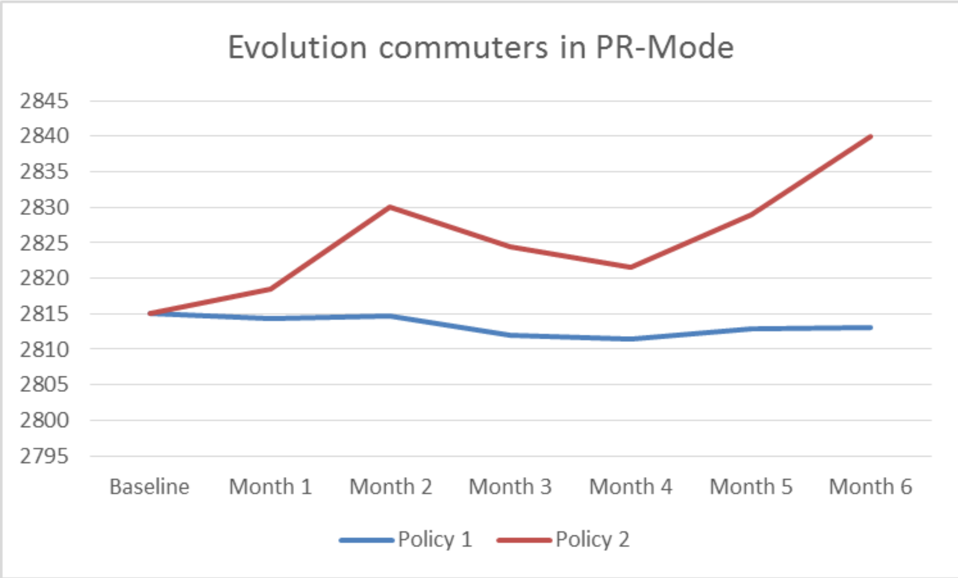


Figure 17 - Evolution Commuters in PR-mode

Table 17 - OD – Pairs travel times under different public policies

	OD - Pair								
Policies	1	2	3	4	5	6	7	8	9
Baseline	35,87	34,89	41,25	30,73	34,88	34,61	24,44	28,47	32,06
Policy 1	35,17	34,84	41,16	30,01	34,74	34,41	24,82	27,52	32,30
Policy 2	36,12	34,93	41,22	30,69	35,06	34,69	24,22	29,41	31,97
Average	35,72	34,89	41,21	30,48	34,89	34,57	24,49	28,47	32,11

In the **Table 17**, we find the results of average travel time. Here the results are unclear, and we should analyse instead an evolution chart found at **Figure 18**. There we can see clearly that an increase in costs, lead to a mode-shift from PR-mode to PT-mode and that way there is a decrease in travel time for PR commuters. During *Policy-2*, a decrease of cost in PR-mode, we can see an increase in travel time, due to the high road usage.

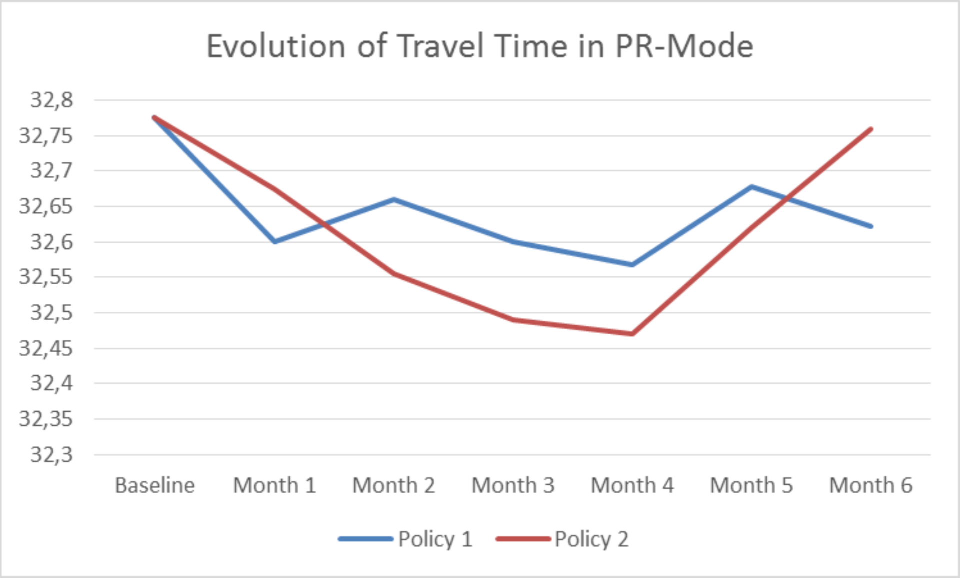


Figure 18 - Evolution of Travel Time in PR-mode

In **Figure 19** we can find the evaluation of the utility in PR-mode. Those results are in line with the previous results. Under *Policy-1*, the results increase from 3.9 to 4.05 but comparing to Policy-2, the results are less 0.05 (4.1). These results are explained in one hand to the high road usage, which leads to a decrease of travel times and the increase in costs, which reflects negatively in the utility evaluation.

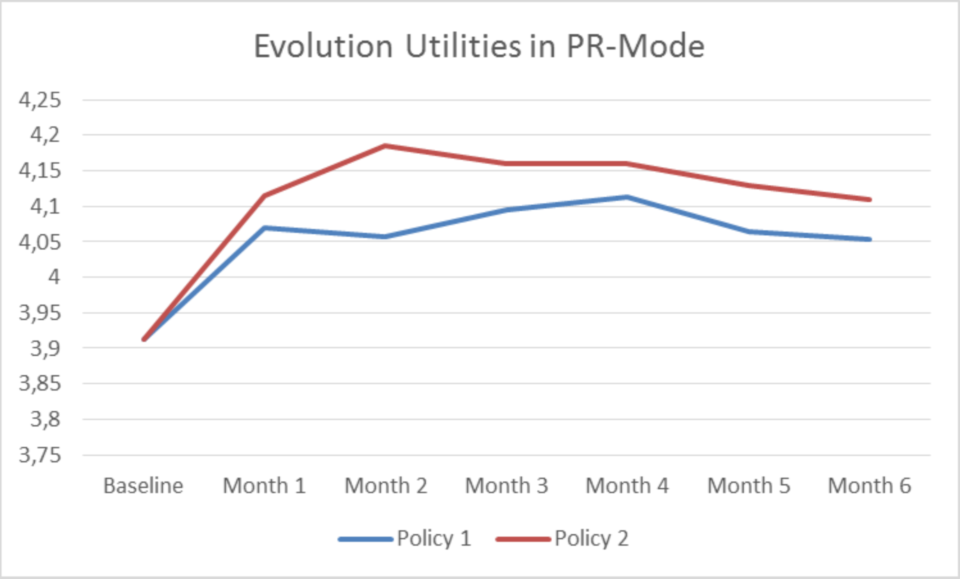


Figure 19 - Evolution Utility in PR-Mode

4.5. Summary

In this chapter, we discuss the implementation of a multimodal and multi-paths transportation network, based in the framework presented at Chapter 3.

In order to represent this network we had to implement a robust traffic assignment model. We decided to opt a traffic assignment model using an iterative game. This model was able to deal with traffic problems and to assign the traffic properly. However, the agents' we not able to distribute evenly in the network as seen in **Table 15**. Those phenomena emerge because the model may need more iterations and a better exploration tool so the agents explore all the possible paths.

In these policies, we conclude that market-based policies are not effective, in this illustration, in a homogenous population in terms of modal-sifts, so they just had inefficiency in a social perspective way, by reducing the utility. On the other way, because agents look at the traffic assignment modal in a self-organization way, they react to the price changes by changing their /routs. Doing that, they often find better ways to reach a new equilibria and so lower travel times.

What we can conclude from this illustrative example is that the transportation planners should anticipate both positive and negative effects of a market-based or an incentive based policy. Trying to achieve a behavioural shift in mode choice needs to be followed by proper investments, and policies that not only deal with monetary incentives but rather incentives that lead to a change in population behaviour (incentives that during the iteration process changes the values of the margin utilities).

Chapter 5 – Conclusions and Future Work

5.1. Final Discussion

Transportation systems should be considered in an integrated manner, due to their properties related to complex systems. ATS seems a promising effort towards this direction. However, much more work needs to be done to advance the research on ATS. The key issues in the development of ATS include modelling, experimenting, decision-making, and computing. This dissertation is only a beginning step in the direction of solving those issues.

The first step, modelling using the agent metaphor, provides a reasonable and promising approach to transportation analysis in many different aspects of transportation systems, as the results of this research illustrate. Specifically, we use a method of bottom-up modelling in which individual behaviour emerges in the system-level behaviour. The system-level behaviour may also be easily observable, but the links between the individual and system-level behaviour are not. This point is the most important aspect of the contribution of ABM in transportation area.

The second step, experimenting, in ABM transportation is a relevant topic. Although domain experts are an important part of the modelling process, whether it is possible to obtain real data or not, experimenting with different parameter selection is necessary. In this dissertation, we do not use any real data, just an artificial society, so experimenting was a big issue. In the first implementation, in chapter 3, we select some random values for the parameters but we did not perform a sensitivity analysis. We decided based on the size of the model we had, since using two routes is a small network. Nevertheless, in chapter 4, we perform a sensitivity analysis in order to detect and understand changes in the output. In own analysis we detect that using a homogenous or a heterogeneous population regarding parameters selection makes a real difference in the output, as seen in results in section 4.4.. Using the ODD protocol to describe and detail the model also helped in performing different experiments in the same model, because it makes easy to reproduce and implemented the same simulation in different environments and computers.

The third step, decision-making in transportation area, is a tricky topic. In order to achieve a good decision making process, we use utility function we each individual commuters tries to maximize their own utility. We developed utility function regarding time, costs and social aspects in order to achieve an individual decision-making that is heterogonous. However, transportation choice-mode is often a result of other social dimensions, like education, social-networks, physical wellbeing, and so on. Nevertheless, to integrate this kind of social dimensions in a transportation decision-making process we need a more comprehensive collection of data regarding social and demographic. Among the possible sources to collect mobility related data are the GPS logs (Freitas, Coelho, & Rossetti) and tweeter messages (Carvalho S. F., 2010), (Carvalho, Sarmento, & Rossetti, 2010)

In this dissertation, we use a simpler and straightforward utility function. We can conclude that transportation choices are influenced by income, costs, time-to-destination, comfort, pollution and waiting-time. Moreover, our conclusion suggests that in organized societies, the implementation of measures with effects on the welfare distribution tends to be complicated due to low public acceptance. This low public acceptance, can be seen in chapter 4, were the agents do not "accept" the rise in transportation cost, and so they do not make mode shift, and in consequence try to achieve a new equilibrium searching for a new route or a new time sift. In a more human level, the social effects of a policy-making can be seen as a problem of trading off between equity and efficiency. An equity problem can be understood (see chapter 3 and 4), when we run policies and the utility increase in one side, commuters who travel in PT-mode, but decreases in commuters in PR-mode on the other side. So a policy that in fact makes the system more efficient (faster travel times) can be, on the other hand, inequity (reduce the utility for some groups). This goes in line with the work of Van Wee (Wee, 2009), explained in detail in Chapter 2 section 2.4.1, where he states that there are six aspects of policy intervention into the decision-making process. If the policy is effective, efficiency, equity, flexible, ease of implementation, and as a long-term robustness.

Another point to emphasise is the findings at the human-level behaviour. In policy making, the agent who makes and plans the decision should take into account that just implementing a one-shot policy in a price, or time incentive, may have diverse effects, causing it to be not accepted or perceived in a bad way. So, the policies should be made in order to change behaviour in long-term introduction nothing new. Policy that changes the utilities parameters are seen as more effective, because the agents tend to learn a new behaviour rather than deal with a different reality.

In the last point, computation is a key issue. The computation phenomenon arises in the 80s and during that time ABM arises too as tolls to combine theoretical models and practical models. In the transportation area, there are different software and programming languages used to compute traffic and network models. However, this traditional software lack in collecting individual social data and information about the individuals that travel in that network, they rather focus on travel behaviour.

Other social sciences simulation tools can be seen as software to collect and understand social phenomena. In this context, NetLogo was created. NetLogo let the user program, define individual parameters, and observe what emerges from a social interrelation. New software tools like MATSim and others are built in order to capture these social aspects while recording the transportation properties from the traditional model. In our approach, we used NetLogo, because NetLogo design only in a social and collective perspective but we implemented the traditional FSM on top.

For a final remark we should say that this framework for social-transportation simulation tool in ATS will be continue to be developed with a timeline defined in the next section, future works.

5.2. Future Work

For future work, we will consider a more realistic large-scale network and demand to better study the performance of the transportation system under various traffic policies. The agent-based ecosystem is the environment where artificial societies grow and breed. Consequently, we will see if a more complex social interaction where some complex phenomena emerge. Such artificial society can be used to design solutions based on individual or social intelligence and participation (social-awareness), or as a test-bed for policy and incentive mechanisms evaluation.

A more realistic large-scale network should use and handle real data. We already have the census data from the Greater Metropolitan Area of Porto (English for: Grande Area Metropolitana do Porto – GAMP) and we will use them as an input that from as artificial society (see appendix C, table 17). The data is open-source and we can find the data in *Instituto Nacional de Estatística* (INE) website[1].

A more complex society can require a different decision making process. A new decision-making process means that one should develop a new utility function. This function must capture social aspects and variables in a realistic way. In this process, the model will need to be more robust in order to support a longer simulation run.

Moreover, the network will need to adapt to new links or new bus lines during the iteration. A methodology in order to create a cost/benefit analysis needs to be implemented. With this cost/benefit analysis one can test several policies where the objective is to realize which of them offers the best trade-off between efficacy and equity in the ATS.

This dissertation used the bottom-up modelling and simulation strategy. This is the method used throughout the literature in order capture the social phenomena. However, different approaches can be used in order to capture the policy-making advisor strategy, i.e., using an up-bottom down modelling. This way, the policies can be modified on the fly in order to satisfy the user-satisfaction.

[1] http://censos.ine.pt/

Appendix

Appendix A

1. The ODD discussion

The ODD protocol is not immune to complaints but on the other hand as emergent benefits, that can be important in the future of Multi-Agent Systems. In this part it is described the main complaints and the benefits (Grimm V. , et al., 2010).

a. Complaints about ODD

1. ODD can be redundant

Three elements of ODD were noted as being sources of redundancy. The first is the Purpose because usually it is described in the papers introduction. The next, Design Concepts is included in the submodels descriptions. The last one is the Submodels because they are described in the Process Overview and Scheduling. The main problem and the main excuse for this redundancy is the use of a strong hierarchal structure of the ODD which is very important for the high methodological level of the ODD protocol.

2. ODD is overdone for simple models

ODD is overdone for simple models in a way that some ABM models are so simple that describing them in an ODD protocol is impracticable. A way to overpass this problem is to have a shorten version of the ODD and just use some parts of the ODD.

3. ODD separates units of object-oriented implementations

The object-oriented programming (OOP) is currently the natural platform for implementing ABMs. Unfortunately, the ODD protocol requires the proprieties and methods to be presented separately. The main excuse for this criticism is that ODD was developed as a language independent protocol and what it means it that any language can be incorporated in an ODD protocol, it just a question how it is made. Nevertheless, the ODD recommends to use a Unified Modelling Language (UML) to describe the model but still the ODD was designed to be language free.

b. Emergent benefits of ODD

1. ODD promotes rigorous model formulation

The ODD protocol represents a natural and logical way to describe a model. A detailed formulation for every Submodels must be given as well as formulation of the model's purpose, entities and state variables high level description. Combined that with the natural and logical way to describe models we find that ODD must be on the future the standard in describing ABMs.

2. ODD facilitates reviews and comparisons of ABMs

The models that are described in the ODD format have a review of their purpose, scales, structure, and process formulation are very simplified. This just facilitates reviews and comparisons because one can pick up the corresponding parts together in a table and scans for similarities and differences.

3. ODD may promote more holistic approaches to modeling and theory

In social sciences a big problem is that sometimes the theory is disperse and not clearly put together in models. The ODD protocol is one way to allow the theoretical aspects of these models to be articulated more clearly, and also for the important theory gaps to be visible. Wide use of the updated ODD protocol would thus facilitate approaches and theory which are holistic in the sense that they link levels of organization, different case studies, and possibly even different disciplines.

Appendix B

1. NetLogo Code for Chapter 3 Model and a Screen Shot

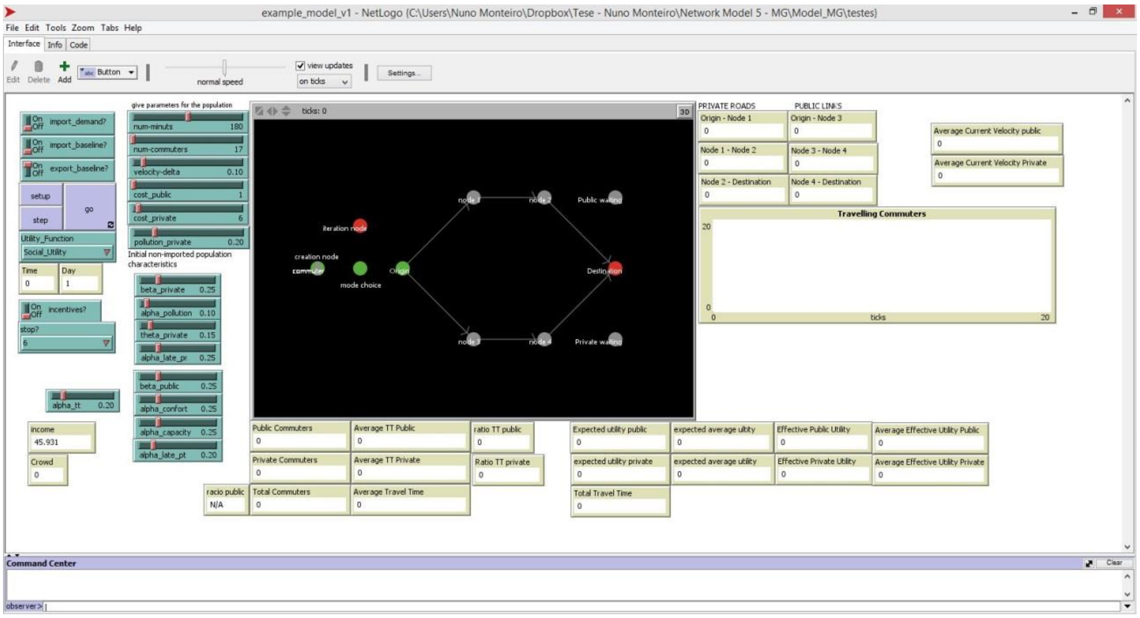


Figure 20 - Screenshot - Model Chapter 3

```
globals [
  crowdness
  ratio_tt_public_sum
  ratio_tt_private_sum

  effective_utility_public_avg
  effective_utility_private_avg
  effective_utility_public_sum
  effective_utility_private_sum
  expected_utility_public_avg
  expected_utility_private_avg
  expected_utility_public_sum
  expected_utility_private_sum
  plot_speed
  plot_commuters_public
  plot_commuters_private
  day
  average_tt_public
  average_tt_private
  inter-arrival-time
  flag ;; flag that setup if the agents are created of not.                                        ;;state
  travel_time_cars ;;procedure "calculate_time_travel_commuters" -> setups the total travel time done by cars
;;state
  time ;; setups a simple timer by tick needed to count the time of entrance of each vehicule. Ticks counter is a list not good.
;;random
  cont-ticks-poisson ;; tempo de entrada for each commuters                                        ;;
  ticks-poisson ;; tempo de entrada for each commuters


  total_commuters ;; a simpler counter to count how many commuters are created in the origin node
  total-commuters-private ;; a simpler counter to count how many red  commuters are created in the origin node
  total-commuters-public ;; a simpler counter to count how many public commuters are created in the origin node

  total_inicial ;; a simpler counter to count how many commuters are created in the origin nod
  total-inicial-private ;;a simpler counter to count how many private  commuters are created in the origin node
  total-inicial-public ;;a simpler counter to count how many private  commuters are created in the origin node

  $list ;; creates a list for all agents that were created
```

$list-private;; creates a list for all private agents that were created
$list-public ;; creates a list for all public agents that were created

;;;;;;;;;;;;
travel_time_initial_general ;; set a counter to know what is the time of entrance
travel_time_final_general ;; set a count to know what is the time of exit

travel_time_initial_public ;; set a counter to know what is the time of entrance
travel_time_final_public ;; set a count to know what is the time of exit

travel_time_initial_private ;; set a counter to know what is the time of entrance
travel_time_final_private ;; set a count to know what is the time of exit
;;;;;;;;;;;;;;;;

travel_time_final_2

count_initial_general ;; creates a list of the total_inicial time travel
count_final_general ;; creates a list of the total_final time travel

count_initial_public ;; creates a list of the total_inicial time travel
count_final_public ;; creates a list of the total_final time travel

count_initial_private ;; creates a list of the total_inicial time travel
count_final_private ;; creates a list of the total_final time travel

temp_1_public ;;creates list to count travel time
temp_2_public ;;creates list to count travel time
temp_3_public ;;creates list to count travel time

temp_1_private ;;creates list to count travel time
temp_2_private ;;creates list to count travel time
temp_3_private ;;creates list to count travel time

temp_1_general ;;creates list to count travel time
temp_2_general ;;creates list to count travel time
temp_3_general ;;creates list to count travel time

contagem_public ;;creates list to remove duplicates in temp_2_public
contagem_private ;;creates list to remove duplicates in temp_2_private

total_inicial_2 ;; creates the sum of the $count_inicial
total_final_2 ;; creates the sum of the $count_final

avg_travel_time ;;the variable that return the average travel time for all the agents
avg_velocity_public ;; the variable that returns the average velocity of all agents currently in the network
avg_velocity_private

count-node-1 ;; counts agents in origin node
count-node-2 ;; counts private agents in origin node
count-node-3 ;; counts public agents in origin node

list_velocity_public ;;creates list to count velocity public
list_velocity_private ;;creates list to count velocity private

road_1 ;; counts agents at road 1
road_2 ;; counts agents at road 2
road_3 ;; counts agents at road 3
road_4 ;; counts agents at road 4
road_5 ;; counts agents at road 5
road_6 ;; counts agents at road 6

```
  road_capacity_1  ;;set ups the max capacity for road  1
  road_capacity_2  ;;set ups the max capacity for road  2
  road_capacity_3  ;;set ups the max capacity for road  3
  road_capacity_4  ;;set ups the max capacity for road  4
  road_capacity_5  ;;set ups the max capacity for road  5
  road_capacity_6  ;;set ups the max capacity for road  6

]

breed [nodes node]
breed [commuters commuter]
directed-link-breed [roads road]

roads-own [ ;;;trabalhar
  capacity
  free flow
  ]

commuters-own [
  commuter-id
  to-node  ;; set up the next node for each agent
  from-node ;; set up the previous node for each agent
  current-node  ;; show the current node for each agent. if agent is on road returns 0
  v  ;; current velocity for each agent
  expected_tt_private
  expected_tt_public
  inicial
  inicial_iteration
  desired_departure ;;tempo de partida desejado
  desired_departure_iteration
  desired_arrival ;;tempo de chegada desejado (ainda sem uso)
  tempo_inicial ;;conta o tempo de partida efectivo
  tempo_final ;; conta o tempo de chegada efectivo
  tempo_de_viagem ;; dif entre tempo_inicial e tempo_final
  income
  mode ;;escolha do modo de
  own_car
  mode_flexibility
  new_mode
  bus_capacity
  expected_capacity
  crowd_public
  expected_waiting_public
  effective_waiting_public
  ratio_tt_public
  ratio_tt_private
  moving_time
  commuters_bus_stop
  can_go
  go_now
  velocidade_acumulada ;;velocidade acumulada (para calculo de vel média por agente) (ainda sem uso)
  hour_stamp
  ;;utilities
  expected_utility_private
  expected_utility_public
  effective_utility_private
  effective_utility_public
  ]

nodes-own[
  node_id
  flag_roads        ;; flag to distinguish public roads from private roads
  ]
```

```
to setup
  clear-all reset-ticks
  set velocity-delta 0.1        ;; set ups a random increase of velocity for each agent so the agents have a random velocity
  ask patches [set pcolor black]

  if export_baseline? [ export-world "baseline-no-training-5-days.csv"]


  ;import-network              ;;imports a network (not working)
  create-network               ;;creates  network
  create_road_capacity         ;;creates roads capacity
  ifelse import_baseline? [ import-world "baseline-training-5-days.csv"] [create-demmand  set day 1]
  set-default-shape commuters "person"


  set flag true

  set $list []
  set $list-private []
  set $list-public []

  set count_initial_general []
  set count_final_general []

  set count_initial_public []
  set count_final_public []

  set count_initial_private []
  set count_final_private []

  set temp_1_public []
  set temp_2_public []
  set temp_3_public []

  set temp_1_private []
  set temp_2_private []
  set temp_3_private []

  set list_velocity_public  []
  set list_velocity_private []


end

to create_road_capacity
  ;;PRIVATE roadS;;
  set road_capacity_1  150
  set road_capacity_2  150
  set road_capacity_3  150

  ;;PUBLIC roadS;;
  set road_capacity_4  150
  set road_capacity_5  150
  set road_capacity_6  150

end

to create_road_volumes

  ;;creates the speed for each driver on each road according to the current conditions in the road.
  ;; Creates the BPR function
```

```
 ;;;;;;PRIVATE roadS;;;;;;

 ask (commuters with [current-node = node 6]) ;;Private roads
    [if (to-node = node 3)
      [if (road_capacity_1 - road_1 < 0) [set v 0.5 + random-float velocity-delta]

       if (road_capacity_1 - road_1 > 20 and road_capacity_1 - road_1 <  50 )  [set v 0.7 + random-float velocity-delta]
       if (road_capacity_1 - road_1 > 50 and road_capacity_1 - road_1 < 150 )  [set v 0.8 + random-float velocity-delta]

       ]]

  ask (commuters with [current-node = node 3]) ;;Private roads
    [if (to-node = node 2)
      [if (road_capacity_2 - road_2 < 0) [set v 0.5 + random-float velocity-delta]

       if (road_capacity_2 - road_2 > 20 and road_capacity_2 - road_2 <  50 )  [set v 0.7 + random-float velocity-delta]
       if (road_capacity_2 - road_2 > 50 and road_capacity_2 - road_2 < 150 )  [set v 0.8 + random-float velocity-delta]
       ]]


 ask (commuters with [current-node = node 2]) ;;Private roads
    [if (to-node = node 1)
      [if (road_capacity_3 - road_3 < 0) [set v 0.5 + random-float velocity-delta]

       if (road_capacity_3 - road_3 > 20 and road_capacity_3 - road_3 <  50 )  [set v 0.7 + random-float velocity-delta]
       if (road_capacity_3 - road_3 > 50 and road_capacity_3 - road_3 < 150 )  [set v 0.8 + random-float velocity-delta]
       ]]

 ;;;;;;PUBLIC roadS;;;;;;


  ask (commuters with [current-node = node 6]) ;;CCL
    [if (to-node = node 5)
      [set v 0.6]
       ]
 ask (commuters with [current-node = node 5]) ;CCL
    [if (to-node = node 4)
      [set v 0.6]
       ]

 ask (commuters with [current-node = node 4]) ;CCL
    [if (to-node = node 1)
      [set v 0.6]
       ]
end

to import-network
 set-default-shape nodes "circle"

 file-open "nodes.txt"
 while [not file-at-end?]
 [
  let items read-from-string (word "[" file-read-line "]")
  create-nodes 1 [
    set node_id     item 0 items
    set size        item 1 items
    set color       item 2 items
    set xcor        item 3 items
    set ycor        item 4 items
    set label       item 5 items
    set flag_roads  item 6 items

  ]
```

```
 ]
 file-close


 file-open "links.txt"
 while [not file-at-end?]
 [let items read-from-string (word "[" file-read-line "]")
   ask get_node (item 0 items)
   [create-road-to get_node (item 1 items) ]
 ]
 file-close
end

to create-network
   set-default-shape nodes "circle"
   ;;create node 0 node 0
   ask patch 0 0 [sprout-nodes 1 ]
   ask node 0 [hide-turtle]
   ;;create Destination Node node 1
   ask patch 20 5 [sprout-nodes 1
   [ if count nodes > 1 [
    set label "Destination"
    set color red
    set size 1]]]
;;;;; Private Network roads ;;;;;;
 ;;create node 2
   ask patch 15 10
   [sprout-nodes 1
    [if count nodes > 1 [
     create-road-to node 1
      set label "node 2"
      set color grey
      set size 1
      set flag_roads 1]]]
  ;;create node 3
   ask patch 10 10
   [sprout-nodes 1
    [if count nodes > 1 [
     create-road-to node 2
      set label "node 1"
      set color grey
      set size 1
      set flag_roads 1]]]

;;;;;; Public Network roads ;;;;;;
 ;;create node 4
   ask patch 15 0 [sprout-nodes 1
   [ if count nodes > 1 [
    create-road-to node 1
    set size 1
    set label "node 4"
    set color grey
    set flag_roads  2] ] ]
 ;;create node 5
   ask patch 10 0 [sprout-nodes 1
   [ if count nodes > 1 [
    create-road-to node 4
    set size 1
    set label "node 3"
    set color grey
    set flag_roads  2] ] ]
  ;;create Origin node 6
   ask patch 5 5 [sprout-nodes 1
```

```
  [ if count nodes > 1[
     create-road-to node 5 ;;road with city center
     set size 1
     create-road-to node 3 ;;road with highway
     set size 1
    set label "Origin"
    set color green ] ] ]

  ;;create creation node 7
     ask patch -1 5 [sprout-nodes 1
  [ if count nodes > 1[
    set color green ] ]]

   ;;create mode_choice 8
     ask patch 1.5 5 [sprout-nodes 1
  [ if count nodes > 1[
    set color green
     ] ] ]

     ask patch 0 6 [set plabel "creation node"]
     ask patch 2.5 4 [set plabel "mode choice"]
  ;;create waiting nodes 9
     ask patch 20 10 [sprout-nodes 1
  [ if count nodes > 1[
    set label "Public waiting"
    set color grey ] ] ]
     ask patch 20 0 [sprout-nodes 1
  [ if count nodes > 1[
    set label "Private waiting"
    set color grey ] ] ]
     ask patch 2 8 [sprout-nodes 1
  [ if count nodes > 1[

    set label "iteration node"
    set color red ] ] ]
end

to count-commuters-on-roads

  set road_1  count commuters with [to-node = node 3 and from-node = node 6]
  set road_2  count commuters with [to-node = node 2 and from-node = node 3]
  set road_3  count commuters with [to-node = node 1 and from-node = node 2]
  set road_4  count commuters with [to-node = node 5 and from-node = node 6]
  set road_5  count commuters with [to-node = node 4 and from-node = node 5]
  set road_6  count commuters with [to-node = node 1 and from-node = node 4]
end

to create_assignment
 if (desired_departure < time) [set desired_departure time + random 3]
 if (desired_departure = time) [ask commuters with [current-node = node 8 and desired_departure = time]
      [ move-to node 6 set current-node node 6 set to-node node 6 ]]
end

to mode_choice
        move-to node 8
        set current-node node 8
        set expected_tt_private  25
        set expected_tt_public  30
        set expected_capacity 25
        set expected_waiting_public 5

        if ( Utility_Function = "Social_Utility" )
            [set expected_utility_private ( (alpha_late_pr * (desired_arrival - (desired_departure + expected_tt_private) ))  +
```

```
                ( ( -  beta_private ) *  ( cost_private / income)) + ( ( - alpha_pollution ) * ( expected_tt_private  * pollution_private )))

              set expected_utility_public  ( (alpha_late_pt * (desired_arrival - (desired_departure + expected_tt_public ) ))   +  ( ( -
beta_public ) *  ( cost_public  / income))
                + ( - alpha_confort ) *( (expected_waiting_public / expected_waiting_public) + ( - alpha_capacity ) *
((expected_capacity / bus_capacity) * expected_tt_public))) ]


        ;;;;;;;;;;;;decision making process;;;;;;;;

        if  own_car = 0     [ set color yellow set label "public" set mode 1 ]
        if (own_car = 1 and mode_flexibility = 0 )[ set color red set label "private" set mode 2 if (hour_stamp = 3 and incentives?) [set
income income + 10 ]   ]

        if (mode = 0 and Utility_Function = "Social_Utility") [
        ifelse (expected_utility_private > expected_utility_public )
            [set color red set label "private" set mode 2]
            [set color yellow set label "public" set mode 1] ]

end

to iterate
   move-to node 8
   set expected_tt_private  tempo_de_viagem
   set expected_tt_public  tempo_de_viagem
   set tempo_de_viagem 0
   set current-node node 8
     ;; update costs functions
      ;; update costs functions
   set expected_capacity commuters_bus_stop
   set expected_waiting_public effective_waiting_public + 1

   if ( Utility_Function = "Social_Utility" )
             [set expected_utility_private ( (alpha_late_pr * (desired_arrival - (desired_departure + expected_tt_private) ))  +
                ( ( -  beta_private ) *  ( cost_private / income)) + ( ( - alpha_pollution ) * ( expected_tt_private  * pollution_private )))

              set expected_utility_public  ( (alpha_late_pt * (desired_arrival - (desired_departure + expected_tt_public ) ))   +  ( ( -
beta_public ) *  ( cost_public  / income))
                + ( - alpha_confort ) *( (expected_waiting_public / expected_waiting_public) + ( - alpha_capacity ) *
((expected_capacity / bus_capacity) * expected_tt_public))) ]


    ;;;;;;;;;;;;decision making process;;;;;;;;

    if  own_car = 0                        [ set color yellow set label "public"   set mode 1 set new_mode 0 ]
    if (own_car = 1 and mode_flexibility = 0 )[ set color red    set label "private"  set mode 2 set new_mode 0]
    if (own_car = 1 and mode_flexibility = 1) [ set color grey   set label "commuter" set new_mode 1 ]

    if (new_mode = 1 and Utility_Function = "Social_Utility") [
        ifelse (expected_utility_private > expected_utility_public )
            [set color red set label "private" set mode 2]
            [set color yellow set label "public" set mode 1] ]

end
to calculate_effective_utility

  set effective_waiting_public tempo_inicial - inicial
  ask commuters with [current-node = node 9 or current-node = node 10] [


              set effective_utility_private ( (alpha_late_pr * (tempo_final - (tempo_inicial + tempo_de_viagem) ))   -
                ( beta_private *  ( cost_private / income)) + ( theta_private * tempo_de_viagem ) + alpha_pollution *
pollution_private)
```

```
            set effective_utility_public  ( (alpha_late_pt * (tempo_final - (tempo_inicial + tempo_de_viagem ) ))  -  ( beta_public  *  (
cost_public  / income))
             + alpha_confort *( (effective_waiting_public / tempo_de_viagem) + alpha_capacity * (commuters_bus_stop /
bus_capacity ))) ]
end

to create-demmand

 ifelse (import_demand? )

  [file-open "pop_2.txt"
   while [not file-at-end?]
   [ let items read-from-string (word "[ " file-read-line " ]" )
    create-commuters 1
     [set commuter-id      item 0 items
      set inicial         item 1 items
      set desired_departure item 2 items
      set desired_arrival   item 3 items
      set own_car         item 4 items
      set mode_flexibility  item 5 items
      set mode            item 6 items
      set income          item 7 items
      set alpha_late_pr     item 8 items
      set alpha_late_pt     item 9 items
      set beta_private      item 10 items
      set beta_public       item 11 items
      setxy -1 5
      set color grey
      set label "commuter"
      set shape "person"
      set size 1
      set current-node node 7
     ] ]
   file-close ]

   [ create-commuters num-commuters
    [set commuter-id    ( who - count nodes + 1 )
    set inicial        time + 1 + random num-minuts
    set inicial_iteration  inicial
    if (inicial >= 0   ) and (inicial < 120 ) [set hour_stamp 1 ]
    if (inicial >= 120 ) and (inicial < 200 ) [set hour_stamp 2 ]
    if (inicial >= 200 ) and (inicial < 300 ) [set hour_stamp 3 ]

    if ( hour_stamp = 1 ) [set desired_departure  time +   1 + random num-minuts ]
    if ( hour_stamp = 2 ) [set desired_departure  time + 60 + random 40 ]
    if ( hour_stamp = 3 ) [set desired_departure  time + 120 + random 50 ]
    set desired_departure_iteration desired_departure

    set desired_arrival    desired_departure + random 50
    set mode           0
    set bus_capacity     70
    set income          20 + random-float 50
    set own_car         random 2
    set mode_flexibility random 2
    setxy     -1 5
    set color grey
    set label "commuter"
    set shape "person"
    set size  1
    set current-node node 7 ]]
end
```

```
to move

  if (to-node = nobody and color = red   )       [move-to node 9  set current-node node 9 set v 0 set moving_time 0]
  if (to-node = nobody and color = green   )    [move-to node 10 set current-node node 10 set v 0 set moving_time 0]
 ifelse (current-node = node 9 or current-node = node 10) [stop] [face to-node]

   ifelse (to-node = from-node and to-node = current-node)
       [set current-node from-node]
       [set current-node 0]
   fd min list v distance to-node
   if distance to-node < 0.001
   [ set from-node to-node
     ifelse (mode = 2)
         [set to-node min-one-of [out-road-neighbors] of to-node [flag_roads]] ;;private
         [set to-node max-one-of [out-road-neighbors] of to-node [flag_roads]] ;;public
     set current-node from-node
     if (current-node = node 6) [set tempo_inicial time set moving_time time ]
     if (current-node = node 1) [set tempo_final time set moving_time time  ]
     if (tempo_final > 0) [set tempo_de_viagem tempo_final - tempo_inicial
                    set ratio_tt_public  expected_tt_public  / tempo_de_viagem
                    set ratio_tt_private expected_tt_private / tempo_de_viagem
                    ]

     set velocidade_acumulada v


     if to-node = nobody [(set current-node node 1) (stop) ]
     face to-node]

end

to capacity_bus_stop
   set commuters_bus_stop count commuters with [current-node = node 6 and mode = 1] - 1
   set can_go 1
   set color green
   set to-node node 5
   set from-node node 6
   set current-node node 6
   set v 0.6
   set tempo_inicial time
end

to go
   set-counter
   tick
   set time time + 1
   ask commuters with [current-node = node 7 and inicial = time ] [ mode_choice ]   ;;mode_choice
   ask commuters with [current-node =  node 8 ] [ create_assignment ] ;;assign
   ask commuters with [current-node != node 6 and current-node !=  node 7 and current-node !=  node 8 and current-node !=
node 9 and current-node !=  node 10 and current-node != node 11  ] [ move ] ;;route_choice
   ask commuters with [current-node =  node 6 and color = red] [ move_red ]
   ask commuters with [current-node =  node 6 and color = red] [move]
   ask commuters with [current-node =  node 6 and color = yellow] [ capacity_bus_stop ]
   create-bus-demand
   if all? commuters [current-node = node 9 or current-node = node 10] [ask commuters [if  (ticks mod 100 = 0) and (ticks > 100)
[calculate_effective_utility go-to-iteration-procedure ]]]
   if (ticks mod 100 = 0 ) and ( any? commuters with [current-node = node 11] ) and (all? commuters [v = 0] ) [reportes]
   ask commuters with [current-node = node 11 and inicial = time] [iterate]

   if ( stop? = 6 ) [ if (day = 6) [ export-world "baseline-training-5-days.csv" stop ]]
   if ( stop? = 11 ) [ if (day = 11) [ stop ]]
```

```
   count-commuters-on-roads  ;; procedimento para a cada iteração contar os agentes nos respectivos roads
   create_road_volumes ;; procedimento para a cada iteração calcular os agentes nos respectivos roads
   calculate_total_commuters
   reportes2
   ;calculate_average_travel_time
   ;calculate_average_velocity
end
to move_red
   set color red
   set to-node node 3
   set from-node node 6
   set current-node node 6
   set v 0.7
   set tempo_inicial time

end

to go-to-iteration-procedure
  move-to node 11
  set current-node node 11
  set color grey
  ifelse (incentives?)
    [ if (hour_stamp = 1 ) [set inicial time + 1 + random num-minuts ]
      if (hour_stamp = 1 ) [set inicial time + 1 + random 30        ]
      if (hour_stamp = 1 ) [set inicial time + 1 + random 60        ]]
    [set inicial inicial_iteration + time + random 10]
  set desired_departure  desired_departure_iteration + time + random 10
  set desired_arrival    desired_departure + random num-minuts
end

to create-bus-demand
   if ( time >   0)   and  (time <=   60 )
   [ask commuters with [current-node = node 6 and color = green ] [ if ( ticks mod 10 = 0 ) [ move reportes3 ]]]
   if ( time >  60)   and  (time <=   120 )
   [ask commuters with [current-node = node 6 and color = green ] [ if ( ticks mod 5 = 0 ) [ move reportes3 ]] ]
   if ( time >  120)  and  (time <=  180 )
   [ask commuters with [current-node = node 6 and color = green ] [ if ( ticks mod 5 = 0 ) [ move reportes3 ]] ]
   if ( time >  180)
   [ask commuters with [current-node = node 6 and color = green ] [ if ( ticks mod 10 = 0 ) [ move reportes3 ]] ]
end


to set-counter
 ask patch  1.5 6 [ set plabel count [commuters-at 0 0] of patch  2 5 ]
 ask patch -1.5 4 [ set plabel count [commuters-at 0 0] of patch -1 5 ]
 ask patch    5 7 [ set plabel count commuters with [current-node = node 6 and mode = 1 ] ]
end


to calculate_average_travel_time
 set avg_travel_time 0
 if (travel_time_cars > 0 and total_commuters > 0)
 [set avg_travel_time travel_time_cars / total_commuters]

end

to calculate_average_velocity
 set avg_velocity_public 0
 ifelse ( total-commuters-public > 0 and v > 0  )
 [ask commuters with [color = green]  [set avg_velocity_public (sum [v] of commuters with [color = green] ) / count commuters
with [color = green and v > 0 ] ]]
 [set avg_velocity_public 0]
```

```
  set list_velocity_public lput precision avg_velocity_public 3 list_velocity_public

  set avg_velocity_private 0
  ifelse ( total-commuters-private > 0 and v > 0 )
  [ask commuters with [color = red]  [set avg_velocity_private ( sum [v] of commuters with [color = red ] ) / count commuters with
[color = red and v > 0 ] ]]
  [set avg_velocity_private 0]
  set list_velocity_private lput precision avg_velocity_private 3 list_velocity_private
end

to calculate_total_commuters

  set count-node-2 count commuters with [current-node = node 2  and color = red ]
  set total-inicial-private count-node-2
  set $list-private lput total-inicial-private $list-private

  let $sum-private 0
  foreach $list-private
   [ set $sum-private $sum-private + ? ]

  set total-commuters-private $sum-private

  set count-node-3 count commuters with [current-node = node 4 and color = green ]
  set total-inicial-public count-node-3
  set $list-public lput total-inicial-public $list-public
  let $sum-public 0
  foreach $list-public
   [ set $sum-public $sum-public + ? ]
  set total-commuters-public $sum-public

  set total_commuters ( total-commuters-public + total-commuters-private )

end

to-report get_node [id]
  report one-of turtles with [node_id = id]
end

to reportes3
  set crowdness mean [commuters_bus_stop] of commuters with [color = green] / bus_capacity
end

to reportes2
    ifelse total-commuters-public  > 0 [set average_tt_public  sum [tempo_de_viagem] of commuters with [color = green]  / total-
commuters-public]  [set average_tt_public 0]
    ifelse total-commuters-private > 0 [set average_tt_private sum [tempo_de_viagem] of commuters with [color = red]    / total-
commuters-private] [set average_tt_private 0]

    set expected_utility_public_sum  sum [expected_utility_public]  of commuters with [color = green ]
    set expected_utility_private_sum sum [expected_utility_private] of commuters with [color = red ]

    ifelse total-commuters-public  > 0 [set expected_utility_public_avg  sum [expected_utility_public]  of commuters with [color =
green ] / total-commuters-public ] [set expected_utility_public_avg 0]
    ifelse total-commuters-private > 0 [set expected_utility_private_avg sum [expected_utility_private] of commuters with [color =
red ]   / total-commuters-private] [set expected_utility_private_avg 0]

    set effective_utility_public_sum  sum [effective_utility_public]  of commuters with [color = green ]
    set effective_utility_private_sum sum [effective_utility_private] of commuters with [color = red   ]

    ifelse total-commuters-public  > 0 [set effective_utility_public_avg  (sum [effective_utility_public]  of commuters with [color =
green ] ) / total-commuters-public ]  [set effective_utility_public_avg 0]
    ifelse total-commuters-private > 0 [set effective_utility_private_avg (sum [effective_utility_private] of commuters with [color =
red ] )   / total-commuters-private ] [set effective_utility_private_avg 0]
```

```
   set plot_commuters_public  total-commuters-public  - (count commuters with [current-node = node 9 and color = green] +
count commuters with [current-node = node 10 and color = green])
   set plot_commuters_private total-commuters-private - (count commuters with [current-node = node 9 and color = red] +   count
commuters with [current-node = node 10 and color = red])

   ifelse total-commuters-public  > 0 [set ratio_tt_public_sum   sum [ratio_tt_public]  of commuters with [color = green] / total-
commuters-public]  [set ratio_tt_public_sum 0]
   ifelse total-commuters-private > 0 [set ratio_tt_private_sum  sum [ratio_tt_private] of commuters with [color = red]   / total-
commuters-private] [set ratio_tt_private_sum 0]
end
to reportes
   export-all-plots  (word "results_day" day  ".csv")
   file-open (word "results_day" day  ".csv")
   file-write "total-commuters-public"        file-write total-commuters-public
   file-write "total-commuters-private"       file-write total-commuters-private
   file-write "average_tt_public"             file-write average_tt_public
   file-write "average_tt_private"            file-write average_tt_private
   file-write "expected_utility_public_sum"    file-write expected_utility_public_sum
   file-write "expected_utility_private_sum"   file-write expected_utility_private_sum
   file-write "expected_utility_public_avg"    file-write expected_utility_public_avg
   file-write "expected_utility_private_avg"   file-write expected_utility_private_avg
   file-write "effective_utility_public_sum"   file-write effective_utility_public_sum
   file-write "effective_utility_private_sum"  file-write effective_utility_private_sum
   file-write "effective_utility_public_avg"   file-write effective_utility_public_avg
   file-write "effective_utility_private_avg"  file-write effective_utility_private_avg
   file-write "public_ratio_tt"               file-write ratio_tt_public_sum
   file-write "private_ratio_tt"              file-write ratio_tt_private_sum
   file-write "crowdness"                     file-write crowdness
   file-close
   set day day + 1
   set $list-private []
   set $list-public []
   clear-all-plots
end
;;;;;;   Nuno Monteiro /// FEP 120414020 /// FEUP /// 2014    ;;;;;;;
```

2. NetLogo Code for Chapter 4 Model

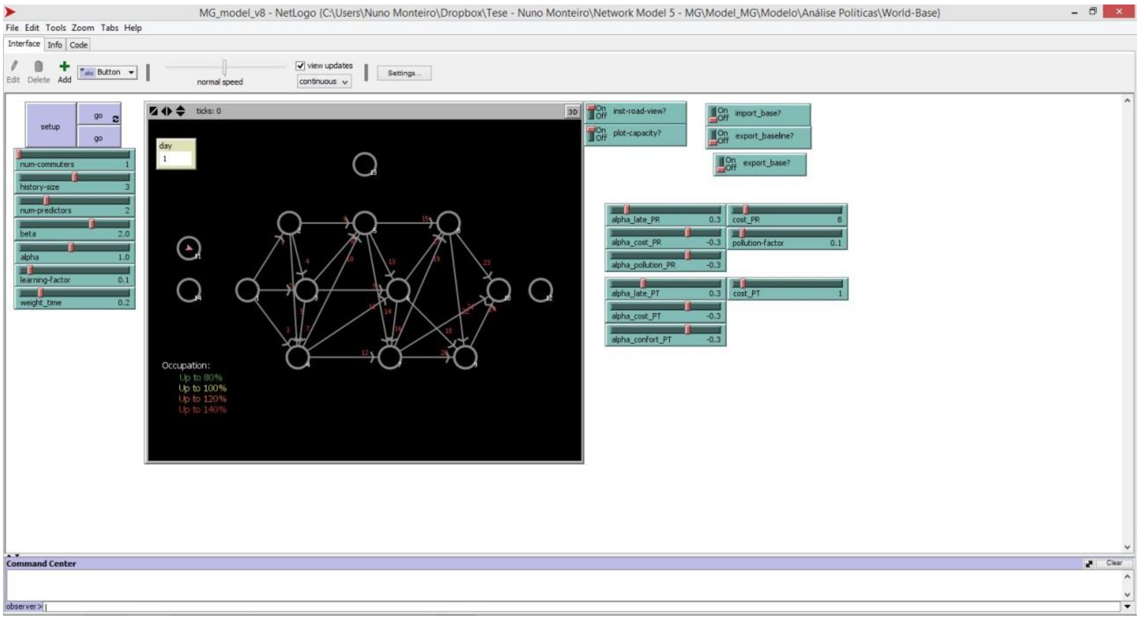


Figure 21 - Screenshot - Model Chapter 4

Source Code:

```
globals [
  day
  num-intersections
  num-roads
  ideal-segment-length
  list-uti-world-PR
  list-uti-world-PT
  list-uti-PR
  list-uti-PT
  list-tt-PR
  list-tt-PT
  list-uti-world
  list-count-PR
  list-count-PT
]

breed [ intersections intersection ]
breed [ commuters driver ]

directed-link-breed [ roads road ]

intersections-own [
   x y
   id
]
roads-own [
  road-id  ;identificador da via
  capacity ;capacidade [130:250]
  num-drv  ;numero de motoristas
  opt-num-drv ;numero proporcional de motoristas
  avg-num-drv ;ocupacao real media
  avg-opt-drv ;ocupacao proporcional media
  fftt  ;free-flow travel time
  travel-time ;tempo de viagem
  previous-time ;tempo da viagem anterior
```

```
  history ;historico de ocupacao
]
commuters-own [
  current-route ;lista de road-id descrevendo a rota atual
  route-weight  ;peso da rota a ser calculado na chegada
  actual-tt     ;tempo de viagem real do motorista
  previous-tt   ;tempo de viagem real do motorista passada
  par-OD        ;variavel para assinalar qual o par od dos viajantes
  optimal-route ;rota otima (menor #nos ate o destino)
  expected-tt   ;tempo de viagem esperado (considera os motoristas no mesmo par OD
  roads-weight  ;lista com o peso das rotas TODO: sera' necessario?
  origin        ;ID do no' de origem
  destination   ;ID do no' de destino
  current-node  ;ID do no' atual
  ;;;nuno
  end-node      ;ID do no' final antes da iterata
  beg-node      ;nó onde a demmand é construída
  iter-node     ;ID do no' onde o agente vai iterar para começo de um novo dia
  mode-node     ;ID do no' onde o agente vai fazer a escolha do modo -> calculo das utilidades -> relevancia social
  time          ; tempo de saida
  timeplus      ;assegura que o tempo em cada dia é o mesmo. mantem integridade do sistema.
  travelling    ;se o agente está a viajar
  mode          ;modo escolhido pelos agentes
  accessibility
  exp-uti-PR
  exp-uti-PT
  income
  current-road  ;via atual (a via mesmo, nao o ID)
  predictors       ;lista com 'num-roads' conjuntos de 'num-predictors' preditores
  predictors-score ;lista com 'num-roads' conjuntos de 'num-predictors' pontos p. preditores
  best-predictors  ;lista com o indice do melhor preditor por via (?)
to setup
  __clear-all-and-reset-ticks
   build-network
   ifelse (import_base?) [ import-world "baseline_no_training.csv" ] [setup-commuters set day 1 ]
   ask intersections [ set label id ]
   set-lists
   if (export_base?) [ export-world "baseline_no_training.csv" ]
end
to set-lists
  ;;listas para retirar os resultados de forma continua- das utilidades e dos tt
  set list-uti-PR []
  set list-uti-PT []
  set list-tt-PR []
  set list-tt-PT []
  set list-uti-world-PR []
  set list-uti-world-PT []
  set list-uti-world []
  set list-count-PR []
  set list-count-PT []
end

to go
  if all? commuters [current-node = end-node] [ ;;reset the commuters to the begging
   export-results
   reset-road-network ]
  if day = 180 [ write-file export-world "baseline_training_180.csv" stop]
  mode-choice ;;faz com que os agentes escolham um modo para viajar
  create-assignment ;;coloca os agentes a andar na rede
  step ;; onde os agentes "aprendem" a circular na rede
  experience-travel-times
  update-predictors-score
  update-history
  update-roads-visual
  tick
end

to step
```

```
  distribute-commuters-proportionally
  choose-next-road-PR
  choose-next-road-PT
  advance
end

to mode-choice
  ask commuters with [((beg-node = current-node) or (iter-node = current-node))]
   [set current-node 14
    let myorig origin
    let mydest destination
    let modenode mode-node
    ;ifelse [auto_fact_uti?]
    ;;set the utility factors
    ;let alpha_late_PR 0.4
    ;let alpha_cost_PR 0.4
    ;let alpha_pollution_PR 0.2
    ;let cost_PR 5
    ;let pollution-factor 0.2
   ; let alpha_late_PT 0.4
    ;let alpha_cost_PT 0.4
    ;let alpha_confort_PT 0.2
    ;let cost_PT 1 ]
    let bus_cap 50
    let exp_bus_cap 50
    set exp-uti-PR (
        ( alpha_late_PR * ( expected-tt - previous-tt ))
      + ( alpha_cost_PR * ( cost_PR / income  ))
      + ( alpha_pollution_PR * ( expected-tt * pollution-factor ))
      )
    set exp-uti-PT (
        ( alpha_late_PT * ( expected-tt - previous-tt ))
      + ( alpha_cost_PT * (  cost_PT / income))
      + ( alpha_confort_PT * ( ( bus_cap / exp_bus_cap ) ))
      )
   ;;;;;;;;;;;;decision making process;;;;;;;;
   if (myorig = 1 and mydest = 8)  [set accessibility 1]
   if (myorig = 1 and mydest = 10) [set accessibility 1]
   if (myorig = 2 and mydest = 8)  [set accessibility 1]
   if (myorig = 3 and mydest = 8)  [set accessibility 1]
   if ( accessibility = 0 )  [set mode 1] ;;; se não tem acesso a transporte vai de carro
   if ( accessibility = 1 )  [
     ifelse  ( exp-uti-PR > exp-uti-PT ) [set mode 1] [set mode 2]
     ]
   if mode = 1 [set color white]
   if mode = 2 [set color red]
  move-to one-of intersections with [id = modenode]
   ]
end

to create-assignment
  ask commuters with [ (mode-node = current-node) and  (timeplus = ticks)  ]
  [let myorig origin
   let mydest destination
     move-to one-of intersections with [id = myorig]
     face one-of intersections with [id = mydest]
     set current-node origin
     set travelling true
  ]
end

to setup-commuters
  create-commuters num-commuters [
     set origin 1 + random 3  ;origem em nos 1, 2 ou 3
     set destination 8 + random 3 ;destino em 8, 9 ou 10
     if (origin = 1) and (destination = 8 ) [ set par-OD 1]
     if (origin = 1) and (destination = 9 ) [ set par-OD 2]
     if (origin = 1) and (destination = 10) [ set par-OD 3]
```

```
    if (origin = 2) and (destination = 8 ) [ set par-OD 4]
    if (origin = 2) and (destination = 9 ) [ set par-OD 5]
    if (origin = 2) and (destination = 10) [ set par-OD 6]
    if (origin = 3) and (destination = 8 ) [ set par-OD 7]
    if (origin = 3) and (destination = 9 ) [ set par-OD 8]
    if (origin = 3) and (destination = 10) [ set par-OD 9]
    set current-node 11
    set current-route []
    set optimal-route calculate-opt-route origin destination
    set beg-node 11
    set end-node 12
    set iter-node 13
    set mode-node 14
    set travelling false
    set mode 0
    set income 20 + random-float 50
    set time 0 + random 5
    set timeplus time
    set predictors n-values num-roads [random-predictors]
    set predictors-score n-values num-roads [initial-scores]
    set best-predictors n-values num-roads [random num-predictors]
    set roads-weight n-values num-roads [1]
    let myorig beg-node
    let mydest origin
    move-to one-of intersections with [id = myorig]
    face one-of intersections with [id = mydest]
  ]
  calculate-ett
end

to distribute-commuters-proportionally
 ask intersections [
   let drv-at-intersection count commuters-here with [current-node != destination];desconta os motoristas que ja chegaram
   let total-capacity sum [capacity] of my-out-links
   ask my-out-links [
    let proportion capacity / total-capacity
    set opt-num-drv opt-num-drv + (proportion * drv-at-intersection)]]
end
;   atualiza o historico de ocupacao das vias, inserindo a ocupacao da rodada atual
to update-history
 ask roads [
   ;show history
   let occupation (num-drv / capacity) * 100
   if occupation < 60 [set occupation 60]
   if occupation > 140 [set occupation 140]
   set history remove-item (length history - 1) history
   set history fput occupation history
   if length history = 1 [show (word "error " history)]]
end

;calcula o tempo de viagem esperado para cada motorista
to calculate-ett
 ask commuters [
   let drv-same-od 0
   let exp-drv 0
   let ett 0
   let myorig origin
   let mydest destination
   set drv-same-od count commuters with [origin = myorig and destination = mydest]
   set exp-drv drv-same-od ; - 50  + random 101 ;adiciona ruido +-50
   foreach optimal-route [
    ask ? [set ett ett + fftt * (1 + exp-drv / capacity) ^ 2]]
   set expected-tt ett]
end
; reinicia a rede de trafego: coloca os motoristas na origem, reseta as rotas
; reseta os tempos de viagem das vias e a ocupacao
to reset-road-network
 ;export-plots
```

```
  reset-commuters
  reset-roads
end
;reinicia o estado dos motoristas, posicionando-os na origem e resetando as rotas
to reset-commuters
    ask commuters [
     let iternod iter-node
      let myorig origin
      set current-node iternod
      set current-route []
      set mode 0
      ;TODO atualizar os pesos das rotas
      ;set roads-weight n-values num-roads [1]
      move-to one-of intersections with [id = iternod]
      face-nowrap one-of intersections with [id = myorig]
      set timeplus time + ticks]
end
;reinicia o estado das vias (num-motoristas; num-proporcional; tempo-de-viagem)
to reset-roads
  ask roads [
    set num-drv  0
    set opt-num-drv 0
    set previous-time travel-time
    set travel-time 0]
end

;faz cada motorista escolher a proxima via a ser usada
to choose-next-road-PR
  ask commuters with [travelling = true and mode = 1][
    if current-node = destination [
      let endnode end-node
      move-to one-of intersections with [id = endnode]
      set travelling false
       set current-node end-node
       set previous-tt actual-tt
      stop] ;nao faz escolhas se ja tiver chegado
    ;configura variaveis para serem usadas dentro dos asks
    let node-id current-node
    let the-predictors predictors
    let the-scores predictors-score
    let the-roads-weight roads-weight
    let myorig origin
    let mydest destination
    ;inicializa melhor via e menor ocupacao encontrada
    let best-road-id -1
    let lowest-prediction 100000 ;inicializa menor ocupacao com valor grande
    ;a partir da intersecao atual...
    ask intersections with [id = node-id] [
      let will-reach-dest false
      ;...analisa todos os links de saida para achar o melhor
      ask my-out-links [
          ;se ja encontrou aresta que leva ao destino, nao procura mais
          if will-reach-dest [stop]
          if (not in-route myorig mydest) [stop]
          let scores sublist the-scores (road-id - 1) road-id
          let hiscore max (item 0 scores)
          let best-pred-index position hiscore (item 0 scores)
          let curr-predictors sublist the-predictors (road-id - 1) road-id  ;OK - obtem os preditores desta via
          ;set best-pred-index 0
          let best-predictor (item best-pred-index (item 0 curr-predictors))
          let predicted-occ predict-occupation best-predictor history
          let weighted-prev predicted-occ * item (road-id - 1) the-roads-weight

          ;COMPARAR COM MELHOR PREDICAO E AJUSTAR MELHOR VIA
          if weighted-prev < lowest-prediction [
            set lowest-prediction predicted-occ
            set best-road-id road-id
          ]
```

```
      ;];ifelse
     ] ;ask my-out-links
   ] ;ask intersections


   set current-road one-of roads with [road-id = best-road-id] ;;; distinguir aqui de commuters !!!
   ;face-nowrap [end1] of current-road
   ;fd 1

   ask current-road [set num-drv num-drv + 1]
  ]
end

to choose-next-road-PT

  ask commuters with [travelling = true and mode = 2 ][

   if current-node = destination [
     let endnode end-node
     move-to one-of intersections with [id = endnode]
     set travelling false
      set current-node end-node
      set previous-tt actual-tt
     stop] ;nao faz escolhas se ja tiver chegado


   ;configura variaveis para serem usadas dentro dos asks
   let node-id current-node
   let the-predictors predictors
   let the-scores predictors-score
   let the-roads-weight roads-weight
   let myorig origin
   let mydest destination

   ;inicializa melhor via e menor ocupacao encontrada
   let best-road-id -1
   let lowest-prediction 100000 ;inicializa menor ocupacao com valor grande

   ;a partir da intersecao atual...
   ask intersections with [id = node-id] [

     let will-reach-dest false

     ;...analisa todos os links de saida para achar o melhor
     ask my-out-links [
        ;se ja encontrou aresta que leva ao destino, nao procura mais
        if will-reach-dest [stop]
        if (not bus-route myorig mydest) [stop]
        let scores sublist the-scores (road-id - 1) road-id
        let hiscore max (item 0 scores)
        let best-pred-index position hiscore (item 0 scores)
        let curr-predictors sublist the-predictors (road-id - 1) road-id  ;OK - obtem os preditores desta via
        ;set best-pred-index 0
        let best-predictor (item best-pred-index (item 0 curr-predictors))
        let predicted-occ predict-occupation best-predictor history
        let weighted-prev predicted-occ * item (road-id - 1) the-roads-weight
        ;COMPARAR COM MELHOR PREDICAO E AJUSTAR MELHOR VIA
        if weighted-prev < lowest-prediction [
          set lowest-prediction predicted-occ
          set best-road-id road-id
        ]
      ;];ifelse
     ] ;ask my-out-links
   ] ;ask intersections
   set current-road one-of roads with [road-id = best-road-id] ;;; distinguir aqui de commuters !!!
   ;face-nowrap [end1] of current-road
   ;fd 1
  ask current-road [set num-drv num-drv + 1]
```

```
  ]
end

to-report bus-route [orig dest]
  let forbidden []
  if orig = 1 and dest = 8  [ set forbidden  [   2 3 4 5   7 8 9 10 11 12 13 14    16 17 18 19 20 21 22 23 24 ] ] ;;tem linha de
autocarro
  if orig = 1 and dest = 9  [ set forbidden  [ 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 ] ]
  if orig = 1 and dest = 10 [ set forbidden  [ 1 2   4 5 6 7 8 9 10 11    13 14 15 16 17 18 19    21 22 23    ] ] ;;tem linha de
autocarro
  if orig = 2 and dest = 8  [ set forbidden  [ 1 2 3 4 5   7 8 9 10 11 12 13 14    16 17 18 19 20 21 22 23 24 ] ] ;;tem linha de
autocarro
  if orig = 2 and dest = 9  [ set forbidden  [ 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 ] ]
  if orig = 2 and dest = 10 [ set forbidden  [ 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 ] ]
  if orig = 3 and dest = 8  [ set forbidden  [ 1 2 3 4 5 6 7 8   10 11 12 13 14 15 16    18 19 20 21 22 23 24 ] ] ;;tem linha de
autocarro
  if orig = 3 and dest = 9  [ set forbidden  [ 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 ] ]
  if orig = 3 and dest = 10 [ set forbidden  [ 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 ] ]
  report not member? road-id forbidden
end
to-report in-route [orig dest]
  let forbidden []
  if dest = 8  [ set forbidden [18 20 21 22 23 24] ]
  if dest = 9  [ set forbidden [21 23 24] ]
  report not member? road-id forbidden
end

;faz o motorista chegar ao destino da via escolhida e experimentar o tempo de viagem
to advance
  ask commuters with [travelling = true] [
    if current-node = destination [
      let endnode end-node
      move-to one-of intersections with [id = endnode]
      set travelling false
      set current-node end-node
      set previous-tt actual-tt
      stop]
    ;adiciona a via atual 'a rota
    set current-route lput current-road current-route
    ;avanca para a proxima intersecao
    set current-node [id] of [end2] of current-road
    let nid current-node
    move-to one-of intersections with [id = nid]    ]
end

;calcula o tempo de viagem gasto pelos motoristas
to experience-travel-times
  ask roads [
  set travel-time fftt * (1 + alpha * (num-drv / capacity) ^ beta)
  if num-drv > 0 [
      set avg-num-drv ((num-drv - avg-num-drv) / (ticks + 1)) + avg-num-drv
      set avg-opt-drv ((opt-num-drv - avg-opt-drv) / (ticks + 1)) + avg-opt-drv]]
  ask commuters [
    let attR 0 ;inicializa o tempo de viagem do motorista
    ;calcula o custo da rota
    foreach current-route [
      ask ? [set attR attR + travel-time]
    ]

    set actual-tt attR

    set route-weight actual-tt / expected-tt

    ;atualiza o vetor de pesos de rota por aresta
    foreach current-route [
      let rw roads-weight
      let att actual-tt
      let w route-weight
```

```
      ask ? [
        let rid road-id
        set rw replace-item (rid - 1) rw w
      ;replace-item 0 [1 3 3] 3
      ]
      set roads-weight rw
    ]
  ]
end

;atualiza a pontuacao dos preditores de cada motorista
;somente sao atualizados os preditores que foram usados na ultima viagem
;SC = (1-u)SC + u[(Ca / Xa) -1]*ATTR
to update-predictors-score
  ;para cada via...
  ask roads [
    if num-drv = 0 [stop]
    let rid road-id
    let rhist history
    let rocc capacity / num-drv
    ;para cada motorista
    ask commuters [
      let curr-predictors sublist predictors (rid - 1) rid  ;OK - obtem os preditores desta via
      let scores sublist predictors-score (rid - 1) rid
      let bpindex item (rid - 1) best-predictors ;obtem o indice do melhor preditor desta via
      ;obtem o score e o recalcula
      let score item bpindex (item 0 scores)
      set score (1 - learning-factor) * score + learning-factor * (rocc - 1) * actual-tt
      ;coloca o novo score na sub-lista das pontuacoes dos preditores daquela via
      let new-scores replace-item bpindex (item 0 scores) score
      ;atualiza em qual indice esta o melhor preditor
      let bpidx position (max new-scores) new-scores ;OK
      set best-predictors replace-item (rid - 1) best-predictors bpidx
      ;coloca a sub-lista na lista de pontuacoes geral
       set predictors-score replace-item (rid - 1) predictors-score new-scores
      ;show predictors-score]]
  end
;retorna a rota otima entre nos origem-destino
to-report calculate-opt-route [org dest]
  let rid-list []
  if org = 1 and dest = 8  [ set rid-list [ 1 6 15  ] ]
  if org = 1 and dest = 9  [ set rid-list [ 3 12 20 ] ]
  if org = 1 and dest = 10 [ set rid-list [ 3 12 21 ] ]
  if org = 2 and dest = 8  [ set rid-list [ 6 15    ] ]
  if org = 2 and dest = 9  [ set rid-list [ 6 13 18 ] ]
  if org = 2 and dest = 10 [ set rid-list [ 6 15 23 ] ]
  if org = 3 and dest = 8  [ set rid-list [ 9 17    ] ]
  if org = 3 and dest = 9  [ set rid-list [ 9 18    ] ]
  if org = 3 and dest = 10 [ set rid-list [ 9 18 24 ] ]
  let opt-route []
  foreach rid-list [
    set opt-route lput one-of roads with [road-id = ?] opt-route
  ]
  report opt-route
end

to-report predict-occupation [predictor occ-history]
  let prediction sum (map [?1 * ?2] predictor occ-history)
  if prediction < 60 [set prediction  60]
  if prediction > 140 [set prediction  140]
  report prediction
end

;diz se todos os motoristas ja chegaram nos seus destinos
to-report commuters-not-arrived
  let all-arrived true
  ask commuters [
```

```
    if current-node != destination [ set all-arrived false ]]
  report not all-arrived
end

;gera uma lista de zeros como score inicial dos preditores
to-report initial-scores
  report n-values num-predictors [0] ;score inicial dos preditores e' zero
end

;gera uma lista com 'num-predictors' preditores aleatorios
to-report random-predictors
  report n-values num-predictors [random-predictor]
end

;gera um vetor de pesos entre [-1:1] do tamanho do historico
to-report random-predictor
  report n-values (history-size) [1.0 - random-float 2.0]
end

to build-network
  clear-turtles
  file-open "mgta2" ;user-file
  set num-intersections file-read
  set num-roads file-read
  set ideal-segment-length file-read
  repeat num-intersections  [
    create-intersections 1 [
      set id file-read ;id-counter
      set xcor file-read / 1.1
      set ycor file-read / 1.1
      update-node-visual  ] ]
  repeat num-roads  [
    let r-id file-read
    let id1 file-read
    let id2 file-read
    let primary? file-read
    ask intersections with [ id = id1 ]  [
      create-roads-to intersections with [id = id2] [
        set road-id r-id
        set num-drv 0
        set opt-num-drv 0
        set avg-num-drv 0
        set avg-opt-drv 0
        set fftt 5
        set capacity 550 + random 250
        ;set capacity num-commuters / 7.5 ;TODO REMOVER ISSO APOS TESTAR
        set label road-id
        set label-color red
        set history n-values history-size [60 + random 81] ;historico de valores entre 60 e 140]]]
  file-close
   ask roads [
      set shape "default"
      set thickness .2
    ]
end

to update-node-visual
    set shape "circle 2"
    set size ideal-segment-length / 3
    set color 5
end

to do-plots
  plot-travel-times
  plot-roads-occupation
  plot-tt-per-od
end
```

```
to plot-travel-times
  let total-att 0
  let total-ett 0
  ask commuters [
    set total-att total-att + actual-tt
    set total-ett total-ett + expected-tt
  ]
  let avg-att total-att / num-commuters
  let avg-ett total-ett / num-commuters
  set-current-plot "avg-travel-time"
  set-current-plot-pen "actual"
  plot avg-att
  set-current-plot-pen "expected"
  plot avg-ett
end

to plot-tt-per-od
  let counter 1
  let origins [1 2 3]
  let dests [8 9 10]
  set-current-plot "travel-time-per-od"
  clear-plot
  foreach origins [
    let orig ?
    foreach dests [
      let dest ?
      set-current-plot-pen "actual"
      plotxy counter (att-per-od orig dest)
      set-current-plot-pen "expected"
      plotxy (counter) (ett-per-od orig dest)
      set counter counter + 1   ]]
end

to-report att-per-od [orig dest]
  let total-tt 0
  ask commuters with [origin = orig and destination = dest] [
    set total-tt total-tt + actual-tt]
  if total-tt = 0 [report 0]
  report total-tt / count commuters with [origin = orig and destination = dest ]
end

to-report ett-per-od [orig dest]
  let total-tt 0
  ask commuters with [origin = orig and destination = dest and travelling = true ] [
    set total-tt total-tt + expected-tt  ]
  if total-tt = 0 [report 0]
  report total-tt / count commuters with [origin = orig and destination = dest ]
end

to plot-roads-occupation
  set-current-plot "commuters-per-road"
  clear-plot
  set-current-plot-pen "actual"
  ask roads [
    plotxy road-id avg-num-drv ]
  set-current-plot-pen "proportional"
    ask roads [
    plotxy road-id avg-opt-drv
 ;   if road-id = 24 [show (word "error " road-id " " avg-opt-drv)]
  ]
  if plot-capacity? [
    set-current-plot-pen "capacity"
    ask roads [
      plotxy (road-id + .5) capacity]]
  set-current-plot "inst-drv-per-road"
  clear-plot
  set-current-plot-pen "actual"
```

```
  ask roads [
    plotxy road-id num-drv]
  set-current-plot-pen "proportional"
  ask roads [
    plotxy road-id opt-num-drv
  ]
end

to export-results
  export-plots
  export-agents
  export-lists
  set day day + 1
end

to export-plots
end

to export-agents
end

to export-lists
  ;;counting drivers
  let count-PR 0 ;1
  let count-PT 0 ;2
  set count-PR count commuters with [ mode = 1 ]
  set count-PT count commuters with [ mode = 2 ]
  print count-PR
  print count-PT
  set list-count-PR lput count-PR list-count-PR
  set list-count-PT lput count-PT list-count-PT
  ;;utilities
  let avg-uti-PR 0
  let avg-uti-PT 0
  set avg-uti-PR precision ( sum [ exp-uti-PR ] of commuters with [ mode = 1 ] / count-PR ) 2
  ifelse (count-PT = 0 ) [set avg-uti-PT 0 ][ set avg-uti-PT precision ( sum [ exp-uti-PT ] of commuters with [ mode = 2 ] / count-
PT ) 2]
  set list-uti-PR lput avg-uti-PR list-uti-PR ;3
  set list-uti-PT lput avg-uti-PT list-uti-PT ;4
  ;;travel-times
  let avg-tt-PR 0
  let avg-tt-PT 0
  set avg-tt-PR precision ( sum [ actual-tt ] of commuters with [ mode = 1 ] / count-PR ) 2
  ifelse (count-PT = 0 ) [set avg-tt-PT 0] [ set avg-tt-PT precision ( sum [ actual-tt ] of commuters with [ mode = 2 ] / count-PT )
2 ]
  set list-tt-PR lput avg-tt-PR list-tt-PR ;5
  set list-tt-PT lput avg-tt-PT list-tt-PT ;6
  ;;utilities world
  let tot-uti-PR 0
  let tot-uti-PT 0
  let tot-uti 0
  set tot-uti-PR precision ( sum [ exp-uti-PR ] of commuters with [ mode = 1 ] ) 2
  set tot-uti-PT precision ( sum [ exp-uti-PT ] of commuters with [ mode = 2 ] ) 2
  set tot-uti precision ( (sum [ exp-uti-PR ] of commuters with [ mode = 1 ] ) + (sum [ exp-uti-PT ] of commuters with [ mode =
2 ]) ) 2
  set list-uti-world-PR lput tot-uti-PR list-uti-world-PR ;7
  set list-uti-world-PT lput tot-uti-PT list-uti-world-PT ;8
  set list-uti-world    lput tot-uti    list-uti-world    ;9

end

to write-file
  export-world ( word "results_day" day ".csv" )
  file-open    ( word "results_day" day ".csv" )
  file-write "list-count-PR"      file-write ";" file-write list-count-PR     file-write ";"  ;1
  file-write "list-count-PT"      file-write ";" file-write list-count-PT     file-write ";"  ;2
  file-write "list-uti-PR"        file-write ";" file-write list-uti-PR       file-write ";"  ;3
  file-write "list-uti-PT"        file-write ";" file-write list-uti-PT       file-write ";"  ;4
```

```
  file-write "list-tt-PR"        file-write ";" file-write list-tt-PR       file-write ";"  ;5
  file-write "list-tt-PT"        file-write ";" file-write list-tt-PT       file-write ";"  ;6
  file-write "list-uti-world-PR"  file-write ";" file-write list-uti-world-PR file-write ";"  ;7
  file-write "list-uti-world-PT"  file-write ";" file-write list-uti-world-PT file-write ";"  ;8
  file-write "list-uti-world"     file-write ";" file-write list-uti-world    file-write ";"  ;9
  file-close
end

to update-roads-visual
  ask roads [
    let occ avg-num-drv / capacity
    if inst-road-view?
    [set occ num-drv / capacity]

    set color green
    if occ > 0.80 [set color yellow]
    if occ > 1.00 [set color orange]
    if occ > 1.20 [set color red]

   ; show occ
  ]
End
```

Appendix C

Table 18 – GAMP OD-Pairs data – INE Census Data

GAMP OD Pairs	Arouca	Espinho	Santa Maria da Feira	Oliveira de Azeméis	São João da Madeira	Vale de Cambra	Gondomar	Maia	Matosinhos	Paredes	Porto	Póvoa de Varzim	Santo Tirso	Valongo	Vila do Conde	Vila Nova de Gaia	Trofa	Total
Arouca	22984	28	1532	2704	1660	1984	4	28	40	12	440	4	0	24	4	236	0	31684
Espinho	60	22120	5312	168	308	36	104	460	488	40	3620	32	32	40	60	6404	44	39328
Santa Maria da Feira	1080	5432	150820	6768	15312	1028	668	1224	1216	112	9056	64	60	116	124	13932	92	207104
Oliveira de Azeméis	1092	216	4392	84480	13364	3448	40	136	128	12	1172	24	4	36	40	464	8	109056
São João da Madeira	264	84	4656	5788	23272	604	12	108	88	16	804	16	0	8	12	352	4	36088
Vale de Cambra	968	44	596	3424	1008	27000	24	28	20	4	264	0	8	4	4	92	4	33492
Gondomar	36	320	1428	176	204	40	109136	16044	15340	2056	81000	332	920	8120	1440	14308	996	251896
Maia	20	192	620	136	152	72	4656	108372	26812	1268	51140	988	1608	6252	5360	7056	4392	219096
Matosinhos	32	280	696	228	204	96	2852	25476	149576	976	69580	948	1024	2176	5412	9616	1576	270748
Paredes	16	68	144	16	48	8	1724	2740	1856	83056	11484	72	432	5684	196	1356	152	109052
Porto	72	520	1416	324	408	136	6372	15768	24684	1632	236372	892	1384	2840	2468	17612	1064	313964
Póvoa de Varzim	4	48	64	0	12	4	112	1712	1672	68	4768	65268	304	84	12068	596	456	87240
Santo Tirso	8	28	36	8	40	8	276	2072	1004	404	3800	220	75020	1180	564	568	4660	89896
Valongo	12	172	308	48	84	4	7224	18596	9432	5380	33660	280	1852	59248	1072	4332	1152	142856
Vila do Conde	0	52	68	8	28	8	272	7508	6376	116	8156	11900	448	404	74712	1144	2580	113780
Vila Nova de Gaia	192	6412	10316	1016	1112	328	4908	13928	17512	820	102444	460	864	2020	1852	283668	812	448664
Trofa	4	16	20	0	20	0	172	6648	1468	116	3512	280	2224	548	2136	556	36176	53896
Total	26844	36032	182424	105292	57236	34804	138556	220848	257712	96088	621272	81780	86184	88784	107524	362292	54168	2557840

Bibliography

Agerholm, N. (2011). Speed regulating Effects of Incentive-based Intelligent Speed Adaptation in the short and medium term. PhD Thesis, Aalborg University, Faculty of Engineering and Science.

Agerholm, Waagepetersen, Tradisauskas, & Lahrmann. (2008). Intelligent speed adaptation in company vehicles. in Proceedings of the Intelligent Vehicles Symposium, pp. 936–943.

Almeida, J. E., Kokkinogenis, Z., Rossetti, R. J. F. (2012). Netlogo implementation of an evacuation scenario. *Information Systems and Technologies (CISTI), 2012 7th Iberian Conference on, Madrid, Spain, 20-23 June 2012*, pp. 1-4.

Alonso, W. (1968). Predicting best with imperfect data. *Journal of the American Institute of Planners*, *34*(4), 248-255.

Arentze, T., & Timmermans, H. (2008). Social networks, social interactions, and activity-travel behavior: a framework for microsimulation. *Environment and planning. B, Planning & design* , p. 35(6):1012.

Arnott, Palma, & Lindsay. (1991). Does providing information to drivers reduce traffic congestion? *25(5): 309-318*.

Arthur, W. B. (1991). Inductive Reasoning and Bounded Rationality. *The American economic review*, 406-411.

Axelrod, R. (1985). *The Evolution of Cooperation.* New York, Basic Books, Inc.

Axelrod, R., & Tesfatsion, L. (2006). A guide for newcomers to agentbased. *Handbook of Computational Economics , 2*, 1565–1584.

Balan, G. &. (2006). History-based traffic control. Proceedings of the Fifth International Joint Conference on Autonomous Agents and Multiagent Systems, pp. 616-621

Batty. (1997). Cellular Automata and Urban Form: A Primer. *Journal of the American Planning Association*, *63*(2), 266-274.

Batty, M. (2001). Agent-based pedestrian modeling. *Environment and Planning B , 28* (3), 321 – 326.

Batty, M. (2009). Urban modeling. *International Encyclopedia of Human Geography* , 51-58.

Bazzan, A. L., & Klügl, F. (2008). Re-routing Agents in an Abstract Traffic Scenario. *19th Brazilian Symposium on Artificial Intelligence: Advances in Artificial Intelligence,* Springer-Verlag

Bazzan, A., & Klügl, F. (2014). A review on agent-based technology for traffic and transportation. *The Knowledge Engineering Review , 29* (3), 375-403.

Bazzan, A., & Klügl, F. (2014). *Introduction to Intelligent Systems in Traffic and Transportation.* Morgan & Claypool Publishers.

Beckmann, M. (1956). *Studies in the Economics of Transportation.* New Haven, Geoffrey Cumberlege, Oxford University Press.

Beirão, G., & Cabral, a. S. (2007). Understanding attitudes towards public transport and private car: A qualitative study. *Transport policy* , 14(6):478–489.

Ben-Akiva, M., De Palma, A., & Isam, K. (1991). Dynamic network models and driver information systems. *Transportation Research Part A: General 25(5)* , 251-266.

Bigbee, T., Cioffi-Revilla, C., & Luke, S. (2006). Replicating the classic Sugarscape in MASON. *Complex Behavior in Economics: Modeling, Computing and Mastering Complexity*, (pp. 17-21).

Blythe, P. T. (2005). Congestion charging: Technical options for the delivery of future UK policy. *Transp. Res. Part A , vol. 39, no. 7–9, pp. 571–587*.

Boer, Engers, V., & Sileno. (2011). A problem solving model for regulatory policy making. In Workshop on Modelling Policy-making (MPM 2011).

Bonsall, Shires, Maule, Matthews, & Beale. (2007). Responses to complex pricing signals: Theory, evidence and implications for road pricing. *Transp. Res. A , vol. 41, pp. 672–683*.

Braess, D. (2005). On a paradox of traffic planning. *Transportation Science , 39* (4, pp. 446–450).

Bretagnolle, A., Daudé, E., & Pumain, D. (2003). From theory to modelling : urban systems as complex systems. *European Journal of Geography*.

Bureau of Public Roads. (1964). *Traffic assignment manual.* Washington, DC: U.S. Department of Commerce, Urban Planning Division.

Cantarella, G. P. (2006). Heuristics for urban road network design: lane layout and signal settings. *175* (3).

Cantwell, M., Caulfield, B., & OMahony, a. M. (2009). Examining the factors that impact public transport commuting satisfaction. *Journal of Public Transportation* , 12(2):1–21.

Caron-Lormier, G., Humphry, R. W., Bohan, D. A., Hawes, C., & Thorbek, P. (2008). Asynchronous and synchronous updating in individual-based models. *Ecological Modelling , 212* (3), 522-527.

Carvalho, S. F. (2010). Real-time sensing of traffic information in twitter messages. *MSc Dissertation. Faculdade de Engenharia, Universidade do Porto, 2010* .

Carvalho, S., Sarmento, L., Rossetti, R. J. F. (2010). Real-Time Sensing of Traffic Information in Twitter Messages. *Proceedings of the IEEE ITSC 2010 Workshop on Artificial Transportation Systems and Simulation (ATSS'2010), Funchal, Portugal, 19 Sept. 2010*, pp. 1-4.

Cascetta, E., & Nguyen, S. (1988). A unified framework for estimating or updating origin/destination matrices from traffic counts. *Transportation Research Part B: Methodological , 22* (6), 437-455.

Challet, D., & Zhang, Y. C. (1997). Emergence of cooperation and organization in an evolutionary game. *Physica A 246* , 3-4.

Chen, & Ben-Akiva. (1998). Game-Theoretic Formulations of Interaction Between DTC and DTA. *Transportation Research Record: Journal of the Transportation Research Board 1617* , 179-187.

Cheng, B. C. (2010). A review of the applications of agent technology in traffic and transportation systems. *IEEE Trans. Intell. Transp. Syst., , vol. 11,* (no. 2, pp. 485–497).

Chiu, Bottom, Mahut, Paz, Balakrishna, Waller, et al. (2010). A Primer for Dynamic Traffic Assignment. *Transportation Research Board* , pp 2-3.

Costa, I. A. (2012). Toward a Framework for Simulating Agent-Based Models of Public Policy Processes on the Jason-CArtAgO Platform. in International Workshop on Agent-based Modeling for Policy Engineering (AMPLE 2012).

Dender, M. F. (2013). Road pricing with complications," . Transportation (Amst)., vol. 40, no. 3, pp. 479–503.

Dignum, F., Dignum, V., & Jonker. (2009). *Towards agents for policy making.* Multi-Agent-Based Simulation IX, Springer Berlin Heidelberg, pp. 141–153.

Dubey, P. (1986). Inefficiency of Nash equilibria. *Mathematical Operational Reseach , 11* (1, pp, 1-8).

Easton, D. (1965). *A Framework for Political Analysis.* Prentice-Hall.

Elshafei, E. (2006). Decision-Making for Roadway Lane Designation among Variable Modes. Maryland, USA: University of Maryland, USA.

Eltran, B. C. (2009). Transit network design with allocation of green vehicles: a genetic algorithm approach. *17* (5).

Elvik, R. (2010). Strengthening incentives for efficient road safety policy priorities: The roles of cost–benefit analysis and road pricing. *Saf. Sci. , vol. 48, pp. 1189–1196*.

Erath, A. C. (2012). Overcoming challenges in road pricing design with an agent-based transport simulation. Swiss Transport Research Conference 2012.

Ettema, D., Knockaert, J., & Verhoef, E. (2010). Using incentives as traffic management tool: empirical results of the 'peak avoidance' experiment. *Transportation Letters , 2* (1), pp. 39-51.

Farahani, R. Z. (2013). A review of urban transportation network design problems.

Feil, M., Balmer, M., & Axhausen, a. K. (2009). Enhancement and empirical estimation of MATSim's utility function. *STRC* .

Feil, M., Balmer, M., & Axhausen, a. K. (2009). New approaches to generating comprehensive. *Research Report, IVT, IVT, ETH Zurich, Zurich* .

Ferreira, P. A. F., Esteves, E. F., Rossetti, R. J. F., Oliveira, E. C. (2008). A cooperative simulation framework for traffic and transportation engineering. In *Cooperative Design, Visualization, and Engineering. Lecture Notes in Computer Science*, Vol. 5220, pp. 89-97.

Filgueiras, J., Rossetti, R. J.F., Kokkinogenis, Z., Ferreira, M., Olaverri-Monreal, C., Paiva, M., Tavares, J. M. R. S., Gabriel, J. (2014). Sensing Bluetooth mobility data: potentials and applications. In *Computer-based Modelling and Optimization in Transportation*, Springer International Publishing, pp. 419-431.

Freitas, T. R. M., Coelho, A., Rossetti, R. J. F. (2010). Correcting routing information through GPS data processing. *Intelligent Transportation Systems (ITSC), 13th International IEEE Conference on, Funchal, Portugal, 19-22 Sept. 2010*, pp. 706-711.

Freitas, T. R. M., Coelho, A., Rossetti, R. J. F. (2009). Improving digital maps through GPS data processing. *Intelligent Transportation Systems, 2009. ITSC'09. 12th International IEEE Conference on, St. Louis, MO, 4-7 Oct. 2009*, pp. 1-6.

Galib, S. M., & Moser, I. (2011). Road Traffic Optimisation Using an Evolutionary Game. *Proceedings of the 13th annual conference companion on Genetic and evolutionary computation* (pp. 519-526). New York, NY, USA: ACM.

Gallo, M. M. (2011). . The transit network design problem with elastic demand and internalisation of external costs: an application to rail frequency optimization. Transportation. *19* (6).

Gardner, M. (1971). *On cellular automata, self-reproduction, the Garden of Eden and the Game Life.* Scientific American.

Gonçalves, J., Rossetti, R. J. F., Olaverri-Monreal, C. (2012). IC-DEEP: A serious games based application to assess the ergonomics of In-Vehicle Information Systems. *Intelligent Transportation Systems (ITSC), 2012 15th International IEEE Conference on, Anchorage, AK, 16-19 Sept. 2012*, pp. 1809-1814.

Goodwin. (1996). Empirical evidence on induced traffic. *23* (1 , pp 35-54).

Goodwin, P. (2008). Policy incentives to change behaviour in passenger transport. *International Transport Forum on Transport and Energy: The Challenge of Climate Change.*

Grether, Kickhöfer, & Nagel. (2010). Policy evaluation in multi-agent transport simulations. *Transp. Res. Rec. J. Transp. Res. Board, vol. 2175, pp. 10–18*.

Grimm, & Railsback. (2005). Chapter 5. In V. R. Grimm, *Individual-Based Modeling and Ecology.* Princeton: Princeton University Press.

Grimm, V., Berger, U., Bastiansen, F., Eliassen, S., Ginot, V., Giske, J., et al. (2006). A standard protocol for describing individual-based and agent-based models. *Ecological modelling , 198* (1), 115-126.

Grimm, V., Berger, U., DeAngelis, D. L., Polhill, J. G., Giske, J., & Railsback, S. F. (2010). The ODD protocol: A review and first update. *Ecological Modelling , 221* (3), 2760-2768.

Haken, H. (1995). *Principles of Brain Functioning; A Synergetic Approach to Brain Activity, Behavior and Cognition Series, Springer Series in Synergetics.* Springer.

Haken, H. (1984). *The Science of Structure: Synergetics.* Van Nostrand Reinhold.

Henderson, J. V. (1986). Efficiency of Resource Usage and City Size. *19, 47-70*.

Herstatt, L. J. (2008). Innovation communities: Motivation and incentives for community members to contribute. in IEEE International Conference on Management of Innovation and Technology, pp. 350–355.

Heuvelink, G. (2002). Developments in statistical approaches to spatial uncertainty and its propagation. *International Journal of Geographical Information Science , 16* (2), 111-113.

Hill, M. (2009). *The Public Policy Process.* Uitgeverij Pearson Education Limited, Harlow,.

Hoh, T. Y. (2012). TruCentive: A game-theoretic incentive platform for trustworthy mobile crowdsourcing parking services. in 15th International IEEE Conference Intelligent Transportation Systems, pp. 160-166.

Holleis, Luther, Hu, B., Koolwaaij, Peddemors, & Raaphorst. (2012). TRIPZOOM: a System to Motivate Sustainable Urban Mobility.,”. in The First International Conference on Smart Systems, Devices and Technologies (SMART 2012), pp. 10.

Huse, G., Giske, J., & Salvanes, A. (2002). Individual-based modelling. In P. J. Hart, & J. D. Reynolds (Edits.), *Handbook of Fish and Fisheries. Volume 2: Fisheries.* Oxford, UK: Blackwell Science Ltd.

Jennings, N. R. (2000). On agent-based software engineering. *Artificial Intelligence , 117* (2), 277–296.

Kaimowitz, D. a. (1998). Economic models of tropical deforestation: A review.

Kerridge, J., Hine, J., & Wigan, M. (2001). Agent-based modelling of pedestrian movements: The questions that need to be asked and answered. *Environment and Planning B , 28* (3).

Kickhöfer, Grether, & Nagel. (2011). Income-contingent user preferences in policy evaluation: application and discussion based on multi-agent transport simulations. Transportation (Amst)., vol. 38, pp. 849–870.

Kickhöfer, Zilske, & Nagel. (2010). Income dependent economic evaluation and public acceptance of road user charging. in Proceedings of the Kuhmo Nectar Conference on Transportation Economics.

Kitamura, & Nakayama. (2007). Can travel time influence network flow? Implications of the minority game. *14-20*.

Kokkinogenis, Z., Monteiro, N., Rossetti, R. J. F., Bazzan, A. L. C., & Campos, P. (2014). Policy and incentive designs evaluation: A social-oriented framework for Artificial Transportation Systems. Intelligent Transportation Systems (ITSC), 2014 IEEE 17th International Conference on, Qingdao, China, 8-11 Oct. 2014, pp.151-156.

Kveiborg, & Lohmann-Hansen, N. (2001). The use of mechanisms in congestion pricing. *Trafikdage på Aalborg Universitet, 27, 28.*

Levinson, D. (2010). Equity effects of road princing: A review. *Transport Reviews: A Transnational Transdisciplinary Journal , 20,* (no. 1, pp, 33-57).

Li, S. J. (2009). Evaluation of bus-exclusive lanes. *10* (2).

Lorek, H., & Sonnenschein, M. (1999). Modelling and simulation software to support individual-oriented ecological modelling. Ecol. *Ecological Modelling , 115* (2), 199-216.

Lowry, I. (1965). A Short Course in Model Design. *Journal of the American Institute of Planners , 31* (2), 158-166.

Macedo, J., Kokkinogenis, Z., Soares, G., Perrotta, D., & Rossetti, R. J. F. (2013). A HLA-based multi-resolution approach to simulating electric vehicles in simulink and SUMO. Intelligent Transportation Systems - (ITSC), 2013 16th International IEEE Conference on, The Hague, The Netherlands, 6-9 Oct. 2013, pp. 2367-2372.

Macedo, J., Soares, M., Timóteo, I., Rossetti, R. J. F. (2012). An approach to advisory-based traffic control. *Information Systems and Technologies (CISTI), 7th Iberian Conference on, Madrid, Spain, 20-23 June 2012*, pp. 1-6.

Mandelbrot, B. B. (1983). *The fractal geometry of nature* (Vol. 495). New York: WH Freeman and Co.

Maskin, E. S. (2008). Mechanism design: How to implement social goals. *Am. Econ. Rev. , 98* (3), 567–576.

McNally, M. G. (2000). The Four Step Model. In K. J. David A. Hensher, *Handbook of Transport Modelling.* Elsevier Science B.V.

McPherson, M., Smith-Lovin, L., & Cook, J. M. (2001). Birds of a feather: Homophily in social networks. *Annual review of sociology* , pp. 415–444.

Merugu, Prabhakar, & Rama. (2009). An incentive mechanism for decongesting the roads: A pilot program in Bangalore. *in Proceedings of the Workshop on the Economics of Networks, Systems and Computation* .

Mesbah, M., Sarvi, M., & Currie, G. (2008). New methodology for optimizing transit priority at the network level. *2089*.

Metz, D. (2008). National road pricing: a critique and an alternative. *Transport , 3* (pp. 167-174).

Miandoabchi, E. F. (2012b). Bi-objective bimodal urban road network design using hybrid metaheuristics. *20* (4).

Miandoabchi, Farahani, Dullaert, & Szeto. (2012). Hybrid evolutionary metaheuristics for concurrent multi-objective design of urban road and public transit networks. *12* (3).

Moss. (2002). Policy analysis from first principles. Proc. Natl. Acad. Sci. U.S.A, vol. 99 Suppl 3, pp. 7267–74.

Moss. (2008). Policy Modelling: Problems and Prospects. in Proceedings of the 5th Annual Conference of the European Social Simulation Association, no. 2004, pp. 1–12.

Myerson, R. B. (2008). Perspectives on mechanism design in economic theory. *Am. Econ. Rev., , 98* (3), 586–603.

Kickhöfer, B., & Nagel, K. (2013). Towards high-resolution first-best air pollution tolls. *Networks and Spatial Economics*, 1-24.

Nagel, K., Grether, D., Beuck, U., Chen, Y., Rieser, M., & Axhausen, K. W. (2008). Multi-agent transport simulations and economic evaluation. *Jahrbucher fur Nationalokonomie und Statistik*, *228*(2), 183.

Natalini, D., & Bravo, G. (2013). Encouraging sustainable transport choices in american households: Results from an empirically grounded ABM. *Sustainability, 6(1)* , pp. 50-69.

Nisan, N. (2007). Introduction to mechanism design (for computer scientists. in Algorithmic game theory, Cambridge University Press, pp. 2009–242.

Official Journal of the European Union. (2010). on the framework for the deployment of Intelligent Transport Systems in the field of road transport and for interfaces with other modes of transport. *OJ C 277, 17.11.2009, p. 85.*

Ortuzar, J. D. (2001). *Modelling Transport.* Chichester, UK: Wiley-Blackwell, 3rd Edition.

Parker, D., Manson, Steven, Janssen, Marco, Hoffmann, M., et al. (2003). Multi-agent systems for the simulation of land-use and land-cover change: a review. *Annals of the Association of American Geographers , 93* (2), 314-337.

Parunak, H. (1999). Industrial and practical applications of DAI,. *Multi-Agent Systems: A Modern Approach to Distributed Artificial Intelligence* (G. Weiss, Ed. Cambridge, MA: MIT Press).

Passos, L. S., Rossetti, R. J. F., & Kokkinogenis, Z. (2011). Towards the next-generation tracsimulation tools: a first appraisal. *Information Systems and Technologies (CISTI), 2011 6th Iberian Conference on, Chaves, Portugal, 15-18 June 2011*, pp. 1-6.

Passos, L. S., Kokkinogenis, Z., Rossetti, R. J. F., & Gabriel, J. (2013). Multi-resolution simulation of taxi services on airport terminal's curbside. *Intelligent Transportation Systems - (ITSC), 2013 16th International IEEE Conference on*, The Hague, The Netherlands*, 6-9 Oct.*, pp. 2361-2366.

Pereira, J. L., Rossetti, R. J. F. (2012). An integrated architecture for autonomous vehicles simulation. *Proceedings of the 27th Annual ACM Symposium on Applied Computing*, pp. 286-292.

Portugali. (1997). Self-Organizing Cities. *Futures , 29* (4/5), 353-380.

Portugali. (1994). Socio-spatial residential dynamics, stability and instability within a self-organizing city. *26* (4).

Prigogine, I. (1980). *From Being to Becoming.* San Francisco, Freeman and Co.

Railsback, S. (2001). Concepts from complex adaptive systems as a framework for individual-based modelling. *Ecological Modelling , 139* (1), 47-62.

Ratto, S. B. (2003). The role of incentives in the public sector: issues and evidence.

Rentziou, Milioti, Gkritza, & Karlaftis. (2010). Urban Road Pricing: Modeling Public Acceptance. *J. URBAN Plan. Dev , vol. 137, no. 1, pp. 56–64*.

Riley, R. H. (1997). Resolution and error in measuring land-cover change: Effects on estimating net carbon release from Mexican terrestrial ecosystems. *International Journal of Remote Sensing , 18* (1), 121-137.

Robinson, J. (1994). Land-use and land-cover projections. In J. Robinson, *Changes in land use and land cover: A global perspective.* Cambridge, U.K.: Cambridge University Press.

Rosenthal, R. W. (1973). A class of games possessing pure-strategy Nash equilibria. *International Journal of Game Theory , 2* (1: pp 65-67).

Rossetti, R. J. F., Liu, R., & Tang, S. (2011). Guest Editorial Special Issue on Artificial Transportation Systems and Simulation. Intelligent Transportation Systems, IEEE Transactions on, 12(2), 309-312.

Rossetti, R. J. F., Bampi, S. (1999). A software environment to integrate urban traffic simulation tasks. *Journal of Geographic Information and Decision Analysis , 3* (1), 56-63.

Rossetti, R. J. F., Liu, R. (2005). An agent-based approach to assess drivers' interaction with pre-trip information systems. *ournal of Intelligent Transportation Systems: Technology, Planning, and Operations , 9* (1), 1-10.

Rossetti, R. J. F., Liu, R. (2005a). A dynamic network simulation model based on multi-agent systems. Applications of Agent Technology in Traffic and Transportation. Whitestein Series in Software Agent Technologies 2005, pp. 181-192.

Rossetti, R. J. F., Liu, R. (2005b). Activity-based analysis of travel demand using cognitive agents. Harry Timmermans. (Ed.). Progress in Activity-Based Analysis. Oxford: Elsevier, p.139-160.

Rossetti, R. J. F., Almeida, J. E., Kokkinogenis, Z., & Gonçalves, J. (2013). Playing Transportation Seriously: Applications of Serious Games to Artificial Transportation Systems. *IEEE Intelligent Systems , 28* (4), 107-112.

Rossetti, R. J. F., Bordini, R. H., Bazzan, A. L. C., Bampi, S., Liu, R., & Vliet, D. V. (2002). Using BDI agents to improve driver modelling in a commuter scenario. *Transportation Research Part C: Emerging Technologies , 10* (5), 373-398.

Rossetti, R. J. F., Ferreira, P. A. F., Braga, R. A. M., Oliveira, E. C. (2008). Towards an artificial traffic control system. *Intelligent Transportation Systems, 2008. ITSC 2008. 11th International IEEE Conference on, Beijing, China, 12-15 Oct. 2008*, pp. 14-19.

Rossetti, R. J. F., Liu, R., Cybis, H. B. B., Bampi, S. (2002). A multi-agent demand model. *Proceedings of the 13th Mini-Euro Conference and 9th Meeting of the Euro Working Group Transportation (EWGT), Bari, Italy, 10-13 June 2002*, pp. 193-198.

Rossetti, R. J. F., Oliveira, E. C., Bazzan, A. L. C. (2007). Towards a specification of a framework for sustainable transportation analysis. Workshop on Artificial Intelligence Applied to Sustainable Transportation Systems (AIASTS), 13th Portuguese Conference on Artificial Intelligence, Guimarães, Portugal, 3-4 Dec. 2007, pp. 179-190.

Santos, Behrendt, H., Maconi, L., Shirvani, T., & Teytelboym, A. (2010). Part I: Externalities and economic policies in road transport. *Res. Transp. Econ , 28* (1), 2-45.

Santos, G., Behrendt, H., & Teytelboym, A. (2010). Part II: Policy instruments for sustainable road transport. *Res. Transp. Econ , 28* (1), 46–91.

Schepperle, H., & Böhm, K. (2007). Agent-based traffic control using auctions. In *Cooperative Information Agents XI* (pp. 119-133). Springer Berlin Heidelberg.

Schepperle, H., Böhm, K., Bazzan, I. A. L., & Klügl, F. (2009). Valuation-Aware Traffic Control: The Notion and the Issues. *Multi-agent systems for traffic and transportation engineering*.

Seo, Y. P. (2005). A study on setting-up methodology and criterion of exclusive bus lane in urban area. Eastern Asia Society for Transportation Studies.

Sheffi, Y. (1985). *Urban Transportation Networks: Equilibrium Analysis with Mathematical Programming Methods.* Englewood Cliffs, New Jersey: PRENTICE-HALL, INC.

Silberberg, E. (1990). *The structure of economics: A mathematical analysis.* New York: McGraw-Hill.

Small, K. A. (May de 1979). The Schedule of Consumer Activities: work trips. *Econometric Research Program nº 243* .

Soares, G., Kokkinogenis, Z., Macedo, J., & Rossetti, R. J. F. (2014). Agent-Based Traffic Simulation Using SUMO and JADE: An Integrated Platform for Artificial Transportation Systems. In *Simulation of Urban Mobility, Lecture Notes in Computer Science*, pp. 44-61. Springer Berlin Heidelberg.

Sterling, & Pedell. (2012). The benefits of agent-based motivation models in policy formulation and implementation. Advanced Agent Technology, Springer Berlin Heidelberg, pp. 113–127.

Stier-Moses, J. R. (2011). Wardrop Equilibria. *Wiley Encyclopedia of Operations Research and Management Science* (DOI: 10.1002/9780470400531.eorms0962).

Szeto, W. J. (2010). Time-dependent discrete network design frameworks considering land use. *25* (6).

The Volvo Research and Educational Foundations, V. (2011). *10 years with the FUT programme.* Göteborg: Capito AB.

van Engers, T. M., van Haaftena, W., & Snellenb, I. (2011). Policy Making: How rational is it? *Workshop on Modelling Policy-making, (MPM 2011).*

Vasirani, M., & Ossowski, S. (2011). A computational market for distributed control of urban road traffic systems. *Intelligent Transportation Systems, IEEE Transactions on*, *12*(2), 313-321.

Vasirani, M., & Ossowski, S. (2009). A market-inspired approach to reservation-based urban road traffic management. In: *Proceedings of The 8th International Conference on Autonomous Agents and Multiagent Systems-Volume 1*. International Foundation for Autonomous Agents and Multiagent Systems. p. 617-624.

Verhoef, J. R. (2006). Basic economic principles of road pricing: From theory to applications . *Transp. Policy , vol. 2, pp. 106–114*.

Voβ, T. T. (2009). Design and evaluation of road pricing: state-of-the-art and methodological advances," . *Netnomics , vol. 10, no. 1, pp. 5–52*.

Wang, F. Y. (2003). Integrated intelligent control and management for urban traffic systems. In *Intelligent Transportation Systems, 2003. Proceedings. 2003 IEEE* ,Vol. 2, pp. 1313-1317.

Wardrop, J. (1952). Some theoretical aspects of road traffic research. *Proceedings of the Institution of Civil Engineers, Part II* .

Wee, B. V. (2009). Transport policy: what can it and what can't it do? *European Transport Conference.*

White, R., & Engelen, G. (1993). Cellular automata and fractal urban form: a cellular modelling approach to the evolution of urban land-use patterns. *A 25* (8).

Wilensky, U. (1999). NetLogo. Center for Connected Learning and Computer-Based Modeling. Evanston, IL: Northwestern University.

Wooldridge, M., & Jennings, N. R. (1995). Agent theories, architectures, and languages: a survey. In *Intelligent Agents, Lecture Notes in Computer Science* (Vol. 890, pp. 1-39). Springer Berlin Heidelberg.

Wyner, A., Atkinson, K., & Bench-Capon, a. T. (2012). Opinion Gathering Using a Multi-Agent Systems Approach to Policy Selection. in Proceedings of the 11th International Conference on Autonomous Agents and Multiagent Systems, vol. 3, pp. 1171–1172.

Wyner, A., Wardeh, M., Atkinson, K., & Bench-Capon, a. T. (2012). A Model-Based Critique Tool for Policy Deliberation. in Proceedings of 25th Annual Conference on Legal Knowledge and Information Systems, vol. 250.

Zheng, Waraich, Axhausen, & Geroliminis. (2012). A dynamic cordon pricing scheme combining the Macroscopic Fundamental Diagram and an agent-based traffic model. *Transp. Res. Part A Policy Pract , vol. 46, no. 8, pp. 1291–1303*.

Zhou, X., & Mahmassani, H. S. (2006). Dynamic origin-destination demand estimation using automatic vehicle identification data. *Intelligent Transportation Systems, IEEE Transactions on , 7* (1), 105-114.