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AN AGENT-BASED SIMULATION OF URBAN PASSENGER MOBILITY AND RELATED POLICIES. THE CASE STUDY OF AN ITALIAN SMALL CITY

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An agent-based simulation of urban passenger mobility and related policies. The case study of an Italian small city

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Abstract

In this paper we present an agent-based model which reproduces transport choices of a sample of 5,000 citizens of the city of Varese (Northern Italy) and the corresponding PM emissions of their daily commutes. The aim of the model is testing the impact of public policies willing to foster commuting choices with lower PM emissions. Our model, taking inspiration from other existing works, considers the commuters' decisions on the transport mode to be used. A set of preferences, one for each transport mode - private car, bicycle, public transport - is assigned to every agent. Throughout the process, agents decide about the means for commuting on the basis of the relative price of the different means of transport, of the social influence and of the intensity of the policies applied. The initial distribution of preferences for each transport mode are inspired to empirical data on Varese commuters. Results suggest that preference-based policies are more effective if compared to price-based ones. However, the application of a mix of different policies seems to give the best outputs: the same amount of resources in terms of policy intensity produce much better results if they are allocated at the same time to two policies, then to one only.

Keywords: *urban passenger transport, agent-based model, simulation, sustainable urban mobility policies*
JEL: O18, R41, R15

1. Introduction

Urban mobility is a key element of competitiveness for a city in the strong international competition and an important determinant of the citizens' life quality. The consistent external effects produced by an excessive use of road transport in daily commute generated in the last decades an increasing interest towards the identification and the implementation of effective sustainable urban mobility policies. As the European project EVIDENCE has recently underlined (European Platform on Sustainable Urban Mobility Plans, 2016), these policies could stimulate enhanced economic performance and avoid some economic costs associated with a car-dominated transport system, such as poorer public health.

The problem of sustainability in urban mobility is very challenging. Since, according to the European Environment Agency (http://www.eea.europa.eu/themes/urban), about 75% of the EU population lives in or around urbanized areas, producing 70% of the total EU GDP, cities are affected by increasing negative effects of traffic: air pollution, noise, greenhouse gas emissions, delays and traffic accidents. These externalities generate an economic damage which is estimated to be around 100 billion € each year, corresponding to about 1% of the EU's GDP (Erdmenger and Frey, 2010). Air pollution has strong impacts on the health of Europeans, particularly in urban areas, cutting the life duration, increasing medical costs and reducing productivity across the economy through working days loss. The most problematic pollutants in terms of harm to human health are PM, NO_2 and ground-level O_3. In this paper we consider the particulate matter (PM).

The European Environment Agency (2016, p. 7) reports that in 2014 PM10 concentrations above the EU daily limit value (i.e. 50 µg/m_3 not to be exceeded on more than 35 days per calendar year, for short-term exposure) were registered in 21 of the 28 EU Member States, while PM2.5 concentrations above the target value were registered in four. 16 % of the EU-28 urban population was exposed to PM10 levels above the daily limit value and approximately 50 % was exposed to concentrations exceeding the stricter threshold

established by the World Health Organization Air Quality Guidelines (annual mean, for long-term exposure).
The aim of the paper is to present an agent-based simulation of the passenger urban mobility of a northern Italian small city, Varese. The model reproduces the daily transport choices of a sample of 5,000 commuters and the corresponding PM emissions, analysing the behavioural changes driven by public policies aiming at improving transport sustainability. The agent-based modelling (ABM) methodology is used, a kind of simulation which has emerged in social sciences in the last decade and which is now increasingly accepted in the investigation of many economic issues (Arthur, 2010).
The paper is structured as follows. The next section provides an overview on the utility of the ABM methodology for the study of urban mobility, followed by a brief critical literature review on the existing works utilizing ABMs for traffic research. Sections 3 and 4 describe respectively the model framework and the data collection. Then, section 5 discusses the results of the simulation regarding the impact of price-based and motivation-based policies on agents' modal choice and as a consequence on particular matter emissions. In the last section some conclusions are drawn.

2. ABMs and urban mobility: a review

Agent based models (ABMs) combine elements of game theory, complex systems, emergence concepts, computational sociology, and evolutionary programming. This tool has been chosen because, according to the literature (among others, Axtell, 2000; Epstein, 2007; Gilbert, 2008; López-Paredes et al., 2012; Wilensky and Rand, 2015), it is particularly appropriate to represent very complex, dynamic and non-linear social systems. The main reason is related to the fact that in presence of complex systems "the behaviour of the system as a whole cannot be determined by partitioning it and understanding the behaviour of the resultant parts" (López-Paredes et al., 2012:4; Anderson, 1972). In that situation the classic analytic approaches are usually infeasible, without the use of stringent assumptions to simplify them. ABM simulate the behaviour of many simple agents and the interactions among them, capturing system level emergence from the bottom up and complex emergent behavioural patterns (Anand et al., 2016).
The high degree of system complexity is a key characteristics of traffic and transportation issues and, particularly, of urban mobility. In fact, it involves a high number of heterogeneous agents, complex interactions among them and between them and the observable environment.
Many methods are available in order to analyse transportation issues and travel behaviour, but agent-based models present some important advantages: the capability to represent the complex interactions, the diversity and the inherent variability over the time and space which characterise the transport systems (Donnelly, 2007). ABMs could facilitate two tasks: understanding the system and making qualitative and quantitative predictions about the future (Bazzan et al., 2005), considering agents' learning procedures. Due to their generative nature, they allow to consider that in transport agents are highly adaptive, react to changes in the environment at individual level but cause an unpredictable collective pattern and they learn from the past and from their social relations (Bazzan, 2009). Agent-based models allow reproducing adaptive decision behaviour about routes, mode decision or transportation services for realistic simulations (Klügl et al., 2010). Moreover, ABMs allow to deal with the concept of individual bounded rationality and incomplete information of decision makers, two elements that in the reality characterise the travellers' choices. Actually, in fact, since the information is generally incomplete and biased, in a travel decision-making process, a person spends money and time to search and compare some alternatives, choosing the relatively satisfying alternative rather than the best one in theory (Zou et al., 2016; Tversky and Kahneman, 1974; Acquisti and Grossklags, 2005; Weber, 1987). An accurate literature review which describes the advantages of agent-based modelling compared to other travel behaviour models available in literature, based on the utility maximisation theory (e.g. discrete choice models, nested logit models), can be found in the work of Zou et al. (2016).
As regards the public policies impact on stakeholders' behaviour, ABM methodology allows to consider that every agent in a group reacts differently to the introduction of a new policy and that the overall outcome of a public policy is not simply given by the sum of the individual reactions. It is indeed the product of the

interaction among many individual decisions with one another and the policy itself (Ambrosino et al., 2017). Moreover, the individuals, who are not perfectly rational, may react to the policy in ways that the regulator never intended and react also one to each other, often modifying their behaviour according to imitation or learning processes (Ambrosino, 2006; Bandura, 1977).

A critical review of the research on Agent-Based Models (ABMs) applied to urban mobility has been done by the authors in a previous work (Maggi and Vallino, 2016). The most important evidence of this review is that there is still a gap in passenger urban transport AB modelling: the number of developed models is limited and some of them are applied to broader geographical areas than urban one (Smith et al., 1995; Salvini and Miller, 2005; Natalini and Bravo, 2014) or to cities of very different size. A part of the works simulate the whole mobility but the majority focuses on a specific sub-category of citizens. For example, Schelhorn et al. (1999) investigate the pedestrian behaviour in urban University centres; Harland and Stillwell (2007) analyse the daily pupil movements between schools and residences in Leeds, while Shukla et al. (2013) focus on an Australian University campus population. The models' aims are mixed and the agents and, as a consequence, variables used vary. Some of them simulate specific policies, such as the increase of parking supply in a residential area with a shortage of parking places (Benenson et al., 2008) or the impact of different land use regulations on travel behaviour (Lu et al., 2008). Fagnant and Kockelman (2014) use ABM to simulate the environmental benefits of car sharing strategy, compared to conventional vehicle ownership and use. Different models have been developed to design the demand-responsive transportation (DRT) systems; these models have been recently reviewed by Ronald et al. (2015).

More recently than our previous survey, other empirical works on ABM urban mobility simulation appear. The model by Correa et al. (2016) analyses the interaction of road users with and without motorcyclists in Venezuela, with evident road safety implications. Zou et al. (2016) develop an agent-based model for travellers' choices of mode and departure time, evaluating congestion charge policies with various demand scenarios in the second ring road of Beijing (China). Melnikov et al. (2016), using scientific Python and MATSim agent-based freeware, develop a large-scale agent-based traffic simulation system for the Amsterdam urban area, designed for policy making in sustainable city development, emission control and electric car research. A multi-agent based simulation model for supporting the decision making in urban transport planning has been designed by Hajinasab et al. (2016), in order to investigate how different transport infrastructure investments and policy instruments will affect the travel choices of passengers. It considers four main categories of factors influencing the choice of travel: cost, time, convenience, and social norm. Kickhöfer and Kern (2015) propose a new approach which combines activity-based demand, dynamic traffic flows, agent-specific behaviour based on MATSim models, vehicle-dependent emissions, and time-dependent exposure cost calculations to evaluate pricing schemes' effect. This approach was applied to a real-world case study of the Munich metropolitan area in Germany. In the work of Kaddoura (2015) an agent-based simulation is presented to calculate external congestion effects in the Greater Berlin area: a pricing experiment is carried out in which optimal tolls could affect route decisions, whereas mode and departure time choice are fixed.

To the best of our knowledge, despite their potential effectiveness to represent the impacts of different public policies on agent behaviour and on the environment, only few models test policies and have been implemented in the real word by the researchers and/or by policy-makers. Thus, more efforts are needed in order to validate ABM use in simulating urban mobility as a whole complex system. The present paper tries to give a contribution on this issue. In order to achieve this aim, we have developed a model inspired to the one constructed by Natalini and Bravo (2014), which reproduces the modal transport decisions of a sample of USA citizens and the corresponding GHG emissions of their daily commutes. They test ex ante the impact of market-based and preference-based public policies on the commuting choices and on the resulting level of GHG emissions.

As regards the characteristics of our model, similarly to the models analysed in the literature review, the time horizon considered in our ABM is strategic, in the sense that it involves long-term decisions and addresses the question of interest from a broad point of view, without restricting the simulation to sub-dimensions of the problem (Maggi and Vallino, 2016; Davidsson et al., 2005). Moreover, the model structure is dynamic, since the behavioural rules of the agents change according to various criteria during the simulation, like for example the feedback given by the behaviour of the previous time step. This

happens in almost in the totality of the reviewed papers; for example, in the model of Salvini and Miller (2005) higher level decisions (e.g. residential mobility) influence lower-level decisions (daily travel behaviour). In our model, such as in Natalini and Bravo (2014), agents adopt one out of four possible decision rules according to the level of social and material satisfaction of each commute.
The attitude of the agents could be considered mainly cooperative, because they interact among themselves in order to accomplish their tasks and they could be influenced by the social network in which they are included. In one of the analysed works agents have both cooperative and competitive behaviour, depending on their tasks. In other works the attitude is competitive; for example, in Lu et al. (2008) paper agents compete over the use of land, while in Benenson et al. (2008) compete for the parking areas.
As regards the maturity degree of our model, according to Davidsson et al. (2005) classification, it could be considered at the stage of a field experiment, in the sense that the application has been conducted in the environment where the application is supposed to be applied (Varese, Italy).
Finally, such as the other models considered in the review, our ABM is conceived to give a decision support system for decision makers and policy makers.

3. Model specification

The focus of the model is on the commuting choices of 5,000 agents and the corresponding pollution deriving by the means of transportation which are utilized for their urban mobility[1]. The aim of the model is testing ex ante the impact of public policies willing to foster commuting choices which would produce lower emissions. The agents of the simulation represents a sample of citizens of Varese, a small city in Northern Italy of about 80,000 inhabitants and a density of 1,470 inhabitants per square kilometer, located in the Lombardia Region. The sample therefore represents the 6,25% of the total population.
There are two types of entities: the commuter and the government. The agents represent the commuters, whose features, which are also called “state variables”, are the following: their preference for each of the three possible transport modes (private car, private bicycle and public transport); their social and personal satisfaction, the number of their neighbours, their satisfaction derived by the choice of the means of transport, and the uncertainty about their choices overtime. The government is represented in the form of an abstract entity that decides over the policies to be implemented.
Figure 1 shows a conceptual diagram representing the model functioning.
As regards the input, before the beginning of the simulation, that is to say in the “setup” phase, the agents receive a set of preferences that have been assigned to them and which are inspired to real data collected by the Italian National Statistical Office Census in 2011 (http://www.istat.it/it/censimento-popolazione/censimento-popolazione-2011); in the section below we will explain in detail how the data have been collected and processed. Each agent has a certain level of appreciation of each of the three means of transport (private car, private bicycle and public transport), included in a range between 0 and 1, where 0 is the minimum level and 1 the maximum one. Throughout the process, these preferences are influenced by the relative price of the different means of transport, by social influence and by the intensity of the policies applied.
The dimensions x, y and z that each agent has in the 3D space represent the agent’s preference for each of the means of transport. In this version of the model there is no representation of the physical space by a geographical point of view but it is possible to include it in the future.
Always during the “setup” phase each agent establishes a link with all the other agents having sufficiently close preferences. The parameter that determines how close two agents should be in terms of preferences in order to establish a link is decided through a slider in the model interface (“link-distance”). In the simulations this is set to a value that creates a degree distribution approaching a power law, which is a recurring feature in many kind of social networks (Barabasi, 2009; Natalini and Bravo, 2014). The procedure then identifies if any agent is left alone and, if this is the case, it is linked to the closest agent in terms of preferences. This process of network creation was first introduced in the agent-based framework by Hamill

[1] The Netlogo code of the model is available on the Openabm platform, at the following link: https://www.openabm.org/model/5419/version/1/view

and Gilbert (2009) and it leads to the establishment of a “social circle” structure, which includes important features of large social networks, such as high clustering and low density.
The last step happening during the “setup” phase is the configuration of the features of the means of transport. Each of the three choices has an absolute cost per kilometer, a relative cost with respect to the other means, an average level of pollutant emissions per kilometer and an environmental index taking as benchmark the most polluting mean. The monetary costs are expressed in Euro, while the pollutant emissions are expressed in particulate matter (PM). The values of these variables and indexes are derived from empirical data linked to Italian scenarios, which will be described in detail in the section below.
The model considers one main process, that is to say the agents‘ decision about the means of transport it wants to utilize for the commute. At one time step in the model corresponds one commute for every agent. The deliberative process is a complex procedure conceived and applied by different scholars in the field of consumers behavior regarding the diffusion of green products and ecological behavioral patterns (Natalini and Bravo, 2014; Bravo et al., 2013; Jager, 2000; Janssen and Jager, 2002). The agent decides its transportation mode on the basis of two factors: its total need satisfaction and the uncertainty level. In turn, the total need satisfaction is composed by the sum of personal and social needs, divided by the relative price of the means of transport. The personal need satisfaction is made by the relation between agent’s preferences and its commuting choice in the past. A formal representation of the social need satisfaction concept defines it as the proportion of agents in the neighbourhood of i choosing the same transportation mode as i

$$N_{ik}^{S} = \frac{n_i^k}{n_i}$$

where the numerator is the number of agents in i neighbourhood with transportation mode k, while the denominator is the total number of agents in the neighbourhood. The total level of need satisfaction of agent i choosing transportation mode k is given by the weighted sum of social and personal satisfaction, divided by the relative price r_k of the transport modes:

$$N_{ik} = \frac{\beta_i N_{ik}^{S} + (1-\beta_i) N_{ik}^{p}}{r_k}$$

where β_i is an agent parameter randomly distributed in the range [0-1], determining how much personal needs are weighted versus social ones. In the literature peer pressure is considered to be a strong engine for behavioural change (Nyborg et al., 2016). The uncertainty consists of the variation over time of agents’ total satisfaction and, following Natalini and Bravo (2014), Bravo et al. (2013) and Janssen and Jager (2002), it is defined as

$$U_{it} = \sqrt{|N_{it} - N_{i(t-1)}|}$$

where t is the decision time for agent i.
Each agent has two thresholds of tolerance toward total need satisfaction and uncertainty, which are incorporated in two sliders in the model interface. The thresholds values lie between 0 and 1. The first (“uncertainty-tolerance”) indicates the tolerance towards high or low levels of uncertainty overtime, while the second (“min-satisfaction”) indicates the minimum level of satisfaction accepted by an agent. When the thresholds of these two tolerance levels are reached, the agent has an incentive to change his behaviour regarding its commuting choice. At each time step, according to its position with respect of these two thresholds, the agent uses one out of four possible deliberative processes. If satisfaction is above the threshold, but this status is coupled with high uncertainty, the agent imitates the most adopted choice among the members of its network (imitation behaviour). If satisfaction is low, but uncertainty is also below the threshold, the agents utilizes rational deliberation, that is to say it calculates the satisfaction deriving from the use of each mean of transport and it chooses the most satisfactory one. If the agent is both satisfied and certain, it will simply repeat the decision of the previous time step. If the agent faces both dissatisfaction and high uncertainty, it applies the social comparison, which combines the imitation

and the rational deliberation approaches: it compares the satisfaction associated to the repetition of its previous behaviour and the one linked to the adoption of the most common choice among its network members. Summing up, in each simulation step, agents first calculate their level of uncertainty and satisfaction for each commuting choice, then choose the new means of transport following one of the above procedures. The simulation continues until the model reaches an equilibrium, that is to say, agents no longer change their behaviour.

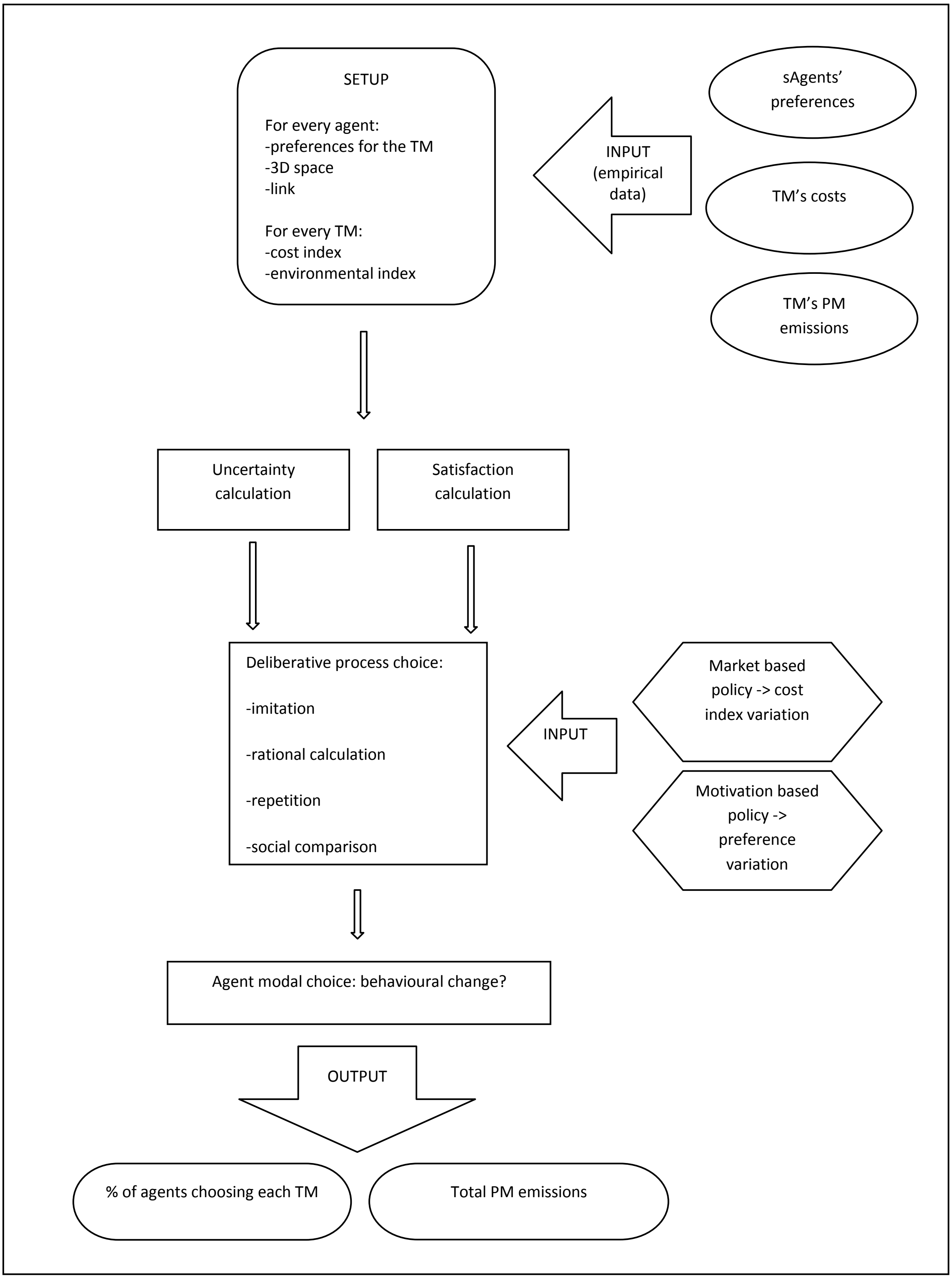

Fig. 1. *TransportVarese* model diagram. At one time step corresponds one commute for each agent. The simulation continues until agents no longer change their choices and therefore an equilibrium is reached. TM = transportation mode. PM = particulate matter.

Two kinds of policies are implemented in order to give incentives to the agents to shift to transportation modes with lower PM emissions. The first is market-based and it is represented by a parameter that increases the price of the use of the private car, which is the most polluting mean of transportation among the three possibilities. In Bravo et al. (2013) and Natalini and Bravo (2014) this kind of policy produces a price increase proportional to the polluting index of the different options, while in our work we simulate an increase of the price only of the most polluting option, leaving the price of the other choices unchanged. In fact, actually the market-based policies aim to discourage the use of the most pollutant transport mode, by increasing its price and on contrary to incentive the less pollutant ones, by decreasing their price or leaving it more or less the same. The second policy is motivation-based and it is represented by a parameter that increases the preference for less polluting means of transportation independently from their price. We represent the policies intensity through two sliders in the model interface having values included in the range [0-1]. The intensity of both policies is decided by the modeller, who, moreover, may test each policy alone, or different combinations of the two (see section 5 below).

Other sliders that are included in the model interface and whose values that can be decided by the modeller are those steering the relative prices of the three transportation modes. The calculations leading to the decision of these values are described in detail in the section below.

The variables of output that are of our interest in each scenario are the share of agents choosing the three means of transportation and the total PM emissions produced by the system. The modeller observes the variation of these variables after the simulation of the policies application. The simulation starts always with 100 percent of the agents choosing the private car option, and after going through all the decision steps, the system reaches a stable path. Therefore one must compare the final values of the “starting” scenario with the final values of the “after-policy” scenario.

4. Data collection

In Table 1 and Table 4 we show the main data used in the model; they concern the absolute and relative financial cost of each transport mode and the environmental emissions’ indexes.

4.1 Monetary cost

For each of the three means of transportation we calculated a monetary cost associated to their utilization, and, consequently, for each of them, an index of relative price with respect to the most expensive one.

Regarding the private car, since the purchase of a vehicle is too variable among all the possible options, we considered the operating costs only. According to different on-line sources, cars on average consume 1 liter of gasoline every 13 km when they drive in the town. If on average the price of gasoline is 1.4 Euro per liter, the average cost of the gasoline for using the automobile in cities is 0.107 Euro per km. Moreover we consider the following fixed expenses, which do not vary with the intensity of utilization: the tax for the ownership of the vehicle, which in Italy is called “bollo” and costs around 150 euro per year; the expenses for the control of specific car components which are around 300 Euro per year, taking the average among different kinds of vehicles (“tagliando”); the payments for the compulsory control about the general secure functioning of the vehicle (“revisione”), which are around 14 Euro per year (http://www.autoinformazioni.org/; http://www.revisioneauto.eu/).

We consider short commutes with travelling of maximum 15 minutes; since the average speed among the three means is about 20 km per hour, we assume that one agent travels for about 5 km during a short commute and 10 km if we consider the round trip. Summing up the costs of the gasoline per day for the private car and its fixed costs per day we obtain that an agent must face the cost of 2.34 Euro per day if it chooses the private motorized transportation option.

Regarding the public transport option, we diminish by 20 percent the one-way ticket price, since we assume that many passengers may have a season ticket, obtaining the amount of 1.12 Euro per ticket. With an average speed of 15 km/h it is possible to travel for 22.5 km with a 90-minutes bus ticket. Therefore the cost per kilometer would be 0.05 Euro and the cost of a standard short commute of 10 km (round trip) would be 0.5 Euro per commuter per day if the public transport option is chosen.

The operating costs of using the bicycle are set to 13 percent of the costs associated to the use of the car; this value is derived from different works focused on bicycle use (Litman , 2012; Natalini and Bravo, 2014).

The indexes of the relative costs are calculated taking as benchmark the car, which is the most expensive mean of transport; the public transport and the bicycle options are divided by the cost of using a private motorized vehicle. In this way the relative cost index of the car is equal to 1, the one of the bus is equal to 0.2 and the one of the bicycle is equal to 0.13, as explained before. These values are visible in the model interface in the three corresponding sliders.

Table 1

Absolute and relative costs of the transportation modes.

Transportation modes	Unit value per commuter per day	Index	Specification	Source
Private car (C)	2.34 euro	1	fuel consumption+taxes+ maintenance cost	Various internet sources
Bicycle (B)		0.13	13% of car cost	Natalini and Bravo 2014, Litman 2012.
Public Transport (PT)	0.5 euro	0.2	Average ticket price	CTPI

Note: CTPI = Consorzio Trasporti Pubblici Insubria.

4.2 Environmental indexes

We choose to consider the amount of particulate matter (PM) as pollutant substance of automobiles and buses because of the higher data availability for each kind of vehicle with respect to data on CO_2 emissions and because of their importance, as it has been explained in the introduction. In Table 2 we present the PM emissions of each class of automobile, according to EU Directives[2], and the percentage of ownership of vehicles belonging to the different EU classifications, within the Municipality of Varese (ISTAT, 2012).

Table 2

Ownership and emissions of different kinds of automobiles in the Municipality of Varese.

Classes of automobiles	Percentage of ownership in the Municipality of Varese	Emissions of PM (g/km)
Euro 0	27.3 %	0.11
Euro 1		
Euro 2		
Euro 3	19.2 %	0.05
Euro 4	38.8 %	0.025
Euro 5	14.7 %	0.005

Source: EU Directives and ISTAT (2012).

[2] European emission standards define the acceptable limits for emissions of new vehicles sold in the EU and in the European Economic Area member states. The emission standards are defined in different EU directives that introduce progressively stringent standards. The stages are referred to as Euro 1, Euro 2, Euro 3, Euro 4, Euro 5 and Euro 6 for light vehicle standards and as Euro I, Euro II, etc. for heavy vehicles standards. The legal framework is made of different EU directives that amend the 1970 Directive 70/220/EEC and that have been issued between 1991 and 2012 (http://www.transportpolicy.net/index.php?title=EU:_Light-duty:_Emissions). The classifications for vehicle category are defined by the Directive 2001/116/EC and by the Directive 2002/24/EC (www.dieselnet.com/standards/eu/).

If we calculate the average emission level among the different classes, weighted by the percentage of ownership of the vehicles belonging to each class in the Municipality of Varese we obtain the value of 0.0125 g/km of PM. Multiplying this value for the average length of the round trip commute of 10 km we calculate that the pollutant emission of a commute realized with a private car is 0.125 PM g/day.
Regarding the environmental impact of the vehicles of the public transportation services, the public transport consortium of Varese (CTPI 2015) provides data about the percentage of utilization of vehicles belonging to the different classes, while ANAV, the National Association of road passenger transport firms, (2013: 26) delivers information about the pollutant emissions of each class of buses, always expressed in g/km of PM (Table 3).

Table 3
Environmental classification of the public transport vehicles and respective pollutant emission levels in Varese.

Classification of buses	Percentage of utilization of buses by CTPI within the Municipality of Varese	Emissions of PM (g/km)
Euro I	-	1.2
Euro II	26.67 %	0.6
Euro III	16 %	0.7
Euro IV	2.67 %	0.3
Euro V + EEV	49.33 %	0.3
Euro VI	5.33 %	0.2

Source: EU Directives, CTPI (2015) and ANAV (2013).
Note : EEV = Enhanced Environmental Friendly Vehicle.

Following the same procedure utilized for the private car, we calculate the average emission level among the different classes, weighted by the percentage of utilization of the vehicles belonging to the different classes within the Municipality of Varese. Therefore the average emission level of the use of one bus is 0.11 PM g/km.
This value of course has to be weighted by the passenger load factor, which in Varese is 19.07% (CTPI 2015: 8). Making the proportion with the maximum number of passengers that a bus can host (*ibid.*), we obtain that the average number of passengers of one public bus in Varese is 16. Therefore, in the context of our simulation, one agent that chooses the public transport option produces 1/16 of PM emissions, that is to say 0.007 g/km, and 0.07 g/commute.
Turning to the bicycle option, and considering only the dimension of its utilization and excluding the production and commercialization processes, its level of pollutant emissions is of course zero.

The environmental indexes of the three means of transportation take as benchmark the most polluting one and are directly proportional to the emissions produced by each of them; they vary between 0 (the most pollutant mean) and 1 (the greenest one). The formula utilized for the calculation of the index is the following: [1 - (emissions of the chosen mode / emissions of the most polluting mode)]. Applying this formula, the index of the private car turns out to be zero, the one of the public transport option is 0.44 and the one of the bicycle is 1.

Table 4
Absolute and relative PM emissions of the transportation modes.

Transportation modes	Unit value per km	Unit value per commuter per day	Index	Specification	Source
Private car (C)	0.0125	0.125	0	weighted by vehicles category	EU Directives and ISTAT
Bicycle (B)	0	0	1		
Public Transport (PT)	0.007	0.07	0.44	weighted by vehicles category, considering average load factor	EU Directives and CTPI

Note: CTPI = Consorzio Trasporti Pubblici Insubria, ISTAT = Istituto Nazionale di Statistica.

4.3 Individual preferences

In order to inform the simulated agents with empirical data about their commuting preferences in the starting scenario, ideally we would need information about the level of appreciation of each individual for each of the three transportation modes, according to the personal motivation, lifestyle and taste. It is realistic to consider that in reality one commuter may not have a binary set of preferences that assigns a maximum appreciation level to one means of transportation and a zero level to the others. On the contrary he/she may enjoy all the three options at different levels, according to needs and tastes, also with independence among the levels. If different datasets in Europe contains information on commuting choices articulated in this particular way, none of them has the detail at municipality level, but only at regional level (European Commission, 2013). Therefore we decide to construct a «reasonable » distribution of such preferences on the base of the actual commuting behaviour of the citizens of Varese. In the 2011 Italian Census questionnaire there was a question that asked to the respondent which means of transport he/she utilized for traveling until the place of work or study in a typical week day (ISTAT, 2011). Isolating the commutes taking place only within the city of Varese, we observe that there is a strong polarization between the use of the private car (44% of the respondents) and the use of the bicycle (37% of the respondents); only the 19% of the respondents declared to use the public bus to go to work or to the place of study. Therefore we construct a virtual distribution of preferences for the 5,000 simulated agents inspired to the actual behaviour of the citizens of Varese observed in ISTAT (2011), from which the single individual preferences values has been derived. These values have been used to inform the initial features of the agents. We assume that the preferences level lies in a range between zero and 1, where zero indicates the minimum appreciation and 1 the maximum one. We also assume independence among the preferences for the three transport modes; in other words, one agent may have high preference for all the three solutions or low for all of them, or high for one and low for the others, and so on.

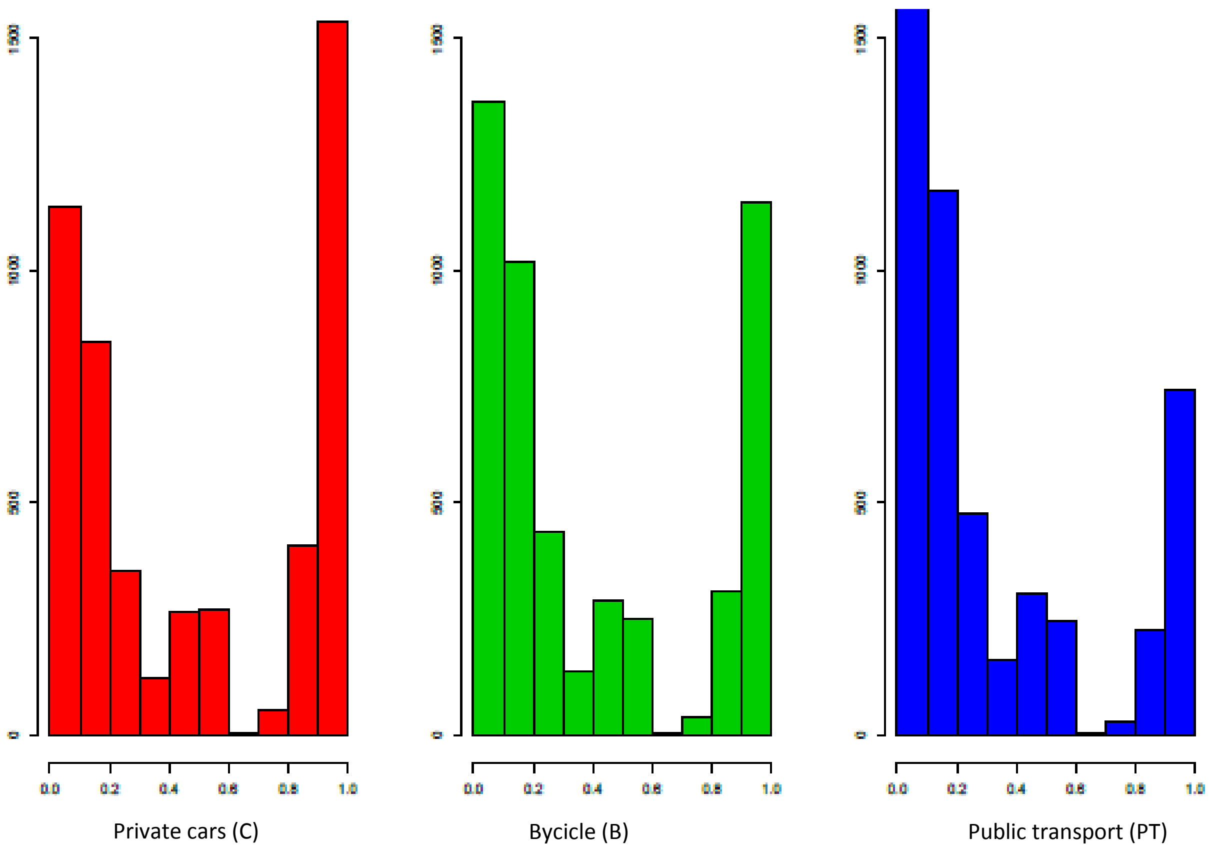

Fig. 2. Agents' preferences distribution, based on ISTAT (2011).

As it is shown in Figure 2, we hypothesize that, regarding the private car use, 40% of the agents has a high preference, above the 0.7 level, 50% has a low preference, and 10% has a uniform distribution between 0.4 and 0.6 level. Regarding the bicycle option we assume that 30% has a high level of appreciation, above 0.7, and the rest is distributed between a medium or a low appreciation level. As concerns the public transport option 20% of the agents has high appreciation for this solution, 70% has a propensity lower than 0.4 and 10% as a uniform distribution within the range 0.4-0.6.

5. Results of policy implementation

We investigate the impact of two groups of policies, namely price-based and motivation-based, which are commonly applied in the urban transport sector, according to the literature (Zhou et al., 2016; Flachsland et al., 2011; Nordhaus, 2008). The debate about the efficiency of one of these policy domains with respect to the other is continuously active (Hu et al., 2010; Graham-Rowe et al., 2011; Huisingh et al., 2015) and a complete review of the arguments in favour and against the two is beyond the scope of this paper. We aim to compare the effects of the two categories of policies and of different levels of combinations of the two when applied to our case study. Regarding the market-based policy, we imagine the implementation of a gasoline tax, or the establishment of cape-and-trade systems. In the field of non-market instruments we imagine policies directed to fostering the intrinsic motivation for greener behaviours, like the design and implementation of information campaigns about actual availability of commuting options and about the benefits of car use reduction, environmental education initiatives, social learning promotion.

5.1 Price-based policy

In the model the implementation of the so called price-based policy consists in the increase of the relative price of the use of the motorised option by an index in the range [0-1], representing the policy intensity. If the policy intensity is equal to 1 it means that the relative price of utilising the private car is doubled.
As it is shown in Table 5 and Figure 3, if the intensity of the policy is in the range 0-0.4, we observe a sharp decrease of the use of the car, a strong increase in the use of the bicycle and a small increase in the use of public transport option. These trends are minor within the 0-0.2 range (C: -4 percentage points; PT: + 1 percentage point; B: +3 percentage points), while between 0.2 and 0.4 behavioural changes are more intense. The use of the car decreases by 22 percentage points, the use of the bicycle increases by 17 percentage points and the public transport choice increases by 5 percentage points. However we notice that a reversal trend between car and bicycle use happens already at the 0.2 threshold. The policy at this level generates minor improvements in absolute terms, but sufficient to produce the important change of bringing the majority of the agents to the choice of a not-motorised option. Nevertheless, regarding the public transport option, it is necessary to reach a 0.4 policy level in order to reach a share of PT use higher than the one of the private car. These results reflect the initial behavioural distribution inspired to empirical data of Varese, where there is a strong preference for either the car or the bicycle and a low attitude toward the use of the public transport system. Therefore it is easy to imagine that the fostering of this last modal choice requires higher public policy effort. Since the policy makes more costly only the use of C and the price of B and of PT does not change, agents that renounce to use C still consider both monetary reasons and intrinsic preferences when they choose between PT and B. Since B is cheaper and since the initial preferences for this option are relatively high, the use of this mean of transport increases much more than the use of PT.
After the threshold of 0.4 policy intensity, the same patterns remain, but changes take place at a lower rate. At the maximum of the policy intensity the car use decreases by 38 percentage points with respect to the scenario in absence of policies (with only 6 % of the agents choosing this transportation mode), the bicycle use increases by 25 percentage points (with a final 62% of the simulated population choosing B) and the PT use rises by 11 percentage points (with a final share of PT choice of 30%). However it is important to notice that from a political point of view it may unrealistic to double the price of fuel, therefore it would be difficult to reach the maximum policy intensity.

Table 5
Share of agents choosing different transportation modes under price-based policy scenarios.

Price-based policy intensity	C	PT	B
0	0.44	0.19	0.37
0.2	0.4	0.2	0.4
0.4	0.18	0.25	0.57
0.6	0.1	0.28	0.62
0.8	0.09	0.28	0.62
1	0.06	0.3	0.62

Note: C=private car. PT=public transport. B=bicycle.

Fig. 3. Agents modal choice under price policy scenarios.

The total amount of pollutant emissions follows the trend of sharp decrease until the policy intensity reaches 0.4 level, while after this threshold it decreases at a lower rate. From the scenario without policy to the one with maximum policy intensity, emissions declines by 61.8%, while they are reduced by 41.2% already in the 0-0.4 range of policy intensity (Table 6 and Figure 4).

Table 6
Total amount of PM emissions under the price-based policy scenarios.

Price-based policy intensity	Emissions (PM g/commute)
0	340
0.2	310
0.4	200
0.6	150
0.8	140
1	130

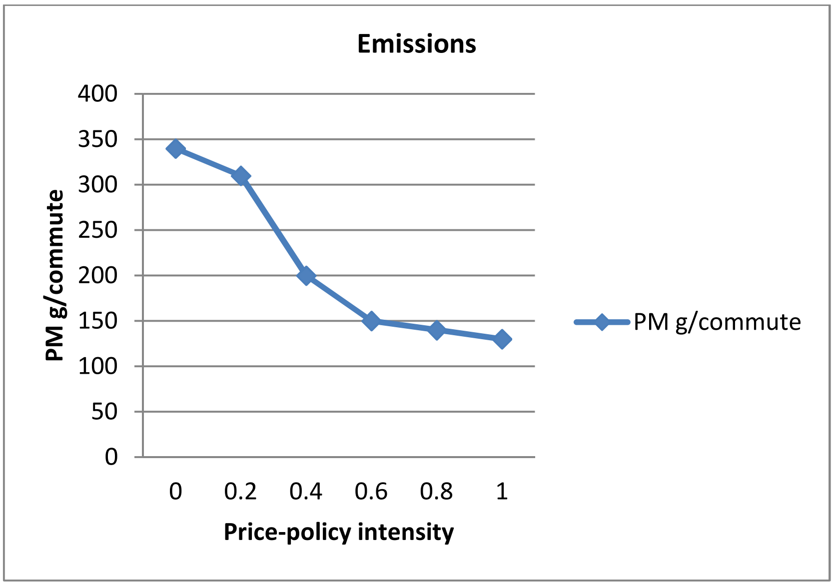

Fig. 4. Trend of total PM emissions under the price-based policy scenarios.

5.2 Motivation-based policies

In the field of motivation-based policies we imagine that the concept of policy intensity may be quantified by the amount of investments made by relevant policy makers and public authorities. In the model this policy is implemented with an intensity in the range 0-1. When it is present, a value between 0 and 1 is subtracted from the preferences for C and it is added as equal amount to those of PT and B.
The model is much more sensible to this policy than to the previous price-based policy (Table 7 and Figure 5). Moreover, it is important to notice that when the intensity is equal to 1, it is tautological that all the agents abandon car use, since their preferences go to zero, and abandon PT, since agents choose the cheapest option, which is bicycle use. This trend is already almost established from the 0.4 level, therefore we will interpret the results only up to this threshold.
Within the intensity range 0-0.2 the policy produces a slight decrease of C, a slight increase of B and no change in PT. Between the policy intensity 0.2-0.4 the same trend is highly intensified, with a decline in C share by 29 percentage points and an increase in B share by 32 percentage points. As in the price-based policy scenarios, at the 0.2 level of policy intensity we observe a reversal trend in the use of car and bicycle. The reversal trend between car and PT emerges indeed at the 0.3 policy intensity, however it happens thanks to a decline of car use and not because of a rise in public transport use.
The result that the share of PT use remains unchanged or declines with in an increase of the policy intensity is counterintuitive and it may be explained with the fact that the agents that choose to leave C because of a preference decline, go for the cheapest option when they face the choice between B and PT. Even if the preferences for both B and PT rise because of the policy, the monetary reasons dominate and more agents are directed towards B.
At the maximum level of policy intensity (0.4), private car use fall by 36 percentage points, PT share diminishes by 1 percentage point and bicycle use rises by 36 percentage points.

Table 7
Share of agents choosing different transportation modes under motivation-based policy scenarios.

Motivation-based policy intensity	C	PT	B
0	0.44	0.19	0.37
0.1	0.41	0.19	0.38
0.2	0.37	0.19	0.41
0.3	0.19	0.19	0.58
0.4	0.08	0.18	0.73
0.6	0.03	0.03	0.92
0.8	0.01	0	0.98
1	0	0	1

Note: C=private car. PT=public transport. B=bicycle.

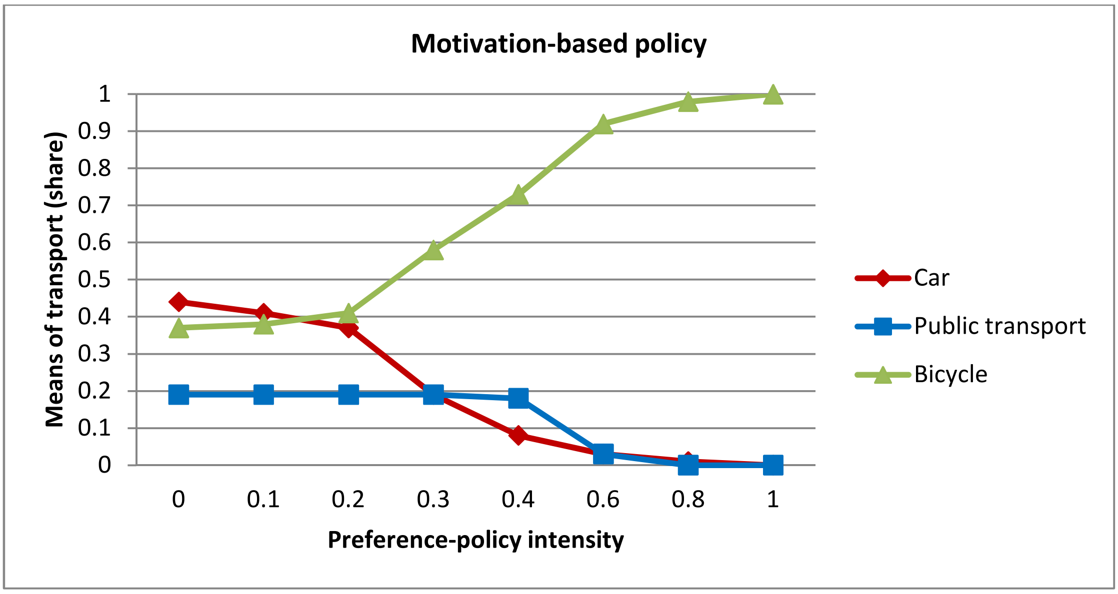

Fig. 5. Agents modal choice under motivation-based policy scenarios.

The emissions trend follows the behavioural changes. Emissions decline at a lower rate between 0 and 0.2 policy intensity and at a sharper speed between 0.2 and 0.4. At the maximum intensity of policy level total pollutant emissions decrease by 67.6% with respect to the scenario without policy (Table 8 and Figure 6).

Observing the final results linked to PM emissions reduction, it seems that preference-based policies are more effective than price-based ones. When policies are at maximum intensities, regarding C use, results are similar between the two kinds of policies, while the preference-based one is more effective in shifting agents behaviour toward B use. At low intensity levels of policy results are similar. At a medium policy intensity level, which is around 0.4 for the price-based and 0.2 for the motivation-based, the first kind of policy is far more effective in producing a decline in car use and a rise in B use.

Table 8
Total amount of PM emissions under the motivation-based policy scenario.

Motivation-based policy intensity	Emissions (PM g/commute)
0	340
0.1	320
0.2	310
0.3	190
0.4	110
0.6	40
0.8	10
1	0

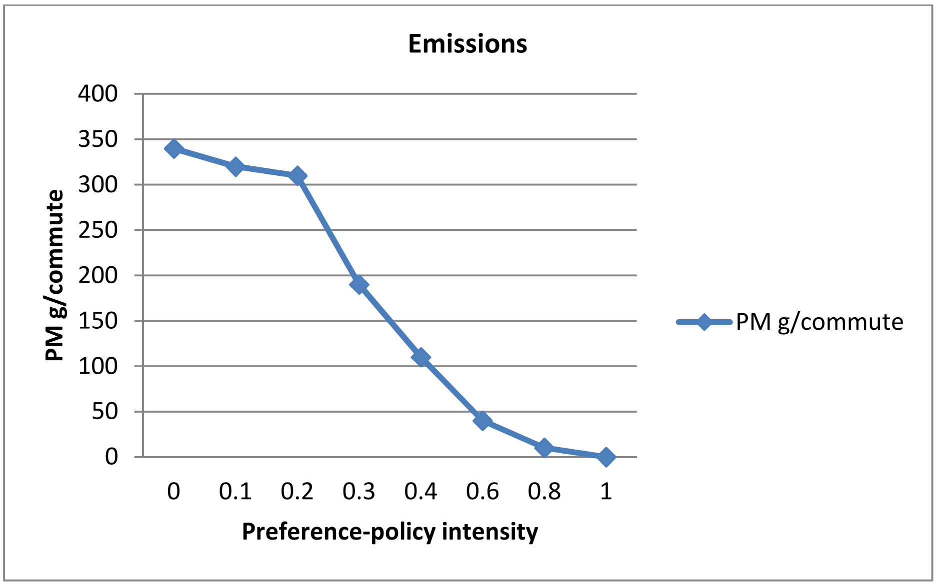

Fig. 6. Trend of total PM emissions under the motivation-based policy scenario.

5.3 Combination of price-based and preference-based policies

Since the model is very sensible to the implementation of both policies at the same time, we run the simulation with the scenarios presented in Table 9. Scenarios II and III have both policies at low intensity (0.1/0.1; 0.2/0.2). Scenario IV contains a high price-based policy (0.8) and a low preference-based policy (0.2), while scenario V includes a low price-based policy (0.2) and a high preference-based policy (0.4 – this level is considered high, since we explained before that we interpret the results of this policy only up to this threshold).

Policies combination produces very positive synergies. In scenario II, when both policies are at 0.1 level only, results are already positive, with a decrease of C from 44% to 37% and an increase of B from 37% to 41%. When only one policy is in place, similar results are reached only when the intensity is at least at 0.2.

In scenario III, when both policies are in place at the same time at the level of 0.2, results are immediately extremely positive. In the previous simulations with only one policy implemented, the same sharp behavioural change is reached only when levels intensity are very high. This means that if the policy maker would choose to implement the two policies at the same time, it would need a lower amount of total

resources than if he would choose one policy only. In scenario III, if we consider the sum of the two policies intensities, we reach a level of 0.4. Applying the price-based policy only at 0.4, results are good but still far from the two-policies scenarios (see par. 5.1). When the preference-based policy only is at 0.4, results are very good and similar to the two-policies scenario (see par. 5.2). Therefore the policy maker, considering political and technical reasons, should reflect whether it is more feasible to invest the resources to a high level of motivation-based policy or to low levels of price-based and motivation-based policies together.
Moreover, when two policies are in place at the same time, results are similar across different intensity levels of each of them (scenarios IV and V), therefore it is difficult to detect which one of the two play a major role. It seems that the strength of the scenario lies in the co-presence of the two kind of interventions.
In any case this result shows the added value of the use of agent-based models. In this case it allows to observe the complex dynamics of interactions that produces the fact that scarce resources produce much better results if they are allocated at the same time to two policies. This can be considered an emergent property of the system.

Table 9
Share of agents choosing different transportation modes under policy combination scenarios.

Scenarios	Policies	Emissions (PM g/commute)	C	PT	B
I	no policies	330	0.44	0.19	0.37
II	a) 0.1 b) 0.1	310	0.37	0.19	0.41
III	a) 0.2 b) 0.2	120	0.06	0.24	0.69
IV	a) 0.8 b) 0.2	70	0.007	0.23	0.74
V	a) 0.2 b) 0.4	70	0.02	0.19	0.78

Notes: C=private car. PT=public transport. B=bicycle. a)=price-based policy intensity. b)=motivation-based policy intensity.

6. Conclusions and future work

One of the most important challenges nowadays is to find effective and structural solutions to reduce pollution and congestion in highly populated urban areas, improving citizens quality of life and city competitiveness. Only policies aiming at modifying some habits and daily commuting choices, which are now strongly car dependent, could reach more sustainability in the long term. The traffic management policies implemented in urban areas since today have not led to satisfying results. The policy makers, in order to identify the best solutions, need to be supported by ex-ante predictions about the impact of policies on travel behaviour and, particularly, on mode switch between car and other less pollutant modes. Mode choice is in fact one of the most important component of travellers' decision behaviour during a trip and that decision determines the entity of transport negative externalities.
The ABM tool could give an important contribution in simulating travel behaviour and ex-ante policy impact for different reasons. It is particularly suitable to describe the high complexity of urban mobility, identifying the emergent overall behavioural patterns of the system from the individual choices, which are based on feedback from experience and on the agents' interactions among them and between them and the environment. It especially takes passengers' preferences into account, providing a wider range of scenarios. In doing that, it considers the individual bounded rationality and the incomplete information available for decision makers, without forcing the reality with stringent simplifying assumptions, such as in classic analytic approaches. Moreover it takes into consideration the nonlinearity of complex systems, in the sense that outputs of the system are not proportional to the inputs, but derive from multiple causalities and indirect effects of interaction among heterogeneous agents (Ambrosino et al., 2017).
The application of ABM methodology to the Varese case study has allowed to give some preliminary predictions about the potential effects of implementation of two kinds of public policies: price-based and motivation-based. The simulation of different scenarios shows that preference-based policies are more effective than price-based ones in terms of modal switch from car to bicycle and PM emissions reduction. The combination of the two policies together demonstrates that the mixed solution is always the most

effective, because it produces very positive synergies. This could be considered one of the most important emergent property of the system simulated by ABM.

These first positive results encourage to make more research efforts on this issue. The future work may be conducted towards the following directions. First, the model developed could be improved by integrated the present tool with the Geographical Information Systems (GIS) instrument, such as other works have done (see among the others, Schelhorn et al. 1999; Benenson et al. 2008; Lu et al., 2008). Very recently, a work by Fosset et al. (2016) presents the GaMiroD platform which includes both agent-based simulation and GIS in order to simulate urban daily mobility and the impacts of pollution policies in some French cities. This kind of integration in our model could allow to better describe the actors' spatial interactions and to consider the particular geographical conformation of Varese city which alternates flat with hilly areas, restricting the use of bicycles to young or to trained and healthy people. Second, real data coming from an *ad hoc* designed empirical survey could help in improving the model validation and testing, considering the different socio-economic characteristics of the agents and running activity-based simulations (Shiftan and Shurbier, 2002). These data could be also useful to compare the actual distribution of the simulated preferences, which in the present work are inspired to ISTAT census information, with a distribution coming from the real survey. Third, other scenarios, including also other different policies, could be designed and compared. For example, it is possible to simulate motivation-based policies which affect only the agents whose preferences for environmentally friendly solutions are already low from the beginning. The aim would be observing whether this focus enhances the results efficacy with respect to the present work, in which all the policies affect the totality of the agents. Finally, a very challenging evolution of the present model could incorporate in the simulated urban mobility system also the freight transport component. In fact, even though the share of urban goods vehicles is estimated to be only 10-20% of passenger traffic, goods vehicles contribute relatively more on total pollution and congestion than private cars, producing 16-50% of the emissions of air pollutants (Dablanc, 2007). The reasons are mainly related to their bigger size and to the fact that the number of vehicles per km travelling in urban areas has quickly grown in the last decades, due to the increase of delivery frequency resulting from just-in-time strategies and warehousing reduction. The authors are now working on the development of an agent-based model to simulate freight flows in the cities, within the general framework of the European project NOVELOG, New cOoperatiVe business modEls and guidance for sustainable city LOGistics, started in June 2015 (http://novelog.eu/).

Nevertheless, the real challenge consists in integrating the passenger dimension with the freight one in a single tool, in order to consider their interactions and the overall effects of the different public policies, which will affect at the same time both people and goods, causing dynamic and complex behavioural changes.

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