POLITECNICO DI TORINO

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Master of Science Thesis

A preliminary study of an Agent-Based Model of a complex adaptive socio-techno-economic system in energy technology diffusion

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Abstract

The diffusion of energy technologies in the cities of the future is the key towards a more sustainable community. The increasing use of renewable energy sources, efficient energy conversion machines, storage systems and ICT solutions, thanks to increasing amount of energy data, will require methodologies to support the decision-making process in long-term urban energy planning. To reach the goal, these technologies have to be integrated and interconnected between them, especially in the urban context, as well as encourage their use, considering the consumer's energy choices end environmental constraints.

This preliminary study aimed to develop an Agent-Based Modelling (ABM) infrastructure to simulate a complex adaptive socio-techno-economic system in energy technology adoption. The model creates an environment with a GIS space representing the San Salvario's district of Turin in which agents are households, and some of them could live in the apartment buildings. They are designed to decide whether to adopt rooftop PV system, following theories of human behaviour on making decisions, of interactions in social networks and techno-economic feasibility. The model predicts the diffusion of PV systems, finding what could be the socio-economic parameters that modify the likely emergent diffusion trend of the whole system.

ABM allows representing a complex adaptive system in a flexible and detailed way describing the decision-making process of agents and the physical and economic environments surrounding them. The agents are entities like individuals or also a group of people like the households of the case under study. They are designed to reach a goal, and they make actions individually considering their states and their decision rules, interacting with their social networks, the resources and with the environment.

The results of the preliminary study shown that the diffusion of the energy technology is not only dependent on technical and economic variables. What is also relevant are the opinions of the consumers and how these change in time due to network influence, social norms, advertising and environmental awareness. This first approach to ABM is a Proof of Concept with the aim of learning the fundamental theories and methodologies to develop a model and to apply to a case study at urban-scale using empirical data. A future validated model could be used to energy policy design and evaluation, knowing how the spatial and temporal diffusion pattern changes acting on parameters like economic incentives, publicising of the technologies on their benefits and costs and more else. Besides, knowing where and when the technologies spread is fundamental to system design and smart infrastructure planning.

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Daniele Salvatore Schiera

The knowledge of others is intelligence,
self-knowledge is enlightenment.
The conquest of others is power,
the conquest of oneself is strength.

Know what is enough, and you will be rich.
Persevere, and you will develop the will.
Stay in the center, and you will always be at home.
Die without dying, and you will live forever.

Tao Te Ching – Lao Tzu – Chapter 33

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1. Introduction

The diffusion of energy technologies in the cities of the future is the key towards a more sustainable community. The increasing of renewable energy sources utilisation, efficient energy conversion machines, storage systems and more use of ICT solutions, thanks to increasing amount of energy data, will require methodologies to support the decision-making process in long-term urban energy planning. To reach the goal, these technologies need to be integrated and interconnected between them, especially in the urban context, as well as encourage their use, considering the consumer's energy choices end environmental constraints.

In Italy, over the last few years, the installed capacity of photovoltaic systems has grown thanks to the implementation of public incentives. However, starting from 2013, the year in which *Conto Energia*[1] expired, the growth took place at less sustained rates [1]. To push more the diffusion of PV systems, especially in the urban context where almost of households live in apartment buildings, it is fundamental to know what are the other factors that affect the adoption, in addition to the effect of supporting schemes.

It is well-known from the literature that the diffusion of PV system depends not only on economic and technical aspects but also depends on socio-demographic factors [2]–[5]. To understand and highlight the influence of these other factors on energy technology diffusion, it is not sufficient to apply the classical diffusion models, e.g., the Bass Model, which is associated to the standard S-shape diffusion function [6]. In this field of study, the cities and their consumers, e.g. the households, should be modelled as a socio-techno-economic system, in the context of the complex adaptive systems [7][8]. The complexity of the system depends on the presence of many different entities that interact with each other and with the environment, as well as the increasing of physical, social and economic interdependencies. Moreover, the system and its elements are intrinsically heterogeneous, therefore the choice on the adoption of the technology is different per each hosuehold, in fact decision-making

[1] Conto Energia, a.k.a. feed-in-tariff, is a policy mechanism designed to accelerate investment in renewable energy technologies offering long-term contracts to renewable energy producers, typically based on the cost of generation of each technology.

of every household is based on a wide range of factors such as technical aspects, income, social pressure, innovativeness, social interactions and many others, that make the final choice, whether to adopting, different per each household. The system has also a dynamic evolution caused by the adaptation, or improvement, of the system's elements over time in relation to the environment [7]. Since the classical diffusion models do not take into account of these complexities and heterogeneity, it is not possible to understand *how* and *where* the adoption will probably grow, but only know *when* will be the peak of installations and *what* is the possible saturation value. Knowing this additional information and data is essential to provide energy policy decision support, aimed at developing a sustainable community, but also to system design and smart infrastructure planning.

The goal of this study is to demonstrate the feasibility of an Agent-Based Model (ABM) applied to the diffusion of energy technology, i.e., the consumer adoption of rooftop PV system in an urban context. The ABM modelling paradigm permits to study the innovation diffusion overcoming the limit of the classical diffusion models. First, it facilitates the modelling of agent heterogeneity, where the agents are the autonomous decision-making units of the model [9]. Second, it enables the modelling of agents' interactions mediated by social networks, like in the case of modelling socio-techno-economic system [10]. Lastly, the ABM applied with GIS model enables to analyse the results in a real spatial context [4][11][12]. The ABMs are used in plenty of scientific domains, and in particular, they have been widely used to study the diffusion of renewable technologies and more recently to study the diffusion of smart metering technologies [13][14]; moreover they are used also, to model explicitly how individuals affect one another in cognitive and psychological terms, like opinion, attitude and subjective norm, thus they have been applied humans behavioural theories such as the Theory of Planned Behaviour (TPB) [5][13][15]–[17] and dynamics of opinions theories such as the Relative Agreement model (RA) [3][11][15][18][19]. The bullet list reports the reviews of some works in literature that have applied ABM in the field of diffusion of energy technologies:

- Sopha et al. [20] present an ABM for simulating heating system adoption in Norway. Their model uses a modified TPB to consider several contributing factors such as household groups, intention, attitudes, norms. The households are grouped using cluster analysis based on income level and basic values available in the survey data to approximate the influence of lifestyle on attitudes towards technology. Moreover, the model uses the meta-theory of consumer behaviour

[21] that consist of assuming that a household randomly follows one of four decision strategies: repetition, deliberation, imitation and social comparison. The model is validated at both macro (aggregated) and micro level.

- Palmer et al. [22] developed an ABM of diffusion of PV systems in the residential sector in Italy; thus the model is applied in the national context. The model is based on utility maximisation of the agents that is defined as the sum of four weighted partial utilities, i.e. payback period for the investment, environmental benefits, household income and social influence. An agent chooses to invest in PV system if its total utility exceeds a specified threshold. The partial utilities are derived from empirical data. In particular, the social influence is modelled by using social networks among agents that are generated according to the Small-World Network (SWN) model [23]. The model parameters are calibrated by matching simulated adoption with the actual household PV adoption in Italy over the 2006-2011 period; then, the model is applied to study the PV diffusion in Italy over 2012-2026 period, but no quantitative validation was done.
- Rai and Robinson [15] developed an empirically grounded ABM of residential PV diffusion to study the design of PV rebate programs in Austin, Texas. The model considers only single-family residential households. It uses the human behaviour concepts as explained by TPB, assuming that two key elements determine adoption decision: attitude and perceived control. The attitudes evolve through agents interactions, following the RA model, with their social networks that are modelled as SWN. If the agent exceeds its attitude threshold, it adopts when its perceived control is lower than the observed payback period. The model was validated at a macro level in the temporal, spatial and demographic domain.

Following the initiatives from the Energy Center Lab (EC Lab) of Politecnico di Torino, the objectives and future works, in the context of urban energy planning, are related to build an integrated urban simulation platform, starting from city-level data, to perform simulation of scenarios with the aim of to make energy planning and policy advise. This thesis is inserted in the context of scenarios simulation at local scale using innovative model paradigm like ABM. Therefore, the purpose of this work is to develop a Proof of Concept (POC) ABM applied to the case study of diffusion of the rooftop PV systems in the urban scale context, which is represented by San Salvario's district of municipality's Turin (unlike Palmer et al. that applies the ABM at national scale in Italy). The ABM of this framework uses the TPB to describe the human decision-making, not modifying its structure and its components (as done by Sopha et al. and Rai and Robinson), but exploiting the conceptual definitions to create a grounded mathematical model. The opinion dynamics are implemented using the RA model and the social structure of the agents is based on Small-Word Network theory. Moveover, in this model the agents considered are not only the single-family residential households, as done in many frameworks in the literature (like Palmer et al. and Rai and Robinson), but what is relevant is the modelling of households that live in the apartment buildings, which are more common in the urban context and to study the collective choice of adoption. The diffusion of emergent patterns, obtained from the simulations of different scenarios, were qualitatively analysed showing how the model parameters change the diffusion and exploring some thematic maps of the district that shows the diffusion behaviour with a spatial (georeferenced) detail.

The results of the case study are not predictions of the PV diffusion because the model is not calibrated and validated at the temporal and spatial domain, but it shows the potential of the implemented ABM framework to reproduce technology diffusion curve based on social-technical-economical evaluation. In fact, as POC, this ABM has some limits and simplified assumptions that will be addressed in future works, eventough this modelling paradigm gave us the capability to explore what are the advantages, drawbacks and opportunities that a PV technology can provide to the energy field at urban scale. Available statistical data were used to define some components of the model, such as the social clustering, the energy demand-side, and also the initialisation of the model is based on more general assumptions, such as the agents' initial opinions. All of these information should be empirically grounded with the real population with the aim of calibration and validation of the model. Furthermore, some of the model parameters are chosen using simplified assumptions, but they should be addressed in the future works to reflect better the real world and reduce degrees of liberty to the model.

Outline of the Thesis

In *Chapter 2,* the materials used and the theoretical and methodological approaches are presented, showing step-by-step the development of the model, from the concepts towards the implementations of these, and the model experiments and scenarios are elaborated. In *Chapter 3,* the model results are addressed and analysed with the discussion of the primary results. The conclusions of the Thesis are given and in *Chapter 4,* where the future perspective of application of the ABMs is presented. Finally, a compendium of the theoretical backgrounds, protocols, diagrams and data sources of all the arguments covered in the C*hapter 3* and *4* are all reported in *Chapter* 5, as an *Appendix,* in order to keep a comprehensive but discoursive style of main text.

2. Materials and Methods

In this chapter, it was described the data sources utilised and the overall methodology applied to develop the ABM as well as all mathematical models, theories frameworks and model assumptions, also describing the experimentations and scenarios simulation. There are four main sections in which is divided by this chapter:

- *Model overview and design concept.* It describes the general composition and design of the model, underlining the essential characteristics and describing each element which composes it;
- *Data sources.* It describes all the data used in the model, also mentioning their references with a brief description of each dataset;
- *Methodologies and theoretical approaches.* It shows step by step the development of the model, starting from its problem formulations, methodologies and theoretical frameworks used, model formalisation and towards model verification;
- *Experimentation.* It is the final section of this chapter which reports the experimental set-ups, scenarios and the assumptions made for the experimental work.

To have a clear and straightforward reading of the text all the theoretical frameworks used are described in more details in Appendix 5.1.

2.1. Model overview and design concepts

The modelling goal is to build a household-level ABM that can generate the emergent temporal and spatial diffusion patterns of the adoption of rooftop PV at urban-scale context. In particular, the agents of own ABM are households that live in a single-family residential house or, most commonly at urban-scale, in apartment buildings (i.e. Condominium).

The case of study is the San Salvario's district of Turin that includes 18,720 households distributed over ~1,290 building blocks. The period of the simulation is from 2017 to 2037 and each time step is configured as a quarter; hence, a simulation runs for 80 steps. For testing purpose and parametric analysis of the model a *dummy city* was used. This is constituted by a square lattice of households (35x35) where key agent properties were taken from data sources.

The simulations tests were performed on a notebook (Intel Core i7 2 GHz, 8 GB DDR3, macOS system), whereas the simulations of San Salvario's district were run using PoliTo's EDA Group server, called Philae (2x Intel Xeon E5-2630v3 2.40 GHz, 128 GB DDR3, CentOS 6.7 Linux system). All the code was developed from scratch in the Python programming language [24] implemented with Mesa, an Apache2 licensed agent-based modelling framework in Python [25], and the most commons and utilised Python's libraries.

The agents' dataset of San Salvario's district was set up using publicly available data sources and data from some other references, with also setting the environmental data and parameters, forming so the inputs of the model, as shown in Figure 2.1. The agents' dataset was generated starting from the GIS data obtained by integration of buildings shapefiles, solar data and census' sections data. Then the data were elaborated data to generate each household (agent): it is positioned in a building and assigned to a social group according to the census' sections incorporated in GIS data and Istat data regarding social groups. The agents also receive an estimated load profile related to the social group which belong to and the numerousness of family. In this way, the agents' dataset is generated, and it contains all the information related to each household: physical boundaries and constraints; social, economic and demographic attributes; initial opinions and uncertainties around those opinions, decision factors, weights and more else. All this information together represents the state of the agent for a particular time step; therefore it might change during the subsequent time steps.

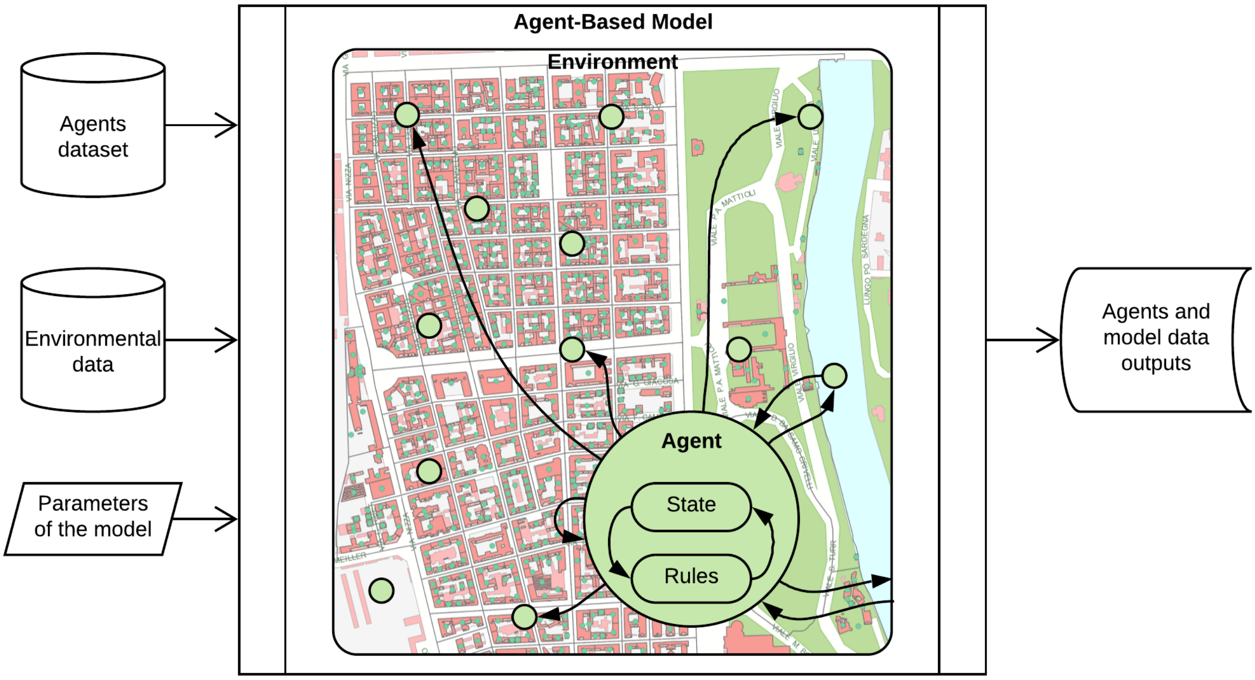


Figure 2.1: The Agent-Based Model overview.

The agents make actions that are well-defined by specific rules. The decision-making behaviour of the households was represented using the framework of the Theory of Planned Behavior (TPB) [16][26], which considers socio-economic and demographic factors that influence households decisions. The TPB methodology comprises of three factors that defined according to three types of beliefs: *behavioural beliefs* that constitute the Attitude Toward the Behaviour (att); *normative beliefs* that constitute Subjective Norm (sn) and *control beliefs* that constitute the Perceived Behavioural Control (pbc). These three components of TPB taken into account togheter determine the final Behaviour (b) of the agents. Each agent interacts, accordingly to the Relative Agreement algorithm [18] with other agents within its social networks, generated from the theory of Small-World Network [23], and thanks to the use of, the opinions evolve making them dynamic. The agents also interact with the environment in order to get external information, e.g. a quote on the investment on rooftop PV, electricity market price and else.

The final choice whether adopting or not is based on a threshold accounted within the decision-making model, having first verified the technical and socio-economic feasibility of the choice; in the case where the agent lives in a Condominium, the final decision is subjected to a collective choice.

Finally, the data analysis of the output results of the model was performed showing the emergent diffusion patterns and spatial distributions of some key performance indicators like ‘self-consumption’ and ‘self-sufficiency’ ratios.

2.2. Data sources

The ABM requires many different sources of measured data to represent a realistic world, in the context of the socio-techno-economic system. This section introduces all the data sources used and processed in the model to characterise the environment and agents. Figure 2.2 represents the data framework used in this ABM project, showing the main steps of data processing.

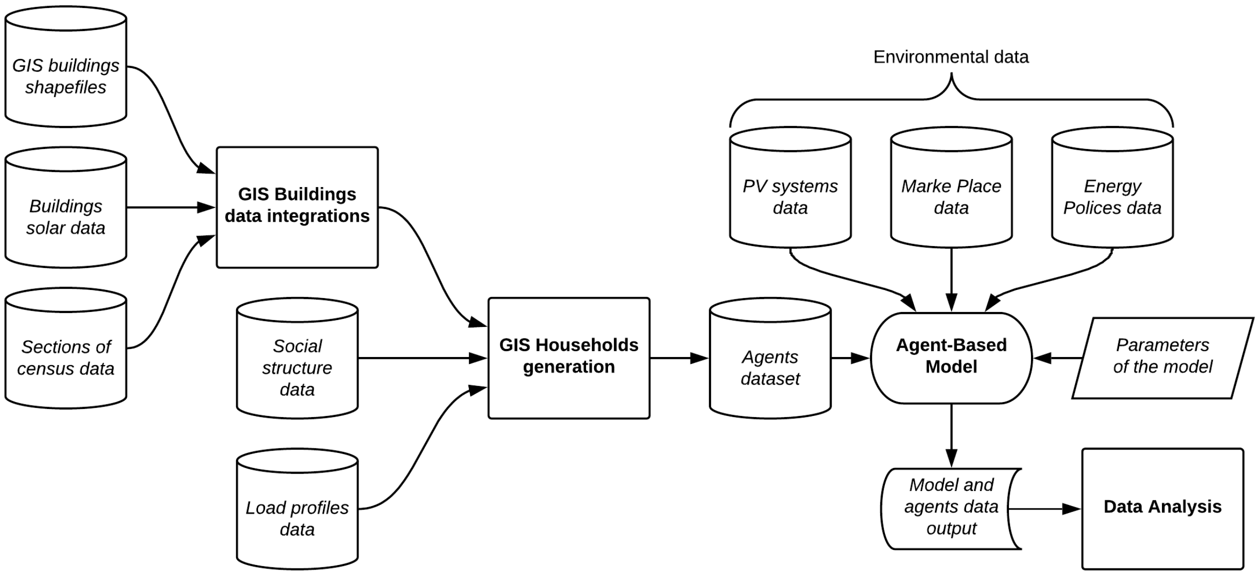


Figure 2.2: Schematic data flows of ABM, showing the main steps of data processing.

The data sources used can be divided into:

- District's GIS buildings shapefiles
- District's census sections data;
- Buildings' solar data;
- Social structure's data;
- Households' electricity load profiles;
- Environmental data.

In the following subsections, each type of data was briefly described remarking the origin of the data and its use.

District's GIS buildings shapefiles

Publicly available data from the Geoportal of Turin's municipality [27] were used to obtain georeferenced buildings polygon of the San Salvario's district as shapefiles in which the used fields are:

- footprint area;
- code name of census' sections;
- date of construction;
- type of building;
- category of use;
- building height and floors.

District's census sections data

The shapefiles were spatially joined with publicly available census data provided by Istituto Nazionale di Statistica (Istat) from the last Italian population and buildings census of 2011 [28]. The census data consist of 134 census variables per each section of the census. From this dataset, it was used 190 census' sections of which is divided the San Salvario's district and taken 20 of census variables per each of section. The selected census variables are of interest for the construction of the model, like the number of residential households, foreigners, job status (workers, unemployed), number of households members, degree (illiterate, primary school, secondary school, university degree, post-degree) and more else. The complete census variables used were reported in Appendix 5.2.2. In summary, thanks to this data, it was possible to define a characteristics distribution of the households per each of census section that reflect the real socio-demographic situation of the district.

Buildings' solar data

Buildings' solar data of the district were provided by the model of Bottaccioli et al. [29]. It is a distributed software infrastructure for modelling and simulating roof-top PV energy generation in the urban context. The software performs simulations in a spatio-temporal domain exploiting geographic information systems together with meteorological data to estimate the solar irradiance profile in real operating conditions. In this study, using this software, the solar irradiance profile [W/m^2] was obtained per each building, considering the direction, slope and also the weather conditions, on a time scale of a year. The profiles were referred to the whole 2011 year, and they were given with a time interval of 15 minutes.

Social structure's data

Each household has his own socio-economic and demographic characteristics that have a decisive influence on the decision-making process. To take into account the heterogeneity of households, the social grouping of Italian households issued by Istat in the newly Annual Report 2017 was used [30]. Starting from the 25 million households residing in Italy, nine different groups were defined following a statistical approach allowing to take into account multiple aspects, to preserve heterogeneity, to represent homogeneous household income levels corresponding to specific combination of other factors among others: education level, citizenship, professional position, number of household members and area of residence [30]. From the report and the public data associated with, the statistics per each of defined social group was used, in combination with the census variables described before with the aim of to associate a group to each household. Thanks to this link, it was possible to give some useful attributes to households in function of the social group in which belonging. For example, the level of a household's income, number of components, and, with some assumptions, a level of innovation and specific weights for some attributes related to the household.

A brief description of the social groups is given in the section 2.3.2.1., while all the statistics were reported in Appendix 5.2.1. for a more straightforward reading of the text. On the other hand, their use and implementation in the model in combination with the census data were explained in section 2.3.3.1.

Households' electricity load profiles

Electricity profiles of households were estimated taking into account the social groups to which they belong and the characteristics that affect the demand profile, e.g., the number and types of household members. To generate the load profiles per each social group, it was used a stochastic semi-markovian model, following some frameworks in the literature [31]–[33]. The model simulates the electricity demand of a single household considering the consumption of the appliances, which are modelled using physically-based models, and the activity patterns of the household members that are modelled using Markov chain. More information was given in section 2.3.3.1.

Environmental data

The environment represents not only space but even all the external information required by the agents. More about the meaning of the environment is given in section 2.3.2.3. The modeller sets most of this information based on the scope of the model, the scenarios of interest. The general environmental data given to the model was made up of three diverse typologies of data taken from different references and only whether they were available:

- *PV system technologies*. The data were founded from literature research of the state of art and research of actual price and trend price of PV systems [1][34][35]. The data also include the actual turnkey price of PV systems and yearly mean trend cost reduction, the efficiency of actual ordinary solar cells, performance ratio, mean lifetime, mean constant degradation ratio, operational and maintenance cost.
- *Market Place*. The estimation of electricity price and tariffs for the next few years is not so trivial. The actual market spot wholesale price, a.k.a. Prezzo Unico Nazionale (PUN), was taken from Gestore Mercato Elettrico (GME), and trend evolution checked from Italian stock exchange [36][37]. The electricity tariffs were assumed constant and equal to the actual situation because, in the last ten years, the values have not sensitively changed;
- *Energy Policies*. At the moment in Italy there are no particular incentives to adopt PV systems except for the 50% of tax reduction on investment cost that returns in ten years. Furthermoere, it is probable taht, in the next year, this reduction will decrease to 36%. Another type of energy policies implemented in the model is the will of government to push towards a more sustainable city through mass media action and advertising persuasion.

2.3. Methodologies and theoretical approaches

The development of ABM requires a multidisciplinary approach, especially in the field of study of complex adaptive systems, like the socio-techno-economic system. It is necessary to understand how the real system behaves and what are the drivers in order to identify the main elements and their correlation, how they interact with each other and what are the limits or boundaries [7]. The comprehension of the system is essential to have a clear overview of the real world and their critical elements, thus be albe to develop a model that is capable of represent adequately the real world features and complexity. Although it is not possible to consider the whole complexity and details of the real world a compromise is necessary. ABM performs this task better than other model paradigms thanks to its ability to represent complex systems and capture emergent behaviour that is similar to what goes on in the real world [38].

From the literature, the use of ABM is relatively recent, especially in the context of the socio-techno-economic system [4][12][15][39][40], this is thanks to increasing of the computational power of computers and the increasingly large availability of data required to describe in details these systems. Eventhough it does not exist a clear and universal methodology to develop ABM, few authors in literature have proposed some methodological approaches to develop and to clearly describe ABMs. In this work, two complementary methodologies were used to build the ABM presented in this work. The first one is the ODD + D (Overview, Design concepts, Details and human Decision-making) protocol [41] which permits a clear and comprehensive description of ABMs following standardised guiding questions. Moreover, it is more suitable to describe social system that includes human decision-making rather than the original ODD protocol [42]. The second methodology adopted consist of a series of steps, derived from literature, used to develop the ABMs [7]:

1. *Problem Formulation and Actor Identification;*
2. *System Identification and Decomposition;*
3. *Concept formalisation;*
4. *Model formalisation;*
5. *Software implementation;*

6. *Model verification;*
7. *Experimentation.*

At the end of these steps, the model is ready-to-use, and it is possible to do data analysis, model validation and finally model use [7].

The model structure and all the related assumptions used in this work is extensively described by the ODD + D protocol was reported in Appendix 5.3 to provide a global perspective of the model. The following subsections report the main steps of model creation with the scope of making explicit the process of development and implementation of my own ABM.

2.3.1. Problem Formulation and Actor Identification

Consumer evaluation and adoption of energy technologies are not only a function of economic factors, but furtherly relevant are the social influence, social norms, experience and opinions of the consumers [11]. More detailed model is required to understand better what are the factors affecting technology diffusion, like rooftop PV system, between consumers and how these factors change the emergent diffusion pattern, especially at the urban scale, to have an instrument to long-term urban energy planning. Therefore, human behaviour in decision-making has to model, as well as the social network in addition to the environmental and technical aspects related to PV systems.

The actors are city households that mostly live in the apartment blocks, a.k.a. Condominium. To install a shared rooftop PV in a Condominium is more difficult due to two main reasons: first a social aspect, in fact it is more complicated to agree with other residents in shared making-decision on the adoption; second a legislative limitations, in fact actually, it is allowed to install a shared PV system only to meet the common property load or, alternatively, it is possible to install a single rooftop PV system per each household in its available PV area.

In addition to this two option that represent the business as usual (BAU) scenarios, it has been considered a new scenario assuming to overcome the actual legislative limit so that is can be possible to install a shared rooftop PV system on the Condominium.

2.3.2. System Identification and Decomposition

In this section, the internal structure of the system was identified and decomposed in all of its parts, to explicitly identify the physical and intangible entities and the links between them. The description of the ABM framework follows a bottom-up approach: first, the *agents* structure is described, as well as their decision-making process, states, social clustering, relationships, interaction topology, then the *resources*, *environment* and the meaning of *time* used in the model. All the parts of the system are described qualitatively in this section and subsequently quantified in the section 2.3.3. This approach was chosen to keep track of the assumptions used and why. It is important to clarify is up to the modeller decide what aspects of the real world were worth to be capturing in the model or not; throughout the entire modelling process, some details or specifics of the real world may look more or less critical to solving the original problem formulated, and consequently they may be added or not considered in the final model [7], making the model, not needless complex.

The ABM system is composed by four essential elements: *agents*, *resources*, *environment* and *time frame*. Figure 2.3 represents a schematic layout of the whole ABM, including the input datasets and model parameters.

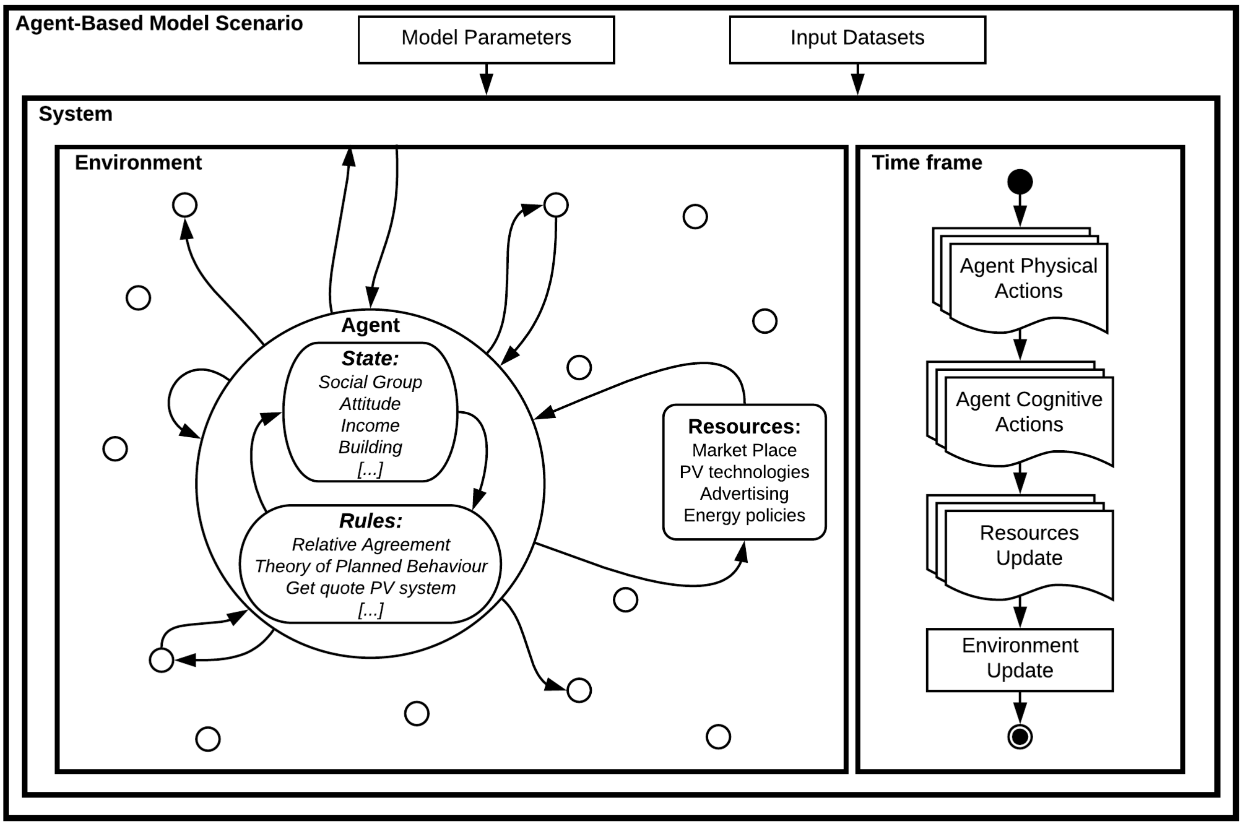


Figure 2.3: Schematic Agent-Based Model layout.

2.3.2.1. Agent

In this work, the agent entity represents a household (the word *agent* will be used as equivalent word of *household* or acronym HH, and it will be indicated in the third person) and it is physically located in the virtual ABM's space at its own home's position, that can be either a residential house or an apartment building, i.e. Condominium. The agent is the active element of the system, in fact, its goal is to decide whether to adopt a rooftop PV system, based on well-defined influential factors and own ***state*** and ***rules*** (an agent's structure is shown in Figure 2.3).

The state of an agent represents the specific collection of parameters that define an agent, or all of the relevant information about what this agent is at a particular moment [7]. The internal state is defined for eacha gent and it belongs to that agent only; it contain the current values of all possible properties assigned to the agent, e.g. income, opinions, state of PV adoption, and so on. Some of these properties can be assumed as static properties like the number of components in a household, while others are dynamic like the state of adoption or the opinions that change over time. Besides, the internal state can be: private, public or a mixture, if some properties are observable by other agents or if a property is observable by only some specific agents [7].

Considering the internal state of the households, they:

- have a position in the space that at the building where the HH lives and do not move in the space. The building can be the single house or a Condominium (in this case, some of the properties of the building are public and shared with the other residents);
- have characteristics like the level of income, number of components, yearly electricity consumption, state of adoption;
- have a social group of belonging with correlated characteristics and statistics;
- have opinions with related uncertainties in those opinions, social pressure level and power control respect to the rooftop PV;
- have a financial specification on the evaluation of PV system investments and feasibility constraints;
- have a social network which interacts with;

- know the building characteristics where it lives, and they are related to possible solar installation like available active surface for rooftop PV or technical feasibility;
- know PV system properties related to a possible installation, get from a quote.

The internal state of an agent changes when it makes actions that perform based on well-defined rules. The rules describe how states are translated to actions or new states [7][43]. An agent's actions are also dependent on the actions and inputs from others with which it interacts, so it can be possible to define a local state that consists of the internal state plus all of the publicly observable properties of the agents that our agent is interacting with. The local state is important because it puts the internal state of an agent into a context, allowing it to act based on not only its internal state but the relationship that internal state has to the others [7].

The rules that describe how the actions are made and modify the internal state are the following:

- The HH makes their social network based on Small-World Network Theory;
- The decision-making process is based on a threshold model, following the framework of the Theory of Planned Behaviour. It depends on various influential factors that drive the behaviour of the HH, and they are of a psychological, economic and social nature;
- The evolution in opinions and its uncertainties, thanks to interactions between HHs, is described by the Relative Agreement algorithm;
- In the decision-making process, the HH gets information from the market on PV technologies to have an idea of the investment costs, the payback period on investment and the feasibility on the installation of the system in the building. If the HH lives in a Condominium, the final decision whether adopting rooftop PV can be dependent on the others.

Decision-making process

The essential factors that drive the behaviour of the households on making investments in rooftop PV systems are psychological, economics and socials. Based on the literature review, there are many different technology adoption models and theories applied to the ABMling [44][45]. The behavioural model chosen in this work is based on the Theory of

Planned Behaviour (TPB), because it is suitable to describe the PV diffusion that is mainly influenced by social norms and interactions [13][15]. A complete overview of TPB is reported in Appendix 5.1.1, while in this section are explained all the assumptions made to create the behavioural model. Below it is showed the TPB structure used in this work and the meaning of its components in relation to the ABM scope; what are the factors that drive the decision-making process of agents which are the inputs of TPB.

According to the theory the human behaviour is influenced by three kinds of beliefs (shown in Figure 2.4) that are aggregated into three corresponding attributes that jointly determine the Behavioural Intention [16]. These attributes are ***Attitude Towards the Behaviour*** or opinions, ***Subjective Norms*** or social pressure, and ***Perceived Behavioural Control*** or power of control. Each attribute evolves depending on the evolution of the beliefs of agents thanks to the interactions with other agents, social norms and feedback from resources or the environment itself. The beliefs depend on background factors that influence the behaviour of agents and they could be divided into three groups: ***behavioural beliefs***, ***normative beliefs*** and ***control beliefs***. The grouping of beliefs is not unique since some background factors can be seen as a type of beliefs or another, e.g. depending on the underlying agent's thought. Also, some of these factors can be influenced by each other, e.g. the level of education might influences the knowledge.

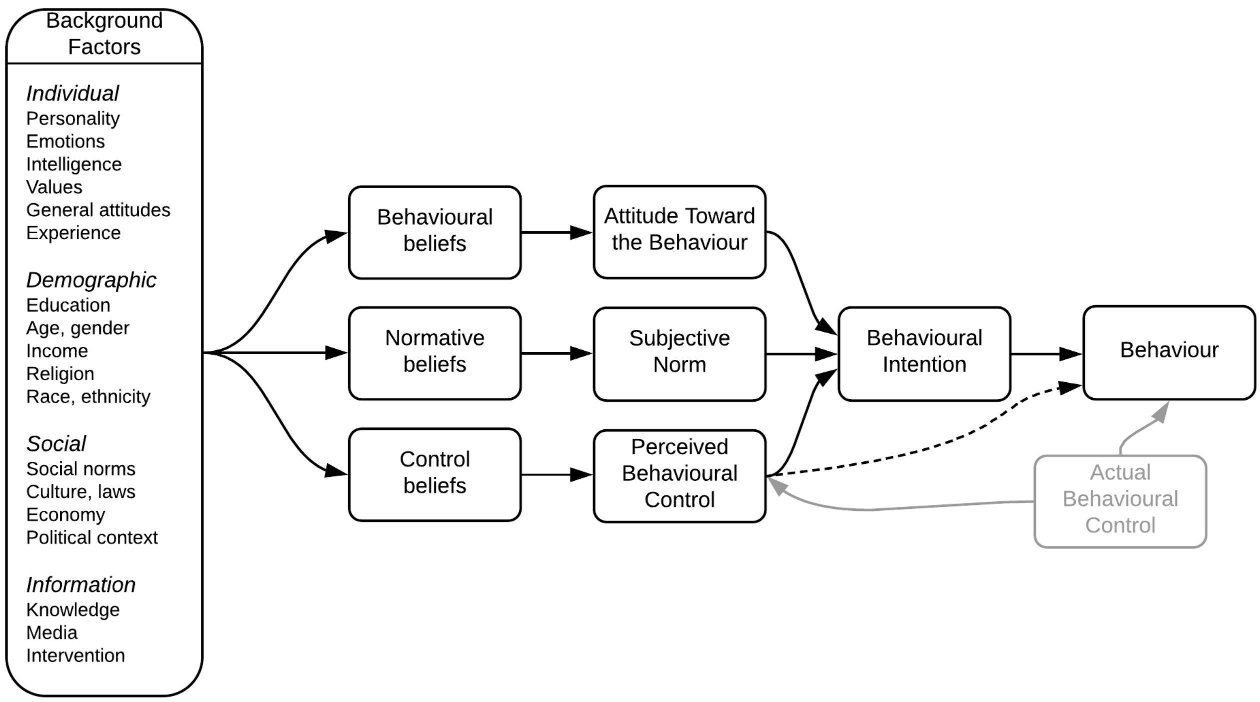


Figure 2.4: Theory of Planned Behaviour diagram with general or universal background factors. Adapted from Ajzen [16].

In this study, the factors are chosen based on literature research on ABM of diffusion of innovative technologies and diffusion of sustainable and renewable technologies [13][15][20][46] and also based on own assumptions in modelling the socio-techno-economic system. Nowadays, in the context of energy technology adoption, the research starts to focus on socio-economic aspects therefore not only economic aspects of decision-making, like for the case of utility optimisation, but also social aspects, like the influence of society or social networks in the adoption process, and the importance of the individuality of an agent [45]. In this perspective, the TPB helps to describe better the behaviour of agents taking into account psychological, social and economic factors. There are plenty of background factors that can be considered in the context of this study, but a selection needs to be made. The model would not be needless complex (as said in the introduction of section 2.3.2) and a certain level of simplicity is needed. If the model is made to complex, the outcomes that might not be easy to interpret [47]. Furthermore, the choices were made considering the conceptual grouping of beliefs as explained by TPB, which should be represented by at least one of the socio-economic factors, and the need for the availability of data.

In the following paragraphs, the decision factors that are used in the ABM were explained. The Figure 2.5 shows an overview of the TPB, applied in this ABM, with also the factors implemented, and it shows an example of questions that agents should be answered from a survey, to obtain the empirical value of each attribute, defining the meaning of all the components of the theory. It is important to note that there are other indirect factors considered in the model, not shown in Figure 2.5. They should affect certain beliefs and the corresponding attributes, both regarding relative weight between them caused by the effect of the social group to which agents belong and also the effect of their evolution in time, e.g. caused by social interactions, social influence, mass media or advertising action. The social clustering of the population, described in the following, permits to have groups of people with similar socio-demographic characteristics and, as a consequence, similar evaluation of the PV adoption. Instead, the evolution in time of specific factors was embedded in the Relative Agreement (described in the next section), because TPB is a static human behavioural model.

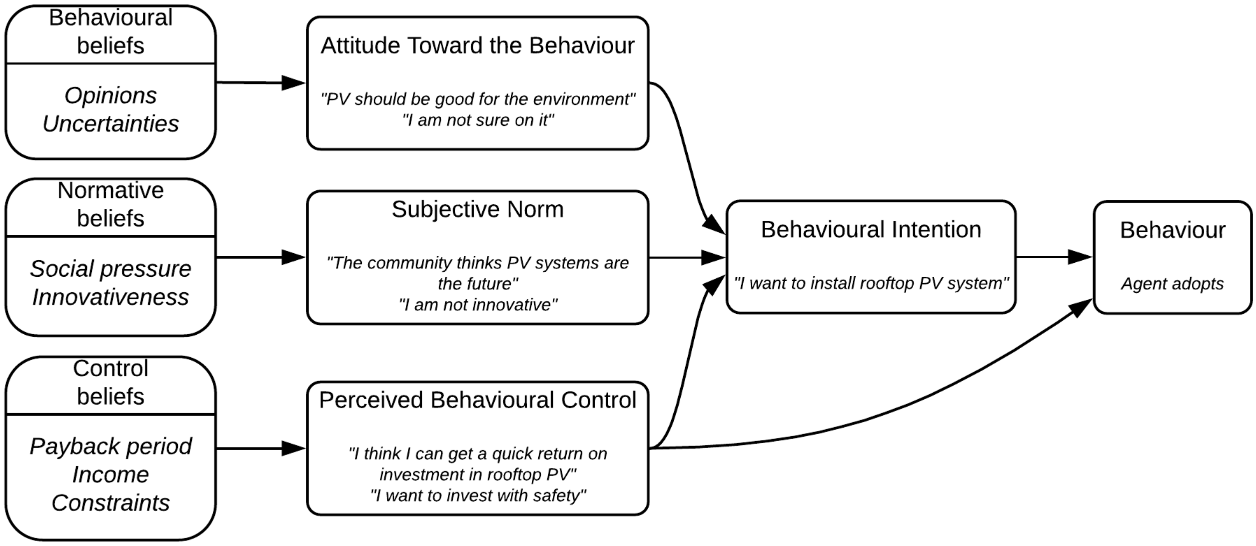


Figure 2.5: TPB diagram with case study examples and factors used in the ABM.

Behavioural beliefs are about the likely outcomes of the behaviour and the evaluations of these outcomes [16]. These beliefs can be generalised as the ***opinions*** of the household on PV adoption and ***uncertainties*** on its opinions. The opinions and its uncertainties change over time, thanks to households interactions in their social networks, and Relative Agreement models it. These interactions represent the word of mouth effect that changes the opinions of the people. The overall opinion forms the Attitude Toward the Behaviour.

Normative beliefs are about the normative expectations of other individual or groups of people and the motivation to comply with these expectations [16]. These beliefs can be seen as the ***social pressure*** derived by the influence of agent's network or the community where it lives which can stimulate to adopt solar PV system or maybe not. Also, it is considered the ***innovativeness*** (or level of innovation) of the households to explain if it is motivated to adopt or it is not interested in. Social pressure is based on influence of the opinions of household's social network that change in time and it could be different for each household based on the area where it lives (e.g. if a household lives in a district with a plenty of PV systems and a good general opinions of neighbourhood, it may have social pressure towards PV adoption). The innovativeness of the household was considered as a static factor, derived from the social group in which it belongs. The overall of social pressure and innovativeness forms the Subjective Norm.

Control beliefs are about the presence of factors that may facilitate or prevent the performance of the behaviour and perceived power of these factors [26]. These beliefs take into account the constraints and strength of obstacles related for rooftop PV adoption. The ***constraints*** are considered as boundary conditions for PV adoption, e.g. the technical feasibility to install the PV on the rooftop or the non-ownership of the house. The strength of obstacles can be of socio-economic in nature, e.g. the feasibility of investments, linked to ***payback period*** parameter, and the level of household ***income*** that can represent a limit to maintain the investment costs. The payback period change in time considering the evolution of market PV price while income was considered a static factor of the household, estimated thanks to the social clustering. The relative importance between payback period and income is also determined by the social group in which household belongs. The overall of the payback period and income, considering the physical constraints, forms the Perceived Behavioural Control.

As a general rule, the more favourable the Attitude and Subjective Norm, and the higher the Perceived Behavioural Control, the stronger should be the Behavioural Intention in question. The Behaviour is finally predicted by Behavioural Intention using the Perceived Behavioural Control (assuming as a good estimator of Actual Behavioural Control) [16].

Evolution of agent's attitude

The evolution of agent opinions plays a key role because these opinions make the Attitude Toward the Behaviour in the TPB and, as a consequence, make the behaviour more dynamic. Besides, the reality of opinion dynamics as a complex and multi-dimensional process makes implementation in the model not so simple. To better account for opinion dynamics, in this ABM, at each time frame, the opinions of agents about the PV systems and the uncertainties around those opinions are modified through interactions with other agents. These interactions are modelled according to the Relative Agreement (RA) algorithm [18][19][48]. In the RA algorithm, at each time-step, pairs of agents i and j interact, where i influences j. The extent to which such interactions alter agent j's opinion depends upon the overlap (the relative agreement) between agent i's and agent j's opinion. In general, with the RA model agents are only influenced by other agents with relatively similar opinions. A detailed formulation of the RA algorithm is reported in Appendix 5.1.2. At each time-step, each agent interacts with a certain number of other random agents taken from its social network (described in the next section). It is important to underline that the RA permits to model and observe the behaviour of extremists in opinions. In fact, the presence or not of agents with very good or terrible opinions on PV systems could direct the general opinions of a population towards positive or negative opinions, respectively. Therefore, the agent that will have some already PV adopter's agents (with high favourable opinion assumed) in its social network, could interact with them and its opinion could evolve towards positive value. As a consequence, like in real society, clustering of opinions in time but also in space may be observed. Finally, the RA permits to model interaction between agents as asymmetric, thus it is possible that i could seek information from j, but j would not seek information from i [49].

Interaction topology

Individual consumer attitudes and social pressure are modified over the time through social influence and interactions. In the ABM framework, the opinions, uncertainties and social pressure evolve based on the interactions and influence a household has with its social network. Agent interactions with their connections (e.g., family, friends or neighbours) depend on the social network topology. The topology was developed based on the Small-World Network (SWN) [23], by analogy with the small-world phenomenon (also known as six degrees of separation theory). SWN lies between two extreme connection topologies: fully regular vs. completely random. The regular network is rewired to introduce increasing amounts of disorder, creating the SWN (a complete overview is reported in Appendix 5.1.3). From the literature, the composition of social networks has shown that links between people can be categorised as mostly local (geographically proximate) connections, with a minority of non-local connections [4][23]. From an empirical point of view, it is challenging to represent specification of social networks, caused by the lack of data, but from the social perspective, social networks can be inferred using attributes such as proximity, wealth similarity and gender [50]. In the ABM framework developed in this work, it was used the neighbours and social group similarity to create the regular network and, from this, some of the links were re-wired to introduce the non-local connections come from the entire environment of the model. Of course, to apply the SWN, the agents must be located in a physical space to calculate the relative distance between agents. The environment provides the space, and it was described in section 2.3.2.3. An example of an agent's social network is shown in Figure 2.6, considering the square lattice space of the dummy city's dataset.

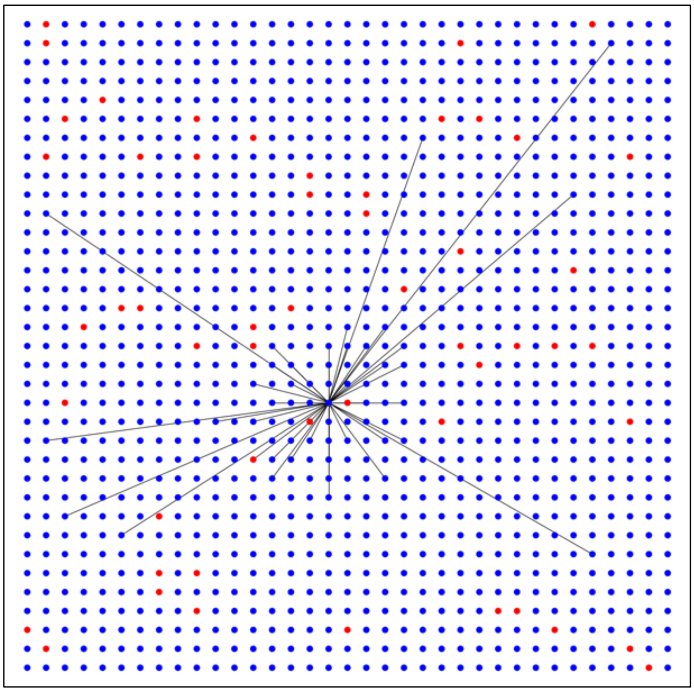


Figure 2.6: Dummy city's dataset, constituted by 35x35 agents in a square lattice with one meter between them. An example of social network of an agent is shown. The already adopters are represented in red and blue the remaining ones.

Households social groups

As already mentioned, consumers investments in new technology are related not only on economic aspects but also to specifics attitudes toward a technology's attributes [51], especially in the context of PV adoption where social aspects are relevant [22]. Also, as already shown in Figure 2.4, the beliefs of people are dependent on background factors of individual, social and demographic type.

Considering the households, each of them has its own socio-economic and demographic characteristics which have a decisive influence on the decision-making process. To take into account the heterogeneity of households, a social structure of the households has been implemented in the model by defining different social groups. Each group is representative of households displaying similarities in their socio-economic and demographic behaviour and consumption patterns; thus each group has shared values and attitudes toward work, family type, leisure, money, and consumption.

Following examples available in the literature on social clustering implementation in ABM modelling of socio-technical system [22][46], the social groups have been incorporated in the model and their attributes by referring to the newly social clustering of Italy proposed by Istituto Nazionale di Statistica (Istat) and published in the Annual Report 2017 [30].

The report has the scope of looking at the social structure through the characteristics of groups who make up Italy's society. Each social group has a plurality of dimensions and is described from many points of view. Starting from the 25 million households residing in Italy, nine different groups were defined following a statistical approach allowing to take into account multiple aspects, to preserve heterogeneity, to represent homogeneous household income levels corresponding to specific combination of other factors: among others, education level, citizenship, professional position, number of household members and area of residence [30]. The classification method adopted by Istat is of a hierarchical type, like a classification tree, as shown in Figure 2.7: in the progressive partition of households, each branch of the tree represents a characteristic, whose trunk represents the set of Italian households and their members. The key variable of the classification method is the equivalent income, a measure that takes into account the different household size and composition by age. The first variable considered as the most important variable to define social identity is the occupational status of the reference person (member of the household that is the breadwinner). Citizenship of the household members occurce only once to discriminate groups. The number of family members is another strongly discriminant variable, although its correlation to the income is less significant than other variables such as professional status, education, age and gender. The last discriminant is the education level of the household reference person, that is strictly correlated with income so particular related to the high-income level social groups [30].

Thanks to the features and statistical data provided by Istat regarding each social group, it was possible to make some assumptions related to the generation of the households in the environment of the ABM. Correlating the data of the social groups with those of the census sections (georeferenced), it was possible to create the agent and assign a social group and derive some other attributes, e.g. the income value per each household, the number of components, the level of innovation, the weights for the attributes of TPB. In particular, referring to other works in the literature it has assumed a level of innovation [22][46][51], i.e. the innovativeness, per each agent according to the social group of belonging that characterise them.

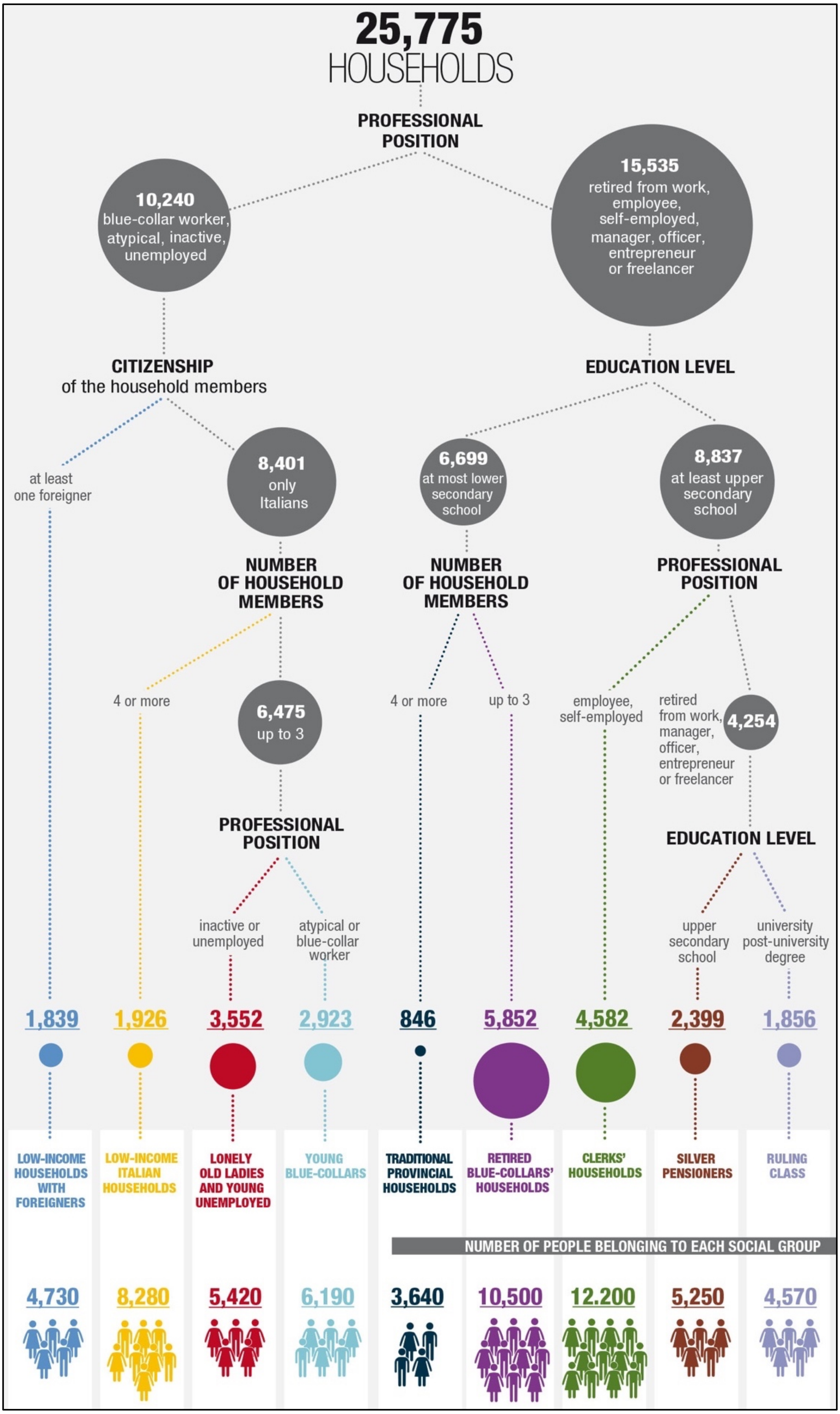


Figure 2.7: Classification tree of Italian households by social group (in thousands). Illustration from Annual Report 2017 of Istat [30].

A complete overview of social groups' statistical attributes used for the scope of own ABM is reported in the Appendix 5.2.1 and how they have been applied is explained in the section 2.3.3.1. From Annual Report 2017 of Istat, a brief and salient description of the social groups (classified by the highest income equivalent to the lowest) were reported in the following bullet list:

1. *Ruling class* (RC). They are the 7.2% of total households, and they are composed on average of couples with children. They have the highest equivalent income, with a nearly +70% respect to the average. The reference persons always have a university degree and, regarding the employment situation, they are on average managers, entrepreneurs, freelancers and a small part retired from work;
2. *Silver pensioners* (SP). They are 9.3% of total households and, in most of the case, they are couples without children. It is a high-income group and the reference persons are retired from work and always have an upper secondary school diploma;
3. *Clerks' households* (CH). They are the group with the closest income to the average one, and they are the 17.8% of total households. Half of them are couples with children, and the reference person has on average at least an upper secondary school diploma and one out of four also has a university degree. They are almost all clerks and nearly half of the self-employed;
4. *Young blue-collars* (YB). They are 11.3% of total households, have 2.1 family components on average and is composed for one third by couples without children. The reference person has on average a lower or higher secondary school diploma and has a permanent contract as a blue-collar or manual worker.
5. *Retired blue-collars' households* (RB). They are the largest group regarding households (22.7% over the total). The reference person has on average at most a lower secondary school diploma. They are small-size households and in most of the cases they are single-person households or couples without children. The group is prevailingly composed of households whose the reference person is a pensioner. Income is close to the national value;
6. *Lonely old ladies and young unemployed* (LY). They are 13.8% of the total household and, in most of the cases, these are lonely people, as evidenced by the very small average number of components equal to 1.5. The reference

person, in almost the cases, is inactive and a minority of households whose reference person is unemployed. Also, they have, on average, a low education level;

7. *Traditional provincial households* (TP). They represent the smallest group in terms of both households and individuals (3.3% and 6.0% of the total, respectively). The number of components is high due to the widespread presence of couples with children. The reference person has on average at almost a lower secondary school diploma. The combination of low qualifications and a high number of components affects the economic well-being negatively;
8. *Low-income Italian households* (LI). They are 7.5% of total households, but they are large in number of individuals, composed by couples with children in more than nine cases out of ten. The reference person has a low level of education: over half of them have at most a lower secondary school diploma. This group is characterised by low income, about 30% less than the national average od equivalent income;
9. *Low-income households with foreigners* (LF). They are households where there is at least one non-Italian citizen. They are the 7.1% of the total. They are the poorest among the groups, in fact, they have an income of -40% respect to the average. They are often composed of single members or couples with a son. Although the employed are predominantly in unskilled positions, half of the reference persons hold an upper secondary school diploma and one in the has a university degree.

2.3.2.2. Resources

Agents interact not only with other agents but also, directly or indirectly, with other elements of the system such as the resources and the environment. The resources are the elements (physical or intangible) of the system which are passive, thus, in general, they are used by the agents to get external information and make the actions. The resources can also be seen as part of the environment because of the passive nature that makes them utilities for the agents. However, it is useful to split the concept of utilities or resources that are present in the environment that could be not logically connected with the concept of the environment itself. The resources of the system can be divided by their function with respect to the agent (more information about resources' attributes were reported in section 2.3.3.2 and on the Data Structure in Appendix 5.4), and they are:

- Market Place of electricity: all information about the electricity tariffs are given by the marketplace that establishes the price of energy taken, sold and the tariffs related to the tariff convention about PV system;
- Available PV technologies: the agent takes the technical and cost information from the market of available PV technologies;
- Energy policies: if the Institution gives incentives or subsidies to PV technologies, they are collected in the energy policies resource;
- Advertising: it contains the information related to the advertising on PV systems if it is present.

2.3.2.3. Environment

As said in section 2.3.2.1, in the ABM the households are physically represented in the space in their buildings' positions. The environment provides the structure in which the agents are situated, and it contains all the information external to the agent used in the decision-making process, e.g. solar buildings data, neighbours, technology costs, electricity's price and so on, where some of this information are embedded and controlled by the resources. Thus, the environment contains everything (see Figure 2.3), and provides all the things an agent needs to know, and all the ways to do the things that it does, and that are not contained in the agent state itself, like the resources already explained in section 2.3.2.2. Agents can affect the environment and be affected by it as a consequence of the specific rules they use for actions [7].

Information

Aspects of the environment could be provided by the model itself, like the neighbourhood of an agent, while the modeller could set others and they can be considered as model parameters. These parameters can be static or dynamic, and they can represent the relevant information used by agents, included in the resources or in the environment itself, and whole sets of these parameters are often considered scenarios that the modeller is interested in [7]. For example in this ABM, the total cost of a PV system is designed to start from an initial value, and then it yearly decreases with well-defined constant rate, or the action of the advertisements on agents can be controlled by parameters given by modeller, or still the price of the electricity market provided as global information to the agents. Other aspects of the environment could be provided by emergent properties of the model itself rather than directly by the modeller, for example, the mean income value of the HH PV adopters, used to calculate the income factor (explained later in section 2.3.3.1).

The type of information controlled by the relative resources has been already explained in the section 2.3.2.2. The others information related to the environment itself are the solar buildings' data that includes all the important data of buildings linked to PV feasibility such as solar irradiation, active surface available, the slope of rooftop and the direction.

Space structure

For testing and verification purpose, the agents' dataset used is a "dummy city" that is comprises of agents arranged in a regular pattern as a square grid, spaced one meter apart, with toroid boundary conditions to prevent edge effects (see Figure 2.8). Otherwise, in the final model, the agents are situated in the physically defined space within a GIS map of San Salvario's district of Torino (see Figure 2.9). The choice of use GIS map has been made for different reasons. First of all, thanks to GIS application, it is possible to refer the ABM to a real urban case, with the possibility to use all the georeferenced data available such as: topographic buildings where neighbourhood is defined in terms of actual distance between buildings; solar buildings data that can be georeferenced with the buildings' position; socio-demographic data per each census section of the district that have been used in combination with the social groups data with the aim of statistically recompose the households in the buildings of the district. Secondly, to describe better the social network of an agent that depends largely in part on the neighbourhood, thus from the real position of the agents and with from others. Finally, to bring more complexity and realism to the model, that is an important part of modelling a complex adaptive system exploiting the capability of the ABMling paradigm. Figure 2.9 is shown the spatial structure of San Salvario's district, distinguishing the buildings in red and the PV available area in yellow. For simplicity, the households are represented as points in map located in the centroids of their homes. If some households have the same position, it means that they live in a multi-family house or, more frequently, for the urban area considered, in the Condominium.

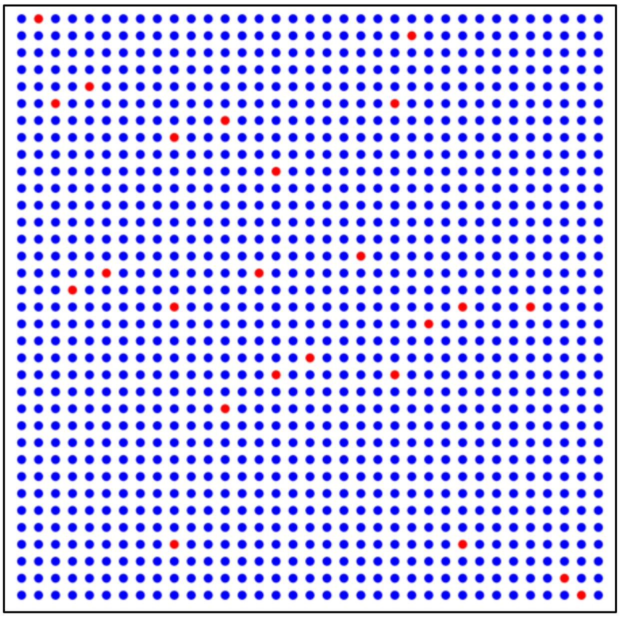


Figure 2.8: Map of the dummy city's dataset. It is constituted by 35x35 agents in a square lattice with one meter between them. In red the already PV adopters are shown.

Figure 2.9: Map of the San Salvario's district. It shows the buildings and their centroids, the available PV area per each building and the section of the census.

2.3.2.4. Time

Time can be considered part of the environment but is better to separate this concept caused by its fundamental role in the ABM and how it is implemented. The real world complex adaptive systems take place in continuous real time, and with their elements acting in parallel [7]. The ABM is forced to simulate in the discrete time of computers, thus given instructions are performed within a time step called tick as the smallest unit of time, and it is meant to represent an amount of real-time chosen by the modeller. Regarding parallelism, in order to represent it, all actions are scheduled to occur one after the other but are assumed to happen at the same time [7]. This assumption can create problems because it is important to assure that the final goal of the agents at each tick is not directly influenced by the tick of the past of other agents that have not yet taken the actions.

In this work, each tick or time frame represents a quarter ideally, and at each one the agents perform actions that are distinguished in two phases (see Figure 2.10), considered as substeps of the time frame: phase of “physical actions” where all the agents of the system perform actions related to real physical actions like exchange opinions, take information from the resources; phase of “cognitive actions” where all the agents of the system perform actions regarding the reasoning, thought and elaboration of the information, making a choice whether to adopt rooftop PV or not. All agents perform in a random order the first phase before moving on to the next phase where they also perform in a random order. This procedure is done to guarantee that, at each time frame, all agents choose whether adopt at the “same time” without influencing other agents that have made a choice before. This separation of the tick in two phases can be the solution of the problem of parallelism, but also this procedure has limitations because actually, the agent has a look in the future when it already knows the opinions of other agents with which it interacts. When all the agents have made the actions, and before a new tick begins, it is time to update all the dynamic elements within the resources and the environment.

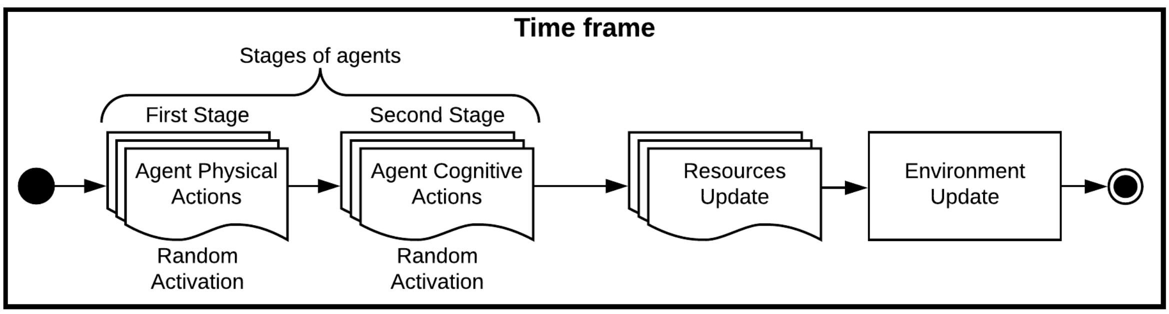


Figure 2.10: Flowchart of a time frame of a model’s step.

2.3.3. Concept formalisation

After it has identified the system and its components, in this section the concepts were formalised describing the mathematical definition, also in terms of quantity defining the domain and the range, with the aim of transfer this concepts in a computer language and explicit the relationship between them and, as consequence, between the components of the system. A Data Structure of the model was reported in Appendix 5.4 to have an overall sight of the attributes per each component.

2.3.3.1. Agent state and rules

Each agent is described by own state, a set of all relevant attributes which describe the agent in that particular time step. These attributes can be either static or dynamic, and they mostly come from the data sources described in section 0, while other attributes are created in the model itself during the fulfilment of the rules, e.g. during the decision-making process, it is requested the value of Attitude Toward Behaviour, Subjective Norms and Perceived Behavioural Control to do the TPB.

In this section, the most crucial agent attributes, the ones that are viable for understanding the functioning of the model, will be described. These attributes are:

1. The initial opinion and uncertainty around that opinion;
2. The feasibility of investment;
3. The income of the household;
4. The number of components of the household;
5. The yearly electric load profile;
6. The level of innovativeness;
7. The list of agents in own social network;
8. The investment parameters and PV related properties;
9. Standardized decision factors;
10. The weights factors of TPB.

The **initial opinion**, (opi) of each agent was generated from a normal distribution as a real number in the range of -1 (extremely negative opinion) and +1 (extremely positive opinion). Because of the lack of data regarding today's opinion of the agents, the choice of random initial normal distribution of opinions was made following other researchers in the literature [15][48] and from the empirical evidence of the people that mostly not have a strong positive or negative opinion, thus are neutral. For the same reason, the uncertainties (unc) around those opinions are initialised, following the Equation *2.1*.

$$unc = -2(opi^2 - 1) \qquad 2.1$$

Hence, the **uncertainty** is a real number in the range of [0; 2] and, as the initial condition, they are greater when the agents are neutral. Note that for software implementation issue, the minimum uncertainty was set equal to 0.1, to avoid zero-division. The Figure 2.11 shows the relationship between initial opinions and uncertainties with the frequency of opinions among households.

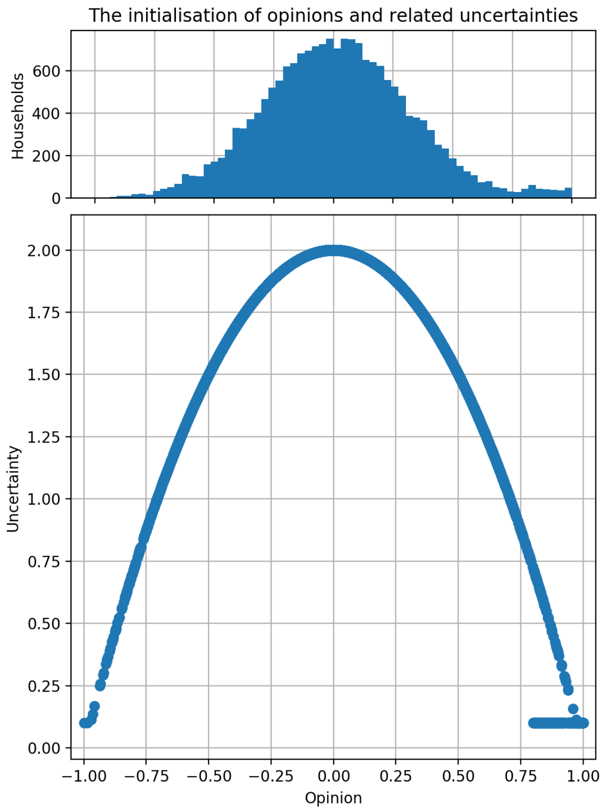


Figure 2.11: Initialisation of opinions and the uncertainties around those opinions.

Note that in Figure 2.11, there are agents with high attitudes and very low uncertainties. These agents are the already adopters of the system, and it was supposed them as extremist [18] with an opinion level higher or equal to 0.8 and uncertainty fixed to 0.1.

The distributions of the initial opinions and uncertainties of the agents are fundamental to initialise the model. Thanks to a statistical poll study of the population on photovoltaics, following the structure proposed by Ajzen for the TPB [16][52], will be possible to better initialise the opinions due to the greater realism in modelling the population, especially if the survey is done in the area of study.

The opinions and the uncertainties around those opinions evolve, thanks to the interactions of agents in their social networks. Relative Agreement algorithm is used to describe the dynamic of opinions [18], and the whole algorithm, with the mathematical definitions, was reported in Appendix 5.1.2. The *number of interactions* ϕ, which an agent makes during a time-step, and the *convergence speed* of the opinions μ of RA algorithm were set as parameters of the model.

The **feasibility** of investment per each agent depends on two type of feasibility: socio-economic feasibility and technical feasibility. The first one depends on whether the household is for rent or the home/apartment is owned. Of course, the households for rent have not the faculty to choose whether to install a rooftop PV system; thus they are excluded. The probability of being a family's rent is obtained by the statistical data of the social group which belonging. The second feasibility is related to the technical possibility of installing rooftop PV system. The feasibility or not is, therefore, the constraint represented in the decision-making process, and it was set as a binary value (0 or 1).

The **income** of a household is fundamental in the decision-making process. The income is estimated using the statistical data of the social group (SG) which belonging the agent. In fact, it is known the equivalent income level of the social group related to the national mean income of households and the Gini coefficient per each group that describes the internal variance of income. Following the literature in the calculation of income from Gini coefficient [22], the income [€] is obtained from the Equation *2.2*.

$$INCOME = rand.lognorm(\mu = 0; \sigma = Gini_{SG}) \cdot \overline{INCOME_{Italy}} \cdot INCOME_{eq,SG} \qquad 2.2$$

The **number of components** of a household was estimated considering the social groups and their classification with respect of the discriminant variable *number of household members* that can be 4 or more (max 8) or up to 3. Knowing also the mean of the number of household members per each social group, the number of components (rounded up natural number) was generated randomly from a triangular distribution, assuming that the mean is also the mode, as shown in Equation *2.3*.

$$N_{HH} = rand.trian\left(min = N_{min,SG}; mode = \overline{N_{SG}}; max = N_{max,SG}\right) \tag{2.3}$$

The **yearly electric load profile** of the household and the relative yearly electricity consumption was estimated thanks to a semi-markovian process [31]–[33]. It is possible to simulate the load profile of a household given as inputs the number and the type of household members, thus estimating which, when and for how long the appliances are used, with a timestep of 15 minutes per one year. In this model, it was considered the social clustering of households each social group have common characteristics, e.g. housewife, students, children, workers, elders. In this study, they have created nine referent load profiles, one per each social group, considering the number of household members equal to the mean of the group (see Figure 2.12), then per each household, the profile was scalded to the actual number of components.

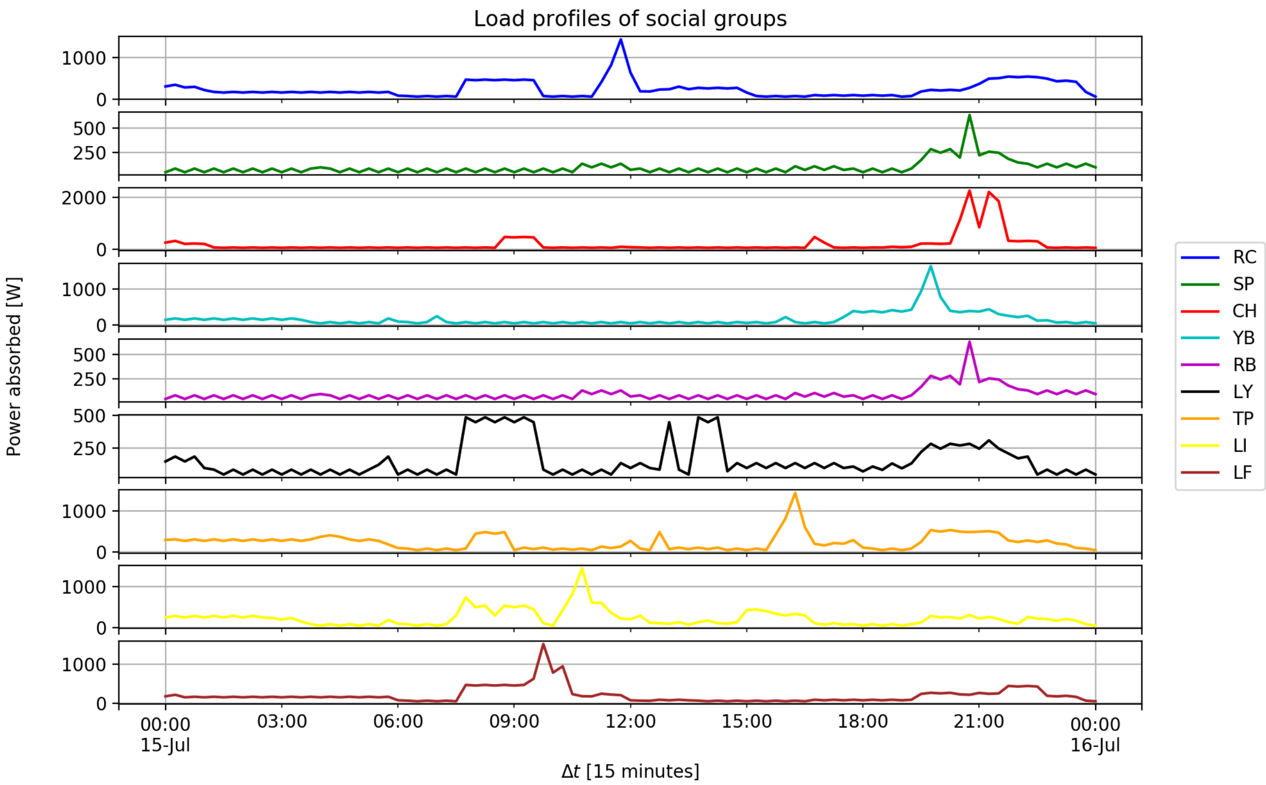


Figure 2.12: Referent yearly load profiles of social groups. Particular of one day load.

The **level of innovativeness** represent the propensity of a household towards the future and in the innovation's technology, in particular referring to the developing new energy technology as the rooftop PV. It is a static attribute, and the household acknowledges this attribute from the social group of belonging. The Istat social groups' data do not offer this type of information per each group, thus it was assumed taking into account other similar social clustering used in literature [22][53] and following the framework of Diffusion of Innovation theory by Rogers [51] that seeks to explain the technology spread showing that exist successive groups of consumers adopting the new technology: innovators, early adopters, early majority, late majority and laggards (see Figure 2.13).

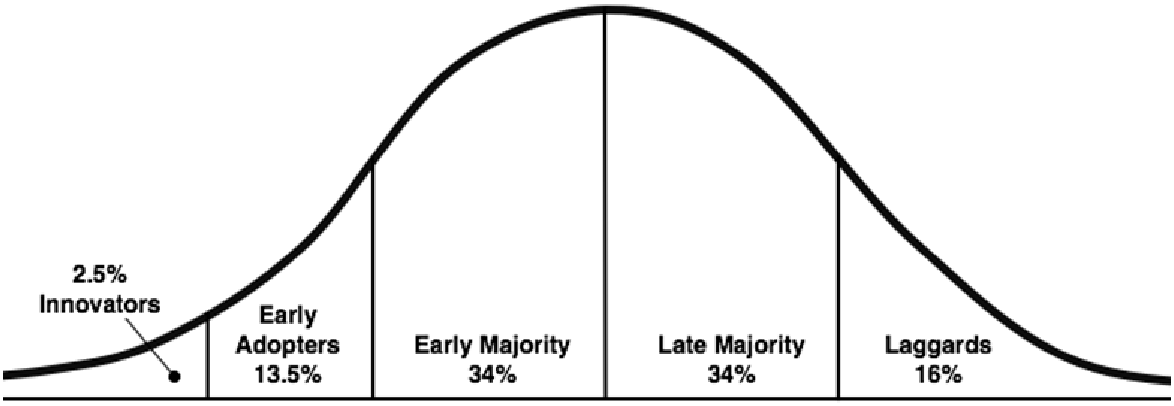


Figure 2.13: Categories of Innovativeness. Source [51].

Therefore, for each social group was given a level of innovativeness, in the domain of natural number from range 1 (very low interest) to 5 (very high interest), considering characteristics as the income, rational-economic thinking, knowledge, education level, influencing, social norms and comparing with the adopter categories by Rogers. The assumptions were shown in Table 2.1.

Table 2.1: Own assumption of Level of Innovativeness per each social group based on Rogers [51] *and other literature frameworks [22][53].*

Social Groups by Istat	***Rogers' adopter categories***	***Level of Innovativeness***
Ruling class (RC)	Innovators, Early Adopters	5
Clerk's households (CH)	Early Adopters	4
Young blue-collars (YB)	Early Adopters, Early Majority	4
Silver pensioners (SP)	Early Majority	3
Low-income Italian households (LI)	Early Majority, Late Majority	3
Lonely old ladies and young unemployed (LY)	Late Majority	3
Traditional provincial households (TP)	Late Majority, Laggards	2
Retired blue-collars' households (RB)	Late Majority, Laggards	2
Low-income households with foreigners (LF)	Laggards	1

The **social network** of a household is created starting from the SWN structure, considering the empirical evidence of the social structure in a community [23]. The process of generating the agent social network begins by selecting the neighbours of the agent within a certain *radius* are obtained. However, the choice of the *radius* to use is not intuitive and straightforward because it could be dependent on factors such as the local population and building density, the type of environmental area, the type of agent and many others. Due to lack of information, in this study, the *radius* was defined in a simple manner by setting a constant value around each household and use this value as a parameter of the model, e.g., the *radius* used in some experiments of the San Salvario's dataset is equal to 50 meters. Following the literature [4][22], the locals are formed by selecting, from the neighbours' list, the agents with social groups that have wealth similar condition, thus considering the social groups that have a similar equivalent level of income. More is similar the wealth condition, and more is the probability of remaining as locals.

Table 2.2: Probabilities to connect to other agents in own social network considering own and other social groups [%].

-	RC	SP	CH	YB	RB	LY	TP	LI	LF
RC	70	10	5	0	0	0	0	0	0
SP	20	70	10	5	0	0	0	0	0
CH	10	10	70	10	5	0	0	0	0
YB	0	10	10	70	10	5	0	0	0
RB	0	0	5	10	70	10	5	0	0
LY	0	0	0	5	10	70	10	10	0
TP	0	0	0	0	5	10	70	10	10
LI	0	0	0	0	0	5	10	70	20
LF	0	0	0	0	0	0	5	10	70

Finally, random connections taken from the whole system were substituted for local connections; therefore, a certain percentage of *re-wiring* rw is used as a parameter of the model to create the small-world structure, i.e., 10% of the local connections were replaced with random non-local connections in anywhere in the population. The final agents within the social network are stored in a list. The list is created at the initialisation of the model and remain static during the simulation. Note that an agent can relate to another agent who is not connected in turn with the first, thus if possible that i could interact with j, but j cannot interact with i.

Investment evaluation

The perception of affordability or lack thereof on investment in rooftop PV is often cited in the literature as the most important barrier to adoption, together with social influence [2][22][44][53]. The economic component was represented by the payback period. It depends on many factors, some related to the PV properties of proposed installation, others related to the PV utilisation and, of course, it depends on purchase and sale price of electricity and tariff options available. Also, some of these factors could change in time as the productivity of PV which undergoes constant degradation. To consider all these factors, the payback period (pp) is calculated as the year in which the Net Present Value (npv) goes from negative to a positive value, as shown in the Equation *2.4* and Equation *2.5*.

$$npv(i, N) = \sum_{y=0}^{N} \frac{R_y}{(1+i)^y} \tag{2.4}$$

$$pp \rightarrow npv = 0 = \sum_{y=0}^{N} \frac{R_y}{(1+i)^{pp}} \tag{2.5}$$

Where:

- y is the year of the cash flow with respect to the year of investment;
- i is the Weighted Average Cost of Capital (WACC);
- N is the final year of the NPV calculation;
- R_y is the net cash flow, i.e. cash inflow – cash outflow, at time y. R_0 is equivalent with the investment I at year zero (with minus sign).

The calculation of the payback period pp depends on the scenario under study. For the sake of simplicity, in this section, a general calculation of pp is provided for rooftop PV considering the actual situation in Italy and the *baseline scenario* in which an agent, that would adopt, chooses the size of PV (the power P, expressed as kW peak [kW_p]) so that the yearly productivity of the PV system E_{PVgen} [kWh/y] is equal to the yearly electricity consumption of the household E_{load} [kWh/y]. In the economic assessment, it is supposed that the yearly electricity consumption E_{load} of the household does not change during the years of calculation, and so the yearly load profile. Meanwhile, the yearly productivity E_{PVgen}

decreases over time due to degradation of the solar cells. All the parametric values used in the economic assessment are reported in Appendix 5.2.

The power of PV system P is calculated from the definition of the productivity E_{PV} by the Equation *2.6*

$$E_{PVgen} = P \cdot A_{PV} \cdot \eta_{STC} \cdot G_H \cdot PR = P \cdot Y_R \cdot PR \qquad 2.6$$

Where:

- P – Power of PV system [kW_p];
- A_{PV} – Total solar panel area [m^2];
- η_{STC} – Rated efficiency of PV modules at Standard Test Condition;
- G_H – Global in-plane irradiation per year [kWh/(m^2y)], obtained from the knowledge of irradiance profile per each rooftop area of the building [29];
- PR – Performance Ratio that includes the different losses of the whole PV system (a.k.a. Balance of the Plant);
- Y_R – Reference Yield or peak solar hours, calculated as G_H/G_{STC} [h/y] where G_{STC} is the reference irradiation at Standard Test Condition [1 kW/m^2].

The total investment is calculated as the Equation *2.7*, considering a year t with respect to the year of initialisation of the model in which it was assumed an initial cost c_0 [€/kW_p] of rooftop PV system and a yearly cost reduction trend $\tau_{c_{PV}}$.

$$I(t) = P \cdot c_0 \cdot \left(1 - \tau_{c_{PV}}\right)^t \qquad 2.7$$

As already said, the productivity of the plant decreases in time due to a constant degradation ratio τ_{PV} of the PV cells, thus considering the year y from the year 0 of installation, where the initial productivity was equal to E_{PVgen_0}, the productivity at year y is obtained from the Equation *2.8*.

$$E_{PVgen}(y) = E_{PVgen_0} \cdot (1 - \tau_{PV})^y \qquad 2.8$$

A part of the electricity produced by PV modules is self-consumed during the year $E_{selfcons}(y)$ [kWh/y], and it can be calculated by the Equation *2.9*.

$$E_{selfcons}(y) = E_{PVgen}(y) \cdot sc_{HH} \tag{2.9}$$

Where sc_{HH} is the ratio of self-consumption of a household, evaluated thanks to the knowledge of the load and production profiles during a whole year, with an accuracy of 15 minutes [29] [31]–[33]. It is defined as the ratio of self-consumed energy with energy produced by PV during the year. The part of the energy that is not self-consumed $E_{export}(y)$ is fed into the grid and sold, and it is obtained by Equation *2.10*.

$$E_{export}(y) = E_{PVgen}(y) - E_{selfcons}(y) \tag{2.10}$$

As a consequence, the yearly energy $E_{import}(y)$ that must be taken from the grid to feed the remained household demand is calculated by Equation *2.11*.

$$E_{import}(y) = E_{load} - E_{selfcons}(y) \tag{2.11}$$

The Figure 2.14 shows an example of the daily energy profiles and their over two selected days.

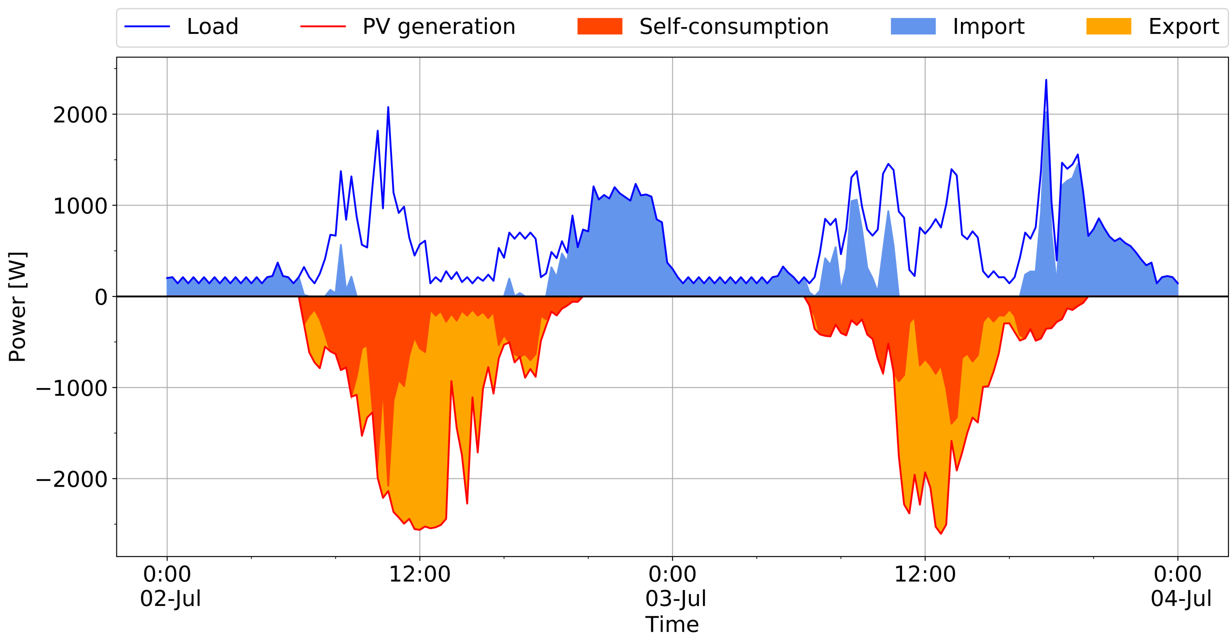


Figure 2.14: Example of two days load (positive) and production (negative) profiles, also showing the energy self-consumed, taken and sold from/to the grid.

Currently, the agent can receive a tax reduction on the PV investment, which is spread over 10 years. In addition, the agent has the possibility to choose between two different tariff mechanisms as currently proposed by GSE [54][55][56], which are:

- *Ritiro Dedicato* (RID) that is a simplified mode available to producers for the marketing of electricity produced and fed into the network. It consists in the sale to the GSE of the electricity injected into the grid by the PV system that can access it, at the request of the producer and as an alternative to the free market, according to principles of procedural simplicity and be applying economic market conditions;
- *Scambio Sul Posto* (SSP, a.k.a. feed-in-tariff) that is a particular form of on-site self-consumption that makes it possible to offset the electricity produced and fed into the network at a certain moment with that taken and consumed at a different time from that in which production takes place. Therefore, the electrical system is used as a tool for the virtual storage of electricity produced but not contextually self-consumed.

The choice of tariff depends on what permits to obtain the best return on the investment, thus the smallest payback period. Therefore, the yearly net cash flow R_t is generally composed by:

$$R_y = R_+ + R_- \qquad 2.12$$

R_+ represents the positive cash flow [€], and it is generally composed by the yearly savings achieved thanks to the PV system as not buying electricity from the network S; the revenue represented by currently fiscal detraction R_{taxr}; the revenue from the particular tariff mechanism adopted R_i. The mathematical definitions were reported in the following equations, considering any year y respect to the year zero of investment:

$$R_+ = S + R_{taxr} + R_i \qquad with\ i = RID, SSP \qquad 2.13$$

$$S = E_{selfcons} \cdot e_{price} \qquad 2.14$$

$$R_{taxr} = (y \leq 10) \cdot \frac{I \cdot taxr}{10} \qquad 2.15$$

$$R_{RID} = E_{export} \cdot e_{sell} \qquad 2.16$$

$$R_{SSP} = \min(O_E; C_{Ei}) + CU_{sf} \cdot \min(E_{export}; E_{import}) + (E_{export} > E_{import}) \cdot (C_{Ei} - O_E)$$

$$O_E = E_{import} \cdot PUN \qquad 2.17$$

$$C_{Ei} = E_{export} \cdot MGP$$

Where:

- $E_{selfcons}$ – Yearly electricity self-consumed by the agent [kWh/y];
- e_{price} – Electricity price that normally the agent face up to in the electricity bill [€/kWh];
- I – Investment cost of the rooftop PV system [€];
- $taxr$ – Tax reduction (or fiscal detraction) of the which is spread over 10 years;
- E_{export} – Electricity fed into the grid and sold [kWh/y];
- e_{sell} – Electricity price of the electricity fed into the grid [€/kWh];
- E_{import} – Electricity purchased from the grid [kWh/y];
- PUN – *Prezzo Unico Nazionale* is the Italian index of electricity market price;
- MGP – *Prezzo del Mercato del Giorno Prima* is the zonal price that is formed on the market of the day before;
- CU_{sf} – *Corrispettivo unitario di scambio forfettario annuale* is a yearly contribution calculated by the GSE to valorizse the tariffs not related to the energy-matter like tariff of transmission, distribution, dispatching and some 'general charges' that are typically applied in the electric bill.

R_{-} represents the negative cash flow [€] and it is generally composed of the yearly operation and maintenance costs needed to make the system work. The mathematical definitions were reported in the Equation *2.18*.

$$R_{-} = I \cdot OeM \qquad 2.18$$

Where OeM is the yearly percentage Operational and Maintenance cost with respect to the investment cost I.

Decision-making process: TPB application on the ABM

The mathematical models of decision factors that affect the TPB's components (att, sn and pbc) and, as a consequence, the Behavioural Intention (bi) and the latter onto Behaviour (b) described in this section. The general structure of the own mathematical model of TPB applied to ABM is reported in Figure 2.15.

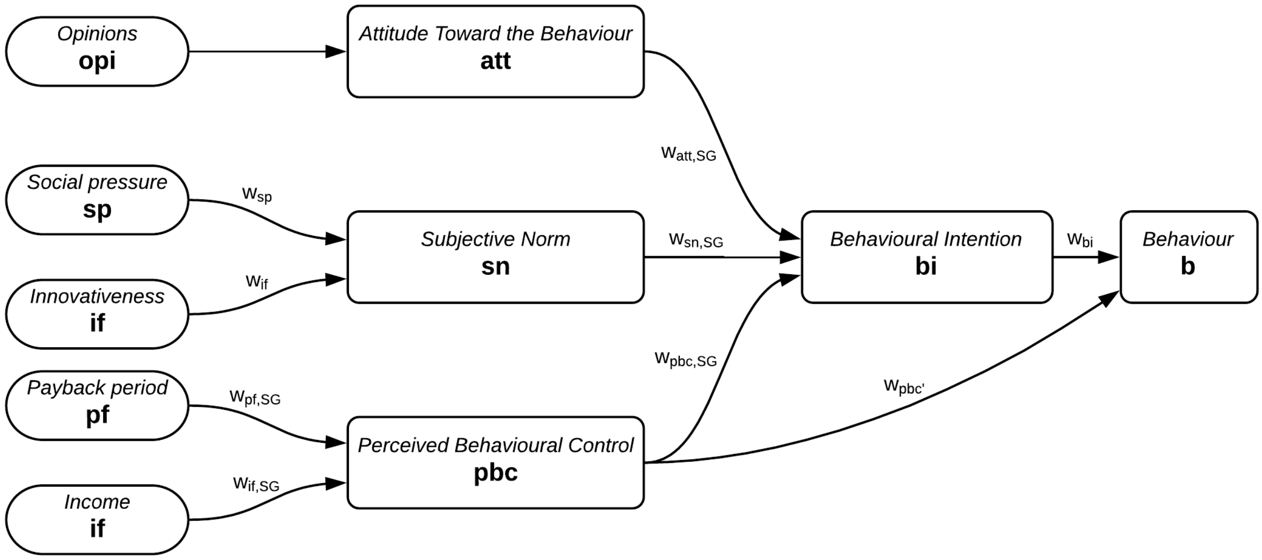


Figure 2.15: Schematic overview of the mathematical model applied to the own TPB in the ABM.

The **Attitude Toward the Behaviour** att is obtained by the general opinions of the households, which evolve thanks to interactions within social networks as already explained. Therefore, the general *opinion* (opi) forms the att as shown in the Equation *2.19*, that it is nothing but a normalisation to the range [0; 1].

$$att = \frac{opi + 1}{2} \qquad 2.19$$

The **Subjective Norm** sn is obtained by the combination of two influential factors: the social pressure and the innovativeness.

The *social pressure* was calculated considering the general influence (not intended as the interaction) that an agent i received from its social network, e.g. when nearby adopters surround an agent, it is more likely that the agent is influenced and vice-versa. To evaluate the influence, it was considered only the general strong opinions (positive or negative) in the social network. Strong opinions were defined when the value of opi is, in absolute value, greater than 0.6 and with related uncertainty unc less than 0.5. After selection of the N

influential agents, the social pressure exerted on the agent j by the influencer i was calculated following the Equation *2.20* and Equation *2.21*.

$$w_{unc} = \frac{\frac{unc_j}{unc_i} - 0.2}{20 - 0.2} \quad 2.20$$

$$sp_{ij} = att_j \left(1 - w_{unc}\left(att_j - att_i\right)\right) \quad 2.21$$

Finally, the total social pressure exerted by the all influential agents in the social network was considered as the mean value:

$$\overline{sp} = \frac{\sum_{j=0}^{N} sp_{ij}}{N} \quad 2.22$$

Therefore, the social pressure can be seen as the mean mostly local influence that receives the agent; thus it depends on the *local state* of the agent.

The *innovativeness*, or level of innovation, of the agent, was normalised to obtain the innovation factor inf in the range [0; 1]:

$$inf = \frac{innovativeness - 1}{4} \quad 2.23$$

The social pressure sp and the innovation factor inf constitute the Subjective Norm sn of the agent as shown in the Equation *2.24*.

$$sn = \overline{sp} \cdot w_{sp} + inf \cdot w_{if} \quad 2.24$$

Where the weights were chosen to equal to 0.5. This assumption was made considering that the social pressure and the innovation factor have the same importance in the evaluation of the Subjective Norm since, in principle, one factor does not exclude the other. In fact, if the social pressure depends on the “nearby” social norms, the innovation factor is an intrinsic evaluation of the social norms that may be important or not for an agent. In conclusion, the sn is the mean value of sp and inf.

The **Perceived Behavioural Control** pbc is obtained by the combination of two influential factors: the payback period and the income. It also accounts of the constraints on adoption of the rooftop PV system.

The calculation of the *payback period* was explained before. The value was linearly normalised to value from 0 to 1, obtaining the payback period factor pf:

$$pf = \frac{21 - payback\ period}{20} \quad 2.25$$

The *income* factor if was calculated getting ideas from work available in the literature [53]. The factor takes into account the yearly income of the household divided into the number of household members and the mean yearly income of the already adopters divided to the mean number of household members of already adopters. This calculation method compares the level of income per capita of the household with the corresponding average value of the household that already have the rooftop PV. Also, the equation was normalised with a logistic function, as explained by Equation *2.26*.

$$if = \frac{e^{\frac{\left(\frac{INCOME}{N_{HH}} - \frac{\overline{INCOME_{adopt}}}{\overline{N_{HH,adopt}}}\right)}{5000}}}{1 + e^{\frac{\left(\frac{INCOME}{N_{HH}} - \frac{\overline{INCOME_{adopt}}}{\overline{N_{HH,adopt}}}\right)}{5000}}} \quad 2.26$$

The factor 5000 was used to have the income of five thousand euros, hence scaled down to a proper value in the exponential relation. The logistic function permits to have an S-shape curve in which the flex of the curve at $if = 0.5$ is obtained when the relative income of the household is equal to the mean relative income of the already adopters. Thus, greater is the distance from the mean value, strongly increases/decreases the if.

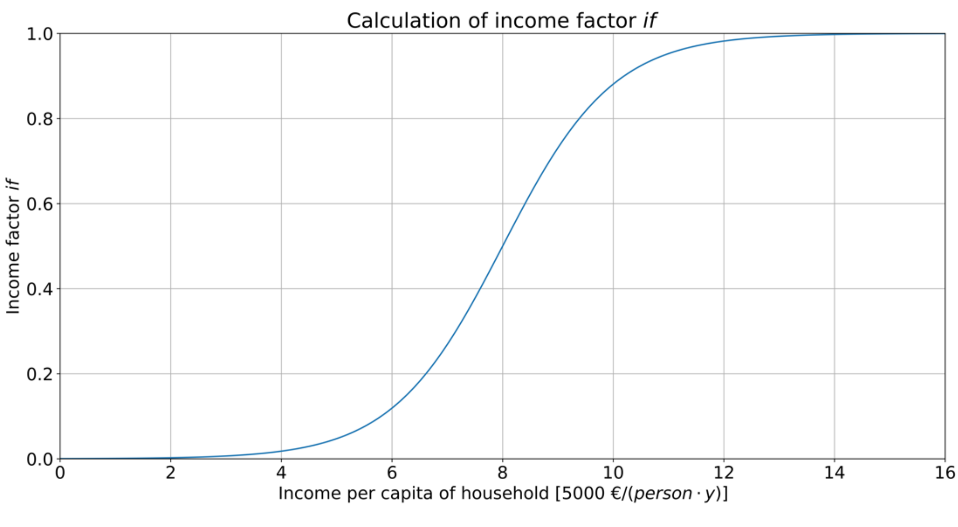


Figure 2.16: Example of the curve of income factor obtained with different values of income per capita of the households.

After checking the constraints of the agent (if there is not feasibility to install, the pf is imposed equal to 0 and feasibility value set to 0), the Perceived Behavioural Control pbc can be calculated using the Equation *2.27*.

$$pbc = pf \cdot w_{pf,SG} + if \cdot w_{if,SG} \qquad 2.27$$

$$w_{pf,SG} = 1 - w_{if,SG} \qquad 2.28$$

The weight factor $w_{if,SG}$ defines the relative importance that a household gives to the income or to the payback period in deciding to invest money on photovoltaics system. In fact, depending on the characteristics of the agent, it is more inclined to spend a relatively significant amount of money assuming more risk, or it is more inclined to the security of the investment, looking to high investment return. This weight of relative importance was set considering the social group of belonging to the household. From social groups' statistics, it is known the fifth of equivalent household's expenditure per each group that represents the distribution of the household's expenditure, made equivalent taking into account some characteristics, dividing them into 5 level of fifth equivalent expenditure, from the lower to the higher. In other words, the fifth highest equivalent expenditure can be a measure of the high spending capacity of a social group, thus more inclined to spend much money. This value was assumed to equal to $w_{if,SG}$ meaning that an agent who can spend more is more likely willing to take more risk on investment, and vice versa. For example, the Low-income Italian households have a low value of $w_{if,SG}$ meaning that having lower spending capacity, they need more financial security on the investment, therefore considering more the payback period. The value of $w_{if,SG}$ per each social group was reported in the Appendix 5.2.1 related to the description of statistics used to the definition of social groups by Istat.

The values of att, sn and pbc obtained by applying the mathematical definitions, are utilised in the calculation of the **Behaviour Intention** bi, using the Equation *2.29*.

$$bi = att \cdot w_{att,SG} + sn \cdot w_{sn,SG} + pbc \cdot w_{pbc,SG} \qquad 2.29$$

Where the weights have the meaning of relative importance among the factors composing the bi. They were defined starting from the analysis of the statistics of social groups considering the socio-demographic factors that characterise each social group and using them to estimate the weights. The values of weights per each social group were reported in the Appendix 5.2.1.

Finally, to the extent that it is an accurate reflection of actual behavioural control (that it may be difficult to predict), the perceived one pbc can, together with bi, be used to predict the **Behaviour** b, as shown in the Equation *2.30*.

$$b = bi \cdot w_{bi} + pbc \cdot w_{pbc'} \quad 2.30$$

$$w_{pbc'} = 1 - w_{bi} \quad 2.31$$

Where w_{bi} was assumed as a parameter of the model. Moreover, in the field of adoption of the photovoltaic system, but also, in general, considering investments not related to having a profit regarding money, but related to having a revenue, the bi is more important in the definition of the final behaviour; thus w_{bi} is generally higher than 0.5. On the other hand, an investment was made to have a profit, the pbc represents the factor that should be considered to make a more rational choice.

In conclusion, the obtained value of the household's final behaviour b is a real number in the range of [0; 1]. The meaning is whether b increase, the likelihood that the rooftop PV system will be adopted increases, in fact, if it reaches or exceeds the b_{thsd} the agent will adopt.

2.3.3.2. Resources and Environment states and rules

The state of resource and environment were assumed as almost static (the values of the parameters were reported in the Data Structure in Appendix 5.4), except to the price variation of the PV system over time. At each time step, the turnkey rooftop PV system price decrease following a yearly constant reduction ratio. From IEA [34], the trend of price reduction, from 2002 to 2016, it was 15.5 % but today we are in a state of maturity, and it is supposed that, in the coming years, the price reduction ratio will become to half; therefore the chosen value of constant price reduction ratio is 8 %. The future trend of the price assumed is shown in Figure 2.17.

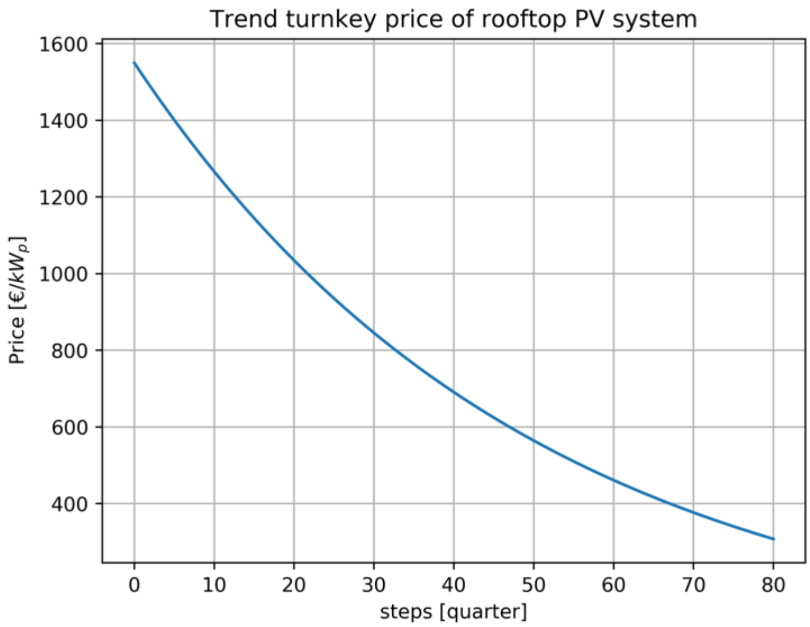


Figure 2.17: The future trend of the turnkey price of rooftop PV system.

The advertising action is modelled by the *Virtual Advertising Agent (VAA)* that is a resource element of the system, but it acts like the agent having an “opinion” and “uncertainty”, set equal to 1 and 0.1, respectively, in such a way that interacts with the household through the RA. A household has a probability of interaction with VAA is given by the *coverage advertising parameter* cov_{ad}, meanwhile, in the same way of the convergence speed factor of RA, the strength of influence of VAA is given by the parameter str_{ad}.

2.3.4. Model formalisation

Once it has been identified what and who is in the model, it is needed to establish who does what and when. To accomplish that was used the Unified Modeling Language (UML) [57], a standard visual modelling language used to describe, specify, design and document a structure and behaviour of a software system architecture. In this section, the aim was explicit and make clear the most important steps of the huge complex algorithm of the model transcending from the particular programming language used to develop and implement it. The UML has many types of diagrams which have simple, standardised notation. Those used in this study are UML Activity diagram and Sequence diagram which emphasised the dynamic behaviour of the system by showing interactions among objects and changes on the internal states of objects. The activity diagram describes a snapshot of the system representing the workflows of the activities and actions, meanwhile the Sequence diagram represents the time sequence of the code execution showing the flow of messages and data among objects and entities in the system being modelled.

For a clear reading of the text, the activity diagram was shown and explained with a model narrative in the following subsections. Meanwhile, the UML Sequence diagram was reported in Appendix 5.5 because is more useful to understand also the data flows during the model execution. Moreover, in the Appendix 5.5, to have a more clear understanding, a UML Activity diagram with the addition of the most important data flows among the actions is reported. Besides, the Figure 2.18 shows the UML Activity diagram of this ABM. It looks like a flowchart but with some tricks to able to visualise the standard programming language constructs. A model narrative is reported in the following page, explaining each action of the algorithm represented in the figure of UML Activity diagram. Note that, the model narrative and the UML diagrams reported in this work, are related to the *baseline scenario* but could be slightly different when considering other scenarios, to fit the model with diverse features.

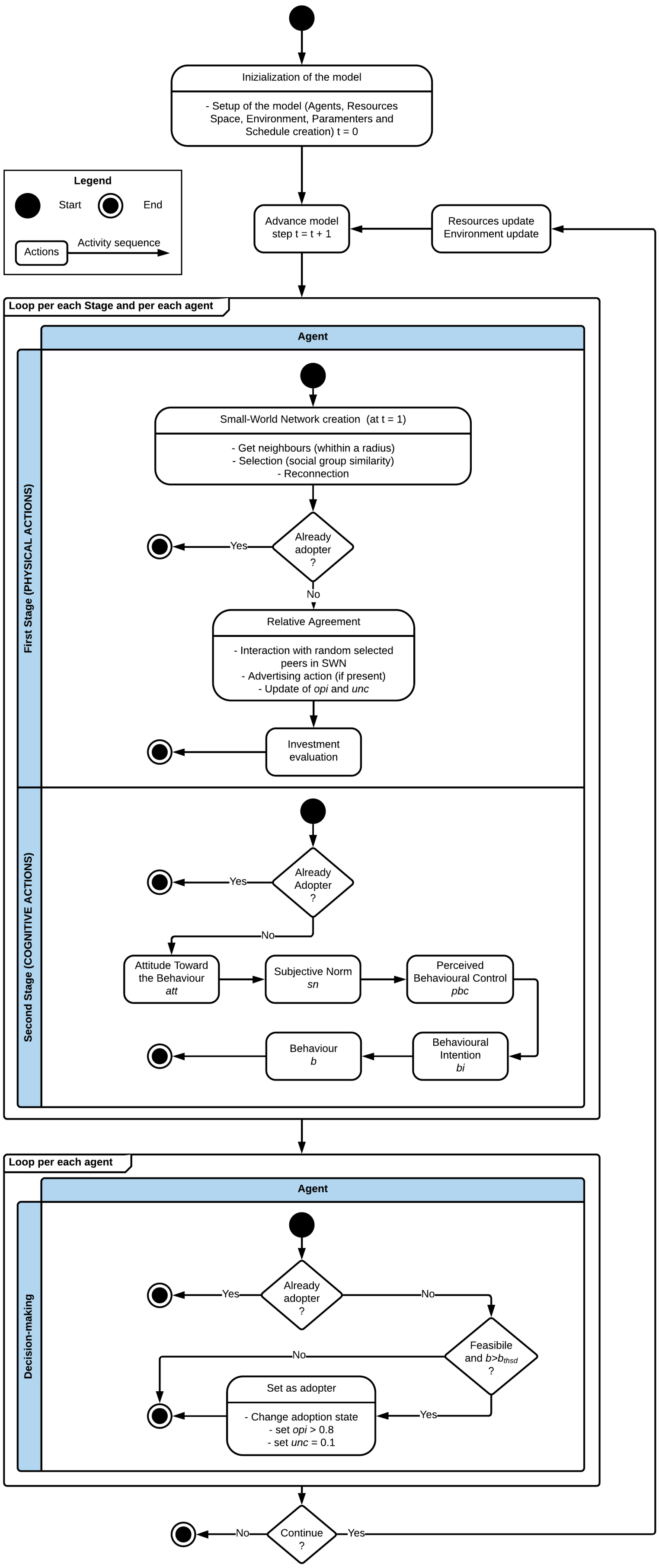


Figure 2.18: UML Activity diagram of this ABM.

2.3.4.1. Model initialisation

The initialisation of the model regards the acquisition of the input datasets (Agents' dataset and Environmental data), the parameters of the model and, what is relevant, the creation of the entities that constitute the ABM as *agent, resources, environment* and *scheduler.* In this phase, taking the information from the inputs, each agent is created with their initial state (sum of all attributes), it is put into space, and it is entered in the scheduler. In the process of agent creation, all the information taken from the input datasets are elaborated to define the attributes. The same thing happens to initialisation of the resources and environment. As explained in the section 2.3.2.4, the scheduler has the task to progress the steps and ensures that all the actions are executed.

2.3.4.2. Model time-step

A step of the model consists of the activation of the scheduler, which activates each agent per each stage randomly, then it updates the agents' final decision-making and the resources and environment. In other words, the scheduler makes the following actions:

- First stage activation: agent physical actions. Randomly, each agent of the system is activated, and it makes the actions related.
- Second Stage activation: agent cognitive actions. Randomly, each agent of the system is activated, and it makes the actions related.

Note that actually, the environmental update also includes the update of final decision-making process (shown in the UML Activity diagram, Figure 2.18), but, for a clear understanding, the agent's final choice is held as a separate process to remark that the update is made for all agents in parallel, thus assuming that all the agents have made the physical and the cognitive actions, and this final part strongly depends on the scenario under study, e.g. when the choice of adoption is taken considering the choice of the majority of adopting between residents of a Condominium.

Agent physical actions

The first action of the agent consists of social network creation as a SWN. The social network was assumed as static; thus, it is an action done at the initial step. The creation of the social network consists of 3 main steps: (1) the neighbours within a certain radius r are selected and they represent the locals; (2) the locals undergo to a selection by social group similarity, reducing the numerosity of them; (3) a certain number of locals (defined by rw) are replaced by non-locals randomly chosen from the whole system.

After that, if the agent already has the rooftop PV system, it does not do anything anymore in this stage. On the other hand, if it has not the rooftop PV system, it starts to interact with ϕ other agents randomly selected in its social network. The agent could be influenced by these interactions, thanks to the application of the RA algorithm (reported in Appendix 5.1.2), and its opinions and uncertainties could change.

Subsequently, the agent asks for a quote of a rooftop PV system in making an investment evaluation, taking the information from the resources.

Agent cognitive actions and decision-making

After checking whether the agent is a non-adopter, the agent starts to elaborate on their new opinion and on the information taken in the previous stage, also considering its state (the specific collection of parameters that define an agent at a step). The cognitive actions correspond to the elaboration of TPB's components: att, sn and pbc. Finally, the agent develops an intention to the behaviour bi and, after checking the actual power control (i.e. pbc), it elaborates the final behaviour b.

2.3.4.3. Resource and environment update

Firstly, after that all the agents have made their actions, the final choices of the agents are updated. If the installation of the rooftop PV system is feasible and the b value is higher than the corresponding threshold level, the agent will adopt, and its opinion opi will set equal to a random value higher than 0.8 and uncertainty unc will set equal to 0.01. This final passage is used to simulate the happiness for the investment, making the agent as an extremist (great opinion and very low uncertainty).

The final substep of the model's step consists of updating the states of the resources and environment, using their rules, e.g., the update of the rooftop PV system price, the update of the mean household income of adopters and the mean number of household members of adopters.

2.3.5. Software implementation

In the previous sections, each component of the model was identified, describing their meaning, structure and mathematical definition and finally, it was shown the workflows of the entire model underlyng the actions sequence of the agents. Subsequentially, the model must be implemented in an appropriate modelling or programming environment. A part of programming language, in the market, there is plenty of ABMling platform and ad-hoc software. A review of these software was made in the literature [58].

For this study, the implementation of the model was made from scratch in Python language [24] using the library Mesa [25] and the commonly used Python's libraries. It was used PyCharm as Integrated Development Environment (IDE) [59], giving a great help in the phase of programming and debugging of the source code of the model (see Figure 2.19). The choice of building the ABM from scratch, directly in Python's programming language, was made for three main reason: an ABM platform could be too driven for the aim of this work, that in principle it is done to study and understand the ABM, starting from almost zero knowledge; many ABM platforms have a cost or freemium with strong limitation; at the root of these platforms, there is always a programming language of which it is made; thus it is worth it to study directly the programming languages instead of that particular software. Obviously there are some drawbacks to this choice: the development of the model start almost from scratch, with only a few helping libraries devoted to ABMling like Mesa, and nothing else, thus everything was created starting from source code, dataset elaboration codes, post-processing code and more else; unlike the ABM platform that have all instruments included, starting from programming language forces to use other software to support the development of the model.

The other softwares used as support for the development of the model are:

- QGIS – software open source used to display, analyse and manage the geographic and spatial data;
- Excel – spreadsheet software used to manage and process the input and output data of the model;
- Gephi – software open source used to visualise and analyse graph and networks as small-world networks.

It has also been used best programming practices when developing the model:

- Direct documentation of the model in the source code;
- Remote private repository used to store source code being able to use VCS;
- Version Control System (VCS), or revision control, is the management of changes to the source code and it permits to create branches. It is used to update the model keeping track of the changes and also to create branches of the model with different features.

The experimental tests were performed in a typical notebook. While the scenarios under study were run using PoliTo's EDA Group server Philae.

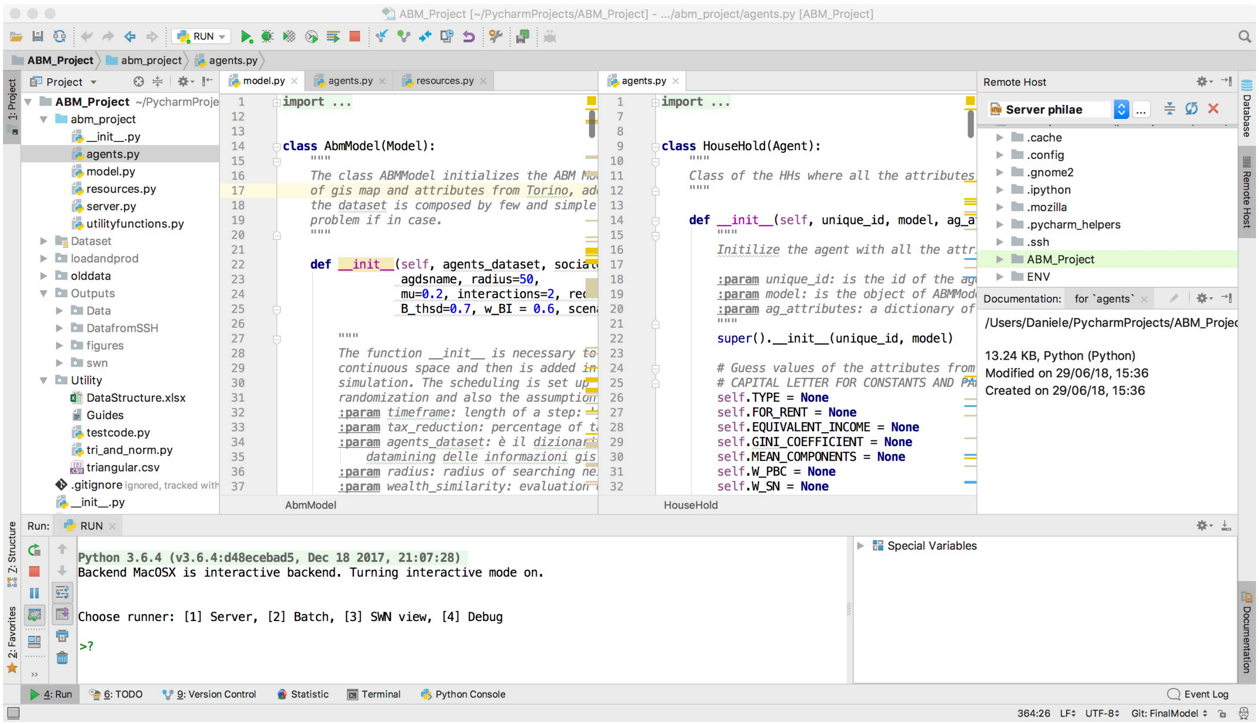


Figure 2.19: A snapshot of the Integrated Development Environment used.

2.3.6. Model verification

After having implemented the model, it is necessary to verify all its parts, to solve all possible semantic errors. Make sure that the code runs well (no syntax errors) and do what is expected. To do so, the verification was made using the dummy city agents' dataset composed of a random value of attributes and parameters. The model verification can be divided into several steps:

1. Recording and tracking agent behaviour, in which relevant metrics were identified and recorded, ensuring that the model is operating as expected;
2. Single-agent testing, in which the behaviour of a single agent was verified, to ensure that the model also works in extreme conditions running a series of benchmark with different input parameters with the aim of breaking the agent and find possible issues;
3. Interaction testing limited to minimal model, in which the interactions between agents were tested;
4. Multi-agent testing, in which the emergent behaviour of multiple agents was examined.

After benchmarking study, several mistakes made during the model implementation phases were then able to be corrected in this way. In the process of testing and verification, it was used the server functionality of Mesa which permits to analyse the model directly when it runs showing all the parameters, charts or map in which we are interested in. An example was reported in Figure 2.20.

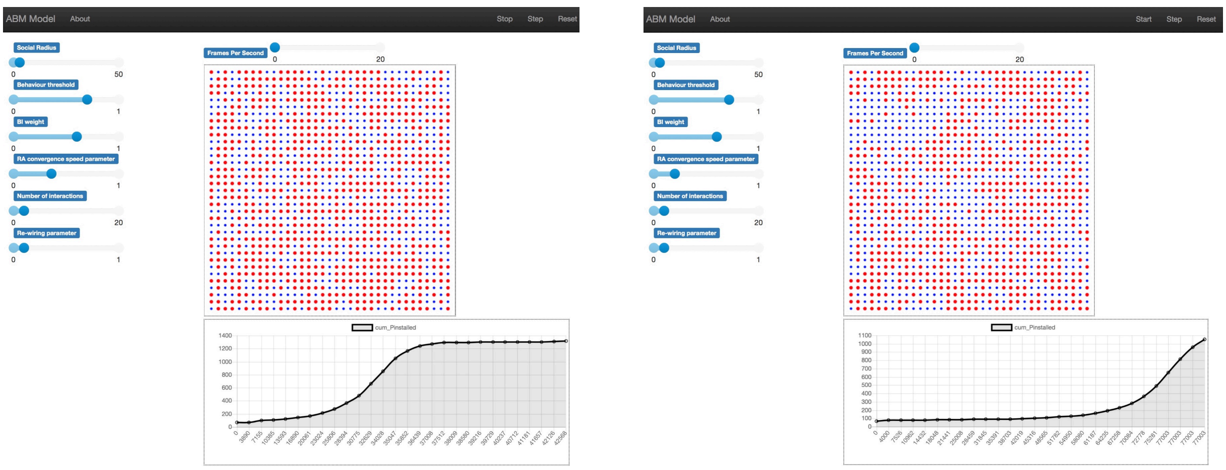


Figure 2.20: Server functionality of Mesa. Examples of use with the dummy city dataset, exploring the behaviour of the model changing the parameters.

2.4. Experimentation

The experimentations were aimed to show a range of clearly identifiable emergent behaviours and regularities that can appear from the ABM of a socio-techno-economic system under study, as the cumulative percentage of kW installed over time with respect to the maximum potentiality of the system. The experimentations do not attempt to recreate the real world but to explore in what worlds we might find the regularity of interest or whether any parameters delay, alter or disrupt the regularity [7]. Therefore, the experimentations were made starting from the simulation of the dummy city's dataset, called ***sc35*** used for testing purpose, exploring emergent behaviours which can be established doing parametric sweep experiments. Then it was analysed the agents' dataset of San Salvario's district, called ***sansa***; the experiments were made considering three scenarios and under the specified conditions, looking the emergent behaviour from the designed ABM and doing in-depth data analysis.

2.4.1. General hypothesis and setup

All the parametric values of the attributes of agents, resources and environment used during simulations were reported in the model Data Structure in Appendix 5.4. Meanwhile, the fundamental parameters of the model were also reported in Table 2.3 with a brief description in the next.

Table 2.3: Model's parameters.

Name of model parameter	***Symbol***	***Domain***	***Range***
Behavioural threshold	b_{thsd}	float	[0,1]
Number of interactions in the social network	ϕ	integer	[0, ..)
Re-wiring parameter	rw	float	[0,1]
Radius of neighbourhood [m]	r	integer	(0, ..)
Relative Agreement speed convergence parameter	μ	float	[0,1]
Weight of Behavioural Intention	w_{bi}	float	[0,1]
Tax reduction on investment cost in 10 years	$taxr$	float	[0,1]
Coverage of Advertising	cov_{ad}	float	[0,1]
Strength of influence of Advertising	str_{ad}	float	[0,1]

The first six parameters on Table 2.3 are related to the model itself and its functionality parts, meanwhile the last three parameters are related to the environmental aspect under study, in fact, they consider the value of the tax reduction on PV investment $taxr$ and, if it is present, the advertising action to push the diffusion of PV system, it is regulated by the coverage con_{ad} and strength of influence str_{ad} parameters. The b_{thsd} establishes the limit beyond which the agent adopts. The ϕ determines the number of interactions that an agent makes within its social network in each timestep. The w_{bi} is the weights of bi used in the calculation of the final behaviour b. The rw describes how much agents in the neighbourhood of an agent are substituted with agents randomly taken from the whole system. The r is the radius of the neighbourhood selection, expressed in meters. The μ is the speed convergence factor used in the evaluation of the dynamics opinion described by RA algorithm.

Given that ABM models are stochastics due to their iterative nature, therefore a single run of an ABM could be an unrepresentative outlier. Thus, it is necessary to do multiple runs for an experiment and descriptive statistics over the entire set of runs. For each experiment, it was calculated the mean of cumulative percentage of kW installed and its standard deviation over time, defining so the diffusion curve, as shown in the example in Figure 2.21. The diffusion curve follows the well-know classical S-shape curve, initially theorised by Bass [6] that describes the process of how new products get adopted in a population. As can see in Figure 2.21, the diffusion curve presents three distinguished phases: (1) slowly initial increment due to the adoption of the people defined as *innovatiors*; (2) the curve starts to rapidly increase due to the adoption of the people defined as *imitators*, reaching the time of the peak of adoption that corresponds to the point of curve inflexion; (3) the growth of the curve slowing-down going to reach the saturation level.

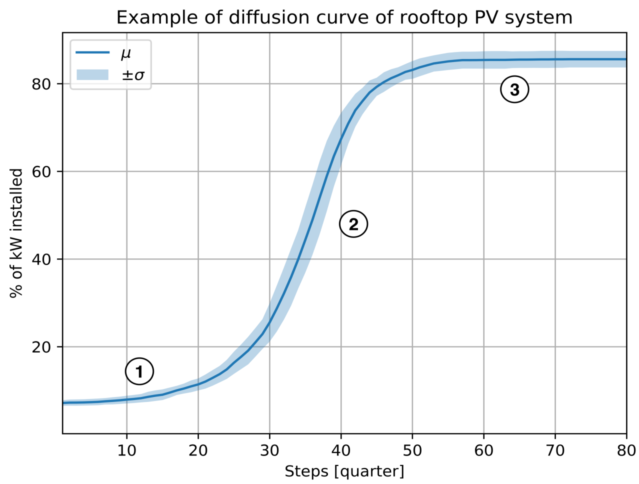


Figure 2.21: An example of a diffusion curve showing the three phases of which is composed.

The runs that make a sample statistically significant could be many runs. Besides, performing many hundreds of experiments might create very large amounts of data and high dimensional parameter spaces (40 parameters are saved from each run). For the aim of this study, a compromise was made, especially for the experiments on *sansa* that is quite large and complex and it requires much time. A single run, using the EDA's group server, may take around 5-7 hours; therefore, they have been chosen ten repetitions to reduce the time of execution to about 3-5 days (it depends on the chosen parameters and scenarios).

Finally, all the experiments are simulated for 80 steps, equivalent to 20 years. The time domain is not calibrated, thus the reference time was arbitrarily chosen as a quarter of year.

2.4.1.1. Setup of agents' datasets

sc35

The dataset was set creating a space structure as a square lattice of points 35x35 spaced a meter. Each point represents an agent, and it is defined by attributes randomly chosen, following the empirical distributions applied in the real application in San Salvario. The sc35 aims to have an agents' dataset as homogeneous as possible to learn the behaviour of the model and its functionality quickly.

sansa

The *sansa*'s dataset was built to be suitable as the input of the model, considering the following steps of creation, also shown in Figure 2.22:

1. *GIS Buildings data integrations.* The data provided by the census' sections, which describes the socio-demographic characteristics of each section, and the buildings solar data, which provides all the data required for the investment evaluation of the PV system, were spatially joined to the GIS buildings shapefiles of the San Salvario.
2. *GIS Households generation.* The data from the previous step was crossed with the social structure data that provides additional information to the households. The households were randomly generated considering the statistical distributions per each section of the census. Then, per each household is assigned a social group crossing the section's census data and the classification tree of the social groups and their statistical distributions. Finally, knowing the social group of each

household, a yearly load profile is assigned considering the social group which belonging.

After this process, the *sansa*'s dataset is complete and ready as input to the model.

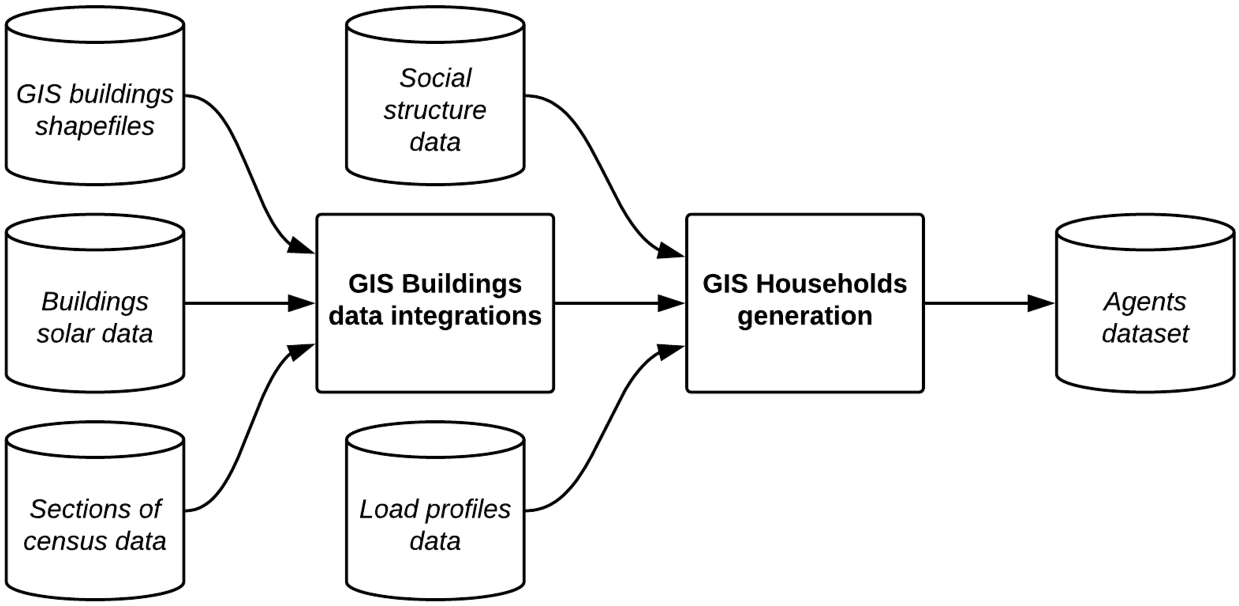


Figure 2.22: Schematic view of the configuration of the sansa's dataset.

2.4.2. Experimental tests on sc35

The experimental tests were conducted on *sc35 (*remarking that is a square city 35x35 agents) to probe the emergent pattern of diffusion, varying model parameters. The dataset *sc35* is small (only 1.225 agents), thus it permits to run simulation quickly and to obtain first results. The hypothesis of adoption is based on choosing a sized PV system to cover the yearly household electricity consumption and following the investment evaluation described in section 2.3.3.1. The simulations done with the relative chosen model parameters were reported in Table 2.4. The analysis of the main results was reported in section 3.1, where the test T13 (blue) was considered as baseline and in the other tests just one parameter (orange) was changed respect to it.

Table 2.4: Model parameters used in the experimental tests on sc35

Test name	b_{thsd}	w_{bi}	rw	$r\,[m]$	μ	ϕ	$taxr$	cov_{ad}	str_{ad}
T13 (base)	**0.7**	**0.6**	**0.1**	**3**	**0.05**	**2**	**0.5**	**0**	**0**
T14	**0.65**	0.6	0.1	3	0.05	2	0.5	0	0
T15	**0.75**	0.6	0.1	3	0.05	2	0.5	0	0
T16	0.7	**0.4**	0.1	3	0.05	2	0.5	0	0
T17	0.7	**0.8**	0.1	3	0.05	2	0.5	0	0
T18	0.7	0.6	0.1	**6**	0.05	2	0.5	0	0
T19	0.7	0.6	0.1	**9**	0.05	2	0.5	0	0
T20	0.7	0.6	0.1	3	**0.1**	2	0.5	0	0
T21	0.7	0.6	0.1	3	**0.15**	2	0.5	0	0
T22	0.7	0.6	0.1	3	0.05	**4**	0.5	0	0
T23	0.7	0.6	0.1	3	0.05	**6**	0.5	0	0
T24	0.7	0.6	**0.2**	3	0.05	2	0.5	0	0
T25	0.7	0.6	**0.3**	3	0.05	2	0.5	0	0
T26	0.7	0.6	0.1	3	0.05	2	0.5	**0.5**	**0.05**
T27	0.7	0.6	0.1	3	0.05	2	0.5	**1**	**0.05**
T28	0.7	0.6	0.1	3	0.05	2	**0**	0	0
T29	0.7	0.6	0.1	3	0.05	2	**0.36**	0	0

2.4.3. San Salvario's scenarios

The experiments on *sansa* were made considering three scenarios: IH-PV, SC-PV and BAU SC-PV, described in the following paragraphs. The parameters of the model used are the same in the scenarios (called Batch 4), and they were reported in Table 2.5. The main results of the data analysis were reported in section 3.2.

Table 2.5: Model parameters used in the sansa's scenarios.

Experiment name	b_{thsd}	w_{bi}	rw	$r\,[m]$	μ	ϕ	$taxr$	cov_{ad}	str_{ad}
Batch 4	0.72	0.6	0.1	50	0.05	2	0.5	0	0

Note that, in the experiment Batch 4, the only environment parameter considered is the tax reduction $taxr$ because it represents the actual situation in Italy in which it is possible to receive a discount of 50% in the PV investment, which is spread over 10 years. The others two parameters related to the advertising action ($\mathrm{cov_{ad}}$ and $\mathrm{str_{ad}}$) are implemented in the model but not considered for this first case study on San Salvario.

Individual Household PV system (IH-PV). The scenario is a business as usual scenario because it represents the actual situation in which a household can install a rooftop PV system in its rooftop available PV area, therefore for the ones that live in a Condominium the total rooftop PV area is equally distributed among the residents. In addition, it is assumed that if the area is not sufficient to install at least 1 kW_p, the adoption is not feasible. The household makes the investment evaluation considering the two types of current tariff mechanisms proposed by the GSE (RID and SSP), as described in section 2.3.3.1, and based on the yearly productivity of its plant, i.e. its yearly load profile and its estimated yearly self-consumption. An example of IH-PV is shown in Figure 2.23, representing the residents in a Condominium which have their PV plants on the rooftop of the building.

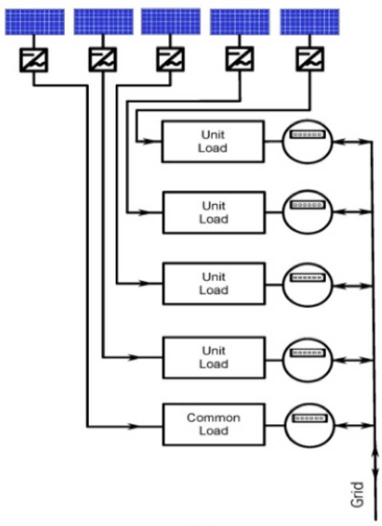


Figure 2.23: Example of IH-PV scenario. Source [60].

Shared Condominium PV system (SC-PV). This scenario consists of the installation of a rooftop PV system, that covers all the available PV area of the building, and it represents a shared resource among residents of the Condominium. Meanwhile, the single-family households can adopt the PV system in their rooftops. The distribution of PV generation throughout the building can be organised with metering used to distribute the on-site generation while households continue to purchase their off-site electricity directly from the grid (see Figure 2.24). At present the Shared Condominium PV system cannot access the feed-in-tariff (SSP) because it is not legally permitted in Italy due to the obligation to coincide with a withdrawal unit with a single consumer unit of a single end customer; more information can be founded in the official documentation from the Italian Regulatory Authority for Energy, Networks and Environment (ARERA) [55][56]. In fact, today the feasible alternative is to install a Condominium PV system to only supply common property energy loads with the risk of a low level of self-consumption.

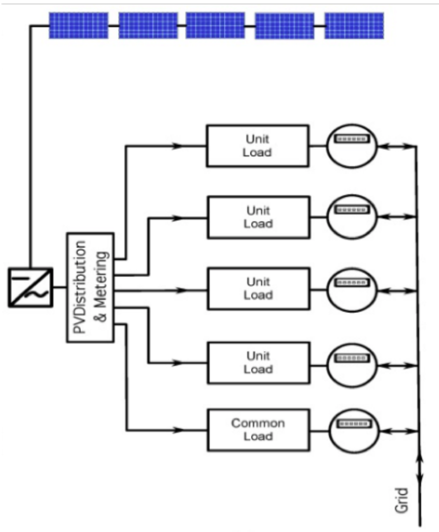


Figure 2.24: Example of SC-PV scenario. Source [60].

The investment evaluation of SC-PV is made considering the assumption of sharing the financial benefits; thus, the investment return is perceived equally by the households of a Condominium. Also, in this scenario, it is assumed the possibility to choose the two current tariff mechanisms proposed by GSE. Of course, the final choice whether to adopt the SC-PV is made if the majority of the households in the Condominium want to adopt, and this could be the most important obstacle to adoption.

Business As Usual Shared Condominium PV system (BAU SC-PV). The last scenario take into account the only possible solution, available at the moment, to install a SC-PV but with some strong limits [55][56]. First, it is necessary that the yearly self-consumption ratio is always more than 70%. Then, the surplus of energy is sold to GSE applying economic market conditions. Of course, this scenario (BAU SC-PV) is more restrictive compared to the hypothetical one (SC-PV), and it is made to show the current possibility with respect to the current classical scenario of the single-family PV system (IH-PV).

3. Results and discussion

In this Chapter, the main outcomes obtained by experimentations on the ABM with the diverse agents' datasets are shown and discussed. These data analyses have the objective to show the potential of the ABM modelling in describing a complex adaptive socio-techno-economic system; therefore, the results should not be considered as accurate forecasting of rooftop PV diffusion but as an exploration of emerging diffusion pattern and behaviours. First, in section 3.1, the parametric sweep done on the dummy city's dataset (sc35) is analysed in detail dividing the model parameters into the components of the system in which they operate and comparing the related diffusion curves. Finally, in section 3.2, the results of the sansa's scenarios were reported showing and discussing the diffusion curves and some thematic maps obtained by data analysis.

3.1. Dummy city parametric sweep

The results of the dummy city parametric sweep, reported in the following subsections, show that the obtained diffusion curves follow the S-shape, as the already mentioned Bass model [6]. Therefore, per each diffusion curve, they can be distinguished the three phases of diffusion over time (as illustrated in Figure 2.21). The segmentation of the diffusion curve in three parts will have used in the next subsections, helping to better describe the results of the experimental tests. As a general result, it can be seen that each experimental test starts from the same point in *phase-1*, because of the same initialisation of the model for all the experiments; furthermore, each experimental test, concerning *phase-3* in the long run, will reach the saturation level that is equal for all the experiments because it is used the same agents' dataset.

TPB parameters analysis: b_{thsd} and w_{bi}

The parameters b_{thsd} and w_{bi} are related to the mathematical model of TPB. As shown in the plot on the left of Figure 3.1, b_{thsd} has substantial impact in the diffusion curve that undergoes to a shift of *phase-2* along the time-axis due because the lower is the value of threshold's behaviour over which an agent adopts the more the number of agents that will adopt at a given step, thus the knee point of the curve in *phase-1* is more defined and occurs earlier. Note that at the initial step, there is a rung in the curve that is more accentuated in the case of lower values of the threshold. This behaviour is because the step 0 of the model begins assuming a constant number of adopters in the system that are not affected by the calculation of TPB; thus, they are not in relation with the threshold value. Finally, because of curve shifting, the saturation points of *phase-3* of diffusion are reached at different times.

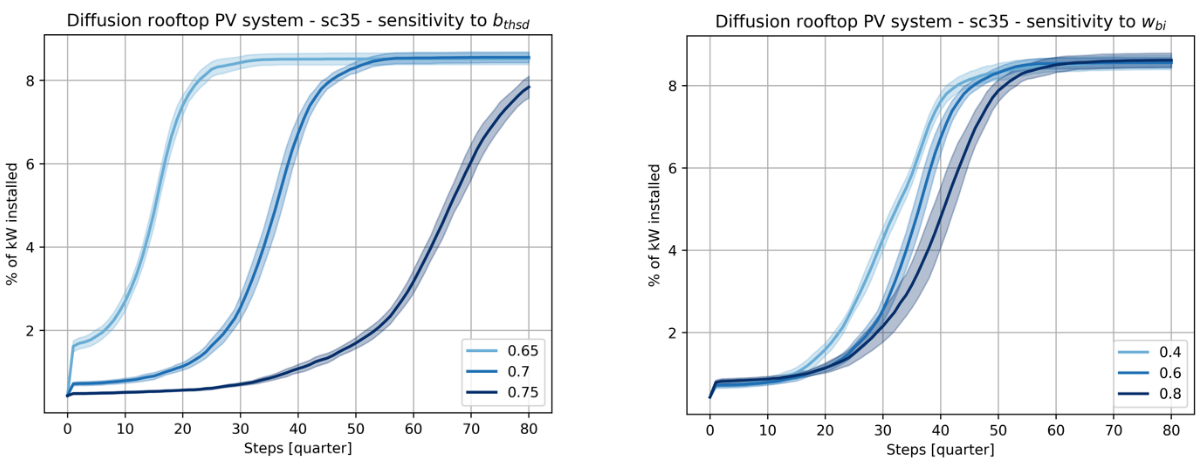


Figure 3.1: Left plot, sensitivity to b_{thsd} (T14, T13, T15); Right plot, sensitivity to w_b (T16, T13, T17)

On the other hand, looking at the plot on the right of Figure 3.1, w_{bi} has less incidence in changing the diffusion curve than the previous parameter but it seems that it affects the *phase-2* of diffusion and the knees of the curve. For values of w_{bi} less than 0.5, more importance is given to the Perceived Behavioural Control pbc with respect to the Behavioural Intention bi (as shown in Equation *2.30*). If w_{bi} does not exceed 0.5, the curve seems that maintains the position of the knee's *phase-3,* changing the slope of *phase-2* and anticipating the occurs of knee's *phase-2.* On the other hand, if w_{bi} exceeds 0.5, the curve seems that maintains the position of the knee's *phase-1,* postponing the occurs of knee's *phase-3.* Thus, the behaviour of the curve depends on the relative values of these two components. Note that the experiments with higher w_{bi} have a more standard deviation. It could be caused by the higher variation of the opinions and social influences over time represented by bi than the more concrete economic factors represented by pbc.

RA parameters analysis: μ and ϕ

The parameters μ and ϕ modify the dynamic opinions modelled by RA algorithm. As shown in the plot on the left of Figure 3.2, μ changes the slope of the inflextion point of the diffusion curve in *phase-2*, keeping almost unchanged the *phase-1*. It can be explained thinking that the parameter describes the convergence speed of opinions; thus, the higher is the value the higher is the speed of clustering of opinions, and with reference on positive opinions, making much higher the Attitude Towards the Behaviour.

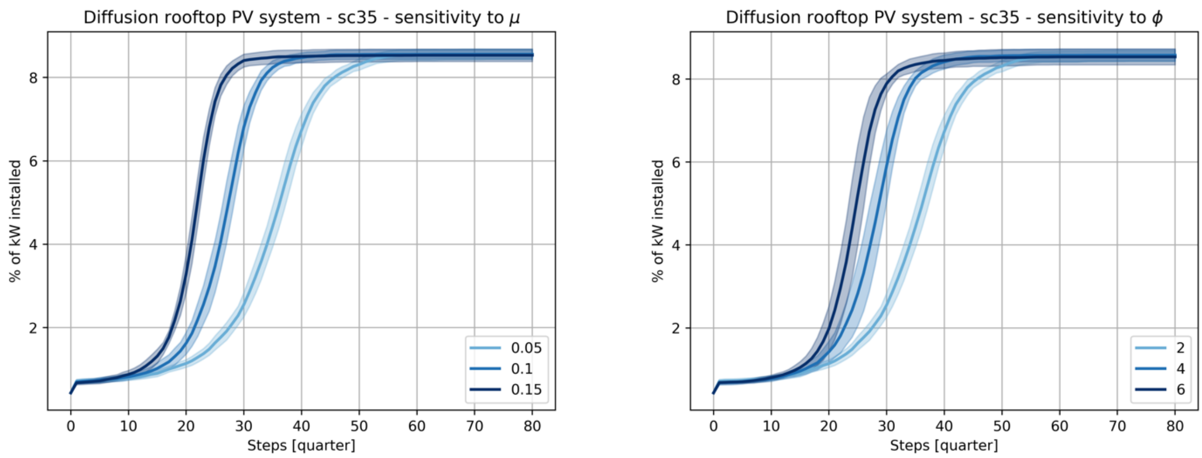


Figure 3.2: Left plot, sensitivity to μ (T13, T20, T21); Right plot, sensitivity to ϕ (T13, T22, T123)

The same behaviour happens with the parameter *ϕ* which describes the number of interactions an agent makes; the difference is in the standard deviation that in the experiments on *ϕ* is higher due to more variability on dynamic opinions. Finally, because of the changing of the slope in *phase-2*, the saturation points of *phase-3* of diffusion are reached at different times.

SWN parameters analysis: r and rw

The parameters r and rw modify the creation of the agents' social networks. As shown in both plots in Figure 3.3, these parameters do not to modify the emergent behaviour pattern of the system, but it is not always so. In fact, this probably happens due to the high spatial homogeneity of the sc35's dataset. Even if with higher radius and rewiring values the emergent diffusion curves do not change so much between them.

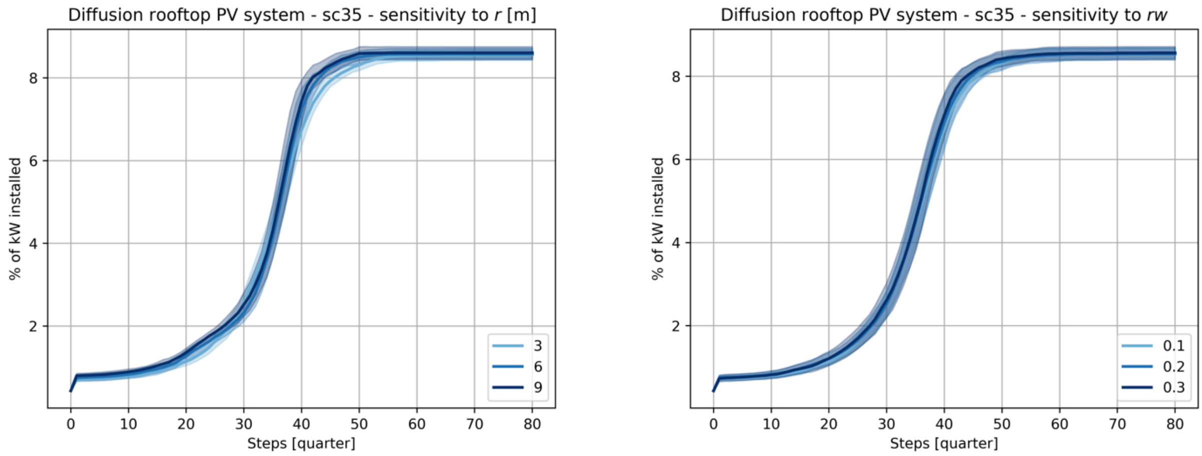


Figure 3.3: Left plot, sensitivity to r $[m]$ (T13, T18, T19); Right plot, sensitivity to rw (T13, T24, T25)

It is very likely that these parameters can strongly affect the diffusion curve in the real urban context, due to the high spatial heterogeneity and clustering of the agents. Also, due the diffusion curve describes an emergent behaviour from the entire population, it possible that modifying these parameters, the differences could be evident by observation of the spatial domain. It is necessary to deepen in the future to better describe the behaviour of these parameters, especially in the real world's dataset, like in sansa's dataset.

Environment parameters analysis: $taxr$ *and* cov_{ad}, str_{ad}

The parameters $taxr$ and the couple cov_{ad}, str_{ad} are related to the environment aspects of the system. Following the left plot on Figure 3.4, higher value of $taxr$ shifts the entire curve towards left, and it is simple to explain this behaviour: high $taxr$ means higher tax reduction on PV system investment, thus higher investment return.

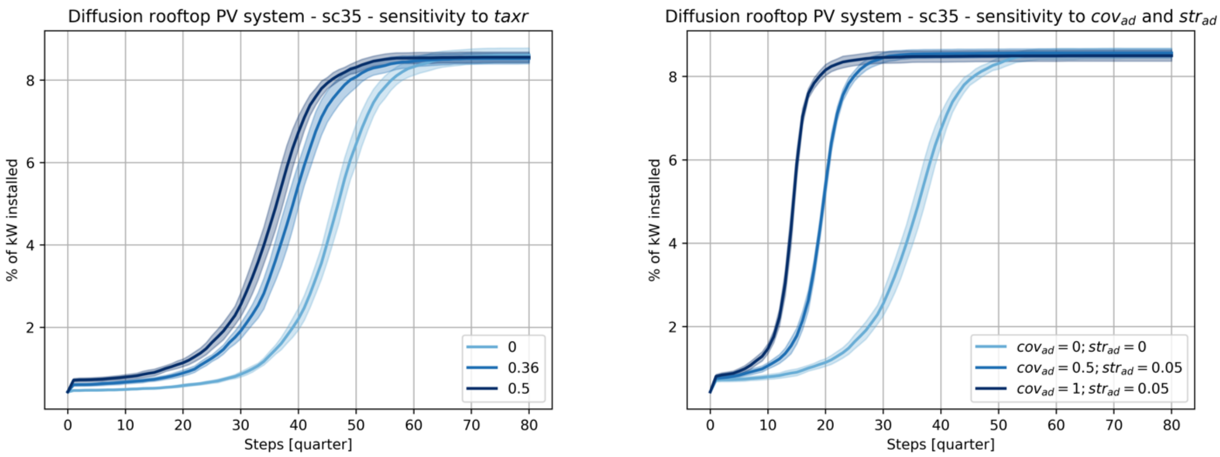


Figure 3.4: Left plot, sensitivity to $taxr$ *(T13, T28, T29); Right plot, sensitivity to* cov_{ad} *and* str_{ad} *(T13, T26, T27)*

The right plot on Figure 3.4 describes the effects of the advertising (in favour of adoption of course) in the emergent diffusion curve, through the coverage and strength of influence parameters. The str_{ad} modify the diffusion curve like the convergence speed factor, described before, while high cov_{ad} anticipate in time the *phase-2* of diffusion because increase the probability that an agent is reached by advertisement, thus increasing the number of adoption in time.

3.2. San Salvario data analysis

Figure 3.5 shows the diffusion curves obtained from the data analysis of the scenarios under study. We can observe the significant differences between the curves towards the final steps. Up to the first 40 steps (equivalent to 10 years in this not calibrated reference time), all three curves increase very slowly, and they do not exceed 10% of kW installed, respect to the total potentiality of the district that is equal to 16.2 MW (calculated thanks to the data sources, reported in section 2.2); the IH-PV curve increases a little more quickly than the others. This behaviour could be explained considering that in IH-PV, each household makes their own choice whether adopting while in SC-PV the choice depends on the behaviours of all residents of Condominium, making the adoption choice more difficult to occur. On the other side, the comparison between the future scenario SC-PV and the actual one BAU SC-PV is that the latter has a lower diffusion respect to the former because it imposes strong limits on adoption of a shared Condominium PV system, like the obligation of the yearly self-consumption ratio always higher than 70%.

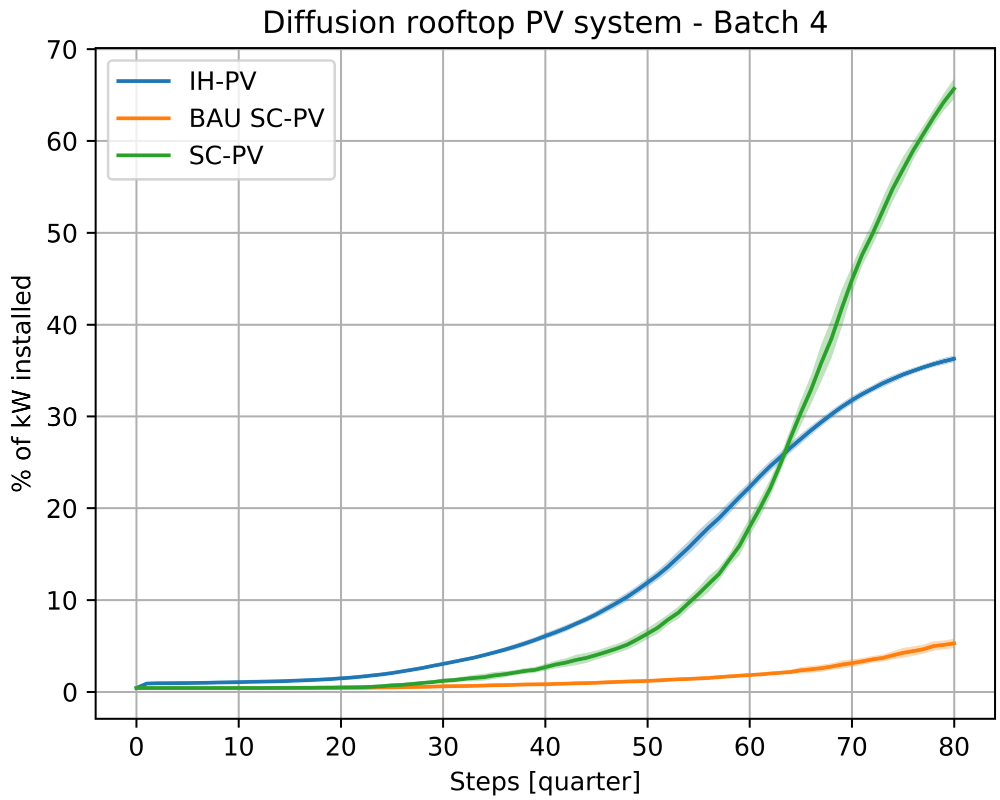


Figure 3.5: Diffusion curves of the scenarios IH-PV, BAU SC-PV and SC-PV (Batch 4).

In the last 40 simulation steps, the behaviours of IH-PV and SC-PV are reversed, where the latter *phase-2* grows more than the former, reaching about 65% of kW installed at the end of the simulation but not reaching the *phase-3* of diffusion saturation; meanwhile, the other one reaches about 36% of kW installed and it seems to reach approximately the *phase-3* of diffusion. Each diffusion curve, in the long turn, goes towards saturation, but with significant different levels.

The saturation levels can be better observed in the diffusion curves in Figure 3.6, obtained from the experiment Batch 2, where the b_{thsd} is set equal to 0.7. In IH-PV scenario, the diffusion curve goes towards saturation level of about 40% of kW installed, and from the data analysis, the cause could be that a plenty of agents do not have the necessary PV area to install at least 1 kW_p, thus a constraint that forces to non-adopt. Meanwhile, in the scenario SC-PV, the saturation level is reached at about 75% of kW installed suggesting that the elimination of the current legislative constraints on adopting shared Condominium PV system, together with the lowering of PV prices and good opinions on this, could be the right choice to push the diffusion on the district at a high level.

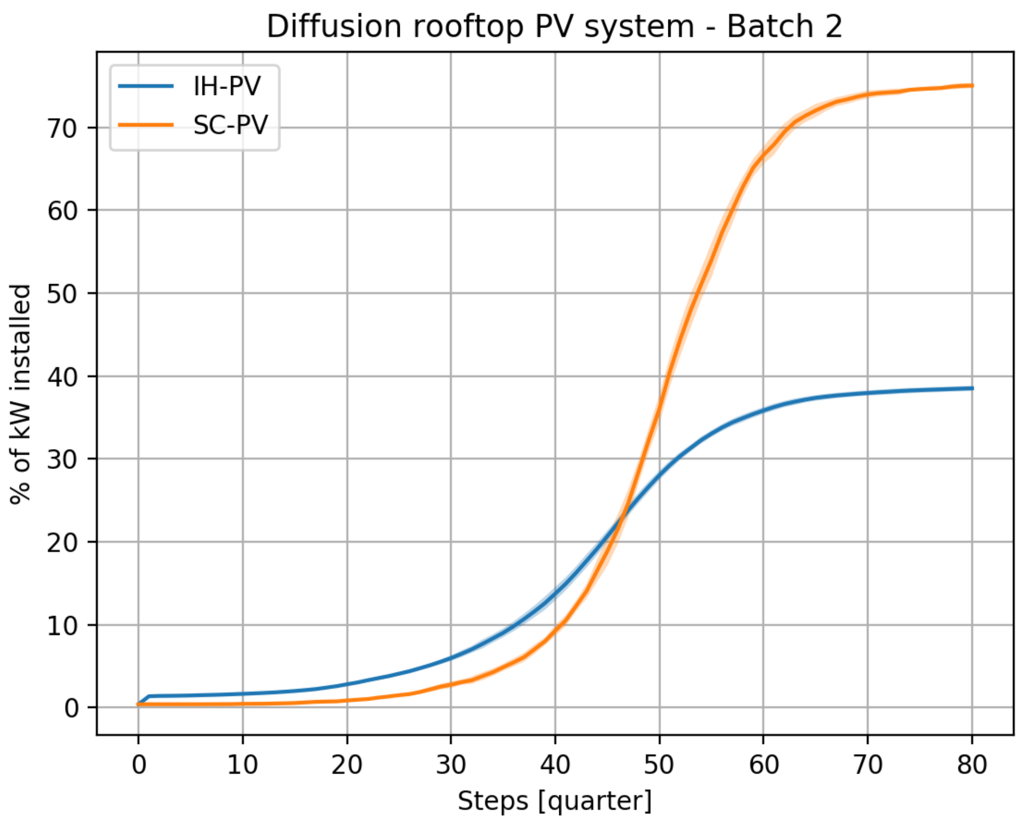


Figure 3.6: Diffusion curves of the scenarios IH-PV and SC-PV, from experiment Batch 2 ($b_{thsd} = 0.7$).

As said in the previous chapters, the socio-demographic factors play an essential role in the agent decision-making process. To analyse their effects in the decision-making model, it could be useful observe the average on all agents of each TPB's component over time (see Figure 3.7) and of which they form the final behaviour b, remembering that while the pbc is an attribute that depends on the *internal state* of an agent, like economic factors and feasibility constraints, the att and sn are related to the *local state* of an agent, meaning that depends on its social network, thus from the spatial properties of each agent.

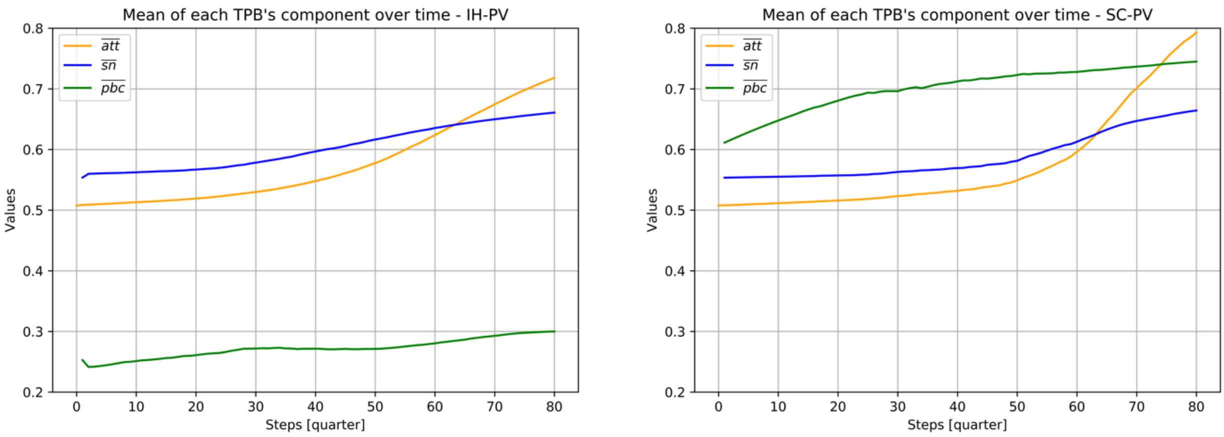


Figure 3.7: Average on all agents of each TPB's component over time (left IH-PV, right SC-PV).

As shown in the plot on the left in Figure 3.7, the diffusion on scenario IH-PV is slowed down by the low values of $\overline{pbc}$, mostly caused by many agents which cannot adopt (their pf values are zero), although the general attitude towards the behaviour increases over time. Besides, in the future scenario SC-PV, shown in the plot on the right in Figure 3.7, the $\overline{pbc}$ has a higher value than the previous scenario, thanks to a high number of potential adopters, and it increases over time which might be caused by lowing PV price and income affordability. However, the general attitude gives a forceful push to diffusion, thanks to more already adopters that generate more good opinions over time and so on.

3.2.1. Thematic maps

In this section, the thematic maps of San Salvario's district were reported. Considering the scenarios IH-PV and SC-PV, the thematic maps are elaborated by data analysis at census's sections level. From each scenario, they were extracted the data from the final step of a simulation taken from the sample of each experiment. The spatial distributions considered are related to the following parameters:

- The percentage of kW installed that is the kW installed normalised to the maximum potential per section of the census;
- The average per section of the census of Self-Consumption ratio;
- The average per section of the census of Self-sufficiency ratio.

An example of map creation of the percentage of kW installed is shown in Figure 3.8. It shows the parameter per each section of census that is subdivided into 10 classes in the range from 0% to 100%, and coloured based on the magnitude value of each class. As already said, they were picked the parameter's values taken from the data of the 80th step of a simulation from the experimental sample.

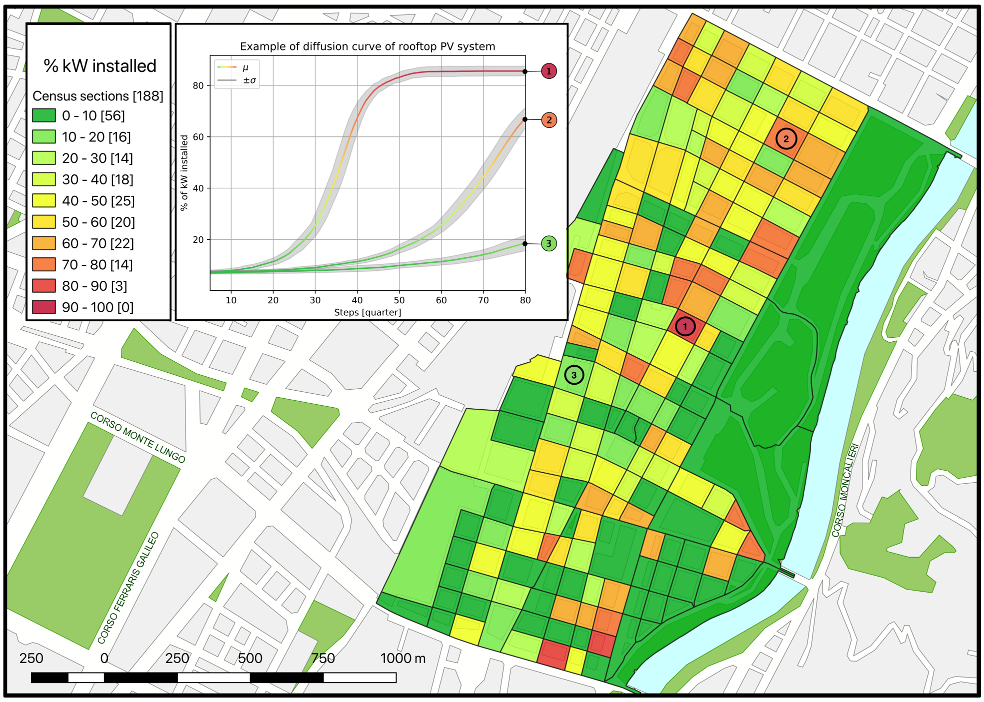


Figure 3.8: Example of making map of the percentage of kW installed per census section, taking the final step (80th) of a simulation from the sample of an experiment.

To compare the scenarios respect to the values of Self-Consumption and Self-Sufficiency, it was considered the whole potential PV production per each section of the census and the total potential electrical demand of all agents that could feasibly adopt a PV system (therefore, the buildings with zero PV area are excluded). The BAU SC-PV was not considered in the analysis of the thematic maps because the resulting PV diffusion has a level of diffusion too low to be considered, therefore the comparison was made only between the currently classical scenario IH-PV and the future scenario SC-PV.

Maps of the percentage of kW installed

As it can see in Figure 3.9, the scenario IH-PV presents 56 (of 188 in total) of census's sections which do not exceed the 10% of kW installed. The other census's sections are roughly equally distributed on the classes from 10% to 80% with lower values on above these (see also the histogram in Figure 3.10). On the other hand, the scenario SC-PV shows 83 census's sections with high percentages of kW installed which exceed the 90%, but also 33 census's sections which are under 10%; it could be caused by apartment buildings with a high number of residents, making more difficult, from the social point of view, the adoption of a shared PV system (of course, also considering the sections that could have many commercial or institutional buildings of which are not considered).

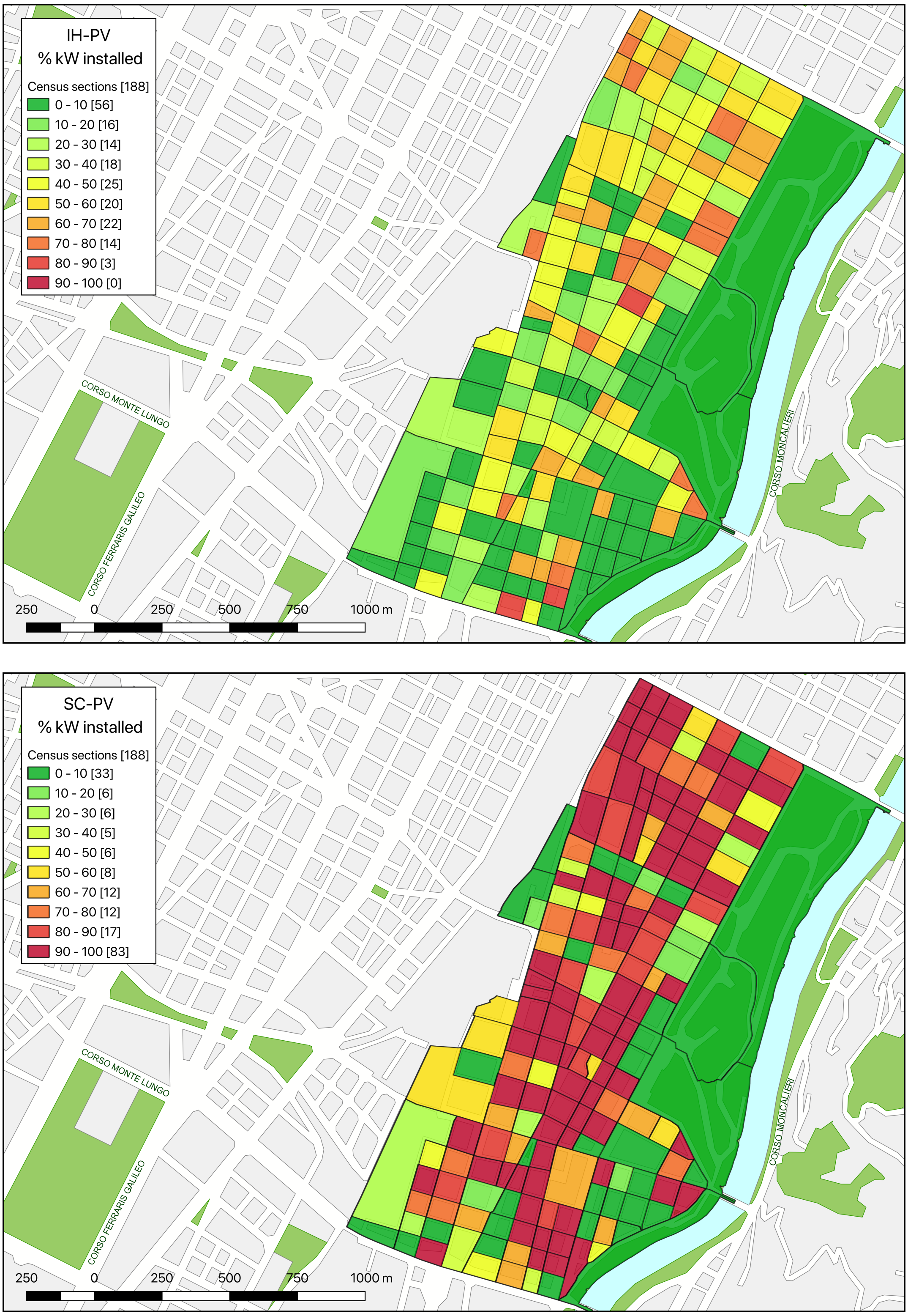


Figure 3.9: Maps of the percentage of kW installed. Top IH-PV, Bottom SC-PV.

In Figure 3.10 is showed a comparison of the two scenarios regarding the percentage of kW installed per each section of the census, using a histogram in which the x-axis reports the classes of the % kW installed, while the y-axis reports the number of census's sections that belong in a class.

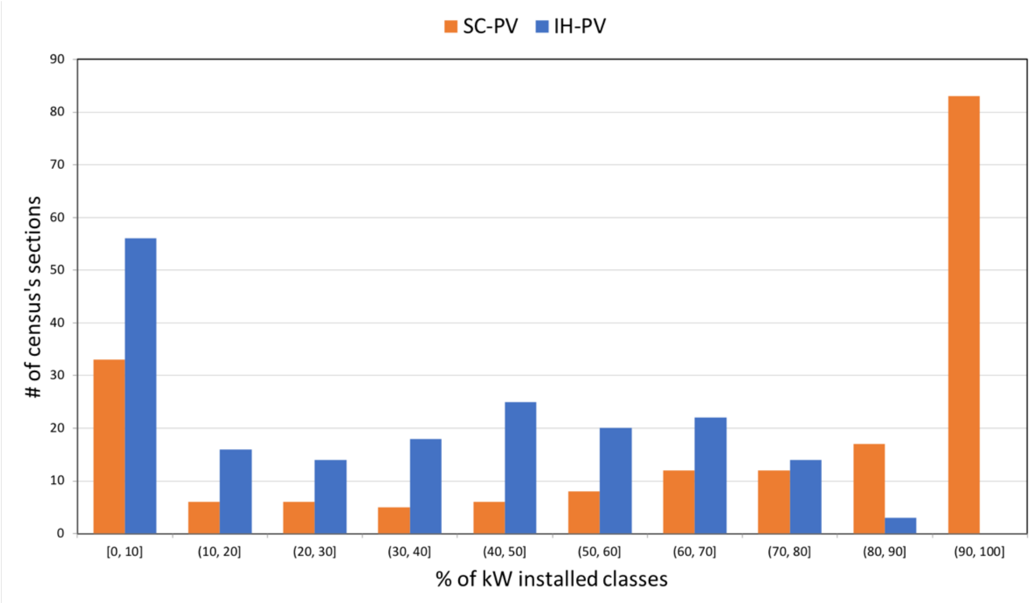
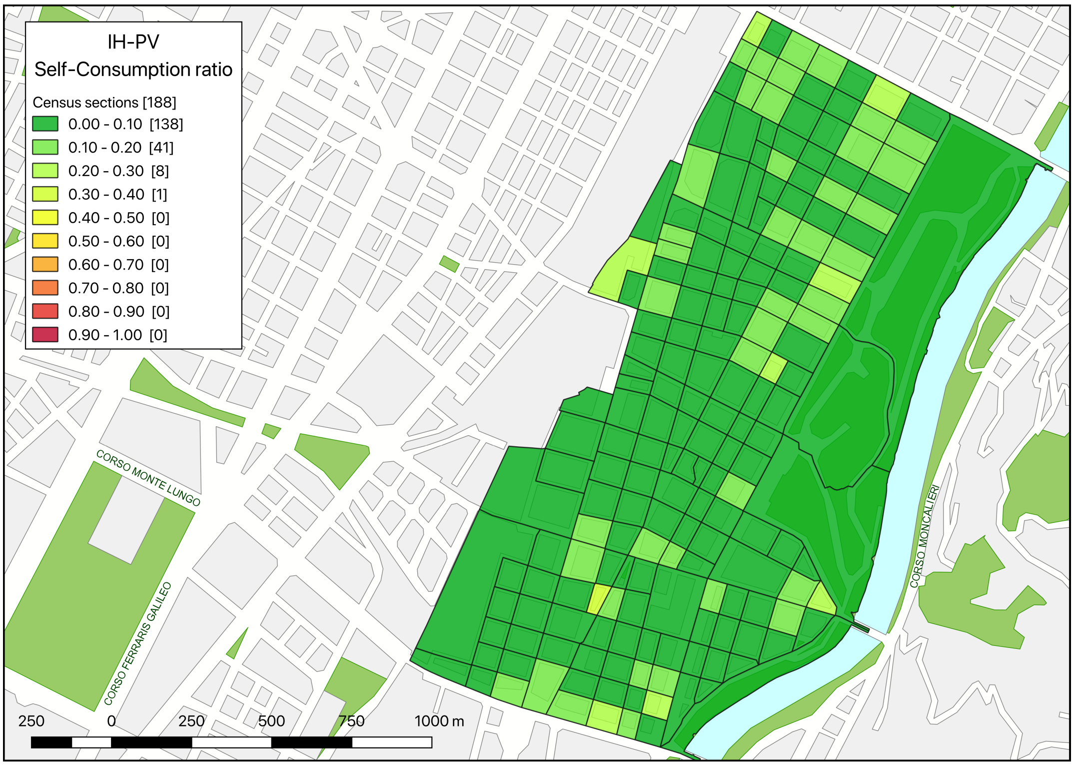


Figure 3.10: Number census' section for each class of % kW installed for the IH-PV (blue) and SC-PV (orange) scenarios.

Maps of the average Self-Consumption ratio

Concerning the Self-Consumption ratio, there is a big difference between the scenarios IH-PV and SC-PV, as shown in the maps in Figure 3.11. Considering the scenario IH-PV, no census section exceeds the 40% of self-consumption and most of them (138) are under 10%. Meanwhile in the scenario SC-PV, 40 census's sections are in the range of 50% - 60%, and the others are more distributed along the classes of Self-Consumption ratio.



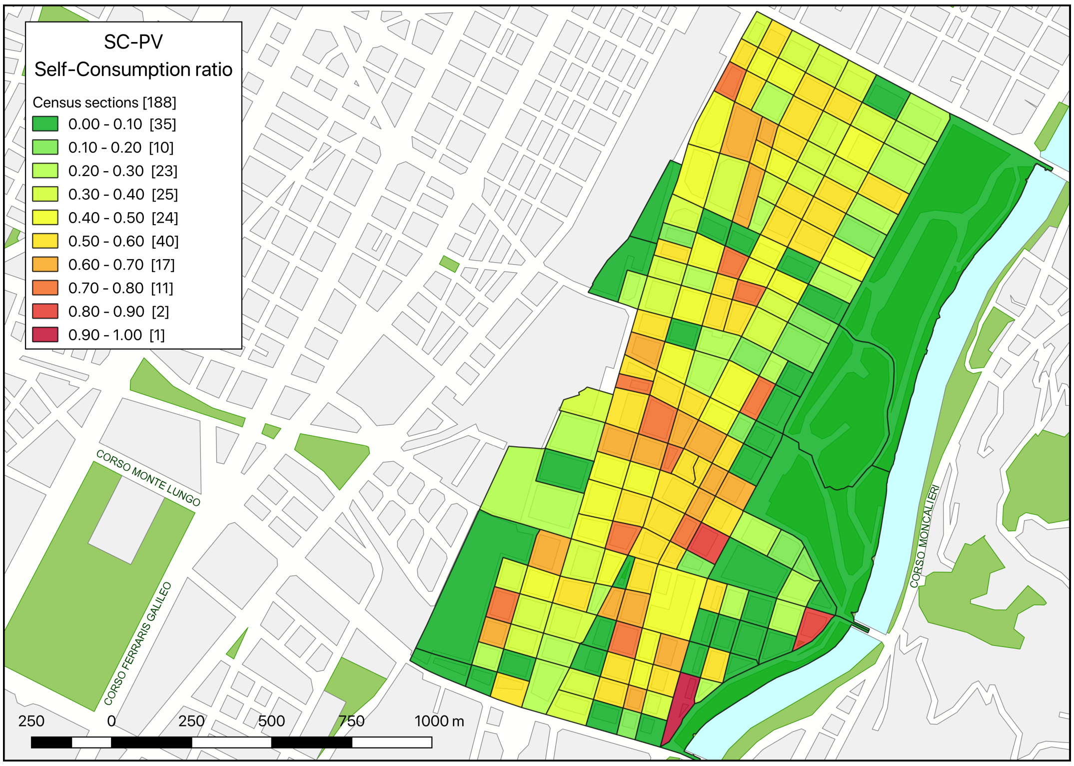


Figure 3.11: Maps of average per section of the census of Self-Consumption. Top IH-PV, Bottom SC-PV.

To better understand this important difference that comes from the results of the two scenarios, it could be useful to make a comparison of them in the same conditions. Suppose a Condominium with 30 residents and each household install one kW_p of rooftop PV system for a total of 30 kW_p per whole building. This circumstance is equivalent to the scenario IH-PV, meanwhile, if all the residents of the Condominium install a single shared rooftop PV system of 30 kW_p is equivalent to scenario SC-PV. What happens is well explained by Figure 3.12 that shows a typical daily net power import and export profile for both scenarios, thus already considering the self-consumptions. Regarding the scenario IH-PV, we can see the simultaneous presence of power import and export because, at a given time, there are some of the households which export part of PV generation that is in excess with respect to their consumptions, meanwhile, on the contrary, other households must take energy from the grid because their PV plants cannot adequately cover the demand. The conclusion is that in the scenario IH-PV, the rooftop solar area of the building is not exploited efficiently and cost-effectively. On the other hand, in the scenario SC-PV, the PV production is firstly shared among the residents and only eventually then is sold to the grid. The conclusion is that in the scenario SC-PV, there is not the simultaneous presence of power import and export and their magnitudes are significantly lower in comparison with SC-PV, resulting in a higher Self-Consumption ratio.

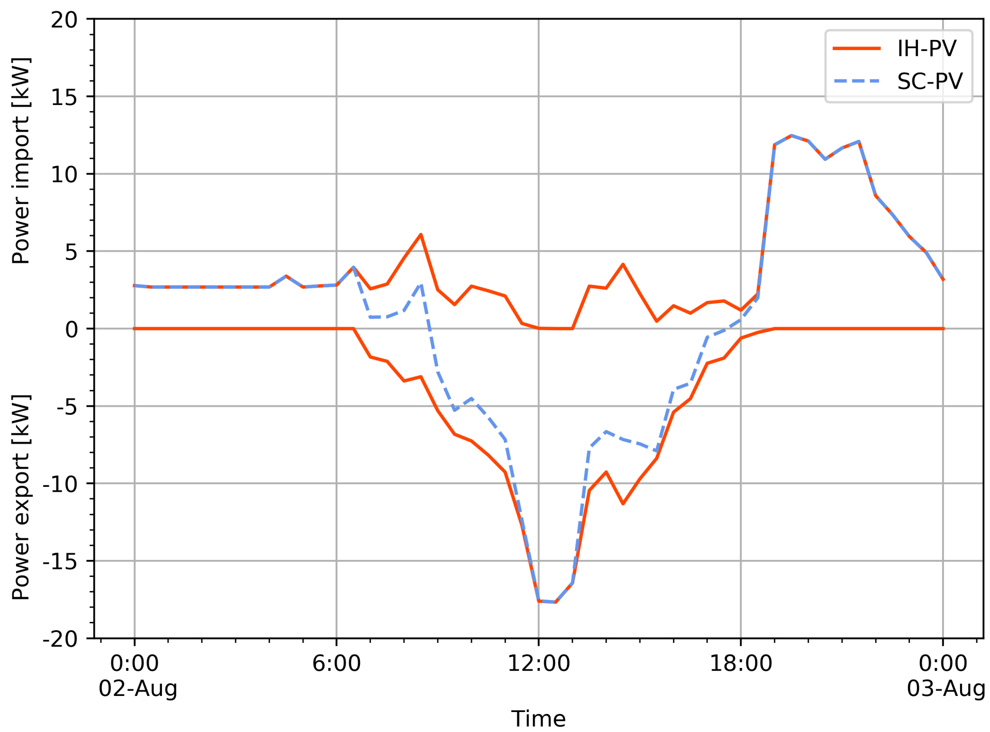


Figure 3.12: Comparison between scenarios IH-PV and SC-PV of the power import/export in a typical daily load for a Condominium (with 30 kW_p installed).

Finally, there is a general consideration in the Self-Consumption that could be interesting to highlight. As explained in the model description, the household of the district are generated randomly following the statistical distribution from the census's sections and social groups data. In the system analysed, there are many households which belonging in social groups that have an estimated load profile tending to higher demand in the evening than in the afternoon (see distribution of social groups in the district in Figure 3.13 and the reference load profiles per each group in Figure 2.12). Consequently, the Self-Consumption ratios do not reach very high values in general. A solution to increase the self-consumption could be the use of energy storage systems that is not considered in this work but can be implemented in a future study.

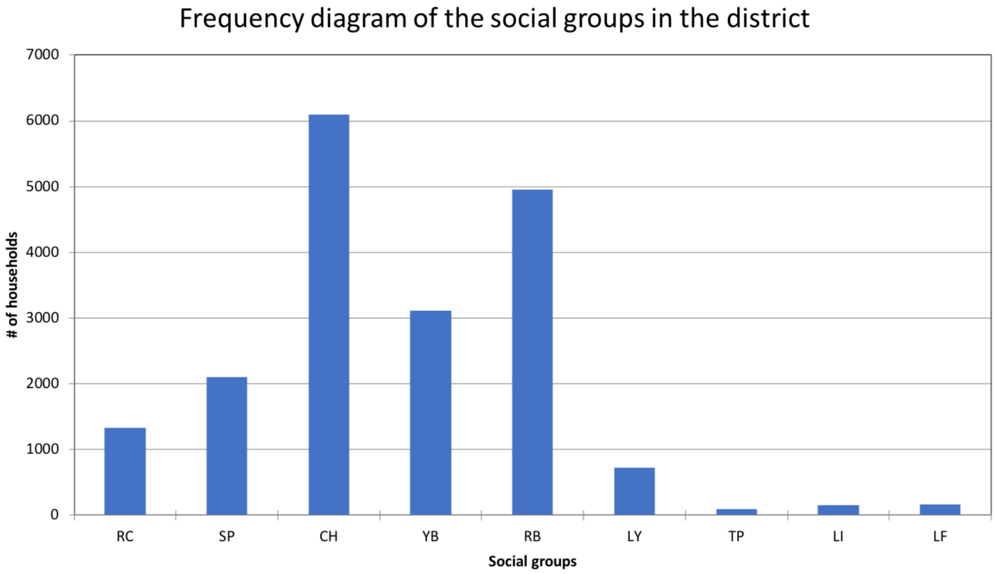
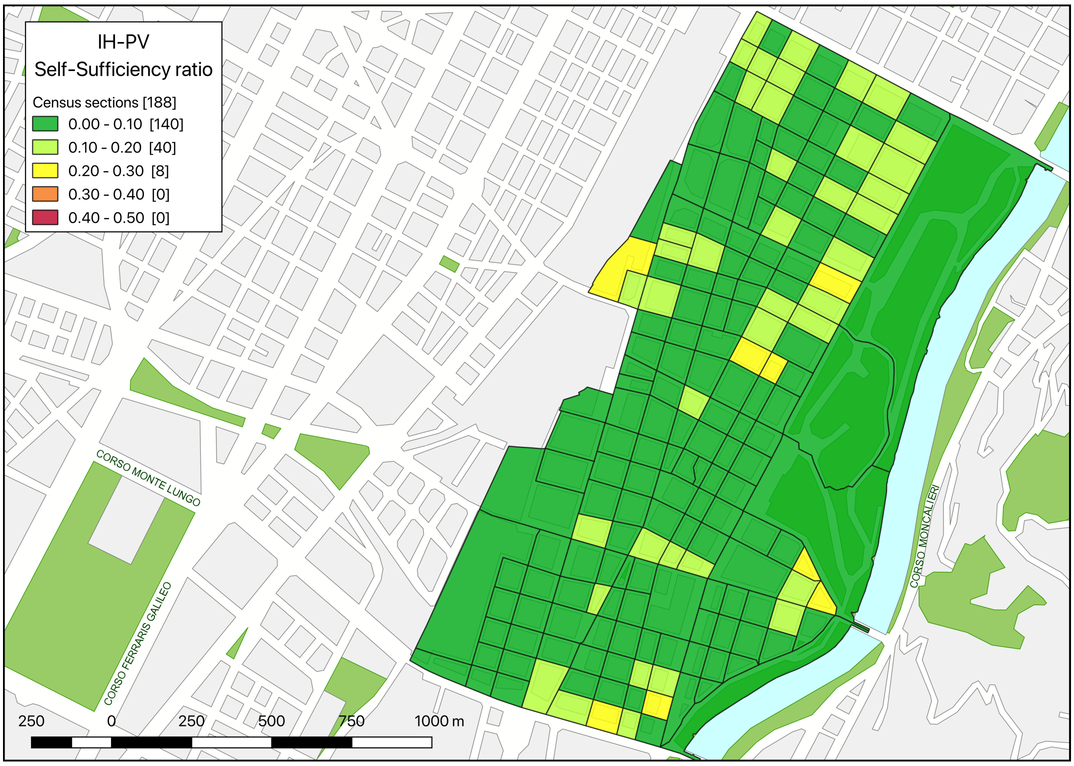


Figure 3.13: Frequency diagram of the social groups of the households in the district.

Maps of the average Self-Sufficiency ratio

The Self-Sufficiency ratios are always under the 0.5 for all sections of census, in both scenarios, as shown in the maps of Figure 3.14. This result significantly depends on the load profiles and its magnitudes with respect to the PV production. Remembering that both scenarios' maps of Self-Sufficiency ratios have been constructed with the same total energy demand of the district, it is evident that the Self-Sufficiency ratios of scenario SC-PV have higher values due to the generally higher exploitation of PV production than the scenario IH-PV.



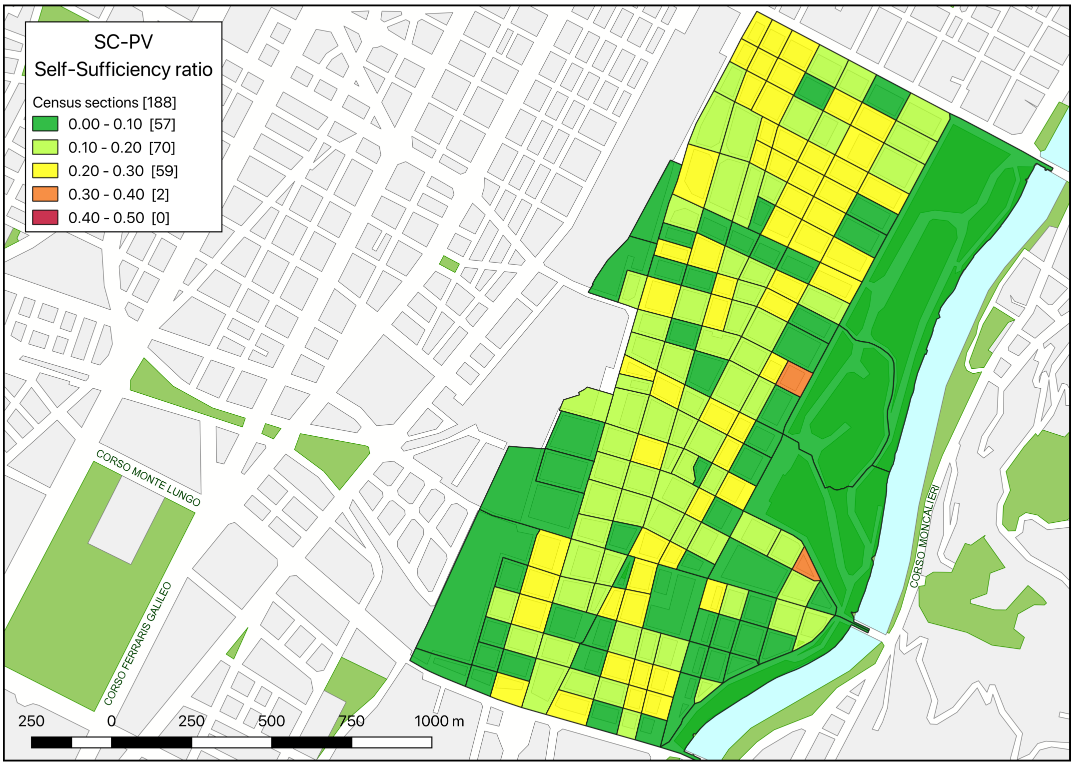


Figure 3.14: Maps of average per section of the census of Self-Sufficiency. Top IH-PV, Bottom SC-PV.

3.3. General discussions and expectations

As shown in the sections above, the ABM modelling has the potentialities to study the decision-making process of consumers in energy choices in a complex system and explore what could be happened varying environment parameters, not neglecting the important role of the social influence and social interactions in combination with the economics and constraints factors that an ABM can describe and simulate. What is more, the data analysis of the results from the ABM modelling could allow understanding better the behaviours, the emergent patterns and evolution over time at a granular level of data, like as example made in this work with data analysis at urban-scale, allowing to develop new targeted energy policy strategies. Of course, it will be necessary to validate and calibrate the model in order to use it as a predictive model of diffusion patterns, and it will be necessary a more accurate study of the behaviour of the model parameters, the assumptions and statistical data used to describe the agents and to initialise them, with the aim of empirically ground the model at the real population.

Some of the future applications, related to the case study, could be many: research of where and when might arise some bottlenecks in the energy infrastructure, caused by the diffusion forecasted; how to push more the adoption in some sections of the district, acting with some local energy policies, for example, it might have significant social influence if the public buildings of the considered sections installing a PV system, advertising and incentivising them; analyse the simultaneous presence of other energy technologies, like the energy storage systems in combination with PV system, and better understand how to system design and smart infrastructure planning.

4. Conclusion

In this work an Agent-Based Model simulating the diffusion of residential rooftop PV systems at the urban scale has been developed. The goal was to develop a model that can represent the human decision-making and the complexity and heterogeneity of the real-world, modelling the behaviour of households, especially those living in the Condominiums.

The ABM of this framework is based on theoretical and empirical aspects of model design. The model is fed by different streams of data including district's census sections data, buildings shapefiles and solar data, social structure, households' electricity load profiles and environmental data, like electricity market, PV technologies and energy polices; all this information are necessary to model a grounded realistic world, described as a complex adaptive socio-techno-economic system. From the theoretical point of view the agents' adoption decisions are driven by the Theory of Planned Behaviour that describes the human behaviour as influenced by three main factors: attitude toward the behaviour, subjective norm and perceived behavioural control; each of these is determined by some beliefs that are well-defined by the modeller. The attitude is influenced by opinions and uncertainties in those opinions, thus it depends on psychology and social interactions of the agents; the subjective norm depends on the social pressure and innovativeness of the agents; the perceived behavioural control depends on economic aspects like payback period and income of agents, and also on the feasibility in the adoption of rooftop PV systems. The model also integrates the opinion dynamics following the Relative Agreement model that describes how the opinions and uncertainties in those opinions change when the agent interacts with another. Social interactions occur within the agents' social network that is modelled using the Small-World Network Theory.

The ABM developed in this work has been used to perform some experimentations aimed to identify a range of emergent behaviours and regularities that can appear from the ABM of a socio-techno-economic system under study. First, a dummy's city dataset was used to do a parametric sweep of the model, observing how the model parameters modify the resulting diffusion curves from the experimental tests and giving explanations of these behaviours. The results have shown that the diffusion curves follow the classical S-shape diffusion function and they strongly depend on some of the parameters of the model, like the behavioural threshold. Then, the model is applied to San Salvario’s district of Turin as a realistic case study, in order to simulate three different energy policy scenarios: business as usual in which a household install its PV system in its rooftop available area (IH-PV); business as usual Condominium scenario, in which the current restrictions in adoption of shared Condominium PV system are considered (BAU SC-PV); future scenario, in which no legislative restriction exists in the adoption of shared Condominium PV system (SC-PV). The scenarios’ diffusion curves, as the cumulative percentage of kW installed over time with respect to the maximum potentiality of the system, have shown the strong effect that the energy policies restrictions have in the exploitation of the district’s potentiality; in fact, the scenario BAU SC-PV does not exceed the saturation level of 6% and IH-PV reaches 40%, while the future scenario SC-PV reach 75%. What is more, thematic maps of % kW installed, self-consumption ratio and self-sufficiency ratio, regarding each section of the census, have been constructed, showing the potentiality of analysing the diffusion PV in the spatiotemporal domain with the aim of finding likely strengths or weaknesses in the diffusion.

As a general outcome, the ABM is a very promising modelling paradigm that could be useful in many researches in energy field like the study of the energy transition from centralized generation system to decentralized one, concerning the energy technologies, energy infrastructures, electricity market dynamics, institutional, regulation and social issues. The ABM modelling could be used to do experiments on how a system reacts to specific interventions, like in the policy-making context, being able to show how complex socio-technical interactions evolve based on the implementation of diverse applications of energy policies gives to the policy makers an insight into possible effects of those policies. Therefore, the ABM can show *what could be* a system under different scenarios, in contrast with the traditional optimisation and equilibrium models that show *what should be* a system [61]. On the other hand, since the design of energy infrastructures is becoming ever more complicated due to the energy transition, the ABM modelling can help to explore and explain when and where the technologies spread, giving to institution and utilities the information to how could invest in the infrastructures and to how the energy demand could become, especially on the urban scale, thus being able to plan best future energy demand-side management system.

The main drawback of ABM modelling use is the lack of data to construct the complex system grounding with empirical data and, consequently, to make an appropriate validation of the model. The use of more empirical data in ABM modelling would serve to increase their validity and applications. Thanks to the increasing of the computational power, the evolution of Data Science in using new machine learning and data mining algorithms and the increasing availability of granular data over time, it will be possible to give the right materials and instruments to the researchers on developing validated ABMs, especially in the energy field, which could help the Institution, policymakers and utilities to develop methodologies to improve decision-making process pushing the communities towards the smart, efficient and rational management of energy in all its forms boosting emerging sustainable technologies.

5. Appendix

5.1. Theoretical backgrounds

In this Appendix it has been reported the theoretical backgrounds of all the arguments covered in the main section of the Thesis, with the aim of a clear reading of the text maintaining the fil de rouge. It can be found more information and explanations of the theories and algorithms used giving also some examples.

5.1.1. Theory of Planned Behaviour

The Theory of Planned Behaviour (TPB) was developed by Ajzen and it is a widely applied theoretical framework to understand and predict behaviour [16][26]. It is commonly used in psychology and for modelling consumer agents' behaviour in application with diffusion models [13][15][46][62]. According to the theory, human behaviour is guided by three kind of beliefs that are aggregates into three corresponding attributes that jointly determine the Behavioural Intention (BI) (see diagram of TPB in Figure 5.1). These attributes are: Attitue Toward the Behaviour, Subjective Norm and Perceived Behavioural Control.

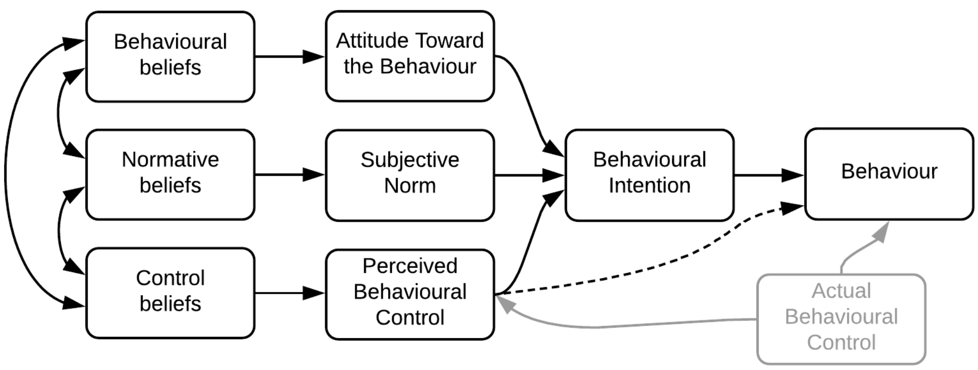


Figure 5.1: Theory of Planned Behaviour diagram. Adapted from [16].

Behavioural beliefs are about the likely outcomes of the behaviour and the evaluations of these outcomes [16]. Behavioural beliefs (b) in combination with the subjective values of the expected outcomes (e) produce a favourable or unfavourable **Attitude Toward the Behaviour (ATT)** creating the general opinion of the behaviour. It can be expressed by the following formula:

$$ATT = \sum_i b_i e_i \tag{5.1}$$

Normative beliefs are about the normative expectations of others and motivation to comply with these expectations [16]. They refer to the perceived behavioural expectations of such important referent individuals or groups (e.g. family, friends, state or government etc.). These normative beliefs (n), in combination with the person's motivation to comply with the different referents (m), result in perceived social pressure or **Subjective Norm (SN)** creating the general influence from other people or from a community. It can be expressed by the following formula:

$$SN = \sum_i n_i m_i \tag{5.2}$$

Control beliefs are about the presence of factors that may facilitate or impede performance of the behaviour and the perceived power of these factors [16][26]. They represent the strength of obstacles or physical constrains related to the behaviour. These control beliefs (c) in combination with the perceived power (p) give rise to **Perceived Behavioural Control (PBC)**. It can be expressed by the following formula:

$$PBC = \sum_i c_i p_i \tag{5.3}$$

A person may hold many beliefs with respect to any behaviour and some of this beliefs can be correlated with more than one attribute and only a relatively small number are readily accessible at a given moment.

In combination, Attitude Toward the Behaviour, Subjective Norm, and Perceived Behavioural Control lead to the formation of a Behavioural Intention, as shown in the following formula:

$$BI = ATT * w_{att} + SN * w_{sn} + PBC * w_{pbc} \tag{5.4}$$

Where w_{att}, w_{sn},w_{pbc} are the weights with the meaning of magnitude of attention and interest that a person has with respect of the three attributes.

As a general rule, the more favourable the ATT and SN, and the greater the PBC, the stronger should be the person's intention to perform the behaviour in question. Finally, given a sufficient degree of actual control over the behaviour, people are expected to carry out their intentions when the opportunity arises [26]. Behavioural Intention is an indication of a person's readiness to perform a given behaviour, and it is thus assumed to be the immediate antecedent of Behaviour. To the extent that it is an accurate reflection of Actual Behavioural Control (that it may be difficult to predict), Perceived Behavioural Control can, together with Behavioural Intention, be used to predict the Behaviour (B), as shown in the following equation.

$$B = BI * w_{BI} + PBC * w_{pbc}, \qquad 5.5$$

Where w_{BI}, w_{BI} are empirically derived weight/coefficients.

5.1.2. Relative Agreement algorithm

The RA algorithm was developed from Deffuant and permits to model the opinion dynamics [18][19]. Therefore, in this work, considering that the TPB is a static theory, the RA model is used to model the process through which the agent opinions and uncertainties related to those opinions evolve through interactions among agents, in their network structure. The network is modelled as a small-world network model [23].

In the RA algorithm, as the model moves forward through the simulated time frames, pairs of agents interact. Each agent i interacts with one other random agent j from its social network, where i influences j. Considering the following opinion segments (represented also in Figure 5.2):

$$\begin{aligned} s_i &= [opi_i - unc_i; opi_i + unc_i] \\ s_j &= [opi_j - unc_j; opi_j + unc_j] \end{aligned} \qquad 5.6$$

where opi is the opinion of an agent that goes from -1.0 to 1.0 and its uncertainty unc around the opinion is between 0.0 and 2.0.

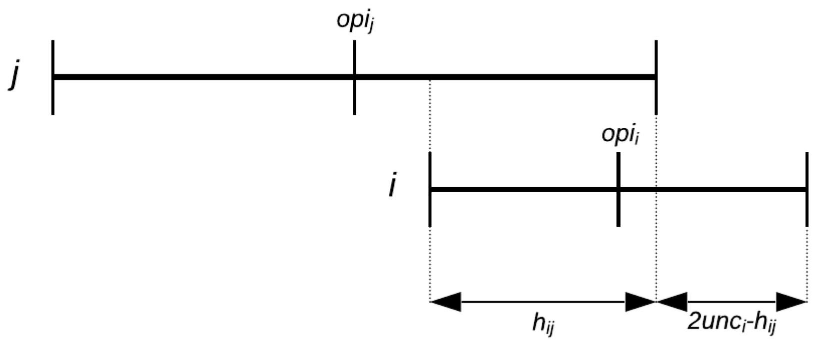


Figure 5.2: Schematic representation of agents' attitudes and its uncertainties with opinion overlap and non-overlap. Adapted from [18].

The interaction determines the opinion overlap h_{ij}, therefore the agents are only influenced by relatively similar attitudes.

$$h_{ij} = \min\big((opi_i + unc_i); (opi_j + unc_j)\big) - \max\big((opi_i - unc_i); (opi_j - unc_j)\big) \qquad 5.7$$

Equation *5.7* returns the overlap of the two agents' opinions but does not take into account the part of the influencer's opinion that is not overlapped, in turn decreasing their potential for exchange. The agreement is defined as the difference between overlap minus the non-overlap:

$$h_{ij} - \left(2unc_i - h_{ij}\right) = 2\left(h_{ij} - unc_i\right) \qquad 5.8$$

The relative agreement is the agreement divided by the length of opinion segment s_i because it's represent the range of opinion i in which an agent j is willing to consider. The relative agreement is shown in Equation *5.9*.

$$\frac{2\left(h_{ij} - unc_i\right)}{2unc_i} = \frac{h_{ij}}{unc_i} - 1 \qquad 5.9$$

If the overlap $h_{ij} > unc_i$ then the opinion and its uncertainty of agent j is increased or decreased by the amount of relative agreement, as shown in Equation *5.10*.

$$\begin{aligned} opi_j &= opi_j + \mu\left(\frac{h_{ij}}{unc_i} - 1\right)\left(opi_i - opi_j\right) \\ unc_j &= unc_j + \mu\left(\frac{h_{ij}}{unc_i} - 1\right)\left(unc_i - unc_j\right) \end{aligned} \qquad 5.10$$

where μ is a constant parameter which controls the speed of convergence in the opinion dynamics. If $h_{ij} \leq unc_i$, there is no influence of i on j.

The RA algorithm gives dynamic on the agents' opinions ensuring that extremists do not influence each other but allows asymmetric influence in which certain agents with lower uncertainty will be more influential [18]. This make the interactions more realistic as new adopters that are firm in their convictions will probably influence others to adopt [19], thus permits to observe the clustering of attitudes in time and also in the physical space where the agents are and depending on their small world networks.

5.1.3. Small-World Network theory

Agent interactions depends on the social network structure. The researchers have shown that the connections between people are composed by the major part of local connections, that are geographically proximate, and the minority part of non-local connections which are random links taken from the whole system considered [4][23].

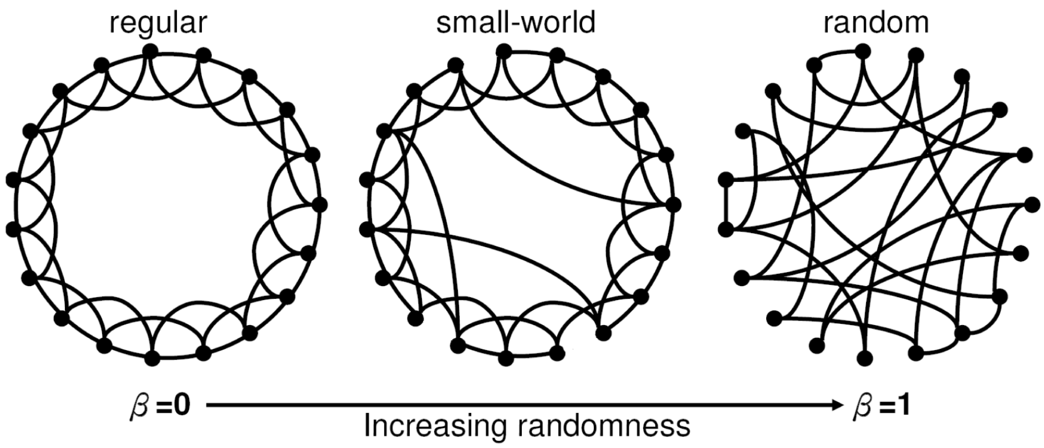


Figure 5.3: The parameter β is the probability of establishing a connection randomly. Adapted from [23].

The small-world network (SWN) theory can describe this type of social networks [23], by analogy with the small-world phenomenon (also known as six degrees of separation theory). SWN lies between two extreme connection topologies : wholly regular or completely random. The regular network is rewired to introduce increasing amounts of disorder, creating the SWN. Following the Figure 5.3, the SWN is obtained starting from the regular topology made by a ring lattice with n vertices and k edges per vertex, it rewires each edge at random with probability β. Thus increasing β, it increases randomness. As explained by Watts [23], the structure of the SWN can be described by two properties:

- The characteristic path length $L(\beta)$. It is defined as the number of edges in the shortest path between two vertices, averaged over all pairs of vertices. In the social network context, it has the meaning of the average number of friends in the shortest chain connecting two people.
- The clustering coefficient $C(\beta)$. Considering a vertex v with k_v neighbours. Between the neighbours can almost exist $k_v(k_v - 1)/2$ edges. It defines C_v as the fraction of these allowable edges that actually exist. Finally, C is defnined as the average of C_v over all v. In the social network context, it has the meaning of the extent of friends of v are also friends of each other.

A network is defined as SWN when, considering a broad interval of β, L grows logarithmically with n and C is not small. Therefore, the social networks are constructed based on the theory behind the SWN.

5.2. Data Sources

5.2.1. The social groups in Italy (Istat)

The main attributes of each group, used in the classification process, are explained in the section 2.3.2.1 and shown in the classification tree diagram reported in Figure 2.7. Meanwhile in this section, in the Table 5.1 is reported an overview of each group related to the all statistics and characteristics used and, reporting also the own assumptions made for the purpose of the agent-based model.

Table 5.1: Properties from Istat social groups and own assumptions used for ABM.

Properties \ Social groups	***RC***	***SP***	***CH***	***YB***	***RB***	***LY***	***TP***	***LI***	***LF***
Mean of number of household members	2.5	2.2	2.7	2.1	1.8	1.5	4.3	4.3	2.6
Equivalent income[1]	1.694	1.323	1.135	0.965	0.934	0.804	0.758	0.707	0.606
Gini coefficient within the group	0.28339	0.25668	0.23198	0.24594	0.22604	0.32352	0.28241	0.28992	0.28266
Share of total households population [%]	7.2	9.3	17.8	11.3	22.7	13.8	3.3	7.5	7.1
Risk of poverty and social exclusion whithin the group [%]	7.6	12.7	12.8	24.5	26.9	53.9	38.7	43.7	54.5
Fifth highest equivalent household expenditure within group [%]	51.6	35.1	27	22.5	15.1	10.7	5.5	5.7	5.2
Distribution of the group in center and suburban area [%]	40.14	35.09	32.67	24.04	24.13	24.27	23.63	21.78	30.68
$w_{if,SG}$[2]	0.516	0.351	0.270	0.225	0.151	0.107	0.055	0.057	0.052
$w_{att,SG}$[3]	0.611	0.518	0.465	0.408	0.306	0.171	0.117	0.116	0.084
$w_{sn,SG}$[3]	0.331	0.360	0.392	0.304	0.340	0.270	0.350	0.308	0.345
$w_{pbc,SG}$[3]	0.058	0.121	0.143	0.288	0.353	0.559	0.533	0.576	0.571
Level of innovation[4]	5	3	4	4	2	3	2	3	1
Mean household members type[5]	Couple with one worker and one student	Couple in pension	Couple workers with kid	Couple partial workers	Couple in pension	Old female and an unemployed	Couple workers with children	Couple partial workers with children	Couple partial worker with kid

[1] In 2017, the mean income of household in Italy is 29,988 euros (std 2,500 euros); [2] Assumed from the fifth highest equivalent household expenditure; [3] Weights of *att*, *sn* and *pbc* derived from the fifth equivalent household income, distribution of group per type of municipality and risk of poverty and social exclusion, respectively. Each weight is normilised between groups and finally normilised between the components of the TPB to have the sum of the weights equal to 1; [4] The level of innovation is assumed based on literature comparison of other social clustering and Rogers's work; [5] The type of household members was used in the estimation of the load profile per each group.

5.2.2. Census variables

The last census data of Italy (2011) is available from the portal of Istat [28]. The dataset is composed by rows that represent each section of census and columns, or fields, one per each attribute or census variable. In addition to the columns that identify the section of census by region, province, city and the final number of section, there are up to 153 fields describing the census variables. After having examination of whole variables, twenty have been selected for generation of the household in the model. These census variables were reported in the Table 5.2, reporting the field code and a brief description per each.

Table 5.2: Census variables from Istat used to generate the households.

Field's Name	Definition
P1	Total residential population
P46	Total residential population of six years and more
P47	Residential population with graduation
P48	Residential population with high school
P49	Residential population with secondary school
P50	Residential population with elementary school
P51	Literate residential population
P52	Illiterate residential population
P60	Total residential population of 15 years and more belonging to the total work force
P61	Total residential population of 15 years and more employed
P62	Total residential population of 15 years and more unemployed and in searching
P130	Total residential population of 15 years and more housewives
P131	Total residential population of 15 years and more students
P135	Total residential population of 15 years and more in other condition
P139	Total residential population of 15 years and more income earners from work or capital
ST1	Total foreigners and stateless
PF1	Total residential households
PF6	4 components residential households
PF7	5 components residential households
PF8	6 components and more residential households

5.3. ODD + D protocol

Template of ODD + D including guiding questions [41].

Table 5.3: Template of ODD + D protocol with model description.

Outline		Guiding questions	Model description
I. Overview	I.i Purpose	I.i.a What is the purpose of the study?	The purpose of the study is to demonstrate the promising applied field of the ABM in the context of diffusion of energy technology or innovation diffusion (thanks to in principle of the modern power computer and available data) such as solar adoption or storage system (maybe in general ABM applied to consumer energy choices). In particular, regarding the difference results obtained by using a simple economic model to innovation diffusion with a more suitable model that includes not only economic aspect but also techno and social aspect of the innovation diffusion. In fact, from literature is shown that two main factor influence solar adoption: economic and social effects.
		I.ii.b For whom is the model designed?	More in general, thanks to developing an ABM for energy demand studies diffusion, it is possible to use for policy design and evaluation and for system design and infrastructure planning. In energy technology adoption, the ABM is designed to make right strategies from policymaker to push the community to be more sustainable.
	I.ii Entities, state variables, and scales	I.ii.a What kinds of entities are in the model?	In principle, there is one type of agent: the Household (HH). HH could live in a house or a group of HHs live in a Condominium. As resources in the system, there are the solar technologies, market place, advertising, energy policies. The Environment is made up of a spatial system of San Salvario's district (TO) with all of the necessary gis data, attributes related to the spatial system. The environment has also the 'agent' institution, a regulator such as a national government authority.

		I.ii.b By what attributes (i.e. state variables and parameters) are these entities characterised?	The UML Class diagram and the Data structure show all the attributes fo the all the entities fo the system.
		I.ii.c What are the exogenous factors/drivers of the model?	Legislation, advertising, social pressure, environment.
		I.ii.d If applicable, how is space included in the model?	The model has a gis-based component. And it is implicit.
		I.ii.e What are the temporal and spatial resolutions and extents of the model?	The time step is a quarter of yea. The spatial resolution is unit of meter.
	I.iii Process overview and scheduling	I.iii.a What entity does what, and in what order?	At the start of the model, all the scenario is set up with initial data. For each step, the agent takes a decision to adopt or not through the TPB and interacting with other agents and the environment. The UML Activity diagram can explain better the process and the UML Sequence diagram can explain better the time sequence.
II. Design Concepts	**II.i Theoretical and Empirical Background**	II.i.a Which general concepts, theories or hypotheses are underlying the model's design at the system level or at the level(s) of the submodel(s) (apart from the decision model)? What are the link to the complexity and the purpose of the model?	Theory of Planned Behaviour, Relative Agreement, Small-World Network, Threshold decision-making model, social clustering, GIS integration
		II.i.b On what assumptions is/are the agents' decision model(s) based?	Cognitive models such as TPB that integrates economical aspect and social aspect of the agents
		II.i.c Why is a/are certain decision model(s) chosen?	From the different frameworks present in literature, it has chosen the best for the purpose of the study, that permits to model the social influence and the interactions of the agent with others.
		II.i.d If the model / a submodel (e.g. the decision model) is based on empirical data, where does the data come from?	Istat statistics census sections, spatial data from Geoportale Torino, Istat social grouping data, load and production data from framework by Bottaccioli et al [29] , GSE, GME, IEA for resources and enviromental data.

		II.i.e At which level of aggregation was the data available?	The level of aggregation of data is household but also group level like residents (that they can make shared decision whether adopt or not).
	II.ii Individual Decision Making	II.ii.a What are the subjects and objects of decision-making? On which level of aggregation is decision-making modelled? Are multiple levels of decision making included?	The subject of decision-making is to choise whether adopt or not rooftop PV system by household or from group of households that live in Condominium, thus they adopt if the majority of the residents want to adopt.
		II.ii.b What is the basic rationality behind agents' decision-making in the model? Do agents pursue an explicit objective or have other success criteria?	The agent makes a decision through a behaviour intention made up of three principle elements: PBC, SN and ATT
		II.ii.c How do agents make their decisions?	Basically, is the weighted sum of the component described above in which of each of them is composed of functions.
		II.ii.d Do the agents adapt their behaviour to changing endogenous and exogenous state variables? And if yes, how?	The ATT changes based on opinions evolution due to interaction. The SN depends on the social influence so the change over time. The PBC changes based on the payback period calculation and on the income factor that is related to the already adopters in the system.
		II.ii.e Do social norms or cultural values play a role in the decision-making process?	Yes with SN that incluedes the innovativenees of the agent
		II.ii.f Do spatial aspects play a role in the decision process?	The location of an agent influence the outcome of his decision because it makes interactions in its social network and it is influenced by the surrounding
		II.ii.g Do temporal aspects play a role in the decision process?	The opinions evolve over time and can bring to a cluesting of opinions
		II.ii.h To which extent and how is uncertainty included in the agents' decision rules?	The uncertainty was inclueded by using the Relative Agreement algorithm
	II.iii Learning	II.iii.a Is individual learning included in the decision process? How do individuals change their decision rules over time as consequence of their experience?	No
		II.iii.b Is collective learning implemented in the model?	No
	II.iv Individual Sensing	II.iv.a What endogenous and exogenous state variables are individuals assumed to sense and consider in their decisions? Is the sensing process erroneous?	Many of endogenous and exogenous state variables are presents and derived from social groups or the census sections
		II.iv.b What state variables of which other individuals can an individual perceive? Is the sensing process erroneous?	Opinions and uncertainties

		II.iv.c What is the spatial scale of sensing?	Urban scale
		II.iv.d Are the mechanisms by which agents obtain information modelled explicitly, or are individuals simply assumed to know these variables?	Through networks in local way and with information given by the environment like the resources
		II.iv.e Are costs for cognition and costs for gathering information included in the model?	No
	II.v Individual Prediction	II.v.a Which data uses the agent to predict future conditions?	-
		II.v.b What internal models are agents assumed to use to estimate future conditions or consequences of their decisions?	TPB
		II.v.c Might agents are erroneous in the prediction process, and how is it implemented?	-
	II.vi Interaction	II.vi.an Are interactions among agents and entities assumed as direct or indirect?	Mediated by the environment
		II.vi.b On what do the interactions depend on?	Spatial distance and affinity with other agents
		II.vi.c If the interactions involve communication, how are such communications represented?	Relative Agreement
		II.vi.d If a coordination network exists, how does it affect the agent behaviour? Is the structure of the network imposed or emergent?	Is imposed by the application of Small World Network at the initialisation stage. It can evolve over time.
	II.vii Collectives	II.vii.a Do the individuals form or belong to aggregations that affect, and are affected by, the individuals? Are these aggregations imposed by the modeller or do they emerge during the simulation?	Human networks can emerge during the simulation and change over time
		II.vii.b How are collectives represented?	-
	II.viii Heteroge neity	II.viii.a Are the agents heterogeneous? If yes, which state variables and/or processes differ between the agents?	The model will be data-driven in initial step. Each agent have attributes coming from its social group which belonging

		II.viii.b Are the agents heterogeneous in their decision-making? If yes, which decision models or decision objects differ between the agents?	No
	II.ix Stochasticity	II.ix.a What processes (including initialization) are modelled by assuming they are random or partly random?	The opinions initialised as normal distribution and uncertainties initialised as function of opinions.
	II.x Observation	II.x.a What data are collected from the ABM for testing, understanding, and analyzing it, and how and when are they collected?	DataCollector used to extract all model and agents data
		II.x.b What key results, outputs or characteristics of the model are emerging from the individuals? (Emergence)	Emergent diffusion pattern
III. Details	**II.i Implementation Details**	III.i.a How has the model been implemented?	Python using Mesa library
		III.i.b Is the model accessible and if so where?	Private repository
	III.ii Initialisation	III.ii.a What is the initial state of the model world, i.e. at time t=0 of a simulation run?	-
		III.ii.b Is initialization always the same, or is it allowed to vary among simulations?	The adopters are the same.
		III.ii.c Are the initial values chosen arbitrarily or based on data?	Based on data
	III.iii Input Data	III.iii.a Does the model use input from external sources such as data files or other models to represent processes that change over time?	Data to sources provided from data files: agents' dataset, resources' dataset, parameters of the model.
	III.iv Submodels	III.iv.a What, in detail, are the submodels that represent the processes listed in 'Process overview and scheduling'?	Staged Random Activation
		III.iv.b What are the model parameters, their dimensions and reference values?	See Data Structure
		III.iv.c How were submodels designed or chosen, and how were they parameterized and then tested?	-

5.4. Model Data Structure

The model Data Structure (DS) helps to identify all the relevant variables and parameters of the entire model. The table below reports the DS. Per each data is given the following fields: the category in which the data is related and can be found; a brief description of its function; the name of the data used in the code; the type of data e.g. int, float, list, tuples etc.; the range of the data or the content if it is a list of objects; if the data represent a physical quantity, the unit of measure is given.

Table 5.4: Data Structure of the model.

Category	***Data description***	***Code name***	***Data Type***	***Range/Content***	***Unit***
Agents	State of adoption	adoption	binary	0 or 1	
Agents	Agent position	pos	tuple	(X,Y)	m
Agents	Agent type	TYPE	Binary string	'HH' or 'OTHERS'	
Agents	Agent Unique ID	unique_id	integer	[0,+inf)	
Agents	Area of active surface of rooftop PV (depending on scenario)	AREA_PV	float	[0,+inf)	m^2
Agents	Behaviour	b	float	[0,1]	
Agents	Behavioural Intention	bi	float	[0,1]	
Agents	Coefficient of Gini	GINI_COEFFICIENT	float	[0,1]	
Agents	Equivalent income	EQUIVALENT_INCOME	float	(0,+inf)	
Agents	Feasibility of PV system	feasibility	binary	0 or 1	
Agents	ID Building	ID_BUILDING	integer	[0,+inf)	
Agents	Income	INCOME	int	(0,+inf)	
Agents	Income factor	income_factor	float	[0,1]	
Agents	Innovation factor	INNOVATION FACTOR	float	[0,1]	
Agents	Internal Rate of Return	irr	float	[0,1]	
Agents	Investment PV	inv_pv	float	(0,+inf)	e
Agents	Level of Innovation	LEVEL_INNOVATION	integer	[1,5]	
Agents	Levelized Cost of Electricity	lcoe	float	[0,+inf)	€/kWh
Agents	Normalised Attitude	att_norm	float	[0,1]	
Agents	Number of household members	FAMILY_NUMBER	integer	[1,8]	
Agents	Opinion (or attitude)	att	float	[-1,1]	
Agents	Payback Period	payback_period	float	(0,21]	
Agents	Payback Period factor	pp_factor	float	[0,1]	
Agents	Perceived Behavioural Control	pbc	float	[0,1]	
Agents	Pmpp (depending on scenario)	p_mpp	int	[0,+inf)	kW
Agents	Pmpp using total PV area available	p_mpp_max	int	[0,+inf)	kW
Agents	Probability of a rent household	FOR_RENT	float	[0,1]	
Agents	Productivity of PV	productivity	float	[0,+inf)	kWh/y
Agents	PV area useful to cover early electricity consumption	area_pv_design	float	[0,+inf)	m^2

Agents	Self-consumption	self_cons	float	[0,1]	
Agents	Self-sufficiency	self_suff	float	[0,1]	kWh
Agents	Small World Networks	swn	list	[1 .. +inf) agents	
Agents	Social Group	SG	integer	[0,8]	
Agents	Social pressure	sp	float	[0,1]	
Agents	Socio-economic feasibility	socioeconofeasibility	binary	0 or 1	
Agents	Subjective Norm	sn	float	[0,1]	
Agents	Technical feasibility	techfeasibility	binary	0 or 1	
Agents	Type of PV tariff adopted	sol	string	'RID' or 'SSP'	
Agents	Uncertainty	unc	float	[0.1,2]	
Agents	Vote (depending on scenario)	vote	binary	0 or 1	
Agents	Weight of Attitude	W_ATT	float	[0,1]	
Agents	Weight of Income	W_INCOME	float	[0,1]	
Agents	Weight of Perceived Behavioural Control	W_PBC	float	[0,1]	
Agents	Weight of Subjective Norms	W_SN	float	[0,1]	
Agents	Yearly electricity consumption	EL_CONS	float	(0,+inf)	kWh
Model	Behavioural threshold	B_THRESHOLD	float	0.72	
Model	Coverage of Ad	COVERAGE_AD	float	0	
Model	Mean Income of Adopter	mean_income_adopters	float	(0,+inf)	
Model	Mean Italian household income	mean_hh_italy	integer	(0,+inf)	
Model	Mean of number of household members of Adopter	mean_family_num_adopt	float	(0,+inf)	
Model	Re-wiring parameter	RECONNECTION_PARAMETER	float	[0,1]	
Model	Number of interactions in the social network	INTERACTIONS	integer	2	
Model	Radius of neighbourhood	RADIUS	integer	50	m
Model	Relative Agreement speed convergence parameter	MU	float	0.05	
Model	Strenght of Ad	STRENGTH_AD	float	0	
Model	Weight of Behavioural Intention	W_BI	float	0.6	
Resources/Market	Corrispettivo Unitario di Scambio Forfettario	CU_SF	float	0.13	€/kWh
Resources/Market	Electricity price	ELECTRICITY_PRICE	float	0.28	€/kWh
Resources/Market	Electricity sell price	ELECTRICITY_SELL	float	0.04645	€/kWh
Resources/Market	Interest rate	INTEREST_RATE	float	0.06	
Resources/Market	IVA	IVA	float	0.1	
Resources/Market	Prezzo del Mercato del Giorno Prima	MGP	float	0.0535	€/kWh
Resources/Market	Prezzo Unico Nazionale	PUN	float	0.0535	€/kWh
Resources/Market	Tax reduction on investment cost in 10 years	TAX_REDUCTION	float	0.5	
Resources/PvSystems	Initial cost of PV system	cost	float	1550	€
Resources/PvSystems	Lifetime of PV	LIFETIME	int	20	y
Resources/PvSystems	Mean constant degradation ratio of pv	DEGRADATION_RATIO	float	0.01	
Resources/PvSystems	Mean constant reduction ratio by year of rooftop pv cost	COST_REDUCTION_RATIO	float	0.08	
Resources/PvSystems	Operation and Maintenance cost respect to investment	O_E_M	float	0.0125	
Resources/PvSystems	Performance Ratio	PR	float	0.85	
Resources/PvSystems	PV efficiency STC (reference m-Si)	EFFICIENCY_STC	float	0.17	

5.5. UML diagrams

UML Activity diagram

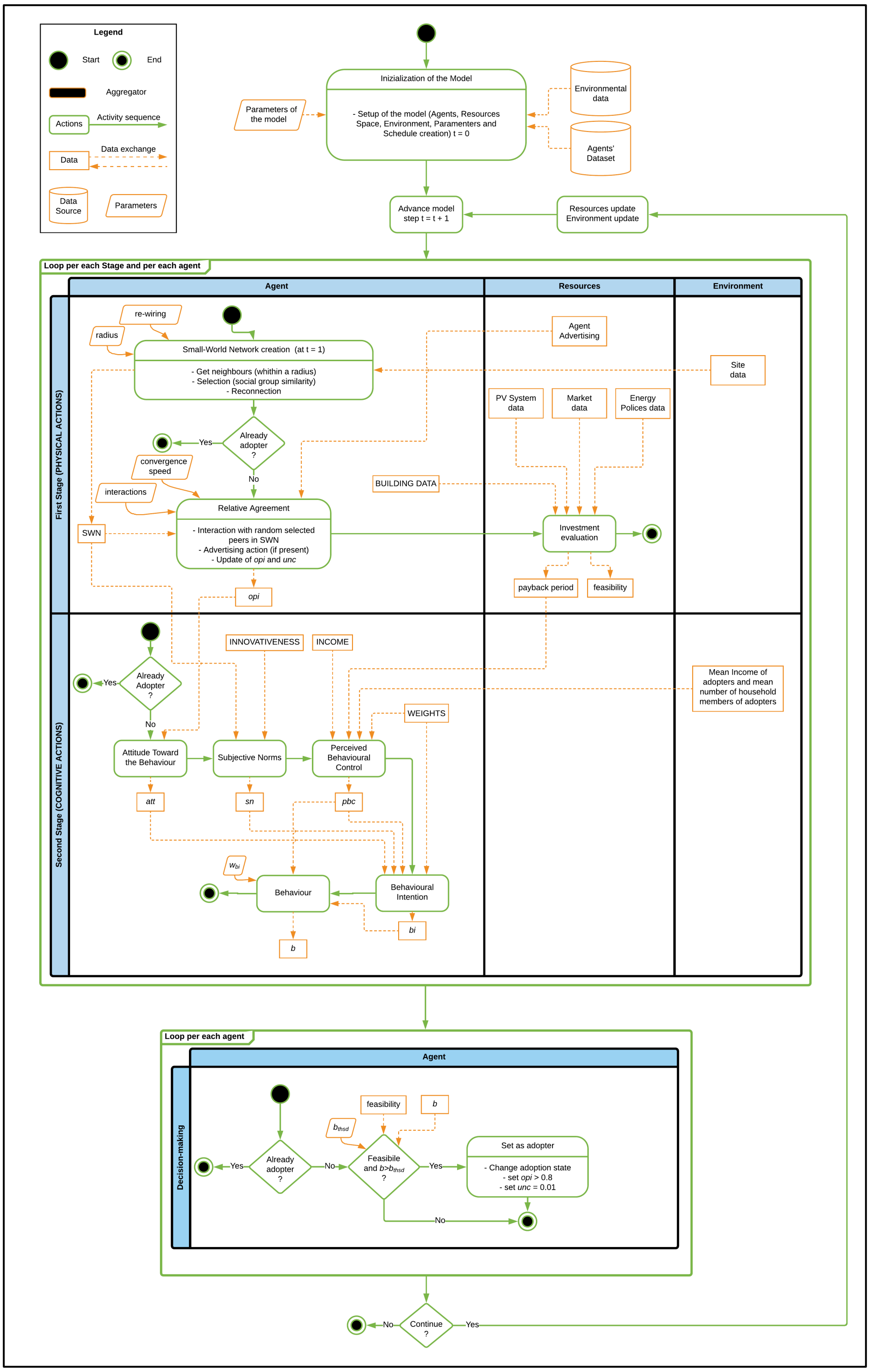


Figure 5.4: UML Activity diagram of the model, extended version showing data flows.

UML Sequence diagram

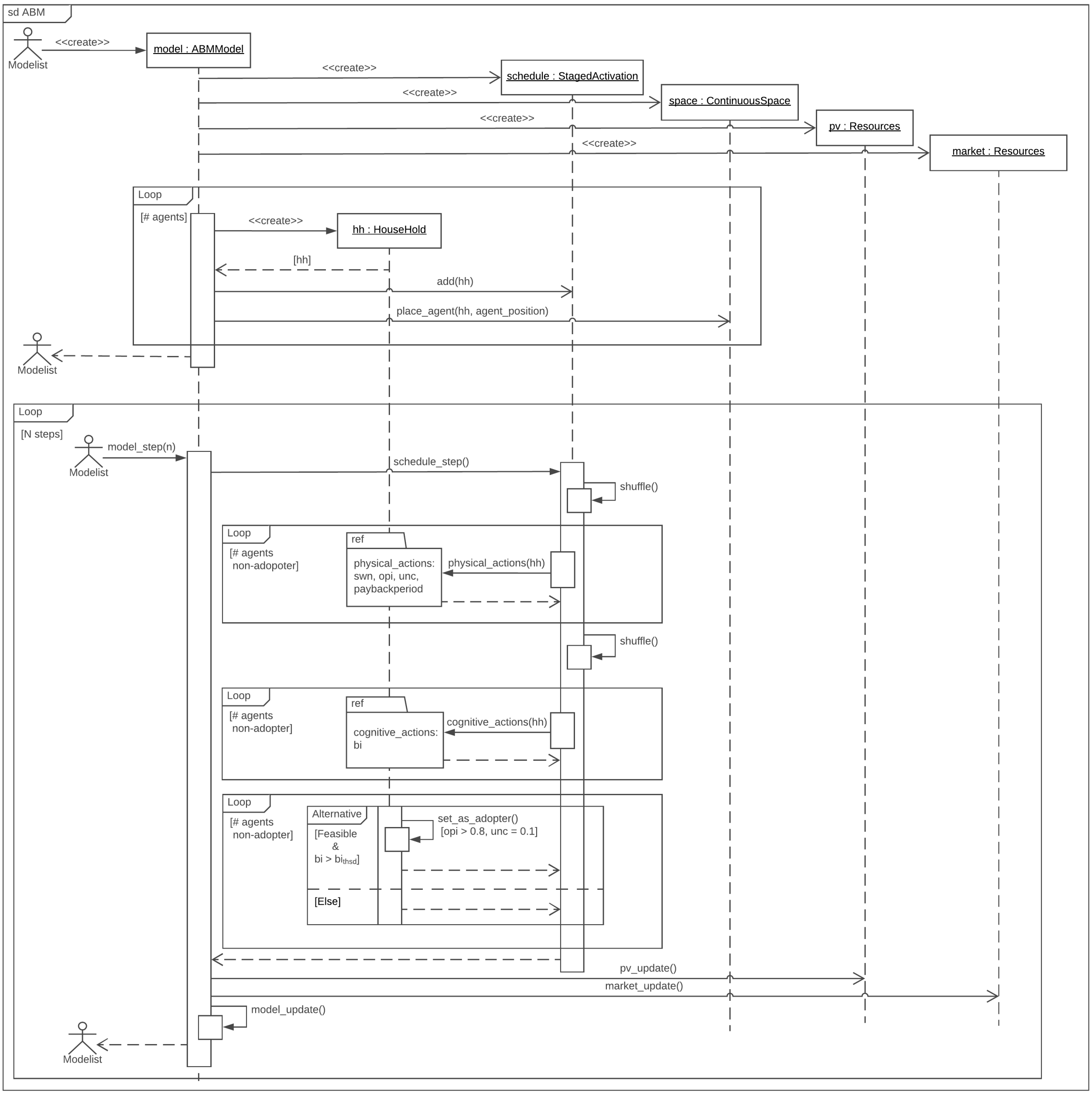


Figure 5.5: UML Sequence diagram. Part 1 – sd ABM.

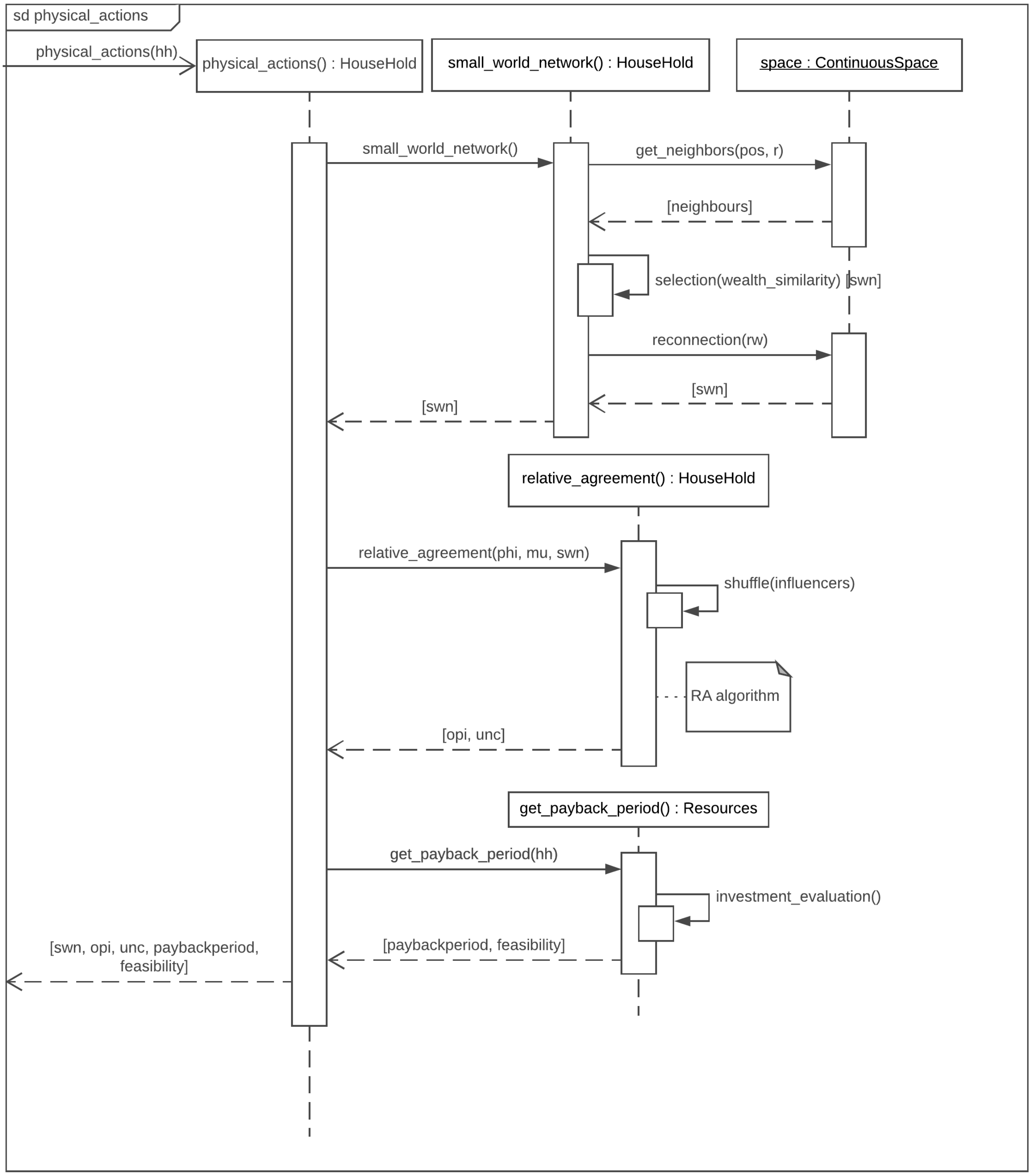


Figure 5.6: UML Sequence diagram. Part 2 – sd physical actions.

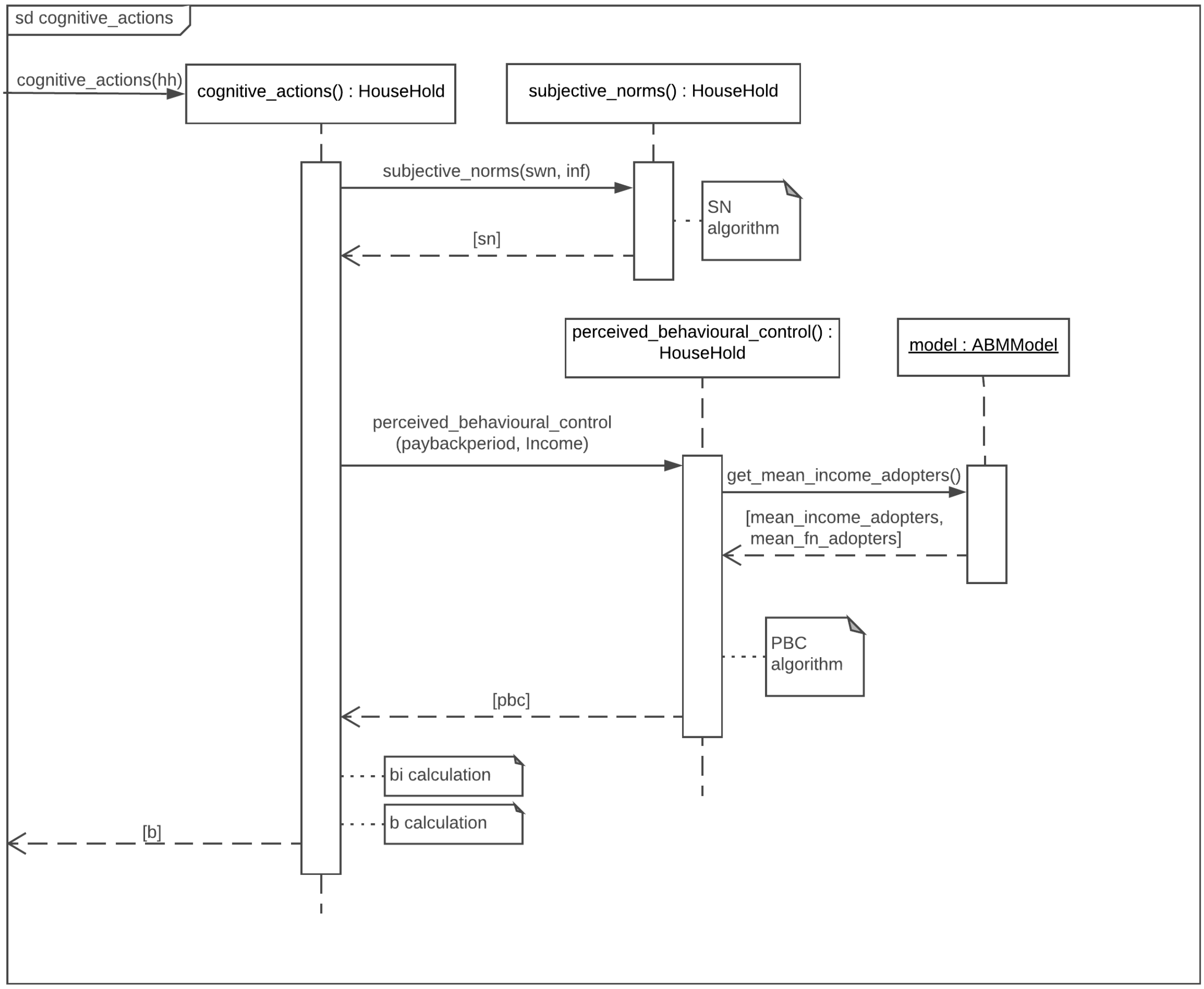


Figure 5.7: UML Sequence diagram. Part 3 – sd cognitive actions.

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