

# Developing a MATSim Santiago Scenario: First illustrations evaluating a congestion pricing scheme

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## ABSTRACT

## Summary + contributions.

## INTRODUCTION

Urban agglomerations are a complex phenomenon. Taking a bottom-up perspective, cities are places where interactions occur constantly. Such a system poses different challenges in terms of both data gathering and modeling approaches, being the activity-transportation system and their interactions of particular interest. Given the constant growth of cities and the increasing concern about climate change, new methods to model and measure transport externalities properly are necessary in order to make better predictions and ultimately take better decisions.

In this work an alternative to traditional modeling approach is applied to Santiago de Chile, where each transport user is simulated as a single agent who learns from its context based on repeated iterations that represent some real conditions. This model is later compared illustratively to the classical 4-step model using a congestion pricing scenario. Since Santiago combines different transport related conditions such as pollution problems during the winter season, concentration of work and study places in the wealthier north-eastern district and the existence of a tolled urban highways network, it represents an interesting case of study for the application of a metropolitan-scale transport and activity simulator (Kicköfer et al., 2016).

24        The aim of this work is twofold: from one part, it represents an entry point to evaluate the general utility of this model at a metropolitan-scale in terms of both theoretical and practical terms. In  
25        addition to this, it is intended to demonstrate the capability of this approach to simulate a congestion pricing scheme and assess its impact using a classical modeling approach as a benchmark.  
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28        This paper is organized as follows: ...

## 29        **LITERATURE REVIEW: TRANSPORT SYSTEM MODELLING APPROACHES**

30        To understand transport system modeling approaches it is useful to split them into two different subsystems: demand models and assignment models, the former including everything related to people behavior and their decision processes with exception of route decisions and the latter including route choice plus all the physical models of network flows (supply models) (Flügel et al., 2014).  
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32        Typically, both subsystems are interacted such as demand models determine travel intensity which are subsequently used by the route-choice step, allowing the modeler to get the level of service of different network elements via the supply models. Repeating this process should finally end in an stable point which represents an equilibrium state. Traditionally, these systems have been framed in the Four-Steps model, which in its basic version suppose the generation, distribution, modal split and assignment steps applied in a sequential manner. From its birth, research efforts have been put to a great extent into enhance the single steps of this model system (Boyce, 2007).  
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34        In this way, generation step has evolved from growth-factor modeling to discrete choice modeling where the choice of travel frequency is used as dependent variable, distribution step has evolved from growth-factor modeling to entropy maximization models and modal split step has evolved from zonal-level models to individual choice modeling using random utility theory (Ortúzar and Willumsen, 2011), being the logistic regression and its variants the most widely used model. Assignment, on the other hand, contains supply models, dominated by travel time-flow curves, and route choice, whose models can be classified depending on the consideration of congestion, random effects on the perception of travel costs by users, and users heterogeneity (Willumsen, 2008).  
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36        Drawbacks of this modeling approach can be found either in each step separately, e.g. lack of inclusion of transport costs in generation models or the fact that errors in original trip tables are  
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replicated and amplified in forecast trip tables in the distribution step, and also when analyzing the system as a whole, usually associated with how the steps mentioned above are integrated. From a more theoretical perspective, this modeling approach has been criticized for the fact that it ignores the derived condition of travel demand from the necessity of people to engage in activities located in different points of space and time, ignoring the restrictions that emerge from the relationship between activities and trips in people's choice process (McNally and Rindt, 2008). Examples of software that incorporate the Four Step modeling approach are Cube<sup>1</sup>, EMME<sup>2</sup> and Visum<sup>3</sup>, all of them offering the possibility to include feedback between the different steps of the model system. In addition to the already named software, ESTRAUS offers the possibility to find the so called simultaneous equilibrium between demand and supply, such as the determined flows ensures consistent levels of service in distribution, modal split and assignment steps through the use of a hierarchical demand structure (de Cea et al., 2003). Together with the traditional approach, other ways to model how people travel have been explored. This is the case of the Activity-Based approach, in which tours or complete days are modeled and where transport users are part of synthetic populations to represent heterogeneity (Flügel et al., 2014). As they represent demand models, the results of their application are generally transformed into Origin-Destination matrices to feed static assignment models, or are directly used in dynamic traffic assignment (Lin et al., 2008). The general purpose of these models is to determine in which activities individuals participate during a certain period of time, the location and timing of these activities and the particular sequence of them, which in turn is translated to a particular transport behavior (Ettema, 1996). Usually, it is assumed that individual activities are born from the household activity pattern, which are transferred to the household members through interactions and joint choice processes which are shaped by different types of restrictions (McNally and Rindt, 2008). A relevant example of this modeling approach is the work carried out by Ben-Akiva et al. (1996), who using the novel ideas of Hägerstrand (1970) and other researches, propose a general framework useful to understand the

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<sup>1</sup><http://www.citilabs.com/software/>

<sup>2</sup><https://www.inrosoftware.com/en/products/emme/>

<sup>3</sup><https://www.ptvgroup.com/en/welcome-to-the-ptv-group/>

76 choice process of individuals in terms of trips and the corresponding activities in which individuals  
77 engage, recognizing the existence of long-term choices usually associated with mobility behavior  
78 and life-style of households and their members, and some mid to short-term choices associated  
79 with trips and activity planning and its dynamics. One possible classification of the models be-  
80 longing to this approach can be found in **Bhat and Koppelman (2003)**, who define the concept of  
81 episode as the discrete engagement of a person in a particular activity, classifying the models in

- 82     • Single activity episode participation models,
- 83     • Activity episode pattern models:
  - 84         • Activity episode scheduling models,
  - 85         • Activity episode generation and scheduling models

86 As the name suggests, single activity episode participation models focus on determining how dif-  
87 ferent characteristics of the activities, the individuals and the relation between them and their  
88 household affects the participation in single activity episodes and one or more of the activity char-  
89 acteristics (such as duration or location). Activity episode scheduling models look for determine  
90 how individuals create sequences of episodes given a basic activity set, models that have been  
91 classified as incomplete since they rely in the activity generation in an exogenous way (**Bow-**  
92 **man, 2009**). Finally, activity episode generation and scheduling models focus in both how activity  
93 episodes are generated and how they are sequenced, including the two fundamental pieces that  
94 define people's choice process and which underlies the observable behaviour (as cited in **Scott and**  
95 **Kanaroglou (2002)**, pp. 877). One relevant example of this category is the model of **Bowman**  
96 and **Ben-Akiva (2001)** who based on the work of **Ben-Akiva et al. (1996)**, present the activity  
97 generation and scheduling as a sequence of choices using a nested Logit formulation.

98 While the activity-based modelling represents an alternative demand modelling approach, dy-  
99 namic traffic assignment is considered the alternative of static assignment. In general terms, dy-  
100 namic assignment takes into account the fact that flows are time-varying in every link of the net-  
101 work, including also other characteristics such as the consideration of First-In-First-Out queue

models, queue dissipation in finite time, and the existence of a capacity that is not exceeded (Ortúzar and Willumsen, 2011). This family of models consider two general types of solution: equilibrium and not-equilibrium states (Friesz et al., 2007). Peeta and Ziliaskopoulos (2001) classify these models in two main categories, analytical and simulation-based ones, the former formulated using mathematical programming, optimal control or variational inequalities, the latter focused in representing the traffic propagation with sufficient reality. A relevant example in the simulation based models is the Cell Transmission Model (Daganzo, 1994), which represents a numerical solution of the Kinematic Wave Model, in which traffic behavior is assumed to be similar to a fluid (Flügel et al., 2014). The main challenges for the application of simulation-based dynamic traffic assignment models in large-scale highly-congested urban networks are related to computational efficiency, scalability and model precision, existing an important trade off between efficiency and precision (Wei, 2010). Another big challenge of this models' family is calibration, which consists in finding the correct values for a set of parameters  $\beta_h^G$  (where  $h$  represent the temporal period and  $G$  the network conditions) such as supply, demand and the interaction between them is represented with enough reality by the model (Balakrishna, 2006). The challenges lie in the size of  $\beta_h^G$  and the relation between its element, which calls for formulating correct calibration methods, usually associated to optimization (Balakrishna, 2006). An approach that has been explored in more recent years in the transport area is the agent-based modelling, which can be defined as a computational method that allows the experimentation on objects, entities or fictitious individuals (agents) that interact in a determined environment through simulation (Gilbert, 2008). A relevant characteristic of this approach is that it allows to represent the learning and adaptation process of every agent, useful for complex systems where it is not possible to know every single action and behavior of the individual entities (Weiβ, 1995). Some examples of agents' learning methods are learning by instructions, learning from examples and by practice, or learning by analogy (Wei, 2010). An important example of this modelling approach in the transport field is TRANSIMS, which considers traffic micro-simulation based on cellular automata (Smith et al., 1995; Nagel et al., 1996). Part of the TRANSIMS developer team continued their research efforts independently, from where MAT-

129 Sim (Multi-Agent Transport Simulation) (Horni et al., 2016) was born. Agent-based models act  
 130 as an interface between activity-based models and dynamic traffic assignment, keeping the iden-  
 131 tity of every agent with its activity-travel chain through the simulation, taking advantage of both  
 132 approaches (Rieser et al., 2007). As agent-based models are simulation based, they suffer from  
 133 the same difficulties in terms of calibration as the pure dynamic traffic assignment models that are  
 134 based on simulation. Advice to calibrate this kind of models can be found in Fehler et al. (2004),  
 135 mentioning that calibration techniques should be recognized as a first task the inter-dependency be-  
 136 tween the different model's parameters and also make use of their modular structure, aiming to  
 137 reduce the complexity and the computational time of the complete process.

## 138 MATSIM

139 In this work, MATSim was used as the modelling framework to represent the Santiago's trans-  
 140 port system. The complete algorithm of this model is summarized graphically in Figure 1. In this  
 141 model, every agent represents a transport system user, who interacts with other agents when mov-  
 142 ing from an origin to a destination through the existing infrastructure, generally represented by the  
 143 road network. A MATSim simulation is formed by a predefined number of iterations that repre-  
 144 sents the repetition of an average day. Agents' interaction allow them to evaluate their activity-  
 145 travel chains (also called *plans*) through a performance function which is then used to model the  
 146 choice process between these alternatives. In brief, the three steps of the algorithm are (Kicköfer  
 147 et al., 2016),

- 148 1. Simultaneous execution of plans (mobsim): the plans of all agents are executed simultane-  
 149 ously on the network through the use of a first-in-first-out queue model in every link.
- 150 2. Evaluation of plans (scoring): every agent's executed plan is evaluated with a performance  
 151 function. Mathematically, the scoring function used in this work is represented by (Chary-  
 152 par and Nagel, 2005)

$$153 S_{plan} = \sum_{q=1}^N (S_{act,q} + S_{trav,q}) \quad (1)$$

154 where  $S_{act,q}$  is the utility of an activity  $q$ ,  $S_{trav,q}$  is the (typically negative) utility of travelling

from activity  $q$  to the next one and  $N$  is the agent total number of activities. For every agent, the utility of an activity is calculated as,

$$S_{dur,q} = \beta_{dur} \cdot t_{typ,q} \cdot \ln(t_{dur,q}/t_{0,q}) \quad (2)$$

where  $t_{typ,q}$  represents the typical duration of activity  $q$ ,  $t_{dur,q}$  is its actual duration in the simulation and  $t_{0,q}$  its minimal duration.  $\beta_{dur}$  represents the marginal utility of time as a resource. The utility of traveling between two consecutive activities is computed as,

$$S_{trav,q} = C_{mode(q)} + \beta_{trav,mode(q)} \cdot t_{trav,q} + \beta_m \cdot \Delta m_q + \beta_m \cdot \gamma_{d,mode(q)} \cdot d_{trav,q} + \beta_{transfer} \cdot x_{transfer,q} \quad (3)$$

where  $C_{mode(q)}$  is the Alternative Specific Constant (ASC),  $t_{trav,q}$  the travel time between activity  $q$  and  $q + 1$ ,  $\Delta m_q$  the change in the monetary budget caused by fares,  $\gamma_{d,mode(q)}$  the mode-specific monetary distance rate,  $d_{trav,q}$  the travelled distance and  $x_{transfer,q}$  a binary variable indicating whether a transfer occurred between the previous and the current travel leg.  $\beta_{trav,mode(q)}$ ,  $\beta_m$ ,  $\beta_{transfer}$  represent the direct marginal utility of travel time, the marginal utility of income and the penalty of transfers, respectively. The specific values of the parameters used in this work are presented in Section 4.

3. Change of plans (replanning): after executing the chosen plans, a predefined share of agents are selected to modify some aspects of a random plan already in their memory. For the Santiago scenario, it was assumed agents were able to change between car, public transport, or walk, or to explore new routes.

The repetition of the above steps results in an eventually stabilized scenario which is useful to further analysis.

175      **THE MATSIM SANTIAGO SCENARIO**

176      A MATSim scenario consists in all the necessary inputs used to simulate the transport system of  
177      a particular area of study. In practice, these inputs are the initial demand represented by the agents'  
178      initial plans, the network and the parameters of the behavioural models described in Section 3, in  
179      addition to other optional elements. One of the main steps in this work was the improvement of  
180      these elements with the aim to increase the realism of the simulation.

181      **Inputs Improvements**

182      *Initial plans*

183      The agents initial plans came from the most recent Santiago's Origin Destination Household  
184      Survey (ODS) ([SECTRA, 2014](#)), which covered 45 municipalities within the Santiago's metropoli-  
185      tan region. This survey was applied during the months of July 2012 to November 2013, and con-  
186      sidered two different types of days; the *normal-period days* which are the working days from the  
187      first fortnight of March to the first fortnight of December, and the *summer-period or weekend days*  
188      which are all the other days not considered in the first classification ([Muñoz et al., 2016](#)). The final  
189      sample size of the Santiago's ODS was 18.000 households, which were split into 11.000 house-  
190      holds surveyed during *normal-period days* and 7000 households surveyed during *summer-period*  
191      or *weekend days*. Expansion and correction factors were calculated and applied to the survey in  
192      order to reproduce the total number of households and persons in the study area and to represent  
193      household size and number of vehicles distributions ([Contreras, 2015](#)). The improvements made  
194      in this work started by correcting the original initial plans determined by [Kicköfer et al. \(2016\)](#),  
195      filtering out the *summer-period or weekend days* which were contained on them, ending up with  
196      a population with 28.740 agents. Naming  $\pi_0$  the corrected initial plans, the next step was to clone  
197      every agent  $i \in \pi_0$  a number of times proportional to its corresponding expansion factor in order  
198      to build a synthetic population representative of the 10% of the Santiago's population. In other  
199      words, if  $F_i$  represent the corresponding survey expansion factor, then every agent was cloned  $f_i$   
200      times, where

201      
$$f_i = [\eta \cdot F_i] \quad (4)$$

202 being  $\eta$  determined by,

203

$$\eta = \frac{10\% \cdot T}{\sum_{i \in \pi_0} F_i} \quad (5)$$

204 The above procedure ended up in a 10% population,  $\pi_{10}^0$ , with 665.201 agents. Since all the clones  
205 of a particular agent contained exactly the same information as the original one, some randomiza-  
206 tion were necessary to add variability to the simulations. First, trip start times (equivalently activity  
207 end times) were randomized using Santiago's public transport smartcard data (see e.g. [Munizaga](#)  
208 and [Palma \(2012\)](#)). In this case, data for the period between September 23rd and 27th of 2013  
209 was used as the ground truth to start the randomization process. For every public transport trip  
210 of every agent in  $\pi_{10}^0$ , a new trip start time was chosen assuming it follows a normal distribution  
211 centered in the reported trip start time and a standard deviation (in minutes),  $\sigma \in \{1, 2, \dots, 60\}$ , to  
212 be determined based on a distance measure between the histogram built with the smartcard data  
213 times,  $\mathbf{A}$ , and the public transport trip start times once already randomized,  $\mathbf{F}$ , choosing  $\sigma$  such  
214 as the distance between  $\mathbf{A}$  and  $\mathbf{F}$  was minimum. Since histograms depend on the bin size, five  
215 different sizes were used to find  $\sigma$ , starting in five minutes and ending with thirty minutes. Finally,  
216 for every  $\sigma$  tested and for every bin size, the randomization was repeated ten times in order to get  
217 an average of the distance measure. The distance measure chosen in this case was the  $\chi^2$  distance  
218 ([Pele and Werman, 2010](#)), given by

219

$$\chi^2(\mathbf{A}, \mathbf{F}) = \frac{1}{2} \sum_i^n \frac{(a_i - f_i)^2}{(a_i + f_i)} \quad (6)$$

220 where  $a_i$  and  $f_i$  represent the relative frequency in each bin  $i$  and  $n$  the total number of bins.

221 The above procedure ended up in a  $\sigma_{\chi^2}^* = 33$  minutes, which was found to be the parameter that  
222 minimizes the distance between  $\mathbf{A}$  and  $\mathbf{F}$  (see Figure 2). Finally, this parameter was used for all  
223 the trips of the whole cloned population, ending up with a population  $\pi_{10}^1$ .

224 The next step was to add variability to agents' activity locations. The goal in this case was  
225 to maintain as close as possible the observed land uses, assigning new activity locations to the

cloned agents and maintaining the activity types considered in the original synthetic population (home, work, business, education, health, visit someone, shopping, leisure and other). An official land-registry from a Government institution (SII) was used to this end, which corresponds to a georeferenced data-set with the number of places/buildings by different categories in every block of the city<sup>4</sup>. Blocks extending outside the main urban area were reduced before activity locations re-assignment process. Once already pre-processed, the georeferenced data-set was used to choose new coordinates for every activity of the cloned agents. In particular, new coordinates were chosen randomly based on the original activity type and inside the original traffic analysis zone, similar to the work made by Kickhöfer et al. (2013). An example of the home activity location distribution before and after the randomization process can be seen in Figure 3. This step ends up with a population denominated as  $\pi_{10}^f$ . Agents representing a 1% of the Santiago's total population were randomly sampled from  $\pi_{10}^f$  in order to obtain a more light-weight scenario to simulate, denominated  $\pi_1^f$ .

The final step was the inclusion of tolls to the tollways already included in the scenario network. Information about 2012's tolls was gathered from different resources (Government Institutions such as Ministry of Public Works, Annual Reports from tollways' operators, and other online resources). Since not all the 2012's tolls were available, some of them were adjusted from the last available year to 2012 values, following the expression tollways operators used to update them in an annual basis.

In order to include the tolls in the scenario, a shape file was built with lines crossing the corresponding MATSim network links, which represent the gantries' approximate locations. Finally, the fares were included using the MATSim road pricing module (Nagel, 2016), which applies the corresponding fares when agents enter the tolled links computing the term  $\beta_m \cdot \Delta m_q$  in the performance function (See Eq. 3). This step ended the input improvement process, giving as a result the so-called *improved-scenario*, which was the starting point to the calibration process, step that is necessary to ensure that the model is capable to replicate a set of observed conditions.

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<sup>4</sup>The number of places/buildings by block and the georeferenced data-set with the blocks information had to be merged previously to this step.

252      **Calibration**

253      The main goal of the calibration process is to end up with a model able to replicate some prede-  
 254      fined set of observed conditions, such as modal split, traffic flow or distributions of travel times and  
 255      distances. In this work, the improved-scenario was calibrated to replicate the observed modal split  
 256      and hourly traffic flow in specific counting stations distributed across the city (**SECTRA, 2013**).  
 257      Different initial settings were explored with the  $\pi_1^f$  population in order to know the simulator re-  
 258      sponse with a light-weight scenario. The final initial setting was then applied to the scenario with  
 259      the  $\pi_{10}^f$  population.

260      The initial step in this process was to calibrate the modal split, which was achieved by chang-  
 261      ing the values of the Alternative Specific Constants (ASCs) iteratively based on the expression  
 262      proposed by **Manski and Lerman (1977)**. Let  $P_{obs}(m)$  be the observed modal split of mode  $m$  in the  
 263      ODS and  $P_n^s(m)$  the corresponding modal split in MATSim after  $n$  iterations for the  $s_{th}$  simulation  
 264      <sup>5</sup>, then the correction of the corresponding ASC was made based on,

265      
$$C_m^{s+1} = C_m^s - \ln\left(\frac{P_n^s(m)}{P_{obs}(m)}\right) \quad (7)$$

266      Once the calibration of the ASCs was completed (i.e. when the simulated modal split of the  
 267      calibrated modes where close enough to the observed modal splits), the traffic volumes were cor-  
 268      rected using the *Calibration of Dynamic Traffic Simulations* (Cadyts) tool (**Flötteröd (2010)**, **Flöt-**  
 269      **teröd et al. (2011)**, **Nagel et al. (2016)**). In short, let  $y_a(k)$  be the observed traffic flow during hour  
 270       $k$  in link  $a$  and  $q_a(k)$  the corresponding traffic flow in the simulation for the same hour and link.  
 271      Also, let  $\sigma_a^2(k)$  be the variance of the traffic counts. Then, it is possible to sample from a posterior  
 272      route choice distribution given certain level of services and information of traffic counts modifying  
 273      the prior distribution by adding terms to the scoring function given by(**Flötteröd et al., 2011**),

274      
$$\Delta S_a(k) = \frac{y_a(k) - q_a(k)}{\sigma_a^2(k)} \quad (8)$$

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<sup>5</sup>Recall that a simulation is composed of multiple iterations

275 Assuming that the random variable representing the traffic flow in link  $a$  during hour  $k$ ,  $Y_a(k)$   
 276 follows a Poisson distribution with rate parameter  $y_a(k)$ , then its variance is assumed to be,

$$277 \quad \sigma_a^2(k) = \lambda \cdot \max(y_a(k), \sigma_{\min}^2) \quad (9)$$

278 which is a modification of the variance of a Poisson variable by a scale parameter  $\lambda$  usually  
 279 fixed at 1 and a  $\sigma_{\min}^2$  to avoid numerical issues (Flötteröd et al., 2011).

280 Finally, the modified agents' utility is given by,

$$281 \quad \tilde{S}_i = S_i + w \sum_{ak \in i} \Delta S_a(k) \quad (10)$$

282 where  $i$  represents a particular plan, so the sum in (10) is made over all the links and hours  
 283 within plan  $i$  that contain information about traffic counts, and  $w$  is a weight parameter defined  
 284 before Cadys application. It is important to note that, since the scenarios are scaled in terms of the  
 285 number of agents (1% and 10% of the real Santiago's population) the simulated traffic flows were  
 286 amplified in order to be congruent with the magnitude of traffic counts.

287 When simulating large-scale scenarios, it is recommended to control the oscillations of agents'  
 288 behavior between one iteration and the next (Kickhöfer et al., 2016), which is achieved by con-  
 289 trolling the re-planning step. In this work, the modal split calibration assumed that during the first  
 290 80% of iterations within a simulation, 15% of agents explore new routes, another 15% explore  
 291 new modes (between *car*, *public transport* y *walk*) and the remaining 70% choose between plans  
 292 that were already explored in the past. During the final 20% of iterations, the re-planning step was  
 293 turned off, so agents can choose only between plans already existing in their memories, and forcing  
 294 the convergence of scores through the method of successive averages (MSA). The plan selection  
 295 by every agents is made assuming a changing-plan probability that depends on  $\exp(\Delta_{score})$ , where  
 296  $\Delta_{score}$  is the difference between two plans scores (Nagel and Horni, 2016) Since the calibration of  
 297 traffic volumes started from the iteration with calibrated modal splits, Cadys was applied assum-  
 298 ing that agents could re-plan only in terms of new routes. Similar to the modal split calibration

process, the re-planning in this case was carried out only for the first 80% of iterations, and then turned off for the final 20%.

Two stability-simulations were run for 1% and 10% cases in order to check if changes made by the modal split and traffic volumes calibration processes were stable once Cadysts were turned off . The first stability-simulation (*stability-test with innovation*) considered a re-planning where 15% of agents were able to change between routes, another 15% were able to explore new modes, and the remaining 70% choose between plans already explored for the first 80% of the iterations. For the final 20% of the iterations, agents changed between already explored plans, and scores were averaged through MSA. The second stability-simulation (*stability-test without innovation*) assumed no re-planning at all, so scores were averaged through MSA from the simulation start. Also, the 1% Case was simulated from an increased number of iterations with the ASCs\* already found in the modal-split calibration process in order to check the stability of this particular result (*modal-split stability-test*).

### Calibration and stability tests results

Tables 1 and 2 show the results of the modal-split calibration process for the 1 and 10% cases. It is important to note that, in both scenarios, agents were able to choose only between car, public transport, and walk, so both observed and simulated modal splits were scaled up such that they add up 100%. In both tables, subscripts denote the iteration number inside a given simulation, and superscripts denote the simulation number. In the 1% case, the calibrated scenario was obtained for the 30th simulation, and in the 10% it was obtained for the 7th one. The reference iteration to evaluate the modal splits and their similarity with the observed ones is iteration 100 for both cases.

For the traffic volumes calibration, Cadysts was applied in both 1% and 10% during  $n_c = 500$  iterations from iteration 100 (which corresponds to the modal-split calibrated scenario). The parameters  $\lambda$ ,  $\sigma_{min}^2$  of Equation 9 and  $w$  of Equation 10 were maintained with their default values of  $\lambda = 1$ ,  $\sigma_{min}^2 = 25^2$  [veh/h]<sup>2</sup> and  $w = 30$ . The results are shown graphically in Figures 4 and 5 for the 1% and 10% case, respectively.

In terms of stability, Table 3 shows the evolution of modal splits through the final iterations

326 for the 1% case. The modal-split stability-test corresponds to a  $n_{e1} = 500$  iterations simulation  
327 starting from iteration 0 with ASCs\*. The stability-test with and without innovations corresponds  
328 to a  $n_{e2} = 200$  iterations simulations starting from iteration 600 (modal-split and traffic volumes  
329 calibrated scenario).

330 Similarly, Table 4 shows the evolution of modal splits through the final iterations for the 10%  
331 case. In this case, no modal-split stability-test was run since it was assumed a similar response to  
332 the 1% case from the simulator.

333 Observing the previous tables, it can be seen that the modal-split behavior is stable throughout  
334 the different simulations in both the 1% and 10% cases, in spite of the agents' utility modification  
335 made by Cadys in between. In general, it can be assumed that the iteration 100 is sufficiently  
336 representative in terms of modal splits, such that a higher number of iterations will not affect  
337 significantly the modal splits given the simulator set-up used in this work. To summarize how close  
338 the simulated and observed counts are, Table 5 and 6 show the linear regression parameters built  
339 considering the observed counts and simulated counts as the independent and dependent variable,  
340 respectively, for the 1% and 10% cases (intercept, slope and  $R^2$  statistic).

341 In the case of traffic volume calibration, both Table 5 and 6 show (1) an over-estimation of traf-  
342 fic volumes by the simulator when observed traffic counts are 0 since intercepts are all greater than  
343 2.000 veh/day and (2) a systematic under-estimation of traffic volumes since the slope coefficients  
344 are all lesser than 1. In both cases, it can be seen the effect of Cadys in the three linear regression  
345 parameters, making intercepts decrease towards zero, slopes increase towards 1, and increasing  
346 the  $R^2$  statistic. The *stability-test with innovation* shows, however, that the simulator behavior once  
347 Cadys is turned off, does not persist. This happens because changes made by including adding  
348 terms in the agents' utility function are erased once Cadys is turned off.

## 349 **ILLUSTRATION: SCALING EFFECT AND POLICY ANALYSIS**

350 After the calibration process, the scenarios were useful to make policy analyses. Also, since  
351 this work considered synthetic populations representative of the 1% and 10% of the Santiago's  
352 population, they were also useful to test the scaling effect in the simulation.

353     **Scaling effect**

354       1% and 10% calibrated scenarios were compared in terms of distance and travel times distri-  
355       butions made by car mode<sup>6</sup>. Relative frequency histograms were built with data of the 24 hours,  
356       filtering those trips with null travel times or distances, shown in Figure 6.

357       Observing the traveled distances distribution, it can be seen that there is no notable differ-  
358       ence between 1% and 10% cases, which can be interpreted as no effect in the assignment-step  
359       attributable to the scenario scaling. Traveled distances distribution for the Stability-test with inno-  
360       vation Scenario was also built to ensure that this conclusion was not dependent on Cadyts effect  
361       (see Figure 6, (a) and (b)). These figures validate the use of this type of scaling in MATSim sce-  
362       narios for travel distances analyses, although a more rigorous statistical tests should be carried out  
363       to ensure this conclusion. The above conclusion does not hold for the travel times. Observing  
364       Figure 6, (c), it can be seen that, in general, travel times for the 1% case are greater than the ones  
365       for the 10% case. This phenomenon occur due to the link capacities scaling method, where real  
366       capacities are multiplied by a scaling factor equals to the synthetic population sample rate. In the  
367       1% case, capacities were scaled down to their 1%, affecting most importantly to links with small  
368       capacities. In particular, a great reduction in link capacities creates an over-estimation of the travel  
369       times, since a small amount of vehicles entering those small-capacity links create false congestion  
370       effects. This poses a warning in utilizing scenarios with a reduced number of agents ( $\leq 1\%$ )  
371       and scaled using the method presented in this work, if one wants to use the scenario to travel time  
372       analyses.

373     **Evaluation of a congestion pricing scheme**

374       The Calibrated Scenarios were used to evaluate a particular congestion pricing scheme and  
375       the results were compared with those obtained by [SteerDaviesGleave \(2009\)](#) using the classical  
376       transport modeling approach in order to asses the level of sensitivity of the agent-based model  
377       used in this work.

---

<sup>6</sup>pt and walk mode analyses were neglected since those modes were not simulated in the road network

378     *Schemes description*

379     The types of schemes considered in this work are cordon-based, such as the ones highlighted  
380     in Figure 7. These schemes were originally proposed and evaluated by SteerDaviesGleave (2009)  
381     using the ESTRAUS model (de Cea et al., 2003), applied in its *modal split - assignment* modality,  
382     meaning that the model considered changes in trip modes, routes and start times. The schemes  
383     were actively applied between 07:30 and 10:00 (morning peak, MP) and between 18:00 and 20:00  
384     (evening peak, EP). The scenario used in that case was representative of 2015. The entry-link  
385     charge was defined first since vehicles using those links were considered to increase the congestion  
386     level inside the cordon. Exit-link charge was calculated proportionally to the ratio between exit and  
387     entry flow in the base case scenario. Users traveling inside the area were not charged at all. Given  
388     this input information, the charges used in the present work were the highest ones proposed in the  
389     reference study (see Table 7). Simulations of 200 iterations were run from Calibrated Scenarios  
390     considering the (a) Outer cordon and (b) Triangle cordon schemes, whose results were compared  
391     with the Stability-test with innovation scenario, which represents the *business as usual* case. This  
392     comparison was made for the 1% and 10% cases.

393     *Results*

394     Daily modal splits variations for both 1% and 10% cases are shown in Figure 8. The results  
395     show a decrease in the modal split for car, and an increase in the modal split for public transport  
396     and walk modes, for both the 1% and 10% cases in the Outer and Triangle cordon scenarios (from  
397     now on, OT and TC, respectively), compared to the Stability Test with Innovation scenario (from  
398     now on ST). The magnitude of the variation in modal splits is clearly greater in the OC than in the  
399     TC scenario, in spite of the high fare magnitude considered.

400     The number of car legs for both 1% and 10% cases between 07:30 and 08:30 are summarized  
401     in Table 8, where OC-ST and TC-ST columns show the percentage change between the Outer Cor-  
402     don and the Stability-Test scenario, and between Triangle Cordon and the Stability-Test scenario.  
403     These columns are useful to make a comparison with the results obtained by SteerDaviesGleave  
404     (2009) for the same congestion schemes, where the percentage variations for car trips were found

405 to be approximately -5% and -1,5% for the OC and the TC, respectively, compared to the base  
406 case. This reveals the agents greater sensibility to congestion pricing compared to the traditional  
407 modeling approach.

408 Another interesting variable to analyze is the total traveled time and total traveled distances  
409 during 07:30 and 08:30, summarized in Table 9 and Table 11, respectively.

410 Observing Table 9, it can be seen there exist a reduction in total traveled time in car mode  
411 and an increase in public transport and walk modes, for both congestion schemes and for 1% and  
412 10% cases. Also, it can be seen that the 1% case presents a higher variation in travel times for car  
413 mode compared to the 10% case, result that should be seen with caution since the scenario scaling  
414 affects notoriously the travel time per kilometer distribution, as was already commented in Section  
415 5. Table 10 shows the total traveled time percentage variation if only car and public transport  
416 mode are considered, results that can be compared with the results obtained by [SteerDaviesGleave](#)  
417 ([2009](#)). In this case, the travel time savings for the Outer Cordon in 1% case are about three times  
418 higher than the saving for the Triangle Cordon scenario, results that are closer to the ones obtained  
419 in [SteerDaviesGleave](#) ([2009](#)) who obtained savings for the Outer Cordon about two times higher  
420 compared to the Triangle Cordon. On the other hand, the Outer Cordon in 10% case present travel  
421 time savings about twelve times higher than the ones for the Triangle Cordon scenario.

422 Finally, the total traveled distances summarized in Table 11 show little difference in the per-  
423 centage variation between 1% case and 10% for same scenarios, result that is consistent with the  
424 one commented in Section 5. Again, it is found that the effect of the Outer Cordon is higher to  
425 the corresponding one in the Triangle Cordon, concluding the same as [SteerDaviesGleave](#) ([2009](#)).  
426 MATSim, however, estimates total travel distances percentage variations greater than the ones ob-  
427 tained in the previous study, which corresponds to -5.8% and -1.4% for the Outer Cordon and  
428 Triangle Cordon, respectively.

## 429 **DISCUSSION AND CONCLUSIONS**

430 This work presented the development of an scenario and a first application of an agent-based  
431 model for the capital city of Chile. The MATSim model was used, which maintains the agents

432 identity through the iterations, enabling to simulate the short and medium term decision processes  
433 such as route, mode or trip start time choices. In this model, agents move across the city in order  
434 to participate in different activities, which are capable to learn through the memorization of daily  
435 plans and their respective scores.

436 First, a previous synthetic population ([Kickhöfer et al., 2016](#)) was enhanced in order to increase  
437 the resemble with the real Santiago's population: the number of agents was blown up using ex-  
438 pansion factors determined by [Contreras \(2015\)](#), the activities location of the cloned agents were  
439 randomized using land-use data and their respective trip start times were modified using smartcard  
440 data, process that ended up with two scenarios representative of 1% and 10% of the total popu-  
441 lation of Santiago. In addition to this, some aspects of the network were improved, such as the  
442 addition of the tolls to the tollways. Later, the improved scenarios were calibrated in terms of  
443 modal splits calculated from the ODS and traffic counts from a previous study ([SECTRA, 2013](#)).  
444 Finally, both scenarios were used to asses a congestion pricing scheme and outputs (changes in  
445 daily modal splits, number of car legs, total traveled time by mode and total traveled distance in  
446 car mode) were compared to the ones obtained by [SteerDaviesGleave \(2009\)](#). In general, it was  
447 found that agents in MATSim reacted in a more sensitive way compared to ESTRAUS, estimating  
448 a grater percentage of change in all the indicators analyzed in this study.

449 Possible next steps of this work are continuing the scenario enhancement, this time in terms of  
450 public transport simulation using as input the GPS data of the public transport system of Santiago,  
451 together with a map matching algorithm. Also, it is highly necessary to explore other calibration  
452 methodologies, particularly automatic ones such as the Opdyts tool proposed by [Flötteröd \(2017\)](#)

453

## Bibliography

- 454 Balakrishna, R. (2006). "Off-line calibration of dynamic traffic assignment models." Ph.D. thesis,  
 455 Massachusetts Institute of Technology, Massachusetts Institute of Technology.
- 456 Ben-Akiva, M., Bowman, J. L., and Gopinath, D. (1996). "Travel demand model system for the  
 457 information era." *Transportation*, 23(3), 241–266.
- 458 Bhat, C. R. and Koppelman, F. S. (2003). "Activity-based modeling of travel demand." *Handbook*  
 459 *of Transportation Science*, R. W. Hall, ed., Editorial Springer US, Boston, MA, 39–65.
- 460 Bowman, J. and Ben-Akiva, M. (2001). "Activity-based disaggregate travel demand model system  
 461 with activity schedules." *Transportation Research Part A: Policy and Practice*, 35(1), 1–28.
- 462 Bowman, J. L. (2009). "Historical development of activity based model theory and practice."  
 463 *Traffic Engineering and Control*, 50(2), 59–62.
- 464 Boyce, D. (2007). "Forecasting travel on congested urban transportation networks: review and  
 465 prospects for network equilibrium models." *Networks and Spatial Economics*, 7(2), 99–128.
- 466 Charypar, D. and Nagel, K. (2005). "Generating complete all-day activity plans with genetic  
 467 algorithms." *Transportation*, 32(4), 369–397.
- 468 Contreras, R. (2015). "Encuesta origen-destino santiago 2012: Procesos de expansión y corrección  
 469 en ausencia de datos censales." *XVII Congreso Chileno de Ingeniería de Transporte*.
- 470 Daganzo, C. F. (1994). "The cell transmission model: A dynamic representation of highway traffic  
 471 consistent with the hydrodynamic theory." *Transportation Research Part B: Methodological*,  
 472 28(4), 269–287.
- 473 de Cea, J., Fernández, E., Dekoch, V., Soto, A., and Friesz, T. (2003). "Estraus: a computer  
 474 package for solving supply-demand equilibrium problems on multimodal urban transportation  
 475 networks with multiple user classes.." *Annual meeting of the Transportation Research Board*,  
 476 *Washington, DC*.

- 477 Ettema, D. F. (1996). "Activity-based travel demand modeling." Ph.D. thesis, Technische Universiteit Eindhoven, The Netherlands.
- 478
- 479 Fehler, M., Klügl, F., and Puppe, F. (2004). "Techniques for analysis and calibration of multi-agent simulations." *ESAW: International Workshop on Engineering Societies in the Agents World*, Vol. 480 481 3451, Springer, 305–321.
- 482 Flötteröd, G. (2010). *Cadyts - Calibration of Dynamic Traffic Simulations, Version 1.1.0 manual*.
- 483 Flötteröd, G. (2017). "A search acceleration method for optimization problems with transport 484 simulation constraints." *Transportation Research Part B: Methodological*, 98, 239–260.
- 485 Flötteröd, G., Bierlaire, M., and Nagel, K. (2011). "Bayesian demand calibration for dynamic 486 traffic simulations." *Transportation Science*, 45(4), 541–561.
- 487 Flügel, S., Flötteröd, G., Kwong, C. K., and Steinsland, C. (2014). "Evaluation of methods for 488 calculating traffic assignment and travel times in congested urban areas with strategic transport 489 models." *Report No. 1358/2014*, Institute of Transport Economics.
- 490 Friesz, T. L., Kwon, C., and Bernstein, D. (2007). "Analytical dynamic traffic assignment models." 491 *Handbook of Transport Modelling: 2nd Edition*, Emerald Editorial, 221–237.
- 492 Gilbert, N. (2008). *Agent-based models*. Number 153. Editorial Sage.
- 493 Hägerstrand, T. (1970). "What about people in regional science??" *Papers in regional science*, 494 24(1), 7–24.
- 495 Horni, A., Nagel, K., and Axhausen, K. W. (2016). "Introducing matsim." *The Multi-Agent Trans-* 496 *port Simulation MATSim*, A. Horni, K. Nagel, and K. W. Axhausen, eds., Editorial Ubiquity, 497 London, 3–7.
- 498 Kickhöfer, B., Hosse, D., Turner, K., and Tirachini, A. (2016). "Creating an open matsim scenario 499 from open data: The case of santiago de chile."

- 500 Kickhöfer, B., Hülsmann, F., Gerike, R., and Nagel, K. (2013). “Rising car user costs: compar-  
501 ing aggregated and geo-spatial impacts on travel demand and air pollutant emissions.” *Smart*  
502 *Transport Networks: Market Structure, Sustainability and Decision Making. NECTAR Series on*  
503 *Transportation and Communications Networks Research*, T. Vanoutrive and A. Verhetsel, eds.,  
504 180–207.
- 505 Kicköfer, B., Hosse, D., Turner, K., and Tirachini, A. (2016). “Creating an open matsim sce-  
506 nario from open data: The case of Santiago de Chile.” VSP Working Paper 16-02. See  
507 <http://www.vsp.tu-berlin.de/publications>. TU Berlin, Transport Systems Planning and Transport  
508 Telematics.
- 509 Lin, D.-Y., Eluru, N., Waller, S., and Bhat, C. (2008). “Integration of activity-based modeling and  
510 dynamic traffic assignment.” *Transportation Research Record: Journal of the Transportation*  
511 *Research Board*, 2076, 52–61.
- 512 Manski, C. F. and Lerman, S. R. (1977). “The estimation of choice probabilities from choice based  
513 samples.” *Econometrica: Journal of the Econometric Society*, 1977–1988.
- 514 McNally, M. and Rindt, C. (2008). “The activity-based approach.” *Handbook of Transport Mod-  
515 elling*, D. A. Hensher and K. J. Button, eds., Emerald, 55–73.
- 516 Meister, K. (2011). “Contribution to agent-based demand optimization in a multi-agent transport  
517 simulation.” Ph.D. thesis, ETH Zurich, ETH Zurich.
- 518 Munizaga, M. A. and Palma, C. (2012). “Estimation of a disaggregate multimodal public trans-  
519 port origin–destination matrix from passive smartcard data from santiago, chile.” *Transportation*  
520 *Research Part C: Emerging Technologies*, 24, 9–18.
- 521 Muñoz, V., Thomas, A., Navarrete, C., and Contreras, R. (2016). “Encuesta origen-destino de  
522 santiago 2012: Resultados y validaciones.” *Ingeniería de Transporte*, 19(1), 21–36.

- 523 Nagel, K. (2016). “Road pricing.” *The Multi-Agent Transport Simulation MATSim*, A. Horni, K.  
524 Nagel, and K. W. Axhausen, eds., Editorial Ubiquity, London, 97–102.
- 525 Nagel, K., Barrett, C., and Rickert, M. (1996). “Parallel traffic micro-simulation by cellular au-  
526 tomata and application for large scale transportation modeling.
- 527 Nagel, K. and Horni, A. (2016). “More about configuring matsim.” *The Multi-Agent Transport  
528 Simulation MATSim*, Editorial Ubiquity, London, 35–44.
- 529 Nagel, K., Zilske, M., and Flötteröd, G. (2016). “Cadyts: Calibration of dynamic traffic simula-  
530 tions.” *The Multi-Agent Transport Simulation MATSim*, Ubiquity Editorial, London, 213–216.
- 531 Ortúzar, J. d. D. and Willumsen, L. G. (2011). *Modelling Transport*. John Wiley and Sons, Ltd,  
532 New Jersey, 4a edition.
- 533 Peeta, S. and Ziliaskopoulos, A. K. (2001). “Foundations of dynamic traffic assignment: The past,  
534 the present and the future.” *Networks and Spatial Economics*, 1(3), 233–265.
- 535 Pele, O. and Werman, M. (2010). “The quadratic-chi histogram distance family.” *European con-  
536 ference on computer vision*, Springer, 749–762.
- 537 Rieser, M., Nagel, K., Beuck, U., Balmer, M., and Rümenapp, J. (2007). “Agent-oriented cou-  
538 pling of activity-based demand generation with multiagent traffic simulation.” *Transportation  
539 Research Record: Journal of the Transportation Research Board*, 2021, 10–17.
- 540 Scott, D. M. and Kanaroglou, P. S. (2002). “An activity-episode generation model that captures  
541 interactions between household heads: development and empirical analysis.” *Transportation  
542 Research Part B: Methodological*, 36(10), 875–896.
- 543 SECTRA (2013). “Mediciones de aforos de tráfico y perfiles de carga en servicios troncales en el  
544 gran santiago.” *Report no.*, DICTUC.

- 545 SECTRA (2014). “Actualización y recolección de información del sistema de transporte urbano, ix  
546 etapa: Encuesta origen destino santiago 2012.” *Report no.*, Informe Final, Observatorio Social  
547 Universidad Alberto Hurtado.
- 548 Smith, L., Beckman, R., Anson, D., Nagel, K., and Williams, M. (1995). “Transims: Transporta-  
549 tion analysis and simulation system.” *Report no.*, Los Alamos National Lab., Nuevo Mexico,  
550 Estados Unidos.
- 551 SteerDaviesGleave (2009). “Tarificación vial por congestión para la ciudad de santiago.
- 552 Wei, Z. (2010). “Critical enhancements of a dynamic traffic assignment model for highly con-  
553 gested, complex urban network.” Ph.D. thesis, Massachusetts Institute of Technology, Mas-  
554 sachusetts Institute of Technology.
- 555 Weiß, G. (1995). “Adaptation and learning in multi-agent systems: Some remarks and a bibliogra-  
556 phy.” *International Joint Conference on Artificial Intelligence*, Springer, 1–21.
- 557 Willumsen, L. G. (2008). “Travel networks.” *Handbook of Transport Modelling*, D. A. Hensher  
558 and K. J. Button, eds., Emerald, 35–53.

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**TABLE 1.** Alternative specific constants and modal splits for 1% case.

Modo	$\tilde{P}_{obs}(m)$ [%]	$ASC^0(m)$	$\tilde{P}_{50}^0(m)$ [%]	$ASC^*(m)$	$\tilde{P}_{100}^*(m)$ [%]
<i>Car</i>	30,164	0,000	22,829	1,265	30,811
<i>Public Transport</i>	29,343	-1,058	35,344	-0,695	28,187
<i>Walk</i>	40,493	-0,143	41,827	-1,183	41,002

**TABLE 2.** Alternative specific constants and modal splits for 10% case.

Modo	$\tilde{P}_{obs}(m)$ [%]	$ASC^0(m)$	$\tilde{P}_{50}^0(m)$ [%]	$ASC^*(m)$	$\tilde{P}_{100}^*(m)$ [%]
<i>Car</i>	30,164	0,000	24,762	0,838	29,624
<i>Public Transport</i>	29,343	-1,058	34,263	-1,676	29,331
<i>Walk</i>	40,493	-0,143	40,975	-0,254	41,045

**TABLE 3.** Modal split evolution of car mode through the final iterations for the 1% case.

Scenario	Iteration	$\tilde{P}_n(\text{car}) [\%]$	$\tilde{P}_n(\text{PT}) [\%]$	$\tilde{P}_n(\text{walk}) [\%]$
Modal-split calibrated	100	30,811	28,187	41,002
Modal-split stability-test	500	31,596	27,810	40,594
Modal-split and traffic volumes calibrated	600	30,428	28,767	40,805
Stability-test with innovation	800	31,424	27,985	40,591
Stability-test without innovation	800	30,437	28,760	40,802

**TABLE 4.** Modal split evolution of car mode through the final iterations for the 10% case.

Scenario	Iteration	$\tilde{P}_n(\text{car}) [\%]$	$\tilde{P}_n(\text{PT}) [\%]$	$\tilde{P}_n(\text{walk}) [\%]$
Modal-split calibrated	100	29,624	29,331	41,045
Modal-split and traffic volumes calibrated	600	29,548	29,749	40,702
Stability-test with innovation	800	30,333	29,113	40,554
Stability-test without innovation	800	29,559	29,738	40,703

**TABLE 5.** Linear regression parameters evolution through the final iterations for the 1% case.

Scenario	Iteration	Intercept	Slope	R <sup>2</sup> statistic
Modal-split calibrated	100	9.392,0	0,25	0,04
Modal-split stability-test	500	10.634,7	0,14	0,01
Modal-split and traffic volumes calibrated	600	2.108,8	0,67	0,54
Stability-test with innovation	800	9.981,3	0,19	0,02
Stability-test without innovation	800	4.263,4	0,41	0,26

**TABLE 6.** Linear regression parameters evolution through the final iterations for the 10% case.

Scenario	Iteration	Intercept	Slope	R <sup>2</sup> statistic
Modal-split calibrated	100	9.379,5	0,18	0,02
Modal-split and traffic volumes calibrated	600	4.490,7	0,50	0,28
Stability-test with innovation	800	10.014,9	0,10	0,01
Stability-test without innovation	800	5.661,7	0,36	0,14

**TABLE 7.** Entry and exit charges in Outer and Triangle schemes. Source: [SteerDaviesGleave \(2009\)](#)

Link type	Outer cordon charge [\$2001]	Triangle cordon charge[\$2001]
Entry	6.000	6.000
Exit	3.600	2.650

**TABLE 8.** Total car legs between 07:30 and 08:30.

Case	Calibrated	Stability-Test	Outer Cordon	OC-ST [%]	Triangle Cordon	TC-ST [%]
1%	3.028	3.176	2.431	-23,46	3.035	-4,44%
10%	30.391	31.293	24.195	-22,68	30.011	-4,10%

**TABLE 9.** Total traveled time consumed [hrs] between 07:30 and 08:30 by mode and case.

Scenario	1% case			10% case		
	car	pt	walk	car	pt	walk
Calibrated	1.259,49	3.955,84	2.592,29	7.286,88	42.041,63	25.599,89
ST	1.547,63	3.845,67	2.594,60	10.219,55	41.065,03	25.688,28
OC	989,24	4.172,21	2.714,39	6.642,63	44.203,02	26.631,29
TC	1.422,26	3.897,62	2.627,95	9.698,05	41.552,48	25.911,17
OC-ST [%]	-36,08	+8,49	+4,62	-35,00	+7,64	+3,67
TC-ST [%]	-8,10	+1,35	+1,29	-5,10	+1,19	+0,87

**TABLE 10.** Percentage of variation in total traveled time consumed between 07:30 and 08:30 considering only car and public transport mode.

Scenario	1% case - $\Delta t$ [%]	10% case - $\Delta t$ [%]
OC-ST	-4.30	-0.86
TC-ST	-1.36	-0.07

**TABLE 11.** Total traveled distance consumed [km] between 07:30 and 08:30 for car mode and for each case.

Scenario	1% case - car	10% case - car
Calibrated	25.200,25	239.364,48
ST	25.854,74	243.742,95
OC	20.478,37	194.222,39
TC	24.846,90	235.175,73
OC-ST [%]	-20,79	-20,32
TC-ST [%]	-3,90	-3,51

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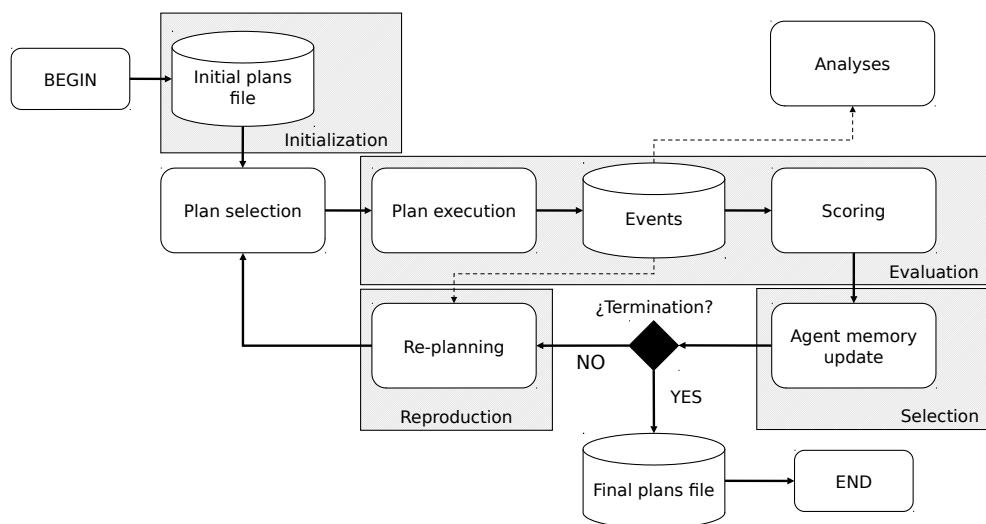
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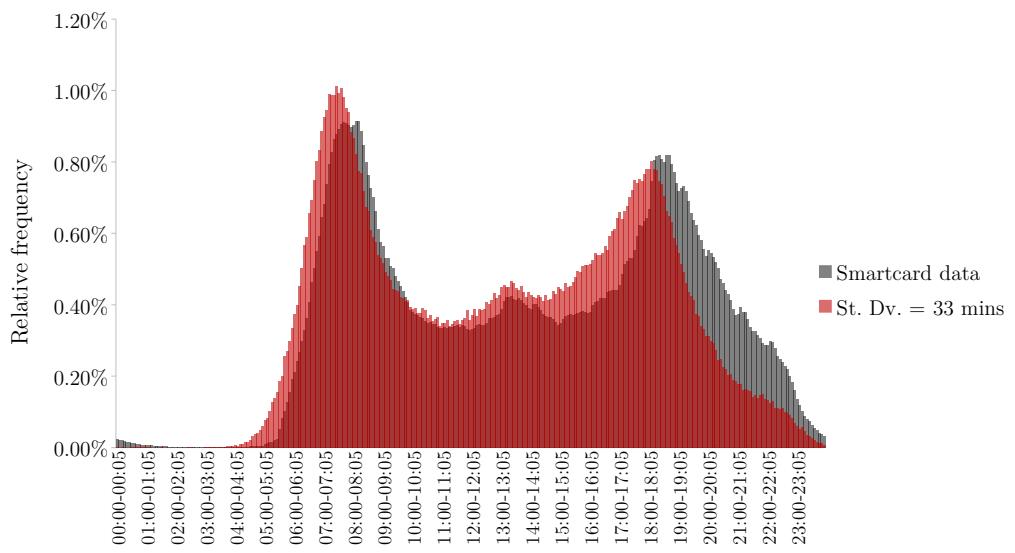
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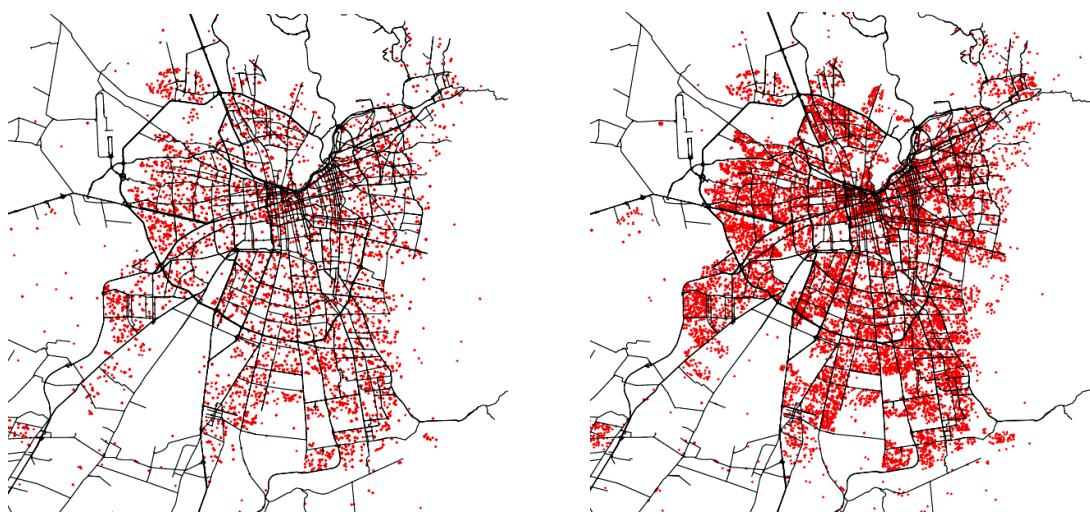
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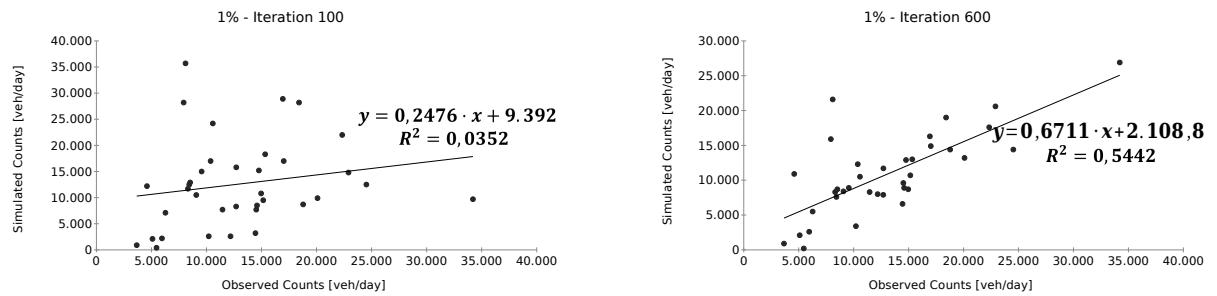
**Fig. 1.** MATSim algorithm. Source: Meister (2011)



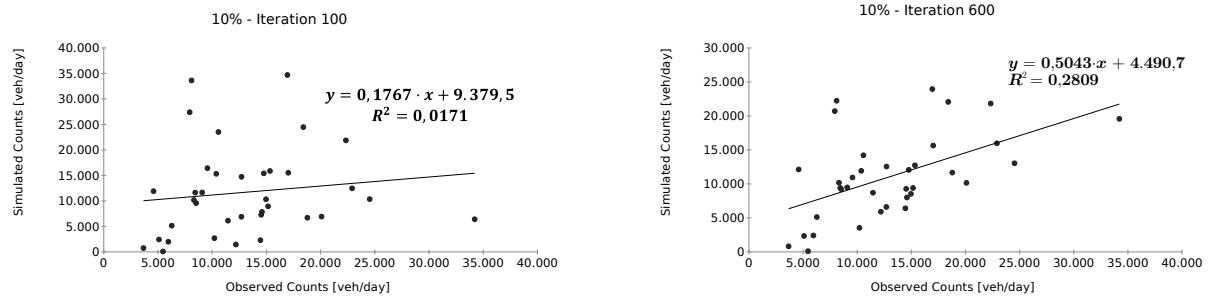
**Fig. 2.** Comparison of randomized public transport trip start times with  $\sigma_{\chi^2}^* = 33$  minutes (in red) and smartcard data (in gray).



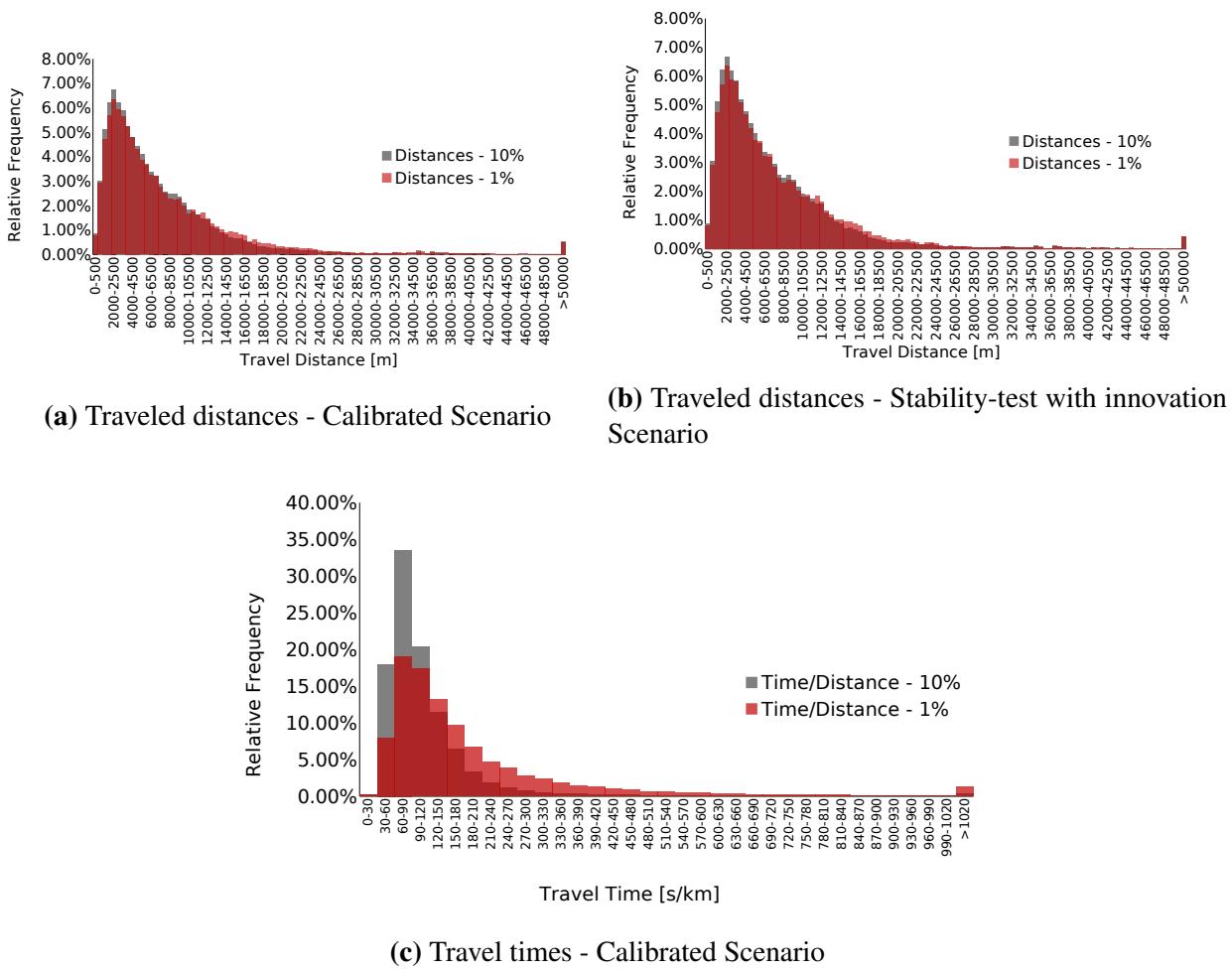
**Fig. 3.** Home activity location at 10:00 AM. Left: Before randomization. Right: After randomization



**Fig. 4.** Observed vs. simulated counts for 1% case. Left: Before Cadrys application. Right: After Cadrys application



**Fig. 5.** Observed vs. simulated counts for 10% case. Left: Before Cadysts application. Right: After Cadysts application



**Fig. 6.** Traveled distances and times distributions



**Fig. 7.** Cordon pricing schemes considered. Left: Outer Cordon. Right: Triangle Cordon



**Fig. 8.** Modal splits variation. Left: 1% case scenarios. Right: 10% case scenarios