An Agent-Based Model (ABM) for the Evaluation of Energy Redevelopment Interventions at District Scale: An Application for the San Salvario Neighborhood in Turin (Italy)

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Abstract. The optimization of mobility connections, the use of renewable energy resources and the retrofit of buildings are only some of the aspects that affect urban transformations and planning. Decision maker and urban planners must be faced with multi-dimensional aspects and objectives in a long-term vision. In that context, different methods have been developed in order to consider these multi-dimensional perspectives. However, only a few approaches try to simulate the effects in a multi-temporal way. Agent-based model (ABM) try to do exactly this, considering, in particular, the interactions among agents through a bottom-up approach. Aim of this research is to apply an ABM to a real case study in the San Salvario neighborhood in Turin (Italy), simulating a complex socio-economic-architectural adaptive system to study the temporal diffusion of energy requalification operations and the willingness of inhabitants to adopt different retrofit actions. The two applications were, firstly, built on a computer grid environment and, then, integrated with GIS maps, in order to analyse the effects in the real distribution of buildings of San Salvario. Agents are designed to choose which system adopt, based on different theories of human behaviors. We discuss limitations of the current models and we suggest future directions of this research.

Keywords: Agent-based model · Energy · Geographic Information System (GIS)

1 Introduction

Nowadays, urban regeneration is a "universal question", a current problem and a crucial factor in new planning trends and it has become an integral part of new urban and housing policies [1]. Problems in the field of urban regeneration and planning concern normally multiple conflicting aspects and incommensurable elements, this requiring specific approaches for the analysis. In particular, sustainable neighbourhood

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policies require a territorial approach, the analysis of a large stock of buildings and the development of scenarios, that need a very large amount of data, of information and of a wide range of criteria. In this context, decision makers held appropriate tools to structure problems, to plan and evaluate alternatives in a multi-temporal, multi-objective and long-term perspective. The present paper investigates the use of integrated evaluation tools for supporting decision problems in the context of urban regeneration operations, focusing in particular on the application of Agent-based model and GIS tools. Geographical Information System (GIS) plays a key role here, because it is able to support decision-making processes by integrating different geospatial data and by producing results that simulate well the real spatial environment with their dynamics.

A real case study, the district of San Salvario in the city of Turin (Italy), is considered in the development of the evaluation.

2 Dynamic Models: A Brief Overview

About 30 years ago, new modelling approaches from different sources come onto the horizon, in order to integrate dynamic to the traditional model [2]. In particular, Cellular Automata (CA), Agent-Based Models (ABM), Systems Dynamics Models (SDM), Spatial Econometric Models (SEM) and Microsimulation Models (MM) all informed the debate [2]. Heppenstal et al. [2] provide a useful overview of the origin and development of this dynamic models, in particular, in their connection in the evolution of spatial models. Starting from this study, in this paper, we briefly describe in Table 1, the most used dynamic models, in order to underline strengths and weakness and to highlight the reasons why we adopted ABM for our simulations. In particular, we focus on the differences in their scale of using, in the construction of population and environment and in their execution and definition of time.

For the dynamic models' comparison, the parameters were defined based on our research question, i.e. the study of the diffusion of more sustainable energy production technologies and retrofit systems at district-scale. So, first of all, the scale and the time were relevant, since the aim was to test in a long-term perspective the effects emerging from the simulation at a specific level of detail, i.e. the district scale. Secondly, the environment parameter was investigated as our objective was to integrate the spatial dimension, in order to represent buildings, their characteristics and the population in a real geographic distribution. Furthermore, the analysis of technology diffusion and retrofit actions adoption in a real-environment requires a population characterized not by homogeneous groups, but by single agents with their own decision rules and specific characteristics distributed in a real space.

Based on this comparison, it is quite clear as agent-based model was chosen for our application. It represents a powerful methodology in decision making thanks to its ability to consider qualitative and subjective aspects together with real data in a multi-temporal and spatial dimension.

Table 1. Comparison between dynamic models in spatial context

Model	Scale	Environment	Population	Time
Agent-Based Models (ABM) (Multi Agent Systems (MAS)) [2]	Small scale (but large scale for land cover)	Environment contains agents (often more passive than population)	Hundreds of autonomous agents (detailed)	Flexible (both short and long intervals)
Cellular Automata (CA) [3]	Quite flexible (often small)	Two-dimensional mesh of finite cells Homogeneus	(environment replaces population)	Flexible
Land Use Transportation Interaction Models (LUTI) [2]	Large scale (aggregate and cross-sectional models)	(population replaces environment)	Location of activities and their interactions	Usually no temporal effects, only spatial (in general short-term dynamics)
Microsimulation Models (MM) [2]	Any scale (composed by individuals)	Large scale population	Population as distribution of characteristics (of a sample)	Flexible (both short and long intervals)
Systems Dynamic Models (SDM) [4]	Quite flexible	Entity flow and resource sharing, it is represented by "processes"	Equations capture decision rules. The focus is on "processes" not on "agents"	Flexible (both short and long intervals)
Spatial Econometric Models (SEM) [5]	Spatial scale varies with the time-scale	Spatial autoregressive structure	Population groups with dynamic relationships	Flexible (in general short-interval time)

2.1 Agent-Based Models (ABM)

Agent-based modeling (ABM) has become a widely used approach in many disciplines in the last 15 years [2], spanning physic, biology, ecology, social sciences, economy and geography [6, 7]. The increasing development of ABM goes in parallel with the study of complex systems, characterized by non-linear relationships between constantly changing entities [8]. These models seem to be particularly successful in these studies, mainly because they rely on the idea of effects and synergetic characteristics emerging from the analysis of subcomponent relationships [8]. In fact, ABM allows to study and verify the influence of decisions at the micro level which effects emerging at macro level [9].

Agents are the crucial component in this model. About them, there is no universal agreement among researchers about the precise definition of agent [6], beyond the essential property of autonomy [8]. The autonomy characteristic means that agents have control over their actions and internal state in order to achieve goals. Certainly, agents are individual objective-oriented entities, which interact with the others inside of a shared environment. This environment can provide only information about the spatial location of each agent, but also a rich set of information and data, which are available for the agent through a GIS integration [8].

The model is often described using the standard ODD protocol (Overview, Design Concepts and Details) [10] to facilitate the readability of the structure and to ensure the replicability of the model. The steps of this approach are the following: formulation of the question, formulation of the hypothesis, definition of the model structure, implementation of the model through software, analysis and revision [10].

Their "exploratory simulation" capability is fundamental in studying complex system. In fact, ABM can be used as a sort of virtual laboratory, where multiple simulation sessions occur varying inputs and changing parameters [11].

3 Materials and Method

3.1 Study Area Presentation and Objective

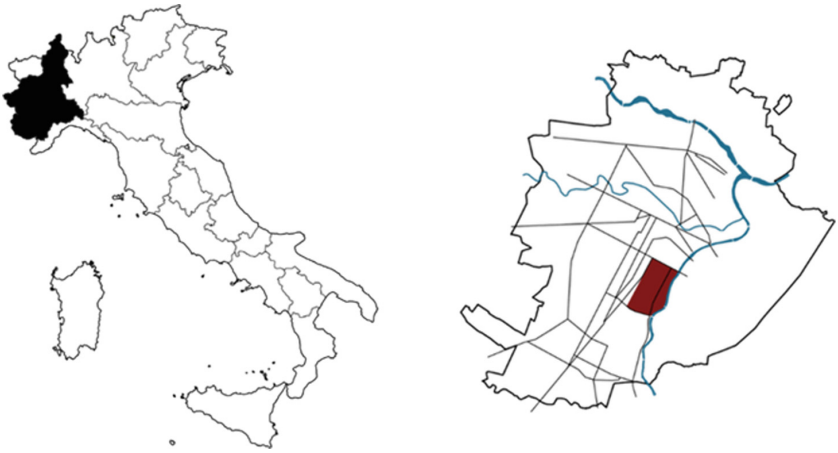

Fig. 1. Location of the area under investigation (San Salvario, Turin, Italy)

San Salvario is one of the 34 districts of the city of Turin (Italy) (Fig. 1). Not far from the city centre and the Porta Nuova railway station, this neighborhood is characterized by a multi-ethnical population, many leisure places and some relevant historical buildings, such as Castello del Valentino [12]. With a surface of about 2.2 km^2 and a diversified population of about 35.400 inhabitants (4% of the total population of the city) [13], it represents an interesting place to test ABM. In addition, the presence of not homogeneous building stock is an occasion to verify different energy savings actions of retrofitting and the diffusion of energy generation systems, in particular, PVs. In fact, ambitious objective, in the Energy Center mind [14], is to transform the San Salvario neighborhood in an exemplary eco-district for the city of Turin, in which experiment different policies and actions, that could be extended to the overall city.

Starting from this context, our research takes place. Through the development of an ABM, the model investigates the choices of individual agents with respect to an architectural and energy requalification at the district scale, considering social and economic aspects. These choices reflect rules and opinions that vary over time. People change their mind when faced with persuasive arguments and influenced by other agents' decisions [15]. The model tries to observe the dynamic trends and behaviors of the agent inhabitants by varying the attributes of agents and considering external factors, such as economic incentives. This happens in an environment in which agents' choices and actions influence the decisions of others after communication and interaction among them.

3.2 Stakeholders Analysis and Agents

As previously mentioned, one of the main characteristics of ABM are the agents. In order to understand in our case study, which actors are relevant, we started from a stakeholder analysis. In fact, as it is well know, urban transformation concerns and involves a large number of stakeholders, characterized by certain levels of power and interest, with respect to different objectives [16]. In our first analysis of the case study, we developed a power interest matrix (see [17]) to highlight mainly the differences among stakeholders. From that matrix, we clustered the stakeholders in four agent classes (Table 2).

Table 2. List of the San Salvario neighborhood stakeholders clustered in four agent classes

INHABITANTS	PUBLIC ADIMISTRATION
Homeowners	Municipality of Turin
Tenants	Metropolitan city of Turin
Surrounding inhabitants	Transport agency (GTT)
Future inhabitants	Politecnico di Torino and Università degli studi di Torino
Young people and students	Government department responsible for the environment and historical building
Neighborhood community	Environmental associations
Multi-etnical community	Water provider (SMAT)
Religious community	Municipal waste management company (AMIAT)
WORKERS AND ACTIVITIES	**PROVIDERS**
Owners of commercial activities	Photovoltaic panels providers
Owners of sports facilities	Energy provider (ENEL/IREN)
Restaurants owners	
Potential entrepreneurs	

The agents, as required by ABM, are heterogeneous autonomous entities [6] characterized by their own attributes and behaviors. They can interact with all the elements in the model, but, the real-world social networks tend to have non-random network structure with properties such as short average path length, excess clustering, and skewed degree distributions [18].

In these first applications, the most relevant agents are the neighborhood inhabitants, because they are directly involved in the transformation. In fact, based on their socio-economic status, they have the final say in the setting of retrofitting systems or the adoption of PVs. They are entities without specialised knowledge, with high interests and expectations, with limited economic resources and with low power to contrast a major intervention, but they are fundamental because without them the realization of the project is not feasible.

In the definition of the agents' objectives, economic and technical aspects were considered (such as investment costs, energy consumption, efficiency and reliability of installed systems, market price, lifetime of each technology, architectural quality).

However, also the municipality has a key role. It cannot act actively in the model, but through different incentives and policies can change the inhabitants' opinions, in particular, with respect to their economic possibilities.

3.3 Simulation Experiments

This section presents different simulation experiments. The first one investigates on the temporal diffusion of the photovoltaic system in the San Salvario neighborhood, whereas the second one tests the adoption of different retrofit systems. Both applications were implemented in NetLogo 6.0.4 [19], a free software based on an evolution of the programming language Logo [20]. It is a powerful data processing system with an intuitive interface, an effective graphic support and an ease of use, also in the code writing [19].

Application 1. The first experiment explores the temporal diffusion of PV microgeneration systems in the San Salvario district, simulating households' choices during a period of 50 years. Many factors influence these choices, such as households age and skills, family income, neighbourhood influence, incentives. The initial state of the model simulates the characteristics of the inhabitants and the environment of the San Salvario neighborhood, based on data obtained from Turin census (2011) [21], information provided by the municipality in their GIS maps [13] (see [17]) and different data from the literature [22–24].

Important parameters considered in the experiment are the percentage of San Salvario buildings equipped with a photovoltaic system and the percentage of homes connected to the national grid. Furthermore, the income is fundamental to identify if a household can or cannot install the PV.

At the beginning of the experiment, the households start to take their decisions. Those who have already had a PV, but its service life is over, can decide to buy another one or to connect to the national grid. On the contrary, those connected to the national grid can choose to install a PV, influenced by the neighbours' choices or by their eager to innovate.

The steps for the construction of this model are the following:

1. replication of the state of art, defining the characteristics of the agents and of the environment. We assumed that 80% of households are connected to the national grid;
2. definition of the current cost of PV and its variation over time (cost reduction trend);
3. consideration of the lifetime of PV. Every 20 years the PV must be substituted, and the households can decide to install another PV or not.

The conditions to install the PV are expressed by Eq. (1):

$$C_{PV} < C_{kWh} \tag{1}$$

where C_{kWh} is the cost of connection to the national electric grid and it is equal to 0.087 €/kWh according to the current Italian charges [25] and C_{PV} is the cost of the photovoltaic system, that considers also the amount of energy produced by the national grid and necessary to cover the total consumption of each households. This cost is given by Eq. (2):

$$C_{PV} = CC_{PV} + \%C_{kWh} \tag{2}$$

where CC_{PV} is the cost of all components of the PV (including operating and maintenance costs) and $\%C_{kWh}$ is a percentage of the costs to be paid to the national grid when the kWh produced by the PVs do not cover the total kWh used by each agent; kW_P (kilowatt-peak) takes into account the family's activity profile, energy demand and usage factor (including non-use rates and system losses) [26].

Many studies show as incentives and subsidies are largely responsible for the rapid growth of photovoltaic installations, emphasizing the importance of public administration in the diffusion of new technologies [27]. For that reason, we subtracted the value of the incentive from the total cost of the PV ($C_{PV-Total}$), as follow:

$$C_{PV-Total} = (CC_{PV} - S_{kWP}) * kW_P + \%C_{kWh} \tag{3}$$

where kW_P (kilowatt-peak) takes into account the available coverage area of the roof for the installation, the efficiency and the losses due to inclination and the environmental factors (at 0.8) and S_{kWP} is the value of incentive that increases, based on the annual kW_P produced for the lifetime of the PV. The diffusion of a new technology depends on its real advantages, its easiness of use and social acceptance. The latter is crucial for the diffusion of new technology and, in particular, for photovoltaic systems characterized by a visual impact. Neighbourhood influence by "early" adopters plays an important role in increasing future adoptions. Visibility (the photovoltaic installed on the roofs) and word of mouth lead to an increase of consumers in a certain radius. These parameters can be measured through two aspects: the detection radius (space of interaction) and the neighbourhood threshold (minimum percentage of neighbours within a detection radius that have already adopted the technology).

Households without PV develop firstly the idea of installing. In the application it has been assumed that this idea depends on the age and the skills of each household, on the level of innovation and on the influence of their neighbourhood. The idea of installing is verified by the following formula (4):

$$(F_{PV/RR}/F_{Total/RR}) * 100 > V_{RR} \tag{4}$$

where $F_{PV/RR}$ is the number of households with PVs in a certain radius RR, and $F_{Total/RR}$ is the total number of households within the same detection radius and V_{RR} it is the proximity threshold.

All the variables used in the aforementioned experiment and their relative numerical values are summarized in Table 3.

Table 3. Variables of Application 1

Variables name	Value	Unit of measure
CC_{PV}	2000	€/kW_P
PV lifetime	20	years
Coefficient of reduction	0.80	–
Energy cost	0.087	€/kWh
Discount rate	0.82	%
Incentives for kW_P	500	€/kW_P
RR	30	buildings
VRR	0.05	–
Energy requirements	30	kWh/m^2
PV production	1250	kWh/kW_P

The initial detection radius is based on the population distribution. Once the idea of installing is verified, the agent checks the economic availability and evaluates all the other economic parameters as explained before.

In order to simulate the behavior of agents, we applied two of the most widespread behavioral theories presented in literature: the theory of planned behavior (TPB) and the Belief-Desire-Intention (BDI) model. The first, proposed by Ajzen [28], states that three aspects (attitude toward behavior, subjective norms and perceived control) shape an individual's behavioral intentions and behaviors. This theory has recently been used in agent-based model to predict diffusions of innovation and adoption of solar plants [29]. The second model (BDI) combines a philosophical model on human practical reasoning, originally developed by Bratman [30], with an abstract logical semantic. The model has been very successful, despite the criticism regarding the low adaptability in describing some behaviors. Based on this model, every agent considers the advantages and disadvantages of alternative options, balancing beliefs, desires and intentions. Beliefs are the set of agent's information. These beliefs need not necessarily be true, they are just the agent's perception of the world with respect to their local view. Desires represent the agent's objectives, that can be multiple and conflicting. Intentions are the agent's commitment to achieving these goals [29].

Starting from these assumptions, two different behavioral models have been built in the present simulation.

Application 2. The second application concerns the temporal diffusion of different types of retrofit: double glazing, envelop insulation and HVAC (heating, ventilation, and air conditioning). As the previous application, also this one takes into account the complexity of a decision in which human actors interact with other ones in an environment with different information and external aspects, as policies and incentives. This model is more complicated than the previous one because the number of parameters and choices are higher. Also in this case, the initial state of the model simulates the characteristics of the state of art of the San Salvario neighborhood, based on data obtained from Turin census (2011) [21], information provided by the municipality in their GIS maps [13] (see [17]) and different data from the literature [23, 24, 31, 32].

In the first simulation, we investigated essentially on the diffusion of a single technology. Otherwise, here, the agents choose among different options. However, as the previous application, the diffusion of a specific technology is based on the social acceptance of the agents (i.e. on the influence of neighbours) and the agents' behaviors follow the Theory of Planned Behavior (TPB) and the Belief-Desire-Intention model (BDI). The aspects that influence agents' choices are both internal, as technical (e.g. energy consumption), economic (e.g. family income), social (e.g. neighbourhood influence, agents own characteristics) and external (municipal policies and incentives).

The first four parameters that affect the simulation are:

- the percentage of San Salvario inhabitants who have already carried out small retrofit operations in order to improve the performance of their dwellings;
- the percentage of inhabitants who did not carry out any intervention;
- the percentage of historic buildings protected by the government department responsible for the environment and historical buildings;
- the energy consumption of each dwelling.

Retrofit technologies are installed only if the family income is sufficient and if:

$$C_{glass/ins/sys} < C_{kWh} \tag{5}$$

where C_{kWh} is the cost of energy consumption per kWh at the initial state and $C_{glass/ins/sys}$ is the cost of the system adopted, given by:

$$C_{glass/ins/sys} = CC_{glass/ins/sys} + \%C_{kWh} \tag{6}$$

where $CC_{glass/ins/sys}$ is the cost of the raw material, the operating and maintenance costs and where $\%C_{kWh}$ is the cost referred to the energy consumption, reduced by a certain percentage based on the different technologies applied. The percentage of cost savings for the energy consumption of each technology results from the values of the Tabula project [33]. In this model, the $S_{\%}$ incentives are calculated in % of the total cost, they are equal to 65% or 50% [23, 34]. The total cost of the $C_{glass/ins/sys\text{-}Total}$ system is given by:

$$C_{glass/ins/sys-Total} = \left(CC_{glass/ins/sys} - S_{\%}\right) + \%C_{kWh} \tag{7}$$

The all variables and their relative values are summarized in Table 4.

Table 4. Variables of Application 2

Variables name	Value	Unit of measure
CC_{glass}	150	€/m^2
CC_{ins}	20	€/m^2
CC_{sys}	1.500	€/m^2
Glass lifetime	25	years
Insulating lifetime	25	years
HVAC lifetime	20	years
Energy cost	0.087	€/kWh
Discount rate	0.82	–
Incentives	50	%
RR	30	buildings

4 Results and Discussion

4.1 Application 1: Temporal Diffusion of PV Systems

1. The first model (Fig. 2) was developed without any integration with GIS environment. Consequently, the distribution of buildings and agents is based only on a regular grid without a real representation of the district.

In this model, a few semplifications have been assumed. Despite the simplifications, the model seems to be useful as it provides verifications on the possible trends emerging from different economic variations.

The agents (inhabitants of the San Salvario neighbourhood) are represented through a "home" shape, that highlight their fixed position, as they decide only for their property. In this experiment, the difference between turtles and patches are totally lost. In addition, the interactions among households of the same apartment buildings do not exist. The properties of each "home" are the result of an average of the attributes of each household that is part of the same apartment building.

This theoretical model shows the variation of trends caused by changes in economic variables, such as reduction of PV cost or increasing of incentives. In fact, after 50 years, the percentage of households that decide to install the photovoltaic (coloured in white) is 37,5% and those who already had a PV (coloured in yellow) are 18,5%. This growth is due to the continuous reduction in PV costs, the increase of neighbours with a PV and of awareness of the socio-economic benefits of PV.

As mentioned before, some parameters were defined *a priori* in the model. Therefore, particularly important is to test how the model changes based on the variations of these elements. By means of a sensitivity analysis, we varied the value of the neighborhood threshold (minimum percentage of neighbours within a detection radius that have already adopted the technology). Maintaining the same detection radius but increasing the number of households with a PV on their roofs (from 5% to 10%), the number of households that adopt a PV decrease. On the contrary, if the detection radius increases the new adopters of PV systems increase. Beyond the final results, these considerations highlight that the definition of these parameters are very important and

can change significantly the results of the experiment. At the same time, the development of this model can be very useful in order to test the effects of different types or levels of incentives (in this specific case, for the diffusion of PV systems).

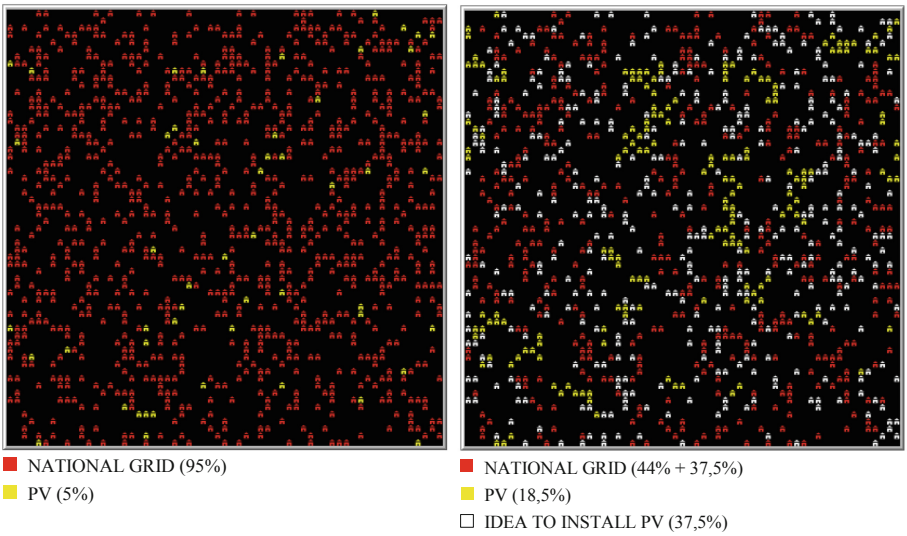

Fig. 2. Initial setting of the model (Application 1), in the year zero (left), and the situation after fifty years (right). (Color figure online)

2. *The second model* (Fig. 3) was developed in a more realistic environment, through the integration of GIS, with the location of the real shape of the buildings of the San Salvario neighborhood. The parameters (Table 3) and the influence model are the same described in Application 1. Compared to the first model, this experiment allows defining clearly and separately patches (buildings) and turtles (households) with their specific characteristics (year of construction, roof dimension, architectural quality, age, skills, number of households and so on). In fact, with respect to the previous simulation, the data and the characteristics are not defined random, but specific for each element of the system.

In addition, the dynamics of interactions among households of the same apartment buildings are presented here. In fact, the PVs can be applied only if a certain percentage of households of the same apartment building agrees in the PV installation. The results of the simulation are shown in Fig. 3 where the buildings with a grey contour are those in which the PV has been applied. In the other buildings, the percentage of households agree are not sufficient for the adoption of this technology.

In this integrated model, different changes in the parameters' values were also tested to verify the possible variations of the results. The most interesting one for this application is related to the minimum percentage of households who must agree on the installation of PV.

Due to the difficulties in the integration of GIS data at this scale of representation, we developed the model in a very small portion of the San Salvario neighborhood. Future applications will go deep on this investigation.

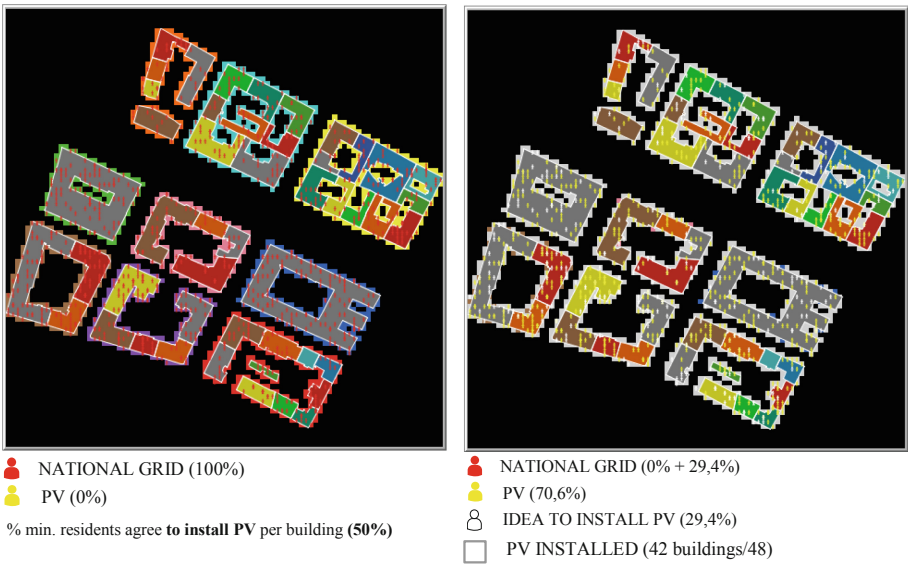

Fig. 3. Initial setting of the model (Application 1_with GIS), in the year zero (left), and the situation after fifty years (right).

4.2 Application 2: Temporal Diffusion of Retrofit Technologies

For this application, only one model was developed (Fig. 4) without any integration of GIS.

The strong increase of retrofit actions from year 0 to 50 is due to many factors, including the decline in the costs of the systems, but, in particular, for the neighbours' influence and for the increasing awareness on the socio-economic benefits of these actions.

As, the previous application, the advantages and disadvantages are quite the same. Certainly, the most relevant aspect of this model is its ability to highlight the reasons that affect mostly the agents' choices, in particular, with respect to the diffusion of information and incentives. However, the quite limited data and the lack of integration with GIS give us only a partial view of the real dynamics of these choices.

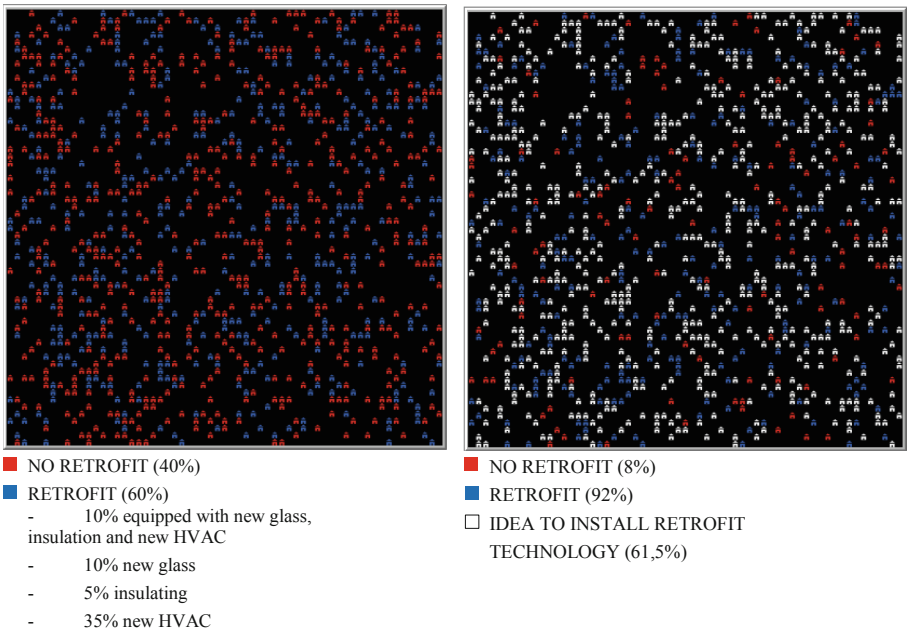

Fig. 4. Initial setting of the model (Application 2), in the year zero (left), and the situation after fifty years (right).

5 Conclusion and Future Insights

Agent-based model is an alternative approach to design heterogeneous agents with different behaviors and to simulate complex interactions among them (non-linear, discontinuous and discrete) [35]. ABM leaves the static nature of most evaluation approaches, in order to analyse different outcomes and effects emerging at different times (hours, days, months, years) [2]. In this way, the model can realistically simulate urban developments or geographical phenomena [2]. The approach offers an opportunity to study and test social theories which can not be easily described using mathematical formulas and this in a well-defined environment, from buildings to entire cities [2].

This paper explores the choices of individual agents with respect to an architectural and energy requalification at the district scale, in particular, investigating on the temporal diffusion of the photovoltaic system (PV) and the willingness of inhabitants to adopt different retrofit actions.

These experiments demonstrate how ABM can serve as a virtual laboratory that contributes to scientific and policy debates on energy requalification of buildings at urban scale. However, as any other approach that tries to analyse a complex system has some limits and their outputs must be interpreted with caution. In fact, the aim of these first applications is not to give quantitative and accurate forecastings of these

phenomena or a solution for policies. Instead, these experiments let to understand which factors affect these energetic and retrofit actions.

The own nature of the modelling system, based on human agents with different and contrasting behaviors and aims, subjective choices and specific characteristics, is very promising, but also not easy to build. Some aspects are difficult to quantify, calibrate and the quality of the inputs data determine significantly the outputs obtained. Therefore, the way of using the results can be also different, as to formulate quantitative forecasts or only qualitative trends. For that reason, it becomes necessary to develop robustness and sensitivity analysis in order to verify the accuracy of the model developed and the elements that vary significantly the outputs.

Future implementations of these experiments will concern exactly the development of these robustness analyses and the collection of more structured data and information about the San Salvario inhabitants through surveys and workshops. This latter is particularly important in order to reduce uncertainties and hypotheses and to recreate a more precise representation of the state of the art from which developing the predictive model.

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