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A System Dynamic Approach for the Smart Mobility of People: Implications in the age of Big Data

Abstract

Mobility of people can be configured as an information intensive process resulting from a complex set of factors. Its effective implementation requires the adoption of methods able to leverage on a set of complex and dynamic variables, and mainly on a huge amount of data available. Moving from this assumption, this paper aims to demonstrate that system dynamics could present a useful approach for optimising decision making for people's mobility. The conceptual model is built by using the principles of system dynamics methodology and is based on causal feedback relationships among the various factors related to the different needs of people's mobility. The causal feedback loops and interrelationship among various parameters illustrate the dynamicity and the influence of parameters on one another. The simulation analysis was conducted to dynamically evaluate six scenarios corresponding to the different solutions available for particular segments of demand. Findings highlight that the modelling approaches could guide the city planners to evolve responsive policy interventions for further developing smart mobility of people. Implications for policy makers regard the developing sustainable mobility scenarios based on the analysis of big data from the adoption of digital platforms grounded on the simulation model.

Keywords – Big Data, Smart Mobility, Data Science, System Dynamics, Simulation Model, Decision Making.

Type paper: Academic Research Paper

1. Introduction

The mobility of people is a critical and relevant driver for cities' smart growth and regions' intelligent development (Eskandarpou, et al., 2019; Albino et al., 2015; Neirotti et al., 2014; Giffinger, et al., 2007). Its continuous evolution is nurtured by the dissemination of digital and smart technologies that have impacted its traditional configuration and are assuring its characterisation as a data driven process (Qiu, et al., 2019). Even if people and users are intuitively central in the design and implementation of smart mobility services, interest in smart mobility issues continues to grow in a multidisciplinary community of scholars and researchers (Faulin, et al., 2019). Despite this, the research has failed to focus on the meaning and implications of smartness from users' perspective, which remains an unexplored area (Qu et al., 2019; Papa and Lauwers, 2015).

The mobility of people presents broad cross-sectorial implications and can offer a relevant contribution to the improvement of people's quality of life, by impacting companies' competitiveness and territories' socio-economic and environmental goals (Faulin, et al., 2019). As a complex system impacting on a large community of stakeholders, such as citizens, government, businesses, environments (Fontoura et al., 2019), the mobility of people requires the adoption of an intermodal perspective (Szyliowics, 2003), increasingly characterized by embracing smart technologies and innovative methods to maximize accessibility, minimize transport consumption, contribute to the mitigation of social and environmental challenges and to improve the quality of life (Schaffers, et al., 2011).

Conceived in a complex scenario characterized by the ubiquity of information and the wide presence of sensors, webcams, and other smart devices, the mobility of people has become increasingly configurable as a data driven process (Badii, et al., 2019). This is because in all phases of mobility, users' access and generate a huge amount of data and also because in designing and executing their mobility, people are called to leverage a large, dynamic set of variables. The development of big data, digital technologies and smart devices has impacted on the transportation systems by producing a radical change in users' behaviour during their journey as well as in the ways they conceive, plan and execute their mobility (Qiu et al., 2019; Del Vecchio et al., 2018).

In such a scenario, management of people's mobility by public and private organisations requires the adoption of smart and dynamic decision-making approaches able to leverage on a large number of variables evolving in real time (Shepherd, 2014). Big data can be generated by a plurality of sources and can present different natures, as structured, semi-structured and unstructured data (Qiu, et al., 2019; De Mauro et al., 2016; La Valle et al., 2011). It is mandatory to identify new data mining and analytics technologies as well as approaches able to allow prediction and simulations results to support managers in the challenge of managing the complex network of relationships around organisations and institutions (De Mauro et al, 2016).

In this context, system dynamics arises as a useful approach for managing the complexity of variables and optimising the decision making process related to the mobility of people in the Big Data context. System dynamics is a recognized methodology to manage the complexity characterising systems when several elements interact with each other, as well as analysing their evolutionary dynamics from a qualitative and quantitative point of view (Gallo, 2008). The recent debate on system dynamics has allowed verifying its wider potential of application in different industrial fields (Bianchi, 2009; Dubois and Holmberg, 2000; Faham et al 2017; Fiorani, 2010; Sterman, 1992; Rodrigues, 1994; Roda et al., 2017) and its usefulness for establishing regional development strategies (Del Vecchio and Oppong, 2019). Despite this, the application of system dynamics in the context of people's mobility is under-researched. Also, to the best of our knowledge, few scholars have attempted to apply it in the context of big data for smart mobility.

Framed in the above premises, this paper aims to contribute to the debate on decision-making methods for people's smart mobility by focusing on system dynamics as a useful methodology for modelling and simulating alternative model solutions for human mobility. The model proposed is a pivotal test with interesting speculations on the perspective of big data and offers the basis for a wider replication in the decision processes of individuals, firms and public stakeholders.

The remainder of the paper is structured as follows: section 2 introduces the theoretical background around the topic of people's mobility and its smart configuration. Section 3 describes the research methodology. Section 4 highlights the evidence related to six simulation scenarios developed with Vensim software. Section 5 discusses the simulation model, and the final section concludes the paper describing the main contributions, its implications for theory and practices, and future research.

2. Theoretical background

2.1. Smart Mobility in the age of Big Data

Smart mobility is a topic of interest to a growing community of scholars and researchers. It has been identified as a buzzword referring to the combination of approaches and technologies for more intelligent and sustainable transportation of people and goods (Faulin, et al., 2019; Papa and Lauwers, 2015). Enabled by the dissemination of the Information and Communication Technologies (ICTs) and smart devices, the smart mobility paradigm presents a social dimension, linked to its implications at individual and community levels, that is still under-researched (Papa and Lauwers, 2015; Batty et al., 2012).

Smart mobility is strictly connected with the issue of smart cities, since it can be seen as cause and effect of a territory's intelligent configuration due to its contribution to the full accessibility of the city, efficient land usage (Papa and Lauwers, 2015), and creation of more sustainable behaviours impacting on the quality of life and services available for users (Eskandarpour et al., 2019; Zhang, et al., 2019). The wide dissemination of digital technologies, Internet of Things (IoTs) and big data has radically impacted the configuration of smart cities as well as the way mobility is designed and managed (Badii, et al., 2019). The wide proliferation of data, resulting from the integration of physical and social sensing, also known as Internet of People and IoTs, presents a great potentiality as platform for cities' mobility management in an ecosystem perspective (Qiu, et al., 2019). As argued by Drchal et al., (2019); a data driven perspective, leveraging on machine learning and intelligent algorithms, is expected to increase mobility and to support its smart configuration.

The broad dissemination of smart devices has impacted the smart configuration of a city and represents a challenge for smart mobility (Qiu, et al., 2019). According to Badii, et al. (2019), the Internet of Things is at the basis of redesign and management of cities' transport infrastructures and is expected to improve citizens' quality of life. This requires the adoption of sustainable and systemic approaches by policies makers and operators aimed to enhance the service quality offered (Zhang, et al., 2019). Due to the complex and differentiated characteristics of stakeholders involved in the mobility of people, its effective implementation requires the adoption of managerial approaches able to provide a dynamic and systemic understanding of the process (Fontoura et al., 2019). In this perspective, the contributions of scholars and researchers have recently experienced its acceptance for supporting decision making in the urban planning process of reducing carbon dioxide emissions, as in the work of Fong, et al. (2019) as well as for capturing the causal relationship in establishing urban transport public policies (Fontoura et al., 2019).

The past few years have seen, from one side, the blossoming of smart mobility initiatives, thanks to the accessibility of big data related to traffic, pollution, meteorology, itineraries and adopted policies, and from the other side the application of the system dynamics approach to this field. The latter aspect aims to analyse the city transportation system (Haghshenas et al., 2015), model urban traffic's energy consumption and carbon emissions in Beijing (Wen and Bai, 2017), evaluate the effectiveness of parking policies without compromising the service level offered (Bernardino and Hoofd, 2013; Mei et al., 2017), and assess the influence of mobility policies in a decision making process (Guzman et al., 2014).

The focus on smart mobility as a data driven system with a growing relevance of knowledge highlights the need to adopt dynamic decision making systems able to offer a comprehensive understanding of the several factors impacting on mobility and to optimize the alternative mobility solutions available. Smart mobility is characterized by a large number of influencing factors that often vary over time. This complex phenomenon can be analysed through the system dynamics approach, to understand what kind of factors influence the people's choices and try to model their behaviours, aiming at optimising transportation systems and, at the same time, improving the quality of life (Shepherd, 2014; Roda et al., 2017; Fontoura et al., 2019).

2.2. System dynamics for optimising decision making in smart mobility

The challenges emerging in the context of people's mobility highlight the need for dynamic and systemic approaches to smart configuration of mobility. Due to the complexity characterising mobility, as a process involving a community of stakeholders with different profiles, system dynamics is assumed as a useful approach for capturing causal relationships among them and for simulating alternative scenarios (Fontoura et al., 2019; Shepherd, 2014).

Due to its several potentials and robustness, in the last years the system dynamic approach has been applied in different industrial fields. Some recent works span different focuses, such as improvement of company performance (Bianchi, 2009), risk modelling and simulation (Dubois and Holmberg, 2000), dissemination and management of innovation (Maier, 1998; Milling, 2002), decision support in strategic management (Fong, et al., 2009), project management (Sterman, 1992; Rodrigues, 1994), analysis and definition of political agendas (Fiorani, 2010), public health (Homer & Hirsch, 2006), supply chain (Del Vecchio et al, 2018), smart mobility (Roda et al., 2017), sustainable development in higher education with the emphasis on the sustainability competencies of students in the field of *sustainability* (Faham et al 2017) and so on. At the light of big data, all these challenges present a more complex configuration in the attempt to combine economic and environmental sustainability of transports with user demands.

The application of system dynamics in the mobility sector has been widely debated. Starting from the contribution of Abbas and Bell (1994), system dynamics has been demonstrated as a suitable approach for decision making in transport. In a literature review on the application of system dynamics in transportation, Shepherd (2014) argued that the approach has been used for modelling scenarios supporting political agendas, evaluating alternative fuel vehicles, and setting up innovative pricing strategy and revenues models in the airlines sector and the supply chain management in transport. This is because system dynamics allow deriving modelling structures useful to explore the several factors behind the demand as well as explaining how to change user perception and behaviour. Models can be built with stakeholders' input and then used in the form of games or flight simulators for policy learning. Despite this, the literature was limited to assuming the users' behaviours and needs as predetermined and missed putting them at the centre of decisions related to mobility.

Initially developed by Forrester (1958) at MIT *Massachusetts Institute of Technology*, system dynamics results from the integration of qualitative and quantitative methods. It has proved to be a valid method with several opportunities of applications in a wide spectrum of disciplines, such as system theory, information science, organisational management, control theory, and cybernetics (Shepherd, 2014). System dynamics is a methodology aimed to manage the complexity characterising systems where several elements interact with each other as well as to analyse their evolutionary dynamics from a qualitative and quantitative point of view (Gallo, 2008). The comprehension of evolutionary trends is in the perspective of a system dynamics approach based on the combination of *systems theory and simulation theory.*

To understand the system dynamics approach and the modelling process, it is important to introduce the following helpful definitions:

- *Variables*, distinguishing endogenous from exogenous, dependent and independent, variables of stock, flows, auxiliaries and constants (Borshchev and Filippov, 2004). *Exogenous variables*, e.g. variables not determined within the model but which have a given value; *Endogenous variables*, e.g. variables explained by other ones; *Dependent variables*, e.g. if there is a relationship between the values assumed by two variables; *Independent variables*, if there is not such relationship; *Stock or Level variables,* with values obtained through a cumulative evaluation of the other variables and modified according to the size of the flows; *Generic auxiliary variables*, the value of which is determined by an algebraic equation in which other variables appear; *Constant auxiliary variables*, the value of which does not change over time; *Flux-type,* the values of which are obtained through an instantaneous evaluation of the other variables.
- *Syntactic rules* related to the arcs used to join distinct variables by highlighting orientation, point of start and end;
- *Causality*, distinguishing between *linear causality*, which exists when a variation in the value assumed by a variable causes a consequent change in the value assumed by the other variable (Borshchev and Filippo, 2004), and *circular causality* that occurs when a change in the value assumed by a variable causes a consequent change in the value assumed by the other variable, and this in turn causes a further change in the value taken from the first variable based on retroactive feedback;

- *Polarity* of the causal links, which can be positive when a change in the value of X produces a change in the value of Y in the same direction, or negative when the change of Y is in the opposite direction.

More recently, system dynamics has been adopted as a useful approach for capturing the causal relationship characterising the urban transport system of the Metropolitan Region of Sao Paulo (Fontoura, et al. 2019). The interest in system dynamics in the context of mobility is due to increasing challenges from smart configuration in terms of improvement of service quality (Zhang, et al., 2019), pollution reduction (Faulin et al., 2019; Fong, et al. 2009), increasing urbanisation and demand for just-in time deliveries (Macário, et al., 2008), flexibility and cost minimisation (Banister, 2008). The system dynamics methodology is well suited to addressing the dynamic complexity characterising many issues related to smart mobility.

Created in 1956 by the American electrical engineer Jay W. Forrester, system dynamics methodology integrates the concepts of feedback control and calculation involving the development of computer simulation models, to explain the behaviour of complex systems and outline actions able to improve performances. Gallo (2008) has defined system dynamics as a methodology aiming to represent complex systems as a set of different elements interacting among themselves, analysing and modelling these systems by paying attention to the dynamic aspects of their behaviour. Its approach emerges from the combination of system theory, where the system is studied as a whole and through the links between the different parts that compose it (systemic approach), via a mathematical model with a finite number of degrees of freedom and which evolves over time according to a deterministic law (dynamic approach), and simulation theory, which aims to define a model able to predict the dynamic behaviour of a series of events based on specific binding initial conditions, through the use of real data.

A system dynamics model consists of a set of elements useful to delineate the simulation model and to perform a qualitative and quantitative analysis of complex systems. It consists of a set of variables, equations, and rules that describe the given issue and is developed from a wide spectrum of real data. The action of modelling the issue includes an iterative process that goes on until the model is able to satisfy requirements regarding robustness, flexibility and ability to reproduce historical patterns, but also to generate useful insights, not only to reproduce the past and manage the complexity of the system, but also to optimize the decision making process (Homer & Hisch, 2006; Del Vecchio et al., 2018).

Moving from the background discussed, in the next section we aim to demonstrate opportunities for adopting system dynamics as an approach for optimising decision making for the mobility of people.

3. Research Methodology

In this paper, we propose an analysis of different scenarios for optimising decision making in smart mobility, based on a system dynamics model simulation, to understand the main dynamic interactions among all the variables involved in such a complex framework and to provide a systemic view to strategically support decision making processes within organisations, outline travellers' profiles, and sustain smart mobility in the widest perspective of improving the quality of life.

The adopted methodology was structured in a double stage approach. The first one was devoted to the comprehension of the phenomenon in terms of variables, causality and dependency. As the transport system and mobility of people are a very sophisticated reality, the issue must be simplified through the detection of all the variables and all the dynamical interactions among them, to well describe the phenomenon and try to build a model as robust as possible. The second approach was focused preliminarily on the identification of a sw tool to be used for the simulation, where all the variables and causalities detected during the first stage were used for delineating the quantitative model, building it inside the tool and, finally, running the simulation. From a careful benchmarking of software for modelling a complex system through system dynamics, the five most used software architectures were identified and compared. Finally, based on a set of parameters concerning the interface with operative systems, the availability of free versions, type of format required for data in input and the friendliness of graphical interface, benchmarking of these alternative solutions has allowed choosing Vensim (www.vensim.com), a simulation platform that supports the performance of a real system, as the most suitable solution.

3.1 Simulation model development

As previously discussed, the system dynamic methodology involves the development of computer simulation models, based on causal diagrams specific to each problem setting. To allow a correct simulation, it is desirable to define the boundaries of the given issue, identify all the flows and variables and define the mathematical relationships among them, identify the feedback circuits, describe the causal and structural map, estimate the initial conditions through statistical methods or other, simulate and, finally, analyse the data found.

Here we focus our attention on the smart mobility scenarios related to mobility of people during intercity and inter-regional trips in a certain geographical context, taking into account people's needs and availability of money and time available to optimize their choices. Since the transport sector offers a wide range of transport alternatives, it was decided to consider as the choice of mode the following cases: travel by plane, bus, train or car. Due to the complexity of the transport system and mobility of people, the proposed model aims to understand the dynamic interactions among all the interdependent variables characterized by a strongly dynamically correlated behaviour and that influence the user during the choice of the means of transport.

Therefore, the scenario to which reference will be made is presented below:

> *A user must arrive at an appointment in a certain place called **X** at a certain hour **h** of a certain date **d** and must choose as the most suitable means of transport his own car, bus, plane and train.*

The model transport decision is noticeably influenced by a large number of variables that push the user to opt for one means of transport rather than another one. All these qualitative variables are reported in **Table 1**.

Table 1- Qualitative variables that influence the model transport decision.

Qualitative variables	**Model variables**	**They depend on:**
The trip's duration, which is represented by a known value when the user opts for public transport (assuming therefore fixed speed and distances).	*Bus/Rail/Air-trip duration*	o *Random uniform Bus/Rail/Air fare*
The car trip's duration, which depends on the travel speed and distance between starting point *O* and the final destination *X*.	*Car trip duration*	o *Car ownership* o *Appointment point* o *Car position* o *Car speed*
The ticket cost, if user opts for public transport.	*Bus/Rail/Air fare*	o *Random uniform Bus/Rail/Air fare* o *Min Bus/Rail/Air fare* o *Max Bus/Rail/Air fare* o *Seed Bus/Rail/Air fare*
The distance between starting point *O* and the departure terminal, in case of public transport	*Distance between bus arrival-departure terminal/ rail station outbound trip/airport and bus/rail/air customers' start point*	o *Bus/Rail/Air-customers' start point* o *Arrival Bus/Rail/Air-terminal outbound trip*
The distance between the arrival terminal and final destination point *X*, in the case of public transport.	*Distance between bus arrival-departure terminal/rail station return trip/airport and appointment point*	o *Appointment point* o *Departure Bus/Rail/Air-terminal return trip*
The need to use a means of transport for movements between the departure point *O* and the departure terminal, or the arrival terminal, or the destination point *X*, and vice versa, in the case of public transport. It depends on the distance between these spatial points.	*Bus/Rail/Air-need for another means of transport*	o *Difference between outbound trip arrival time and appointment time for bus/rail/air/car* o *Difference between appointment time and departure time return trip for bus/rail/air/car.*
The difference between the arrival time and the appointment time.	*Difference between arrival time outbound trip and appointment time for bus/rail/air/car*	o *Appointment time* o *Random uniform bus arrival time outbound trip*
The difference between the appointment time and the departure time.	*Difference between appointment time and departure time return trip for bus/rail/air/car*	o *Appointment time* o *Departure time return trip for bus*

The need for overnight accommodation, whether a customer opts for public transport or chooses his or her own car to travel.	*Bus/Rail/Air/Car-customers overnight stay need*	○ *Difference between arrival time of outbound trip and appointment time for bus/rail/air/car* ○ *Difference between appointment time and departure time return trip for bus/rail/air/car.* ○ *Bus/Rail/Air-need for another means of transport*
Expenditure on fuel, in the case of private transport, which in turn depends on the distance travelled and the presence or absence of tolls.	*Car trip expenditure*	○ *Average consumption* ○ *Fuel price* ○ *Toll*
The weights attributed to all the influence factors of the choice during the simulation.	○ *Bus/Rail/Air fare weight* ○ *Bus/Rail/Air/Car-trip duration weight* ○ *Bus/Rail/Air/Car-customers overnight need weight* ○ *Bus/Rail/Air-need for another means of transport weight*	

Once the scenario has been defined, the next step consists in drawing the causal map. The causal map is the mostly theoretical representation of the model and describes, qualitatively, all the dependencies among all the variables. The second column of **Table 1** **Errore. L'origine riferimento non è stata trovata.** shows the variables used to map out the causal map, while third one declares the dependence from other variables, indispensable for the purpose of obtaining the final structural map.

Table 2 - Stock & Flow variables for the causal map.

Stock Variables	- *Potential Customers* - *Bus Customers* - *Rail Customers* - *Air Customers* - *Car Customers*
Flow variables	- *New bus customers flow* - *New rail customers flow* - *New air customers flow* - *New car customers flow*

Moreover, to obtain the Stock & Flow map that can provide more quantitative information, because it provides the definition of the mathematical equations, two different types of variables were added to the causal map and shown in **Errore. L'origine riferimento non è stata trovata.**.

The characteristic feedback circuit of the model is shown in **Fig. 1**, which identifies the cause-effect cycles existing between the fundamental variables described above. Four different colours are identified, with the intention of facilitating the reading of the model itself.

In particular, the blue colour refers to the section of the model regarding the choice of the plane as means of transport, red characterizes the choice of the bus, the green of the train and the purple of one's own car or other private vehicle.

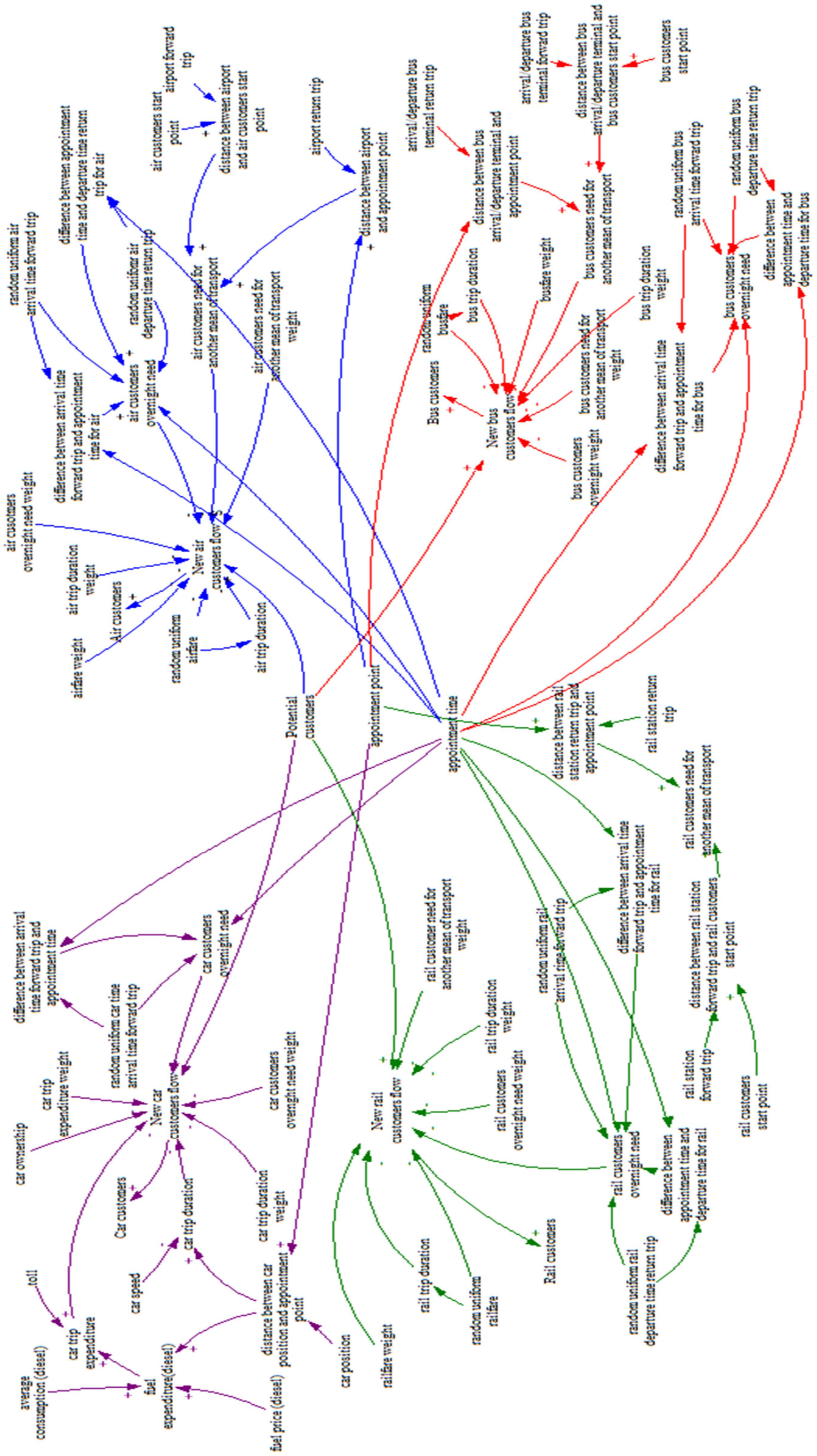

Fig. 1 – Causal Loop Diagram Transport Choice

Finally, in **Fig. 2** the Stock & Flow model, more suited for simulation, is represented.

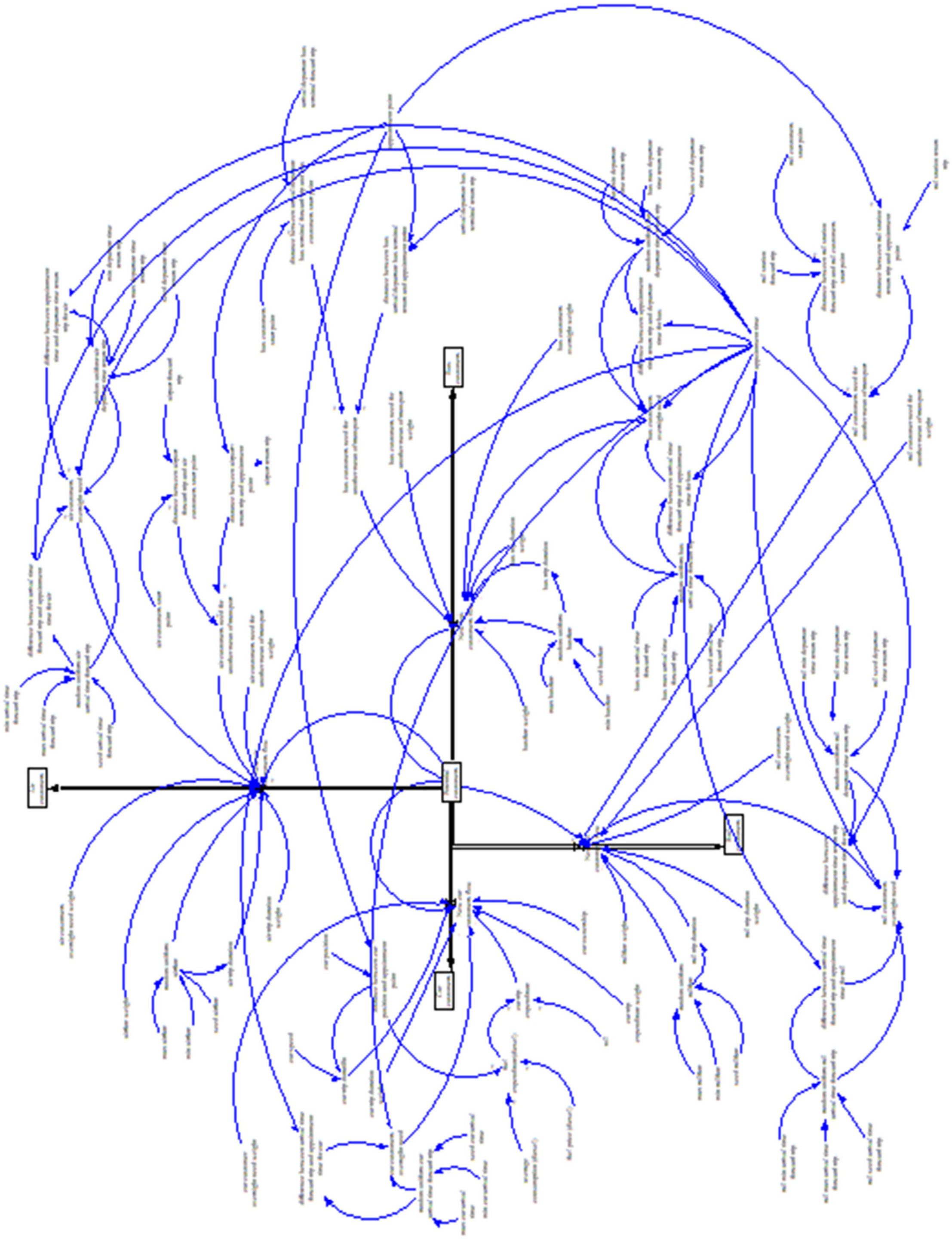

Fig. 2 - Stock & Flow Diagram Transport Choice.

During the simulation, the following assumptions and simplifications were considered:

- The variables relating to the need to stay overnight and the need to use additional means of transport are considered qualitative variables to negatively affects the flow of customers towards one of the four means of transport available for the choice, even ide they don't impact directly on the cost of tickets.
- Potential customers are totally 1000 and at the starting time of the simulation their number for the different model solutions is 0.
- The place of the appointment (*appointment point*), which the user must reach at a certain time on a certain date, is modelled as an exogenous and constant variable throughout the simulation set at 998 km (distance Brindisi-Milan downtown).
- The time of appointment (*appointment time*), the value of which is between 0 and 24, is considered constant during the simulation and set at 10:00, while the arrival and departure times are modelled as random variables fluctuating uniformly between 0 and 24.
- The buses' departure and arrival terminals (*arrival/departure bus terminal outbound trip*), both for the outbound trip and for the return trip, are modelled as constant exogenous variables during the whole simulation. In particular, the bus terminal for the outbound trip is set at 0 km, while the bus terminal for the return trip is fixed at 1018 km (distance Brindisi - Lampugnano station).
- The point where the customer bus is located (*bus customers start point*) is modelled as a constant variable during the simulation, the value of which is between a minimum of 0 km and a maximum of 50 km, which indicate the user's distance from the bus departure terminal.
- The cost of the bus ticket (*bus fare*) is modelled as a random variable fluctuating uniformly between a minimum of €41.8 and a maximum of €65 (values acquired from the site http://goeuro.it for the search for tickets on the Brindisi-Milan route on December 11th).
- The duration of the bus trip (*bus trip duration*) depends on the ticket price with a proportionality shown in **Fig. 3**.

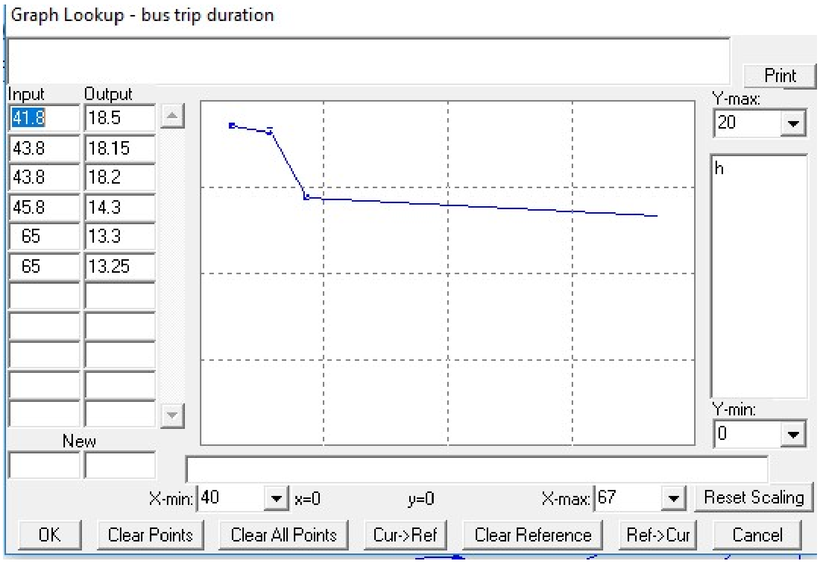

Fig. 3 - Proportionality between bus fare and bus trip duration

- The point where the customer rail is located (*rail customers start point*) is modelled as a constant variable during the simulation, the value of which is between a minimum of 0 km and a maximum of 50 km, which indicate the user's distance from the train station.
- The price of the train ticket (*rail fare*) is modelled as a random variable fluctuating uniformly between a minimum of 73 and a maximum of €149.9 (values acquired from the site http://goeuro.it for the search for tickets on the route Brindisi-Milan on December 11th).
- The duration of the train trip (*rail trip duration*) depends on the ticket price through proportionality expressed in **Fig. 4**.

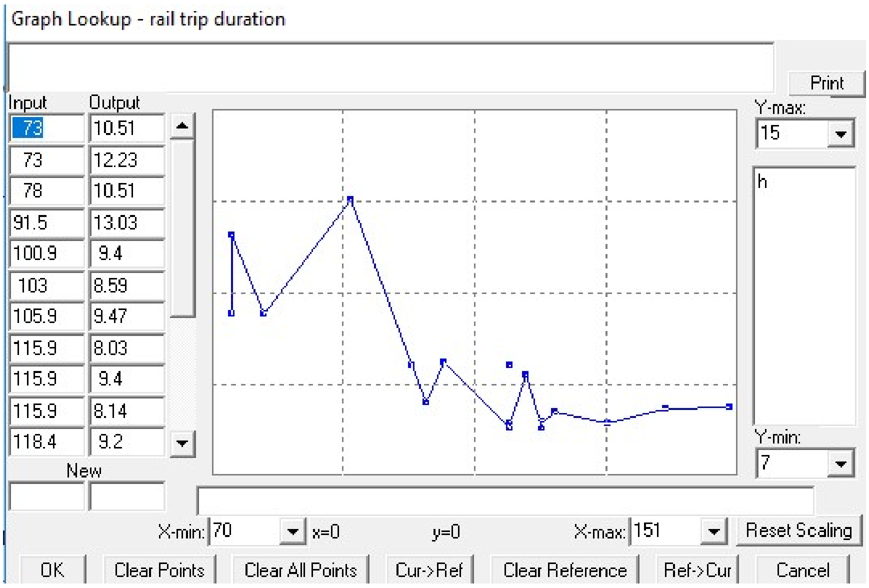

Fig. 4 - Proportionality between rail fare and rail trip duration.

- Train departure and arrival stations (*arrival/departure rail station outbound trip, arrival/departure rail station return trip*), both for the outbound journey and for the return journey, are modelled as constant exogenous variables throughout the simulation. In particular, the train station for the outbound trip is fixed at 0 km, while for the return trip it is fixed at 995 km (distance from Brindisi-Milano Centrale train station).
- The point at which the air customer is located (*air customers start point*) is modelled as a constant variable during the simulation, the value of which is between a minimum of 0 km and a maximum of 200 km, which indicate the user's distance from the airport.
- The airport of departure and arrival (*airport outbound trip, airport return trip*), both for the outbound trip and for the return trip, are modelled as constant exogenous variables throughout the simulation. In particular, the airport for the outbound journey is fixed at 0 km, while the airport for the return journey is fixed at 1042 km (distance from Brindisi airport to Milan Malpensa airport).
- The cost of air ticket (*airfare*) is modelled as a random variable fluctuating uniformly between a minimum of €151 and a maximum of €984.2 (values acquired from the site http://goeuro.it for the search for tickets on the route Brindisi-Milan Malpensa on December 11th).

The duration of the air travel depends on the ticket price with a proportionality shown in **Fig. 5**.

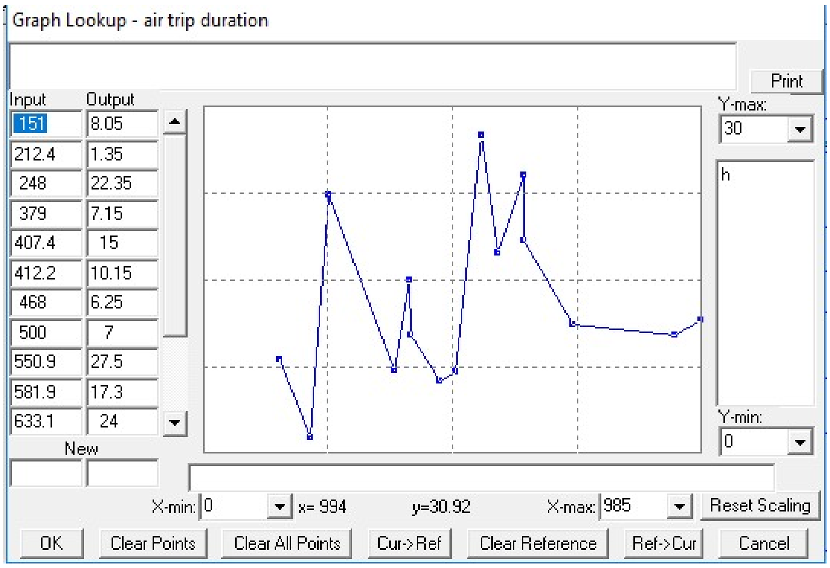

Fig. 5 - Proportionality between airfare and air trip duration.

- The position from which the car departs (*car position*) is set at 0 km.
- The speed of the car is considered constant and equal to 100 km/h.

- The duration of the car trip depends on the speed of the car and the distance travelled. It is therefore constant, being constant both the speed and the distance travelled. In any case, it was modelled to allow any changes to the nature of the variable.
- The fuel type considered for the private vehicles is Diesel; its consumption was estimated as a constant and fixed, in the measure of 4.5 litres per 100 km.
- The price of Diesel, the value of which can vary from €1.00 to €2.00, is considered constant during the simulation and set at €1.35.
- The proportionality between travel duration and ticket price in the case of bus, train and plane, defined based on the data extrapolated for December 11th by the GoEuro site, is considered valid for the entire period of the simulation.
- All weights, e.g. *bus fare weight, bus customers' overnight weight, bus customers' need for another means of transport weight, car trip duration weight, car trip expenditure weight, rail fare weight, rail trip duration weight, rail customers' need for another means of transport weight, rail customers' overnight need weight, airfare weight, air trip duration weight, air customers' need for another means of transport weight, air customers' overnight need weight* are constant variables during the simulation and the value of which can vary between 0.0 and 1.0, with an increment of 0.1.
- The sum of the weights regarding a single portion of the whole model (Bus, Rail, Ari, Car) is 1.
- All weights listed above and present in the same denominator as a fraction (New bus customers flow, New rail customers flow, New air customers flow, New car customers flow) can never be equal to 0 at the same time; one of them must necessarily be ≠ 0 so that the fraction makes sense mathematically, and the simulation of the model can be performed without any error.

4. Findings

Using Vensim software allows running the simulation based on the variables defined in the methodology section. By modifying the value of the influencing factors that become part of the model transport choice, the simulation allows identifying different scenarios related to segments of customers (e.g. customers indifferent to the price or, otherwise, very sensitive to its variations, or customers very sensitive to/not interested in the trip's duration, and so on).

Here, different plausible scenarios were designed and the simulation was run inside Vensim, to point out the particular behaviour of the potential customers called to choose between different means of transport. In particular, the following scenarios were identified:

- Customers not sensitive to the price.
- Customers not sensitive to the trip duration.
- Customers not sensitive to the need to stay overnight.
- Customers not sensitive to the need to use additional means of transport.
- Customers exclusively sensitive to the price.
- Customers exclusively sensitive to the trip duration.

In this way it is possible for a company manager to understand the variables that influence the flow of customers towards the different choices and to what extent, to strategically support decision making processes within companies, outline the travellers' profiles, and sustain smart mobility in the widest perspective of improving the quality of life.

4.1 Scenario 1: Customers not sensitive to the price

The simulation described below analyses the behaviour of the model if customers are disinterested in the price of plane, rail, bus and travel ticket or the price of travelling by their own cars. The assumptions for the simulation of this scenario are reported in **Errore. L'origine riferimento non è stata trovata.**.

Table 3 - Assumptions of simulation for Scenario 1.

	BUS	**RAIL**	**AIR**	**CAR**
ASSUMPTIONS FOR SIMULATION	bus fare weight = 0	rail fare weight = 0	airfare weight = 0	car trip expenditure weight = 0
	bus trip duration weight = 0.6	rail trip duration weight = 0.6	air trip duration weight = 0.6	car trip duration weight = 0.7
	bus customers' overnight need weight = 0.3	rail customers' overnight need weight = 0.3	air customers' overnight need weight = 0.3	car customers' overnight need weight = 0.3
	bus customers' need for another means of transport = 0.1	rail customers' need for another means of transport = 0.1	air customers' need for another means of transport = 0.1	
SIMULATION RESULT	194	257	**312**	237

During the simulation, time is a free parameter, while the initial value of *Potential customers* is set to 1000. The simulation ends when all the *Potential customers* are exhausted, dividing in the four flows related to the four different model transport choices. Nevertheless, from the first moment of the simulation the different trends are glaring. As we can see in **Fig. 6**, the lowest level of customers identifies the choice of the bus for travel, obviously depending on the duration of the journey, which is the highest among the four means of transport. Moreover, while *Rail customers* and *Car customers* have slightly higher and similar trends, the trend of *Air customers* is higher, as air travel has the shortest duration (air travel with zero, one or two changes has been considered). The final value that the four variables assume at the end of the simulation is reported in the last row of **Errore. L'origine riferimento non è stata trovata.**.

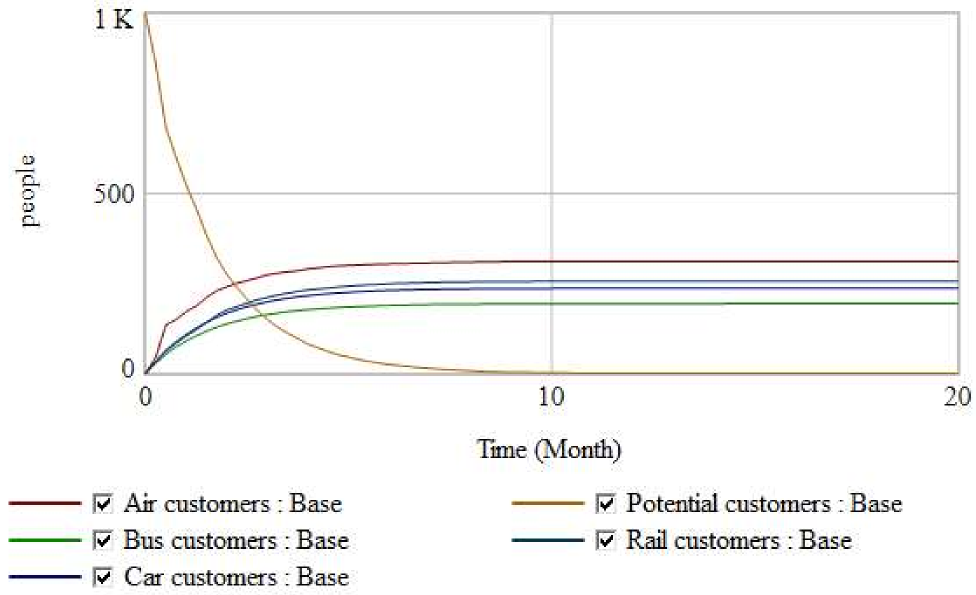

Fig. 6 - Scenario 1: Customers not sensitive to the price.

4.2 Scenario 2: Customers not sensitive to the trip duration

In the simulation of the second scenario described, the behaviour of the model is analysed in the case of customers who are not sensitive to the trip's duration, with regard to both the choice for public transport or private vehicles. The assumptions for the simulation of this scenario are reported in **Errore. L'origine riferimento non è stata trovata.**.

Table 4 - Assumptions of simulation for Scenario 2.

	Bus	**Rail**	**Air**	**Car**
Assumptions for simulation	bus fare weight = 0.6	rail fare weight = 0.6	airfare weight = 0.6	car trip expenditure weight = 0.7
	bus trip duration weight = 0	rail trip duration weight = 0	air trip duration weight = 0	car trip duration weight = 0
	bus customers' overnight need weight = 0.3	rail customers' overnight need weight = 0.3	air customers' overnight need weight = 0.3	car customers' overnight need = 0.3.

	bus customers' need for another means of transport = 0.1	rail customers' need for another means of transport = 0.1	air customers' need for another means of transport = 0.1	
SIMULATION RESULT	**500**	252	63	184

In this scenario, the behaviour of the model changes significantly. As we can see in **Fig. 7**, it can immediately be noticed that the highest level of customers corresponds to the *Bus customers*, while the lowest one refers to the *Air customers*, substantially reversing the situation with respect to Scenario 1. Moreover, the trends of the four curves related to the four choices are clearly distinct. Finally, the growth of the curves has a similar behaviour as in Scenario 1, with a faster rate in the first part of the simulation (especially in relation to the Bus customers) and then with a slower one until it reaches an almost constant trend.
The final value that the four variables assume at the end of the simulation is reported in the last row of **Errore. L'origine riferimento non è stata trovata.**.

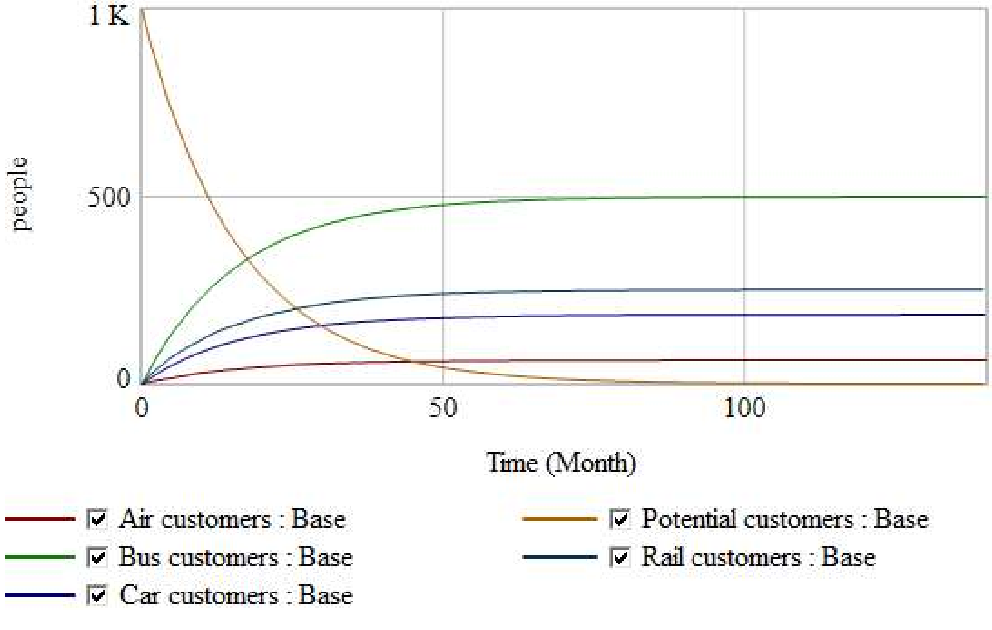

Fig. 7 - Scenario 2: Customers not sensitive to the trip duration.

4.3 Scenario 3: Customers not sensitive to the need to stay overnight

The third scenario analyses the behaviour of the model where customers are not sensitive to the need for an overnight stay before and/or after the appointment.
To set the values for the simulation, it was decided to maintain the weight value related to the need to use an additional means of transport equal to 0.1, to equal the weights regarding the need to overnight to 0,

and to equal the remaining ones among them, as their sum is always equal to 1. The assumptions for simulation of this scenario are reported in **Errore. L'origine riferimento non è stata trovata.**.

Table 5 - Assumption of simulation for Scenario 3.

	BUS	**RAIL**	**AIR**	**CAR**
ASSUMPTIONS FOR SIMULATION	bus fare weight = 0.45	rail fare weight = 0.45	airfare weight = 0.45	car trip expenditure weight = 0.5
	bus trip duration weight = 0.45	rail trip duration weight = 0.45	air trip duration weight = 0.45	car trip duration weight = 0.5
	bus customers' overnight need weight = 0	rail customers' overnight need weight = 0	air customers' overnight need weight = 0	car customers' overnight need = 0
	bus customers' need for another means of transport = 0.1	rail customers' need for another means of transport = 0.1	air customers' need for another means of transport = 0.1	
SIMULATION RESULT	**456**	265	71	207

As we can see in **Fig. 8**, the highest level of customers concerns the *Bus customers* while the lowest is for *Air customers*, noting the results obtained in the simulation of Scenario 2. Also in this case the characteristic curves of the levels grow faster in the first part of the simulation. The final value that the four variables assume at the end of the simulation is reported in the last row of **Errore. L'origine riferimento non è stata trovata.**.

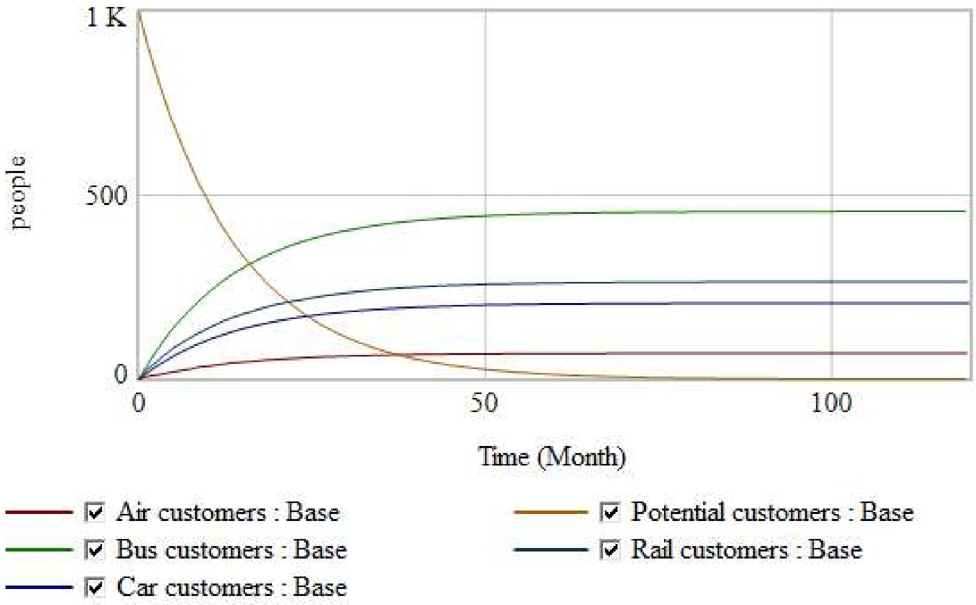

Fig. 8 - Scenario 3: Customers not sensitive to the need to stay overnight.

4.4 Scenario 4: Customers not sensitive to the need to use additional means of transport

In this scenario, customers are totally disinterested in using additional means of transport to move from the departure point to the departure terminal and from the arrival terminal to the meeting place and vice versa. To simulate this scenario, with reference to Scenario 3, the values of the weights regarding the price and trip's duration are left unchanged, while those relating to the need for overnight accommodation and the need to use additional means of transport are reversed.
The assumptions for the simulation of this scenario are reported in **Errore. L'origine riferimento non è stata trovata.**.

Table 6 - Assumptions of simulation for Scenario 4.

	BUS	RAIL	AIR	CAR
ASSUMPTIONS FOR SIMULATION	bus fare weight = 0.45	rail fare weight = 0.45	airfare weight = 0.45	car trip expenditure weight = 0.35
	bus trip duration weight = 0.45	rail trip duration weight = 0.45	air trip duration weight = 0.45	car trip duration weight = 0.35
	bus customers' overnight need weight = 0.1	rail customers' overnight need weight = 0.1	air customers' overnight need weight = 0.1	car customers' overnight need = 0.3

	bus customers' need for another means of transport = 0	rail customers' need for another means of transport = 0	air customers' need for another means of transport = 0	
SIMULATION RESULT	**420**	244	65	271

The results of the simulation are shown in **Fig. 9**. As expected, the behaviour of the model is similar to that of Scenario 3, the two scenarios being similar from the mathematical point of view. However, the trends of *Rail customer* and *Car customers* are exchanged. The final value that the four variables assume at the end of the simulation is reported in the last row of **Errore. L'origine riferimento non è stata trovata.**.

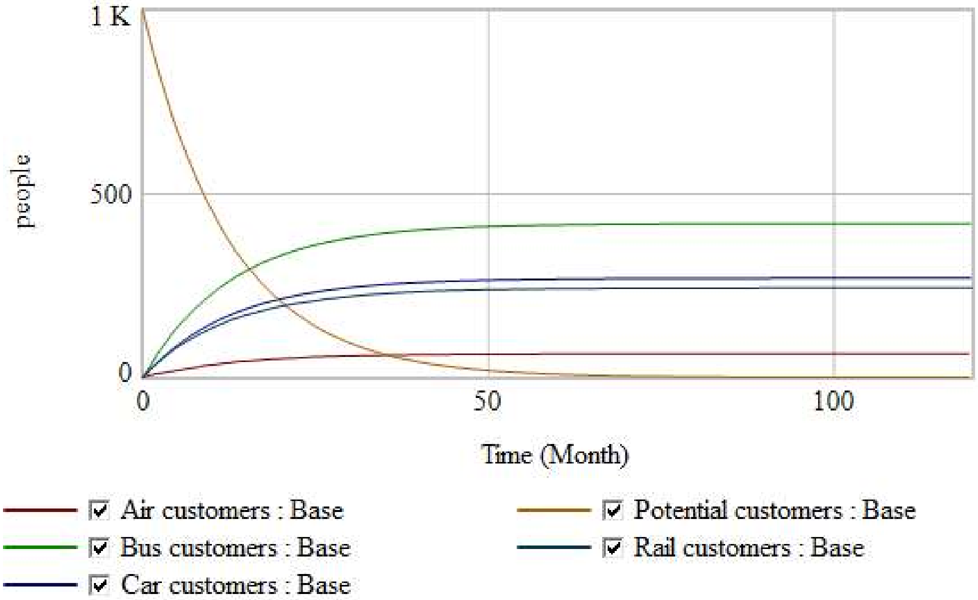

Fig. 9 - Scenario 4: Customers not sensitive to the need to use additional means of transport.

4.5 Scenario 5: Customers exclusively sensitive to the price

In great contrast to Scenario 1, in this case we analyse the behaviour of the model when the *Potential customers* are only interested in the cost of the trip (excluding the cost of a possible overnight stay and the cost for additional means of transport, considered in the model more as qualitative than quantitative variables, the presence of decreases the customer flow towards one of the possible choices).
To model this scenario, the variables related to the weights attributed by customers to the price (bus fare weight, rail fare weight, airfare weight, car trip expenditure weight) were set equal to 1; the other "weight"

variables take on value 0. In **Table 7**, therefore, the assumptions for the simulation of this scenario are reported.

Table 7 - Assumptions of simulation for Scenario 5.

	BUS	**RAIL**	**AIR**	**CAR**
ASSUMPTIONS FOR SIMULATION	bus fare weight = 1	rail fare weight = 1	airfare weight = 1	car trip expenditure weight = 1
	bus trip duration weight = 0	rail trip duration weight = 0	air trip duration weight = 0	car trip duration weight = 0
	bus customers' overnight need weight = 0	rail customers' overnight need weight = 0	air customers' overnight need weight = 0	car customers' overnight need = 0
	bus customers' need for another means of transport = 0	rail customers' need for another means of transport = 0	air customers' need for another means of transport = 0	
SIMULATION RESULT	**487**	243	208	61

As might be expected after a mathematical analysis of the model, the flow of *Potential customers* moves towards the choice of the most economical means of transport represented by the bus. The final results are shown in **Fig. 10**.

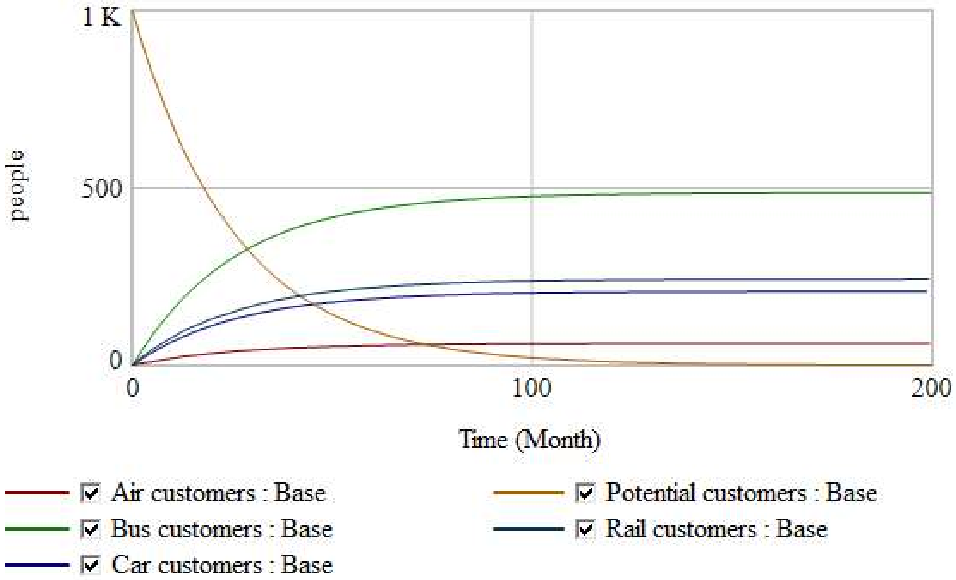

Fig. 10 - Scenario 5: Customers exclusively sensitive to the price.

4.6 Scenario 6: Customers exclusively interested in the trip's duration

This scenario analyses the case in which the customers are interested only in the aspect regarding the trip's duration. To model this scenario, the variables related to the weights attributed by customers to the trip's duration (bus trip duration weight, rail trip duration weight, air trip duration weight, car trip duration weight) were set equal to 1; the other "weight" variables take on value 0. In **Table 8**, therefore, the assumptions for the simulation of this scenario are reported.

Table 8 - Assumptions of simulation for Scenario 6.

	BUS	**RAIL**	**AIR**	**CAR**
ASSUMPTIONS FOR SIMULATION	bus fare weight = 0	rail fare weight = 0	airfare weight = 0	car trip expenditure weight = 0
	bus trip duration weight = 1	rail trip duration weight = 1	air trip duration weight = 1	car trip duration weight = 1
	bus customers' overnight need weight = 0	rail customers' overnight need weight = 0	air customers' overnight need weight = 0	car customers' overnight need = 0

	bus customers' need for another means of transport = 0	rail customers' need for another means of transport = 0	air customers' need for another means of transport = 0	
SIMULATION RESULT	185	257	**297**	260

As can be seen in **Fig. 11**, *Potential customers* move more towards *Air customers*, as air travel has a shorter duration. The characteristic curves of the *Car customers* and *Rail customers* present practically the same trend due to the journeys' similar duration (based on the data extrapolated from the GoEuro site). The variable with the lowest level is *Bus customers*.

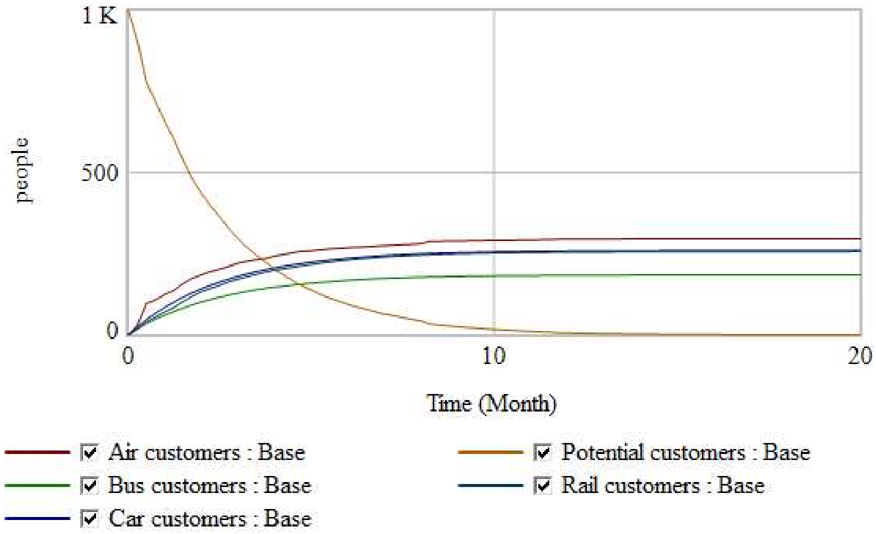

Fig. 11 - Scenario 6: Customers exclusively interested in the trip duration.

The next section will present an overall analysis of all the scenarios to highlight the main differences characterising customers' behaviours in the different mobility solutions available and discuss the different scenarios for the improvement of our model.

5. Simulations discussions

In this section we will discuss the simulation model regarding the six different scenarios of smart mobility of people. The scenarios described above and the simulations carried out highlight the characteristic behaviour of the potential customers of the transport market, called to make the choice of the most coherent transport means. The designed model provides a systemic view of this market and the behaviour of the variables involved, useful during the strategic decision-making process of the company to analyse and understand, basing on the set of values of the influencing variables of the choice:

- the most profitable customers in relation to a means of transport.

- the factors to change for the customers' retention.
- influencing factors can be used to attract more customers.

The model does not include all the variables influencing the choice of the most suitable means of transport to be used for traveling, but it is a discrete simulator including the most interesting influences factors: price of the ticket with regard to the public transport or travel cost for those who choose the private vehicle to travel, trip duration, need to stay overnight and need to use additional means of transport. A summary of the results coming from the simulation of the different scenarios is given in **Table 9**.

Table 9 - Summary of simulation results from the six scenarios.

SCENARIO	DESCRIPTION	BUS	RAIL	AIR	CAR
Scenario 1	Sensitive to price	194	257	**312**	237
Scenario 2	Sensitive to trip duration	**500**	252	63	184
Scenario 3	Sensitive to the need to stay overnight	**456**	265	71	207
Scenario 4	Sensitive to the need to use additional means	**420**	244	65	271
Scenario 5	Exclusively sensitive to the price	**487**	243	61	208
Scenario 6	Exclusively sensitive to the duration	185	257	**297**	260

A comparative analysis among all these scenarios show that the variable *Bus customers* assumes a maximum value in Scenario 2, where customers are not sensitive to the trip's duration, while it is minimal in Scenario 6, where customers are exclusively interested in the trip's duration. In both cases we refer to absolute maximum and minimum.

At the highest value of *Bus customers* corresponds the lowest value is of *Air customers*, while at the lower value of *Bus customers* corresponds again the highest value of *Air customers*.

The *Rail customers* reach the maximum value in Scenario 3, where customers are not sensitive to the need to stay overnight, while the minimum value is reached in Scenario 5, where customers are exclusively interested in the price. In both cases, these maximum and minimum values do not represent the absolute maximum and minimum; e.g., respectively the maximum and minimum reached in all the simulations that were carried out to implement the already illustrated scenarios. In Scenario 3, the highest value is for *Bus customers*, while in Scenario 5 the minimum value is for *Air customers*. Moreover, observing the results reported in all the **Table *6***, the trend of *Rail customers* is noted as practically constant in all the simulations.

Moreover, *Air customers* have the highest value in Scenario 1, where customers are not sensitive to price, while it assumes the minimum value in Scenario 5, in which customers are exclusively interested in the price. In both cases, these values represent the absolute maximum and minimum values of the whole simulation process.

Finally, the *Car customers* have the highest value in Scenario 4, in which customers are not sensitive to the need to use additional means, and it assumes the minimum value in Scenario 2, where customers are not sensitive to the trip's duration. The absolute maximum in Scenario 4 concerns the *Bus customer*, while the absolute minimum in Scenario 2 is for *Air customers*.

It is important to note that the variable related to the need to stay overnight and need to use additional means of transport assume mostly qualitative value, to avoid further complicating the model with variables regarding the cost of accommodation and the cost of using additional means of transport. So, they do not affect the total cost of the trip; instead they directly affect the customer acquisition flow, lowering it when they are different from zero.

A further improvement oriented toward a big data perspective consists in nourishing the model with a dynamic database, able to track real-time values of actual prices, travel durations, and departure and arrival times, therefore making the model as realistic as possible. This could allow overcoming the limited attention reserved by decision makers of private and public transportation organisations to users' centrality in designing and implementing smart mobility services (Qu et al., 2019; Papa and Lauwers, 2015). From the scenarios depicted, it is possible to demonstrate that, due to the broad dissemination of digital and smart technologies, the mobility of people is increasingly configurable as a data driven process (Badii, et al., 2019; Qiu, et al., 2019) impacting companies' competitiveness and territories' socio-economic and environmental goals (Faulin, et al., 2019). By interesting a large community of stakeholders, such as citizens, government, businesses, environments (Fontoura et al., 2019), the adoption of a system dynamics approach as in our simulation allows meeting the challenges of an intermodal solutions and to adopt smart technologies to maximize accessibility, minimize transport consumption, contribute to the mitigation of social and environmental challenges and improve the quality of life (Schaffers, et al., 2011). A decision making process based on system dynamics has demonstrated being scalable and suitable to manage scenarios of growing complexity such as mobility of people with different needs and behaviours.

City planner

Furthermore, in all the phases of people's journeys, starting from mobility planning to the mobility's execution, users access and generate a large amount of data thanks to digital technologies and smart devices, leveraging on a large, dynamic set of variables.

Our study confirms that people's mobility management by public and private organisations requires the adoption of smart and dynamic approaches for the decision making able to leverage on a large number of variables evolving in real time (Shepherd, 2014). The smart configuration of mobility thus depends on the system's effectiveness in managing the huge amount of data available and this requires the identification of new data mining and analytics technologies as well as approaches able to allow mandatory prediction and simulations results to support managers in the challenge of managing the complex network of relationships around organisations and institutions (De Mauro et al, 2016).

In **Fig. 12**, the system dynamic model was depicted in terms of main components.

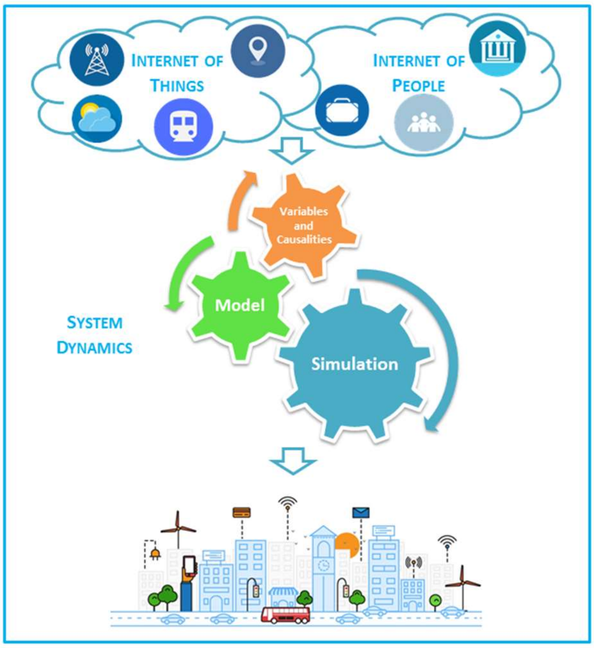

Fig. 12 – System Dynamics Model

As mentioned, the system dynamic process can be outlined as the identification of variables, causality and their interdependence, the definition of the quantitative model, plus the final simulation process. Hence, if the system is nurtured by data coming from different IoT and IoP devices (e.g. all the devices connected wirelessly to a network and having the ability to transmit data, such as sensors, smartphones, beacon, and so on), the final model will be able to grow into a powerful decision-making tool and, with more opportune adaptations, it can sustain smart mobility in the widest perspective of improving the quality of life.

6. Conclusions and implications

Mobility systems were introduced as the backbone of economic and social progress in the twentieth century, although now transport activities are the main cause of unsustainability patterns, especially in urban areas (Moradi and Vagnoni, 2018). System dynamics could emerge as suitable approach for decision making in the smart city context with reference to the mobility of people. Mobility as a service can be considered as a new transport paradigm which aims to integrate different modes of transport, such as buses, trains, and shared cars into a service package (Ruutu et al., 2017).

In this paper, we adopted system dynamics as a useful approach for managing the complexity of variables and optimising the decision making process related to the mobility of people. In this perspective, the study

presented a system dynamics simulation model of smart mobility of people; using the model, we illustrated six possible scenarios with specific factors affecting the likelihood of these scenarios in the final aim to develop a complete platform nurtured by big data.
The simulation has allowed to identify alternative transport solutions for the mobility of people by leveraging on a set of complex and dynamic variables and to demonstrate the versatility of a decision making approach based on system dynamics for the personalization of such services. In contributing to the advancement of the debate on smart mobility, this has allowed to shed new light on the unexplored area related to meaning and implications of smartness in the users' perspective (Qu et al., 2019; Papa and Lauwers, 2015). In addition to this, the study has disclosed the potential benefits associated to the adoption of Big Data as source of information supporting the smart configuration of mobility services tailored made to the needs and profiles of users.
Areas for future research can be identified in terms of replication and contextualization of the simulation model in different contexts as well as in the adoption of more sophisticated mechanisms for segmenting and targeting the demand.

6.1. Implications for policy makers and managers

Implications for policy makers regard the developing sustainable mobility scenarios based on the analysis of big data and simulation models. Opportunities to innovate the transport services at urban and extra-urban level arise. By adopting dynamic decision making systems based on big data, policy makers and city managers could leverage on information intensive evidences for innovating the transport services and for providing more efficient solutions of mobility. In the meantime, the scalability characterizing the model proposed with the implementation of different typologies of variables and data allows to depict interesting scenarios for the design and the monitoring of a more efficient and sustainable service of mobility.
The recent attention reserved to the issue of sustainability assumes in the mobility challenging dimensions due to the pollution and emission charactering this typology of services. The possibility of providing a service of transport on the basis of the real needs of the users and through a methodological dashboard able to provide foresights and simulate the better solutions available can contribute to the achievement of a more ecological and sustainable usage of transport services and to create a major awareness into the users.
In this direction, further implications can be identified for updating the technological infrastructures, the organizational models and human capital involved into the context of smart mobility and into the larger context of the cities and territories.

6.2. Limitations and directions for future research

The simulation model proposed has been focused on the specific territorial needs and conditions. This has allowed to identify a set of variables that could be verified into different contexts. At this purpose, in the future development it could be useful to consider different geographical areas and distance to be covered by the transport services for verifying the goodness of the simulation proposed. In the meantime, it could be useful to verify the correspondence of the different categories of users identified for the simulation scenarios with more consolidated criteria for segmentation and targeting. In this direction, it could be also useful to complete the study through the level of assessment of end users of the different transport services adopting a real time survey.

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