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Analysis of Rooftop Photovoltaics Diffusion in Energy Community Buildings by a Novel GIS- and Agent-Based Modeling Co-Simulation Platform

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ABSTRACT The present work introduces an empirically ground agent-based modeling (ABM) framework to assess the spatial and temporal diffusion of rooftop photovoltaic (PV) systems on existing buildings of a city district. The overall ABM framework takes into account social, technical, environmental, and economic aspects to evaluate the diffusion of PV technology in the urban context. A city district that includes 18 720 households distributed over 1 290 building blocks and a surface area of 2.47 km2 is used to test the proposed ABM framework. Results show how the underlying regulatory framework (i.e., the rules of the internal electricity market) influences the pattern and intensity of adoption, thus realizing different shares of the available potential. Policies that support the establishment of 'prosumers' within Condominiums (i.e., energy community buildings), and not in single-family houses only, is key to yield high diffusion rates. The installed capacity increases by 80% by switching from the *one-to-one configuration* to the *one-to-many* paradigm, i.e., from 5.90 MW of rooftop PV installed on single-family households and/or single PV owners to 10.64 MW in energy community buildings. Moreover, the possibility to spread the auto-generated solar electricity over the load profile of the entire population of Condominium results in self-consumption rates greater than 50% and self-sufficiency ratios above 20% for the majority of the simulated buildings.

INDEX TERMS Agent-based modeling, complex adaptive systems, consumer behavior, distributed power generation, energy technology diffusion, geospatial analysis, photovoltaic systems, public policy, sustainable development, technology adoption, urban areas.

NOMENCLATURE

A. ACRONYMS

1to1	One-to-One configuration
1toM	One-to-Many configuration
ABM	Agent-Based Model
API	Application Programming Interface
CAPEX	CAPital EXpenditure
CEC	Citizen Energy Communities
CH	Clerks' households
EA	Early Adopters
EBM	Equation-Based Model
EM	Early Majority adopters
EU	European Union
GIS	Geographic Information System
HH	Household
IA	Innovator Adopters
JSc	Jointly acting renewable Self-consumers
LA	Late Majority adopters
LF	Low-income households with Foreigners
LG	Laggard adopters
LI	Low-income Italian
LY	Lonely old ladies and Young unemployed
OPEX	OPerating EXpenses
PV	Photovoltaics
RA	Relative Agreement
RB	Retired Blue-collars
RC	Ruling Class
RED	Renewable Energy Directive
RES	Renewable Energy Sources

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REST	Representational State Transfer
RSc	Renewable Self-consumers
SP	Silver Pensioners
TP	Traditional Provincial
TPB	Theory of Planned Behavior
TUS	Time Use Survey
YB	Young Blue-collars

B. CONSTANTS & PARAMETERS

μ	Convergence speed of opinion dynamics
ϕ	Number of interactions
b_{thsd}	Behavioral threshold
$GINI_{k\,i}$	Gini coefficient of the social group k to which the agent i belongs
$INC_{k\,i}$	Income level of the social group k to which the agent i belongs (€)
INC_{NAT}	National mean income of households (€)
$INN_{k\,i}$	Innovation factor of the social group k to which agent i belongs
$N_{k\,i}^{min}$, $N_{k\,i}^{mean}$, $N_{k\,i}^{max}$	Minimum, mean and maximum number of family members of the social group k to which the agent i belongs
rw	Re-wiring of network
w_{bi}, $W_{pbc'}$	Final Behavior weight factors
pbc	Perceived Behavioral Control
W_{sp}, W_{inn}	Subjective Norms weight factors
$WACC$	Weighted Average Cost of Capital
r	Radius of neighborhood
$W_{att,\,k\,i}$, $W_{sn,\,k\,i}$, $W_{pbc,\,k\,i}$	Behavioral Intention weight factors of the social group k to which the agent i belongs

C. VARIABLES & SYMBOLS

$\mathcal{T}$(min, mode, max)	Triangular distribution (min, mode, max)
att	Attitude Toward Behavior
bi	Behavioral Intention
b	Final Behavior
if	Income factor
INC_i	Income level of the agent i (€)
inc_{ad}	Average income of adopters
n_{ad}	Average family size of adopters
npv	Net Present Value (€)
opi	Opinion
$W_{pf\,,\,k\,i}$, $W_{if\,,\,k\,i}$	Perceived Behavioral Control weight factors of the social group k to which the agent i belongs
pf	Payback Period Factor
sn	Subjective Norm
sp	Social pressure
unc	Uncertanty on opinion
w_{ij}	Strength of the influence of agent j on agent i
I	Investment cost (€)
i , j	i-th or j-th agent
k	k-th social group
$\mathcal{LN}(\mu, \sigma)$	Log-normal distribution (mean, standard deviation)
N_i	Family size of agent i
pp	Payback period (years)
$R(y)$	Net cash flow at time y (€)
t	Simulation time-step
X_i	A random variable assigned to agent i
y	Time referred to the year of investment

I. INTRODUCTION

Nowadays more than half of the overall world's population is living in urban areas. Projections state that by 2030, urban areas will host around 68% of people globally and one-third of the population will live in cities with at least half a million inhabitants [1]. Urbanizations are largely energy-intensive as reported by the United Nation habitat division. Cities consume about 75% of the global primary energy supply and are responsible for about 50-60% of the world's total greenhouse gases [2]. Moreover, the majority of the consumed energy is still supplied by fossil fuels (coal, oil and gas).

To engage these issues, the European Union (EU) launched in 2016 the Clean Energy Package [3] for all the Europeans, which is revolutionizing the entire energy system. The ambition of the European energy strategy is to decarbonize the Energy Union energy mix in order to reduce the greenhouse gases emissions (pursuing the Paris agreement) and to increase its energy autarchy. The new EU Renewable Energy Directive (RED II) set an ambitious target for 2030 of 32% share of renewable energy in the energy mix and a −40% of greenhouse gases emissions respect to the 1990 levels [4]. In this regard, the electrification of the final uses is the chosen driver for the penetration of distributed renewable energy sources (RES). A smart citizen-centric energy system is at the center of the energy transition in Europe and worldwide [5], with citizen-prosumer empowered to participate to the energy market in the role of *renewable self-consumers* (RSc), *jointly acting renewable self-consumers* (JSc) or *citizen energy communities* (CEC) [6].

Among RES, solar energy is the most distributed and accessible, even though is not entirely suitable for the residential segments a having low level of energy demand that result in low self-consumption rates and/or high export rates to the grid of the self-generated electricity. Therefore, the aggregation of the energy demand and production through JSc or CEC might succeed in increasing the overall self-consumption and self-sufficiency of prosumers, giving a new boost to the photovoltaic penetration in the residential sector. On the one side, digital and energy technology combined together will provide a framework for a more intelligent and sustainable final use of energy in buildings and cities. On the other side, citizens will need to understand how to interact with smart energy systems and local energy markets. Indeed, new complex socio-techno-economic interactions will take place.

Given this emerging panorama, a better understanding on the dynamics of energy technology diffusion among potential adopters is crucial, as well as the impact that regulation and policy might have on diffusion patterns and penetration levels at the single citizen/household level.

Technology diffusion has been studied in the past decades relying both on theoretical as well as empirical approaches [7]–[9]. In particular, understanding how to support the diffusion of energy technologies in the cities of the future is key to enhance a shift towards more sustainable communities. The integration and interconnection of new energy technologies in the urban fabric is an important aspect to be taken into account, as well as consumer's choices, socio-demographic factors end environmental constraints. To push the diffusion of rooftop photovoltaics (PV) systems in relatively densely populated urban areas having mostly condominiums, it is fundamental to know which are the factors affecting technology adoption more than just supporting schemes. In fact, it is well-known from the literature that the adoption of energy technology depends on not only technical-economical aspects but also on socio-demographic factors, typology and topology of the social structures, time-frame of the diffusion and the high heterogeneity of the system [10]–[15]. Therefore, it is necessary to model the real world as a Complex Adaptive System [16], including all the relevant aspects of the phenomenon under study. To accomplish those goals, city energy planning requires new methodologies with a multi-perspective and holistic approach to describe spatio-temporal dynamics.

In recent years, Agent-Based Modeling (ABM) has been widely used in the energy sector to study both prosumer behavior and technology diffusion [17]–[20]. ABM allows explaining the complexities of social behavior and social interactions on the level of individuals thanks to the increasingly easy access to fine-grained data. Some examples include the study of Eppestein *et al.* [21] developed an agent-based model of plug-in hybrid electric vehicles' adoption incorporating extensive consumer survey data. Dehghanpour *et al.* [22] studied the behavior of the day-ahead retail electrical energy market with price-based demand response through a multiagent framework. Guo and Yin [23] analyzed the effect of mass media on promoting solar energy diffusion in residential sector using the AB approach. Nunna *et al.* [24] proposed an ABM to model smart microgrids with market price sensitive consumers operating demand-side management strategies.

To investigate the success of the new EU policies on energy, we developed a tool that is intended to help decision-makers in exploring decarbonization scenarios at the urban scale. As a case study, we selected a district of the city of Torino (Italy) because it is one of the Italian cities with the higher number of citizens living in condominiums and where the PV penetration is just 0.7%,[1] which is below the national average. If we consider that in the 2018 26% of the Italian population lives in 4 cities with an average of 22 citizens for each building, it is clear the importance of condominium as the entity where citizen aggregation can spread and drive the penetration of RES. In Italy, the actual installed PV power in the residential sector is 3 GW (in 2018), i.e. 15% of the whole installed RES power (19.6 GW), which sets the value of PV penetration at the 1,5% of the potential of about 200 GW of rooftop available on houses and condominium as recently calculated by [27].

The objective of this work is to assess how the regulatory framework affects the adoption rate of rooftop PV in a city district. We analyze the impact of switching from the self-consumer paradigm (i.e., a *one-to-one configuration* in which a single entity benefits from the electricity generated by the installed PV) to a jointly acting renewable self-consumers JSc that is a first embryo of a citizen energy community CEC (i.e., a *one-to-many configuration* in which a plurality of entities benefits from the generated electricity by a single shared installation). To do this, we develop a novel GIS-ABM integrated into a co-simulation platform that enables the integration of third-party data sources and simulators in the simulation process. The quantitative assessment is supported both by the use of fine-grained spatio-temporal data with high resolution and granularity up to the single building, as well as social clustering to enhance the agents' heterogeneity and their spatial characterization. Finally, in the agent decision-making process, we have implemented the Theory of Planned Behavior (TPB) [28] and Relative Agreement (RA) [29]. The proposed co-simulation framework is both scalable and replicable to any urban area for which the relevant city-level data sets are available.

This manuscript first introduces the fundamental theories that constitute the background of the proposed ABM modeling framework in Section II. Section III describes the main differences between non-ABM and ABM approaches to model energy technology diffusion. Within this same section, a detailed comparison of our work with previously published papers dealing with PV diffusion is provided in order to better identify the gaps that we state to fill with the present work. Section IV presents the overall structure of the developed agent-based co-simulation platform, the data sources that we used to feed the model and we describe the rules or equations of every single unit that makes the ABM framework. In Section V, the above-mentioned case study, the overall model setup, policy scenarios, and simulation results are presented. Section VI presents spatially and temporally rich simulation results on rooftop PV diffusion in the urban context under two regulatory schemes. Finally, Section VII brings the conclusions of the article and highlights the strengths and weaknesses of the present framework.

II. THEORETICAL BACKGROUND

A growing area in ABM applications is the modeling of consumer energy choices [11], [18], [30]. First, ABM facilitates the modeling of agent heterogeneity, where the agents are

[1] Calculated using the 2018 data of the installed power from [25] and the PV potential estimated by [26].

the autonomous and proactive decision-making entities of the model [31]. Second, it enables the modeling of agents' interactions with multiple and diverse stakeholders as well as the influence mediated by social networks. Lastly, the integration of ABM with Geographical Information Systems (GIS) enables the possibility to spatially describe the system and ground the results to a real context. Moreover, the intrinsic feature of ABM of describing system heterogeneity is used to model explicitly how individuals affect one another in cognitive and psychological terms, like opinions, attitudes, and norms [7]. The common way used in ABMs to address human behavior and decision-making logic of agents is based on multi-criteria utility function, i.e., a weighted sum of utilities that act like a "desire level" toward the behavior. Another way is to apply human behavioral theories, e.g., the Theory of Planned Behavior (TPB) [28]. It is widely used in social sciences and also for modeling consumer's behavior in application with diffusion models [32]–[35]. Regarding the communications and influence among agents, they interact within the social networks, usually made by selecting some families within the neighborhood or fixing the number of random links. As more complex alternatives, but more realistic, is to use the Small-World theory [36] to define the social networks and generate opinions considering their dynamic and evolution over time [37].

This section introduces the fundamental theories used in the proposed agent-based modeling and simulation framework: Theory of Planned Behavior, Relative Agreement and Small-World Network theory.

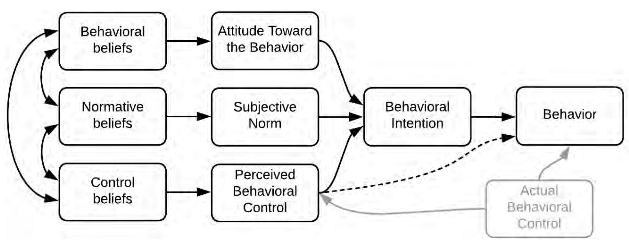


FIGURE 1. **Components of the Theory of Planned Behavior. Adapted from [28].**

A. THEORY OF PLANNED BEHAVIOR

The Theory of Planned Behavior (TPB) developed by Ajzen [28], [38] provides a theoretical framework to understand and predict human behavior as outlined in Fig. 1. According to the theory, human behavior can be described by three mainly attributes: Attitude Toward the Behavior (*att*); Subjective Norm (*sn*) and Perceived Behavioral Control (*pbc*). These attributes lead to the formation of a Behavioral Intention (*bi*) that is an indicator of a person's readiness to take action, thus it is assumed to be the immediate antecedent of the final Behavior (*b*). As a general rule, the higher is *b* and stronger is the engagement of the person in taking action.

The Behavioral Intention (*bi*) is formulated as

$$bi = att \cdot W_{att} + sn \cdot W_{sn} + pbc \cdot W_{pbc}, \tag{1}$$

where W_{att}, W_{sn}, and W_{pbc} are the attribute's weights defined for each person.

The behavior's attributes are deduced by the individual's beliefs and it is assumed that human behavior is guided by three kinds of beliefs: *i) behavioral beliefs*, *ii) normative beliefs* and *iii) control beliefs*. Human's beliefs are affected by many factors such as personal background (personality, emotions, education, economic status), demographic factors (age, gender), social network (role, social norm, social group) and info-sphere (knowledge, media).

i) Behavioral beliefs are the personal conviction for the outcome of the behavior. The more objective behavioral beliefs are combined with subjective evaluations to generate a favorable or unfavorable *Attitude Toward the Behavior* (*att*).

ii) Normative beliefs represent the general influence of others (people or community) on individual behavior. As an individual is influenced by those people or groups that are important to them, e.g. family, friends, state or government. It considers the people's expectations, i.e. the normative beliefs, and the agent's motivations to comply wiht them, which constitute the perceived social pressure or *Subjective Norm* (*sn*).

iii) Control beliefs are the personal conviction for the presence of hindrances to the behavior, which can be actual or just perceived. The strength of real obstacles or physical constraints are the control beliefs that are combined with their perceived power generating the *Perceived Behavioral Control* (*pbc*).

Theoretically, the final *Behavior* (*b*) is generated by the *Actual behavioral Control* (i.e. the control at the time of taking action) and Behavioral Intention (*bi*). Nevertheless, since the *Actual Behavioral Control* is difficult to evaluate, the *pbc* is normally used as its estimator. Therefore, *pbc* and *bi* predict the Behavior (*b*), as follows:

$$b = bi \cdot W_{bi} + pbc \cdot W_{pbc'}, \tag{2}$$

where W_{bi} and $W_{pbc'}$ are empirically derived coefficients.

B. RELATIVE AGREEMENT

The Relative Agreement (RA) algorithm was developed by Deffuant and allows to model the agent's opinion dynamics [37], [39]. The RA imitate the evolution mechanism of opinions, and uncertainties, in consequence of people interaction.

The opinion of an agent is the middle point *opi* of a segment long $2 * unc$, representing the agent's uncertainty, as shown in Fig. 2. The interaction between the agents *i* and *j*, where *i* influences *j*, determines the opinion overlap h_{ij}. Therefore, the agent *j* is influenced only if the interacting agents share a similar opinion. Then, the *agreement* between the agent *j* and its influencer *i* is calculated by the difference between the segment h_{ij} and the not overlapped section of the segment *i*.

Finally, the agents *relative agreement* is the range of opinion *i* that an agent *j* is willing to take into account, calculated as the *agreement* divided by the agent *i* uncertainty $2 * unc_i$. Therefore, when the overlap h_{ij} is greater than unc_i, the agent *j*

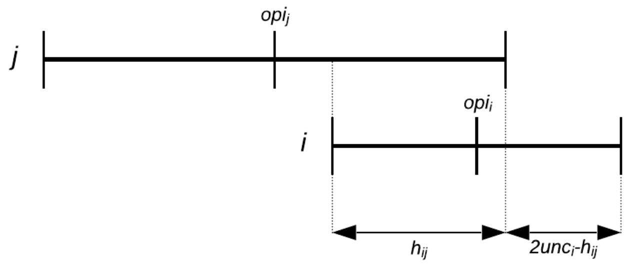


FIGURE 2. Schematic representation of the opinion intervals of agents *i* and *j*. Adapted from [37].

opinion, and its uncertainty are increased or decreased by the amount of the *relative agreement* through the constant parameter μ that controls the speed of convergence in the opinion dynamics. If h_{ij} is minor than unc_i there is no influence of i on j.

C. SMALL-WORLD NETWORK THEORY

The small-world network (SWN) theory is commonly used to describe the social networks structures of the agents [36]. Empirically, the connections between agents are mainly local, i.e. geographically neighbor. While the connection with the other agents is non-local.

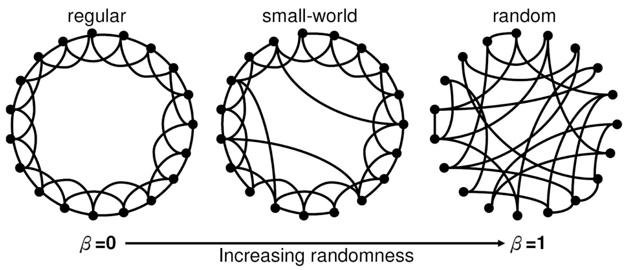


FIGURE 3. An example of increasing of randomness in the network. Adapted from [36].

Therefore, SWN lies between two extreme connection topology: wholly regular or completely random (see Fig. 3). For example, a SWN is generated starting from a regular network of n vertices, which is rewired, by means of random connection, in order to introduce a degree of disorder β. Thus, the randomness increases with the increase of β.

A network is defined as Small-World when the clustering (C) of the n agents is not small and, considering a broad interval of β, the path length (L) grows logarithmically with n. Where L represents the average of the number of connection interposed between two agents, and the clustering C is a measure of the number of connections in the agent's neighbor.

III. LITERATURE REVIEW

This section provides a literature review of diffusion models for energy technology with a focus on PV and rooftop PV diffusion. The increasing deployment of new distributed generation technologies, such as residential PV systems, is changing the functioning of the energy system and the planning of energy infrastructures. In order to promote effective energy policies and interventions, it is necessary to develop new models for looking into transition pathways that take into account social, technical and environmental aspects.

Zhang and Vorobeychik [17] and Moglia *et al.* [18] revised diffusion modeling techniques by comparing traditional equation-based models (EBM) with agent-based ones (ABM). They identified several limitations of the EBMs, despite the efforts of some authors to highly refine this class of models. One of the main issues of EBMs is their limited ability to capture explicit social behavior, geospatial interactions, and non-linear relationships among different individuals. Moreover, EBMs are intrinsically not able to catch the specific behavior of a single individual and thus who makes decisions, why and where. Therefore, the authors argued that EBM are able to predict the aggregate behavior of a population, but they are not effective in the evaluation of complex systems at the individual scale. On the other hand, ABMs seems to be a promising architecture that allows for detail and realistic description of a complex system, including the behavior of agents, their social interactions and the physical and techno-economic environments surrounding them [40].

A. NON-ABM APPROACHES

The modeling of innovation diffusion is a research topic that has been widely studied in the literature. The theoretical foundations of the diffusion process of technology were laid down by Rogers [10] under his framework of *diffusion of innovations*. Starting from this theory, quantitative approaches have been developed, such as EBM. An example is the Bass model [41], [42], which defines the diffusion process through a differential equation by using empirical coefficients. With respect to PV modeling diffusion, the Bass model and its extensions have been recently applied in county and cross-country levels. Kurdgelashvili *et al.* [43] examined the PV market diffusion for 46 counties in California. They used regression analysis to find relationships between several socio-economic factors with the diffusion parameters of a Generalized Bass Model. As the same way using this type of model, Duan *et al.* [44] proposed a framework, which aims to capture cross-national diffusion interaction of PV systems analyzing different types of learning relationships and potential interactive dissemination relationships.

Other approaches have been undertaken using different kind of EBMs. For instance, Selvakkumaran and Ahlgren [45] exploit a System Dynamics model to study the economic, social and political interactions among the citizen and municipalities of Skåne County, Sweden to promote the local energy transitions with a focus on adoption of residential PV systems. Alternatively, Spatial Econometric analysis is able to deal with spatial interdependency of areal attributes and neighbor effects. Kosugi *et al.* [46] applied the spatial econometric framework based on the census-block level in Kyoto City to study the neighborhood effects on the residential PV diffusion. Meanwhile, Dharshing [47] used spatial modeling techniques to determine the impact of regional spillover effects between neighboring counties in Germany and their effect on spatial clustering of PV systems. Another EBM approach was proposed by Candas *et al.* [48], which applied the framework of sociodynamics to the adoption of small-scale PV in Germany and Italy.

Finally, considering methods slightly oriented towards agent-based approach, Cellular Automation requires a grid lattice to make decisions based on neighborhoods of some sort, so even a square or hexagonal lattice. For instance, Zhou *et al.* [49] and Zhao *et al.* [50] developed a data-driven forecasting approach of PV diffusion in Pudong district of Shanghai, China by using a Cellular Automation model based on artificial neural network, where the study region was divided into square cells.

B. ABM APPROACHES

Recently, ABMs have been applied to model the diffusion of innovations. For an extensive review of this research topic, we refer readers to Zhang and Vorobeychik [17] and Huang *et al.* [19].

Zhao *et al.* [51] analyzed the effect that different supporting schemes have on PV diffusion in selected residential areas in the US. The authors developed a spatial-implicit ABM, which is based on a hybrid two-level simulation modeling framework. The decision-making model is based on the classical approach of the utility function as a desire level. Rai and Robinson [52] developed an empirically grounded GIS-ABM of residential PV diffusion to study the design of PV rebate programs in Austin, Texas. They modeled the human behavior starting from the concepts of the TPB framework and applying opinion dynamics RA. Despite the GIS approach, the model considers only single-family residential households. Palmer *et al.* [53] evaluated the diffusion of PV systems in the residential sector applied in Italy at a national scale, using a threshold utility function as a decision-making model. In addition, they have implemented a social clustering, although it was developed by a third-party company, called Sinus Milieus. Zhang *et al.* [54] presented a data-driven ABM to forecast individual and aggregate residential rooftop PV adoption in San Diego County through a logistic regression approach using machine learning techniques to calibrate the model. Alyousef *et al.* [55] studied the adoption of PV and battery systems in Germany evaluating the policies able to improve the adoption of these systems. The decision is based on a logistic regression model. Mittal and Krejci [56] developed an ABM to study the interactions between utility companies and consumers on the adoption of rooftop PV. The consumer agent decision is based on attitude and financial assessments, while the objective of the utility company agent is to maximize its revenue. Pearce and Slade [57] evaluated the impact of Feed-in Tariffs on residential PV diffusion in Great Britain. They modeled only single households characterized by socio-demographic and statistical data at the national level. The decision-making model is based on a utility function as desire level where social interactions are modeled with simple fixed links. Zhang *et al.* [58] implemented ABM with real options analysis and social networks to assess the diffusion of PV systems. The model was applied to the residential PV diffusion in Singapore. Wang *et al.* [59] developed a diffusion model assuming social networks based on the scale-free networks. The model was integrated with anecdotal information and the case study was led for villages in Beijing. Lee and Hong [60] developed a GIS-ABM based on a logistic regression approach with a variable selection process for simulating rooftop PV adoption in a neighborhood of Seoul, South Korea. Brugger and Henry [61] studied how the network segregation can affect the peer effects regarding the solar incentive programs. They modeled the agent behavior through a logistic function. As the same way, Opiyo [62] studied the impacts of neighborhood influence on the diffusion of solar home systems in rural western Kenya. They used surveys data to gather information and then used to inform the ABM. The agent behavior is based on checks of economic affordability and social influence level.

C. COMPARATIVE DISCUSSION AND OUR CONTRIBUTION

In general, non-ABM approaches describe the behavior of the individuals as an aggregate trend, rather than individual decisions [17]. Indeed, they are able to well fit the data of cumulative installed PV capacity in regions or states. However, they frequently assume a fully connected and homogeneous network, neglecting the spatial interactions among individuals and distribution of PV systems.

Spatial econometrics techniques are able to spatially forecast the uptake of PV systems. Despite this possibility, the high complexity of the diffusion phenomenon and its dynamics asks for model that can capture the heterogeneity of individuals and the dynamic interactions among them, with a more highly granular level. Indeed, in order to develop effective energy policies and infrastructural interventions at an urban scale, it is necessary to address the PV diffusion at the individual level.

ABM overcomes the weaknesses of traditional models by representing the complexities, nonlinear interactions, and spatial constraints of the system allowing to model a realistic behavior of each agent considering their socio-economic attributes, social interactions, and their technical constraints. Moreover, ABM holds the opportunity to use accurate and punctual data with the capability to implement GIS applications and cross-external simulators data.

In light of all the above, in this work, we present a novel GIS-ABM framework to assess the spatio-temporal diffusion of building-integrated PV systems in the residential sector at the individual level. The listed authors in the previous subsection, which developed ABM to PV diffusion problems, are summarized in Table 1 and compared with the innovations introduced by the present work.

W.r.t. the modeling purpose, previous works [51]–[55], [57], [59] studied the effectiveness of energy policies either already implemented or new proposals. Meanwhile, other

TABLE 1. Previous applications of ABMs to PV diffusion problems.

Authors	Model purposes	Agents type / Spatial description	GIS application	Time scale[a]	Social influences & structure[b]	Social clustering	behavioral model[b]	Opinion dynamics[b]	Co-simulation
Zhao et al. [51] (2011)	Energy policy	Households / Residential areas	-	W	Peer and advertisement effects (neighborhood)	-	UF	-	-
Rai & Robinson [52] (2015)	Energy policy	Households / Building level	Yes	Q	Word of mouth effect (SWN)	-	TPB (partial)	RA	-
Palmer et al. [53] (2015)	Energy policy	Single- or two-family homes / Regional level	-	Y	Peer effects (SWN)	Yes, closed data	UF	-	-
Zhang et al. [54] (2016)	Energy policy	Households / Urban level	-	M	Peer effects (neighborhood)	-	LR	-	-
Alyousef et al. [55] (2016)	Energy policy	Households / National level	-	6M	Peer effects (randomly links)	-	LR	-	-
Mittal & Krejci [56] (2017)	Understand consumers and utility companies interactions	Consumers and utility companies / Urban level	-	Q	Peer effects (fixed groups)	-	TF	-	-
Pearce & Slade [57] (2018)	Energy policy	Households / Regional level	-	M	Peer effects (randomly links)	-	UF	-	-
Zhang et al. [58] (2018)	Diffusion study	Individuals / Virtual space (soup)	-	-	Peer effects (neighborhood)	-	ROA	-	-
Wang et al. [59] (2018)	Energy policy	Households / Urban level	-	M	Peer effects (SFN)	-	UF	-	-
Lee & Hong [60] (2019)	Diffusion study	Buildings / Building Level	Yes	Y	Peer effects (neighborhood)	-	LR	-	-
Brugger & Henry [61] (2019)	Network effects evaluation	Households / Virtual space (soup)	-	-	Peer effects (network segregation)	-	LR	-	-
Opiyo [62] (2019)	Effects of neighborhood influence	Households / Virtual space (grid)	-	Y	Peer effects (neighborhood)	-	TF	-	-
This work	Energy policy	Households and Condos / Building level	Yes	Q	Peer and word of mouth effects (SWN)	Yes, open data	TPB	RA	Sub-hourly semi-stochastic load profile model, Sub-hourly rooftop solar radiation model

[a] Y = Yearly, Q = Quarterly, M = Monthly, W = Weekly
[b] TPB = Theory of Planned Behavior, RA = Relative Agreement, SWN = Small-World Network, UF = Utility Function (or desire level), LR = Logistic Regression, TF = Threshold Function, ROA = Real Option Analysis, SFN = Scale-Free Network.

works [56], [58], [60]–[62] concentrate on evaluating the effects of social networks and technology diffusion. With respect to such works, we studied a completely new energy policy related to the development of JSc by integrating the effects of the social network in the analysis. To the best of our knowledge, this is the first work that develops an ABM for analyzing JSc.

Looking at the spatial resolution the works [53], [55], [57] uses a high resolution at a national or regional level. Agents are modeled as single households with no integration of GIS data. The works of [51], [54], [56], [59] uses an Urban resolution with agents modeled as single households with no integration of GIS data. Authors in [58], [61], [62] have developed a virtual space environment in which agents are modeled as virtual households obviously with no integration of GIS data. The only works that integrate GIS data and perform an analysis at the building level are [52], [60]. In [60] agents are modeled as single buildings and in [52] agents are modeled as households. W.r.t [50], [53], [54], [54]–[59], [61], [62] we integrate fine-grained GIS data and perform an analysis in a real district with a resolution up to the household level. Moreover, w.r.t [52], [60] we modeled both the single household and the condominium adoption behavior.

A fundamental feature in ABM of socio-technical system is the ability to describe the heterogeneity of the agents and their interactions. Previous works were limited to use aggregated statistical data to infer the socio-economic characteristics of each agent. Only in [53] social groups are used, but they are based on a registered trademark product. W.r.t. all previous work, we used an open data social clustering to enhance the agents' heterogeneity and their spatial characterization.

Regarding the social influence and structure previous works have implemented only the peer effects exploiting the SWN [52], [53], or neighborhood selection [51], [54], [58], [60], [62], or random links [55], [57], or the Scale Free Network [59] or the network segregation [61]. W.r.t reviewed works we integrated two different typologies of social influence the peer effects and the word of mouth that exploits the RA for modeling the opinion dynamics. The interaction among agents is achieved exploiting the SWN that describes the social network of each agent.

Concerning the agent behavioral model, authors of [51], [53], [57], [59] uses a multi-criteria utility function approach. Meanwhile, authors of [54], [55], [60], [61] uses a regression analysis technique. W.r.t. to the reviewed literature approaches, we use cognitive models based on human and social behavior theories TPB and RA, which are more suitable for simulation of the individual's behavior. TPB and RA are as well used by [52], but we implemented them maintaining their integral and original formulation.

Finally, with regard to the solutions presented in Table 1, our framework is integrated into a co-simulation platform [63]. Co-simulation provides the possibility to bundle into a single run-time modeling framework third-party data sources and external simulators. In our case, the co-simulation is achieved among our ABM, a stochastic simulator of household electricity consumption and a solar radiation simulator to assess the sub-hourly electricity production of rooftop PV systems. The use of a co-simulation framework enables the possibility of integrating different simulators and having different time scales: 15 minutes for simulating PV generation and household load profile and a quarter for updating PV adoption.

The overall contribution of our work can be summarized in the followings:

- modeling the effect of the adoption of an energy policy that encourages the uptake of JSc;
- modeling of single-family households and groups, i.e. the condominiums;
- realistic modeling of households by exploiting highly granular spatio-temporal data up to the single building by using of GIS;
- modeling the social influence by integrating the peer effects and the word of mouth theories;
- integrating the social clustering for increasing the heterogeneity characterization of households;
- behavioral model based on trusted social behavior theories and opinion dynamics;
- integration of the ABM framework in a co-simulation platform.

IV. SIMULATION PLATFORM

In this section, we present our agent-based modeling and co-simulation platform to study the diffusion of energy technology at the urban scale.

The design and development of the co-simulation platform followed a microservices approach, which consists of developing software *as a suite of small services, each running in its own process and communicating with lightweight mechanisms* [64]. This approach increases modularity, flexibility, scalability and maintainability because services are *small, highly decoupled and focus on doing a small task* [65].

Fig. 4 show the three layers of the co-simulation platform. By integrating heterogeneous data sources in the *Data Source Layer* it is possible to describe the urban environment with: *i)* different granularity in the spatio-temporal domain; *ii)* its related social structure and in the techno-economical domain. Thus, the system is empirically ground to a real environment. The core of the platform is the *Model & Simulation Layer* that integrates all the modules and algorithms to simulate, in the spatio-temporal domain, the objects, the subjects and the interactions in the diffusion of energy technologies in cities. Finally, the results of the simulations are elaborated and shown in the *Application Layer*.

A. DATA SOURCE LAYER

Our model is spatially described by geo-referenced data coming from different functional layers. Hence, the proposed simulation platform exploits several heterogeneous data sources to represent and describe the urban citizen community. The identified functional layers are the *Environmental layer*,

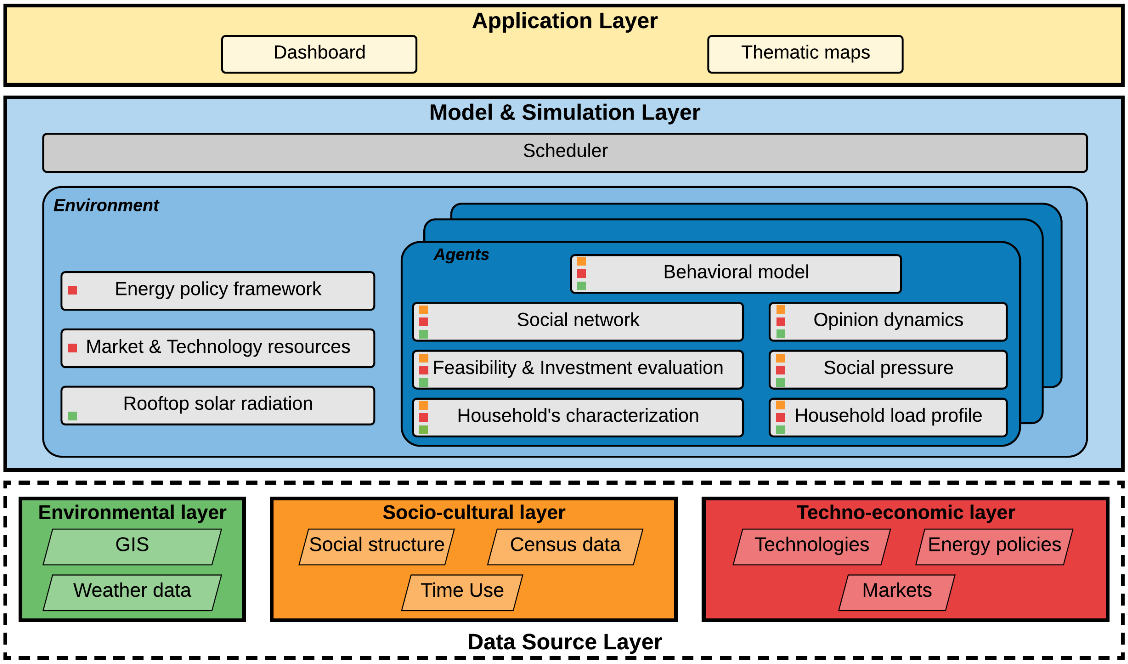


FIGURE 4. Scheme of the proposed agent-based modeling and co-simulation platform. The modules exploit data from the Data Source Layer. The data come from different functional layers that are labeled with diverse colors.

Socio-cultural layer and the *Techno-economic layer*. All the input data are retrieved by the platform automatically from third-party services. Furthermore, the user can set model parameters to define a specific ABM scenario to be simulated. The proposed solution intends to be flexible and reusable in any geographic area by updating the dataset of the area of interest in a plug and play fashion thanks to the micro services approach. Each data layer is described in the following subsections.

1) ENVIRONMENTAL LAYER

a: GEOGRAPHICAL INFORMATION SYSTEM (GIS)

This module integrates all the useful data needed to spatially characterize the city. In particular, it integrates: *i)* census map that is a vector image that represents the census section areas, *ii)* Digital Elevation Models that is a raster image that represents terrain elevation considering also the presence of manufactures and *iii)* a Cadastral map that is a vector image which represents the square footage of buildings and reports the building attributes (e.g. footprint area, type of building, category of use, date of construction, building height, number of floors).

b: METEOROLOGICAL DATA

Weather data are integrated from third-party data sources such as (Openweathermaps or Weatherundegound) that offer API for collecting geo-referenced weather data coming from personal weather stations. Such data is used by the simulation and modeling layer to simulate both the energy production and consumption in the city.

2) SOCIO-CULTURAL LAYER

a: CENSUS DATA

Census data provide statistics on populations and households at a spatial level over the entire nation. Data are obtained from national statistical request services, providing useful information for the spatial characterization of the households, e.g., the number of residential households, foreigners, job status (workers, unemployed), number of family members, degree (illiterate, primary school, secondary school, university degree, post-degree).

b: SOCIAL STRUCTURE

Each household has its own socio-economic and demographic characteristics that have a significant influence on the decision-making process. Thus, the heterogeneity of the households is taken into account by implementing a social clustering. The clustering process divides the households into fairly homogeneous groups. Each group is representative of households displaying similarities in their socio-economic and demographic behavior and consumption patterns (e.g. each group has shared values and attitudes toward work, family type, leisure, money, and consumption)

c: TIME USE SURVEY

Time use Survey (TUS) are performed by National Institutes of statistics of many countries. TUS is conducted every 4-5 years to analyze how people spend their time in both week-days and weekend and in different seasons. TUS consists of a set of time diaries, covering 24 hours, in which respondents (household members) report the activities (e.g., sleeping, cooking and working), with 10 minutes intervals, that they have performed during the day in which they answered to the survey. TUS is an important instrument to analyze behaviors and activities of both adults and children in weekdays and weekends [66], [67]. Thus, TUS becomes a very powerful instrument to feed an ABM because it provides statistical information such as: i) activities and needs, ii) ratio between work-time and free-time, iii) use of communication media and iv) use of spaces and services.

3) TECHNO-ECONOMIC LAYER

a: TECHNOLOGIES

This module provides information about the technology under study. It contains information on both energy performance and costs (e.g., the capital expenditure CAPEX and the operating expenses OPEX). Trends over time of the energy efficiency and other key performance indicators (such as average lifetime, average degradation ratio, etc.) are also included.

b: MARKETS

Electricity prices, levies and other relevant information on tariffs are sourced from the National Electricity Market Administrator.

c: ENERGY POLICIES

This module includes all the information regarding the national energy policy framework and related supporting schemes for technology adoption. Different types of policies can be inserted into the model, e.g., incentives in the form of capital grants, tax reliefs or other supporting schemes (e.g., Net-Billing, Feed-in Tariff, Feed-in-Premium) and mass media advertising actions.

B. MODEL & SIMULATION LAYER

The *Model & Simulation Layer* is the core of the proposed co-simulation platform in Fig. 4. It contains the simulation and modeling modules that are exploited by the platform: agents, environment and scheduler. The scheduler is described in detail in Section IV-B11.

The *agent* is the active element of the system and it is represented as a simulation block that contains its own modeling and simulation modules. Each agent represents a single household, which is characterized accordingly to the statistical distributions of socio-demographic and social clustering data. Each agent takes actions and makes decisions while interacting with the other agents. Each agent (not adopter) decides at each time step whether to adopt or not an energy technology, according to its own *state* and decision-making *rules*. The internal *state* of an agent represents the specific collection of parameters and variables that define an agent and it changes whenever the agent makes actions. Actions are taken based on a well-defined set of *rules*, which are algorithms describing how the *states* are translated into actions or new states [16], [68]. The set of rules are represented within the agent's box in Fig. 4.

The *environment* simulation block contains the agents and the resources of the system, i.e., all the external information they require to make actions, such as energy technologies, market prices and energy policies. Moreover, the environment provides that spatial information needed to describe the virtual ABM's space. The agents live either in single-family residential houses or, as it is most often the case in urban communities such as European cities, in apartment buildings (i.e., Condominiums).

1) OPINION DYNAMICS

Each agent has its own opinions (*opi*) that have a given uncertainty (*unc*), with respect to a specific behavior. The opinion is defined as a real number in the range between -1 (extremely negative opinion) and $+1$ (extremely positive opinion). The value of uncertainty is also a real number in the range [0; 2]. Moreover, there are agents in the system that could be already adopters (at the time the model is initialized). Thus, we included a number of 'extremists', accordingly to Deffuant [37], having an opinion level equal (or higher) to 0.8, and uncertainty fixed to 0.1.

The opinions and the uncertainties around those opinions evolve in time to represent the word of mouth effect. This is achieved thanks to agent interaction within their social network (see Section IV-B2). The Relative Agreement (RA) algorithm is used to describe the opinion dynamics (a detailed formulation is presented in Section II-B). Pairs of agents i and j interact over time. At each time-step t, each agent interacts with a certain number of other random agents within its social network. The number of interactions ϕ is set as a model parameter, as well as the convergence speed of opinion dynamics μ.

2) SOCIAL NETWORK

Individual agent's attitudes and social norms evolve because of the interactions and social influence within the social network. The social network topology has been developed based on the Small-World Network theory (a detailed formulation is provided in Section II-C). In our model, the neighbors and social group similarity are used to create social networks. The process of generating the agent social network begins by selecting the agent's neighbors within a certain radius from its house. The choice of the radius is not trivial since there are factors to be accounted such as the local/building population density, the type of environmental area and the type of agent. However, in our case because of the scarcity of information, the radius was defined by setting a constant value r around each household and used as a parameter of the model. The agent's local connections are formed selecting randomly from the neighbors' list those agents that have a similar social group or equivalent level of income. Thus, agents with similar wealth conditions have more connection's probability. To generate the long-distance connections, some of the local connections are substituted with random agents taken from the whole system. This is expressed by the *rw* parameter that represents the percentage of long-distance connection re-wiring.

3) SOCIAL PRESSURE

The social pressure *sp* (or peer effects) represents the general influence that an agent i receives within its social network. As an example, if a neighbor adopts an energy technology it is more likely that an agent is influenced to do it too, and vice-versa. Influence is evaluated considering only those agents within the social network who have strong opinions, either positive or negative. The agents with strong opinions are those who have an absolute value of *opi* greater than 0.6 and related uncertainty *unc* less than 0.5. The social pressure exerted on the agent i by the influencer j is obtained as follows:

$$w_{ij} = \frac{\frac{unc_i}{unc_j} - 0.2}{20 - 0.2}, \tag{3}$$

$$sp_{ij} = att_i \cdot (1 - w_{ij} \cdot (att_i - att_j)), \tag{4}$$

where the weight w_{ij} represents the strength of the influence. At the increasing of the weight w_{ij}, the pressure coming from negative opinions is greater than the positive ones. This assumption models social behaviors under which people are more influenced by negative opinions rather than the positive one. The total social pressure *sp* exerted by the all N influential agents within the social network was considered as the mean value

$$sp_i = \frac{\sum_{j=0}^{N} sp_{ij}}{N}. \tag{5}$$

4) HOUSEHOLD'S CHARACTERIZATION

Different attributes are used to describe the heterogeneity of households: *i)* social clustering, *ii)* income, *iii)* family size and *iv)* level of innovativeness.

i) Social clustering permits to split the households into fairly homogeneous social groups, based on statistical data. Exploiting the identified social groups and the census data, contained in the Socio-cultural layer, we randomly assign a social group k per each household i, accordingly to the household's statistical distributions.

ii) The household's income is estimated using the available statistical data on each social group k. The income distribution within a social group is described by a normalized income level INC_k, with respect to the national mean income of households (INC_{NAT}), and by the Gini coefficient ($GINI_k$) that accounts the internal variance [69]. Therefore, the income [€] of agent i, belonging to a social group k, is obtained by the following equations:

$$X_i \sim \mathcal{LN}(\mu = 0, \sigma = GINI_{k\,i}), \tag{6}$$

$$INC_i = X_i \cdot INC_{NAT} \cdot INC_{k\,i}, \tag{7}$$

where X is a random variable obtained from the income standard lognormal distribution $\mathcal{LN}$, and σ is the Gini coefficient.

iii) The family size is estimated for each household. It is generated from a triangular distribution $\mathcal{T}$ using the data retrieved from each social group, i.e., the average number of family members N_k^{mean} and the min and max values, as follows:

$$X_i \sim \mathcal{T}(\min = N_{k\,i}^{min}, \text{mode} = N_{k\,i}^{mean}, \max = N_{k\,i}^{max}), \tag{8}$$

$$N_i = X_i. \tag{9}$$

iv) The level of innovativeness represents the propensity toward technological innovation of an individual. In fact, there are socio-demographic aspects that influence the adoption of innovative technology such as personality, human habits and lifestyle [70], [71]. In our model, this attribute is static and each household inherits it from its social group. Moreover, we took into account the well-known framework of Diffusion of Innovations theory by Rogers [10] that divides the adopter customer in innovators, early adopters, early majority, late majority and laggards. Thus, to each social group k a level of innovativeness is associated on the basis of their income, rational-economic thinking, knowledge, education level, attitude to influence, social norms and their adopter category (the values was reported in Appendix B).

5) HOUSEHOLD LOAD PROFILE

The *Household load profile* model presented by Bottaccioli *et al.* [72] has been integrated in the co-simulation platform. The model uses *Time of Use* surveys to create a Non-homogeneous semi-Markov model for simulating the household electricity load profile. The model permits to create households by specifying the composition of the family. Then, the set of appliances in the households are distributed according to statistics obtained from [73]. The simulator uses the created Semi-Markov model to generate household behavior in terms of type and duration of activity and associates to each activity to specific usage of electric appliances (e.g., washing machine, dish-washer, etc.). Thanks to the various type of integrated user typologies, we have created household by taking into account the social group. A reference load profile has been thus obtained for each social group.

6) FEASIBILITY & INVESTMENT EVALUATION

The feasibility of investment depends on two control variables: (1) the socio-economic feasibility and (2) the technical feasibility. The first one verifies if the agent owns the house. In fact, in our model, we assumed that tenants do not invest their money in a rooftop PV system in someone else propriety. For this reason, tenants never adopt and are excluded from the decision-making process. The number of tenants is given by the statistical data for each social group. The second variable concerns the technical possibility of installing the technology, i.e. the availability of rooftop area.

The perception of affordability on an investment, or lack thereof, is often cited in the literature is one of the most important barrier to the adoption, together with social influence [7], [30], [51], [53]. The economic component within the proposed ABM framework is given by the payback period.

The payback period depends by the following factors: *i)* technology under study; *ii)* size of the system, *iii)* utilization of the system; *iv)* the production curve of the system; *v)* electricity prices and *vi)* the regulatory framework. In general, the payback period pp is defined as the year in which the net present value npv break-evens

$$npv = \sum_{y=0}^{N} \frac{R(y)}{(1+WACC)^{y}}, \quad npv = 0 \rightarrow y = pp, \quad (10)$$

where $R(y)$ is the net cash flow, i.e. cash inflow minus cash outflow, at time y and $WACC$ is the Weighted Average Cost of Capital. The net cash flow is initialized equal to the investment I (with minus sign). The composition of the net cash flow is reported in detail in Appendix A because it depends on the case study and the analyzed scenario. Moreover, the economic evaluation algorithm considers the time-varying energy and technology prices.

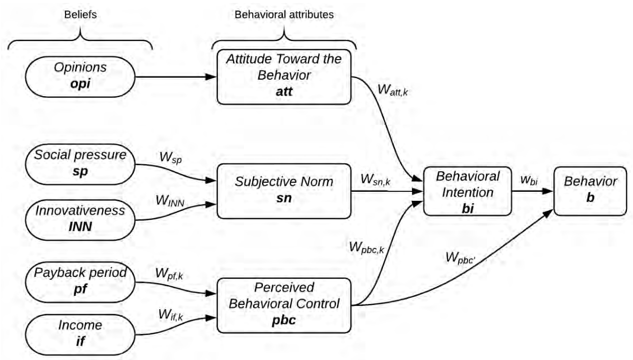


FIGURE 5. Scheme of the mathematical decision-making model based on TPB.

7) BEHAVIORAL MODEL

The agent's behavioral model has been developed starting from the TPB framework described in Section II-A. The mathematical model is illustrated in Fig. 5, which shows the Behavior b as a weighted linear function of the three behavioral attributes. Each of them is derived from weighted linear functions of the associated beliefs. Each component of the behavioral model has a value between 0 and 1, thus the sum of the weights of each linear function is 1. For example, the weight w_{bi} is set as a user-defined parameter of the model and its complementary $W_{pbc'}$ is calculated accordingly.

The Behavior b is the weighted sum of the Behavioral Intention bi and the Perceived Behavioral Control pbc, as shown in (2). The decision to invest takes place when b is greater than a certain threshold value b_{thsd}, which is set as a user-defined model parameter.

The Behavior Intention bi is calculated using (1). The weights are estimated from the statistics that characterize each social group. In our model, we considered those beliefs which are more important for energy technology adoption, as illustrated in Fig. 5 and explained in the following paragraphs. The beliefs, or adoption factors, were chosen according to the wide review of the literature concerning the factors, barriers, and constraints toward technology adoption [11], [12].

i) The Attitude Toward Behavior att is obtained by the general opinions of the households explained in Section IV-B1. Therefore, the att is a simple normalization of the general opinion (opi).

ii) The Subjective Norm sn is the combination of two influential beliefs: the social pressure sp and the innovation factor INN. The first one, explained in Section IV-B3, represents the mean mostly local influence that the agent receives, thus it depends on the local state of the agent. The second one represents the individual propensity to adopt, thus it depends on the internal state of the agent. it is obtained normalizing the innovativeness' level of each agent (explained in Section IV-B4). Therefore, sn is

$$sn_i = sp_i \cdot W_{sp} + INN_{k^i} \cdot W_{inn}, \quad (11)$$

where the both weights were chosen equal to 0.5, assuming that the social pressure and the innovation factor have the same importance in the evaluation of the Subjective Norm.

iii) The Perceived Behavioral Control pbc is the combination of two influential beliefs: the payback period factor pf and the household income factor if. The first one takes into account the payback period and the constraints on technology adoption. The second one considers the capability of the agent to money investment based on income level. Thus, pbc is

$$pbc_i = pf_i \cdot W_{pf,k^i} + if_i \cdot W_{if,k^i}, \quad (12)$$

where $W_{pf,k}$ and $W_{if,k}$ are weight factors. The pf is obtained normalizing the payback period calculated by Feasibility & Investment evaluation module, considering the lifetime of the plant. Moreover, if there is no feasibility to install pf is set equal to 0.

The income factor if indicates the capability of a household to purchase a PV system and is calculated, accordingly to [51], as follows:

$$if_i = \frac{1}{1 + e^{-\frac{\left(\frac{INC_i}{N_i} - \frac{inc_{ad}}{n_{ad}}\right)}{5000}}}. \quad (13)$$

The logistic function compares the level of income per capita of a household (INC_i/N_i) with the average income value of the adopters (inc_{ad}/n_{ad}). The factor 5000 is used to scale down the income in the exponential relation, similarly to [51].

The weight $W_{if,k}$ defines the relative importance that a household gives to the income rather than the payback period when deciding whether to invest money on a PV system. In fact, depending on the characteristics of the agent, it might be more inclined to spend a relatively significant amount of money, taking more risk, or it might be more inclined to look at the security of investment, looking for short payback period. From social groups' statistics, it is known the distribution of the household's expenditure. Therefore, we used the expenditure as an indicator of the high spending capacity of

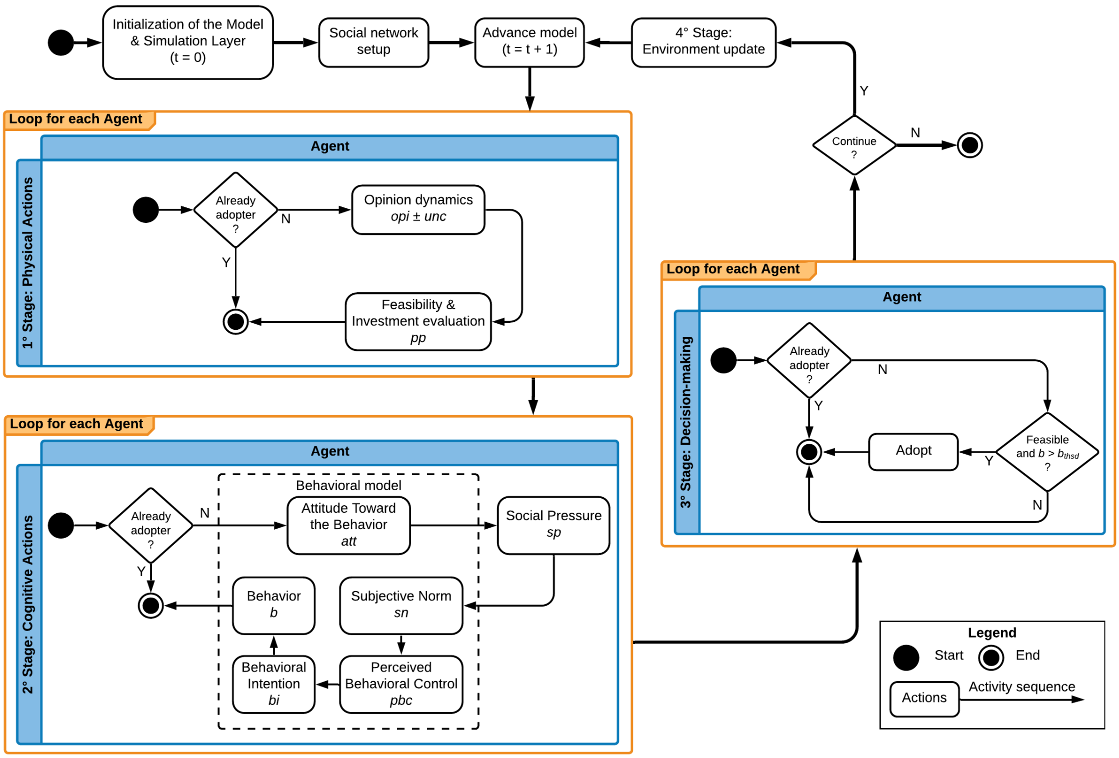


FIGURE 6. **UML Activity Diagram of our ABM framework. The diagram shows the activity sequences of the entire model algorithm. The orange box represents a loop for each agent, meanwhile the blue boxes show the different agent steps.**

a social group and so to define their willingness to spend money. The value of expenditure is assumed to equal to $W_{if,k}$. Nevertheless, this attitude represented by the $W_{if,k}$ is important only in the evaluation of the *pbc*, which represents the more rational component of the behavioral model. In fact, an agent may also adopt in spite of low spending capacity and high risk as for the case of innovators (with high level of innovativeness).

8) MARKET & TECHNOLOGY RESOURCES

This module controls the resources as market and technologies and communicates with the environment module in order to share the data among agents. Both are treated as passive elements of the system that evolve and act whenever it is requested by the household, e.g., when the feasibility and economic evaluation is requested. For example, the price of energy technology is generally a time-dependent variable. Therefore, at each time-step, the CAPEX can decrease following a user-defined constant reduction ratio.

9) ENERGY POLICY FRAMEWORK

The implementation of energy policies is strictly connected to the national regulatory framework. The supporting schemes and the regulatory framework have a strong impact on the economic evaluation of the single household and thus on the dynamic of adoption. Our platform has been designed to be flexible toward the possibility of plugging different policy measures and simulate different policy scenarios.

10) ROOFTOP SOLAR RADIATION

Thanks to the flexibility of the simulator presented in [74] we integrated the *Rooftop solar radiation* module. This specific module allows to estimate the PV potential and to simulate the solar radiation profiles in real-sky condition with high spatio-temporal resolution (e.g. 50 cm^2 and $15-minutes$). The module uses: *i)* GIS data of the environmental layer to draw rooftop information in terms of slope, orientation, possible encumbrance and shadows; *ii)* weather data from the nearest weather station to calculate the incident solar radiation in real-sky condition. A detailed description of this module and evaluation of its capability in simulating solar radiation in different seasons (e.g. Winter and Summer) and in different day type (sunny, cloudy and rainy) is presented in [74].

11) SCHEDULER

The time evolution of the model is managed by a scheduler, as shown in Fig. 4. The scheduler ensures that all the actions and activities of the system are executed in a well-defined order for each simulation time step. The scheduling process is shown in Fig. 6 using the Unified Modeling Language (UML) Activity Diagram [75].

The initialization of the model regards the acquisition of the input data sets, the user-defined parameters of the model and the creation of the entities that constitute the ABM as the agents, the environment and the scheduler. In this phase, each agent is created with its initial state belonging to a specific geographical space, and it is inserted into the scheduler. In this process, all the information taken from the input data sets is elaborated to define the diverse attributes of the agent. The same procedure applies for the initialization of the environment.

After the initialization, the model creates the social network structure *SWN* for each agent. The social network is assumed as a static attribute of an agent. The creation of the social network consists of 3 main sub-steps: (1) the neighbors within a certain radius r are selected and they represent the local interactions; (2) the local agents community is filtered by a criterion of social group similarity; (3) a certain number of local agents (defined by rw) are randomly replaced by non-local ones, which are chosen from the whole community.

The steps of the simulation are managed by the scheduler. At each simulation time step t, the scheduler activates each agent, updates the agent final decision and the environment. The chosen scheduler's type is the *Random Staged Activation*. This type of scheduler allows the simulation to be divided into four stages: *1)* agent's physical actions, *2)* agent's cognitive actions, *3)* agent's decision-making and *4)* environment update. All agents execute one stage before moving on to the next. Moreover, the scheduler activates each agent once per stage, in random order, with the order reshuffled every stage.

1) The first stage consists of physical actions taken by the agent. If the agent has already adopted, it takes no actions. Otherwise, it starts to interact with ϕ other agents randomly selected in its social network (the so-called word of mouth effect). The agent is thus influenced by these interactions in its opinions and uncertainties about technology adoption with the speed convergence μ, according to the rules of the RA algorithm. Subsequently, the agent gets the knowledge about the cost of the technology and it makes an investment evaluation, taking the information from the environment and Feasibility & Investment evaluation module.

2) The second stage consists of cognitive actions of the agent, where it generates its new opinion based on its *state* and on the information taken in the previous stage. The cognitive actions correspond to the elaboration of TPB's components: att, sn and pbc. Finally, the agent develops an intention to the behavior bi and, considering the weight of the Behavioral Intention w_{bi} with respect to the actual power control (i.e. pbc), it elaborates the final Behavior b.

3) After executing the first two stages for all the agents, the final choices are updated. If the installation of the technology is feasible, and the b value is higher than the corresponding threshold level b_{thsd}, the agent takes the decision to adopt. Its opinion will be set equal to a random value higher than 0.8 with an uncertainty set equal to 0.01. This assumption is done in order to simulate the happiness for the investment and making the agent behaving like an extremist (e.g. great opinion and very low uncertainty) [37].

4) The final stage consists of updating the states of the environment, i.e., the update of the technology price, the update of the mean household income of the adopters and the mean family size of the adopters.

Note that the fourth stage also includes the update of the final decision-making process, which is actually part of the cognitive actions. However, the agent's decision-making is held as a separate process, as it is shown in Fig. 6. This distinction helps to remark the assumption that all agents make choices simultaneously in a simulation time step. Moreover, the update of the final choice strongly depends on the scenario under study, for example, when the choice of adoption is taken considering the collective choice among residents of a Condominium.

C. APPLICATION LAYER

The *Application Layer* is the highest layer of the proposed platform (Fig. 4). This layer is the platform Graphical User Interface that returns and shows the simulation results. In particular, it provides: *i)* a dashboard, which contains inspections tools, such as graphs and tables; *ii) thematic maps* that show the spatio-temporal distributions of PV diffusion, self-sufficiency and self-consumption.

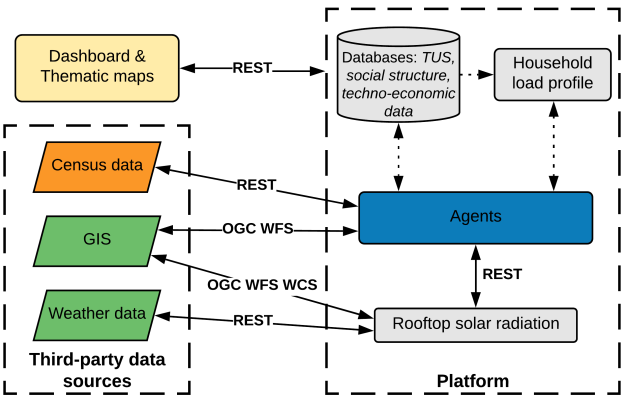


FIGURE 7. Data flow scheme of the co-simulation platform.

D. CO-SIMULATION DATA FLOW

Here we describe the data flow of our co-simulation platform represented in Fig. 7. The platform takes advantage of third-party data sources and two external simulators, the *Rooftop solar radiation* [74] and the *Household load profile* [72]. The *Household load profile* profile simulator has been integrated into the ABM framework directly and takes the data from the internal platform database. Meanwhile, the *Rooftop solar radiation* simulator is integrated exploiting the Representational State Transfer (REST) API that exposes GeoJSON data. Furthermore, the *Rooftop solar radiation* requests from third-party data-sources weather condition exploiting REST API. Finally, thanks to the use of the Open Geospatial Consortium web services, it is able to collect the required maps directly from third-party data-source by exploiting both Web Feature Service and Web Coverage Service. Moreover, the ABM framework collects though both

REST API and Open Geospatial Consortium standards data from GIS databases (e.g. census section maps and building footprint) and from Census databases respectively.

V. CASE STUDY

The proposed platform has been used to analyze the diffusion of roof-top PV systems of two scenarios under different regulatory schemes in a real-world case study. The first scenario called one-to-one configuration (*1to1*) simulates the PV diffusion under the actual Italian regulatory framework. On the other side, second called one-to-many configuration (*1toM*), implements the new EU energy policy on energy citizen communities and joint self-consumption citizen, presented in the Clean Energy package [3]. Both scenarios are applied to have as a case study a district of the city of Torino called *San Salvario*.

A. DATA SOURCES

GIS data are collected from third-party public available sources. In particular, cadastral and census section[2] maps are retrieved from the Geoportal of Turin's Municipality. Meanwhile, the digital surface map is collected from the Geoportal of the Piedmont Region. *Weather data* needed for the solar radiation module are collected from third-party data source [76].

The data of the *Socio-cultural layer* (Fig. 4) are collected from the National Bureau of Statistics (Istituto Nazionale di Statistica - Istat [77]). *Census sections* (or census blocks) data are taken from the last Italian census of population and buildings [78]. *Time Use Survey* data are referred to the last Italian survey performed between the years 2012-2013 [79]. *Social Structure* data are obtained from the annual report on social grouping [80]. The report identifies the following nine groups: *1)* Ruling class (RC); *2)* Silver Pensioners (SP); *3)* Clerks' households (CH); *4)* Young blue-collars (YB); *5)* Retired blue-collars' households (RB); *6)* Lonely old ladies and young unemployed (LY); *7)* Traditional provincial households (TP); *8)* Low-income Italian households (LI); *9)* Low-income households with foreigners (LF). The social groups are generated by Istat classifying the population by income, professional position, education level, citizenship of the household members and the number of household members. The model generates the households agents accordingly to the statistical data of the census blocks and classifies them in social groups by their attributes similarly to Istat.

The households within each social groups have similar characteristics, therefore the weights of the behavioral model are set at the same value for each social group. Moreover, the level of innovativeness for each social group is expressed as a number in a range from 1 (very low interest) to 5 (very high interest). More details were given in Appendix B.

The data of PV technology and costs have been taken from the Italian Energy Services Utility (Gestore Servizi Energetici [81]) and from the International Energy Agency [82]. We assumed the standard module crystalline silicon that constitutes more than 85% of market share, assuming an average roof-top PV system efficiency of 14.45% (considering also the balance of system). In Italy, in 2016 the turnkey price of small size grid-connected roof-top PV systems was from 1340 to 1730 €. Considering that the PV cost decreased at a rate of 15.5% from 2002 to 2016 and that today's PV technology is a mature one approaching the grid parity, we assumed for our simulation a constant yearly price reduction of 8%. Electricity prices have been taken from the Eurostat database [83] and the Italian Stock Exchange [84]. Such data provides the actual and future trend of national electricity prices.

B. POLICY SCENARIOS

The scenarios are defined starting from the actual Italian regulatory framework concerning decentralized electricity production [85]. In the actual policy framework, the energy authority (regulator) imposes the correspondence between the electrical production unit and the electrical consumption user. Furthermore, there is just a single point of delivery to the public grid. This is equivalent to the *one-to-one configuration*.

Nowadays, the only active supporting scheme for PV in Italy consists of 50% tax relief on the investment cost, spread out over ten years. After the end of the last feed-in premium scheme in 2013 [86], the remuneration on the self-generated and the net exported PV electricity consist of a Net-Billing scheme. Otherwise, the net energy exported to the grid can be sold at market price conditions [81], [85], [87].

Starting from this context, we simulated two different policy scenarios, described in detail in the following paragraphs and illustrated in Fig. 8.

1) ONE-TO-ONE CONFIGURATION (1TO1)

This scenario is a business-as-usual scenario, in which only the single household can install a rooftop PV system and self-consume the generated electricity. The size of the system is chosen as the optimum value of the payback period (as described in detail in Appendix A) with the constraints of the yearly electricity consumption of the household and the available area. For those who live in a Condominium, we assume that the overall rooftop area is equally distributed among the residents. In addition, if the area cannot accommodate at least 1 kWp, the adoption is not feasible. Finally, every single household decides individually whether to adopt or not.

2) ONE-TO-MANY CONFIGURATION (1TOM)

This scenario simulates the possibility to share the electricity produced by a single PV unit with many citizens. This policy scenario changes the agent's behavior in Condominium but not in the single-family house. Here, we model the creation of a condominium energy community where is possible to install a shared rooftop PV system that covers all the available roof-top area of the building. The choice to install a shared PV

[2]The census section is the minimum unit of detection of the municipality, which consists of a single polygonal area. The sum of all the census sections reconstructs the entire national territory.

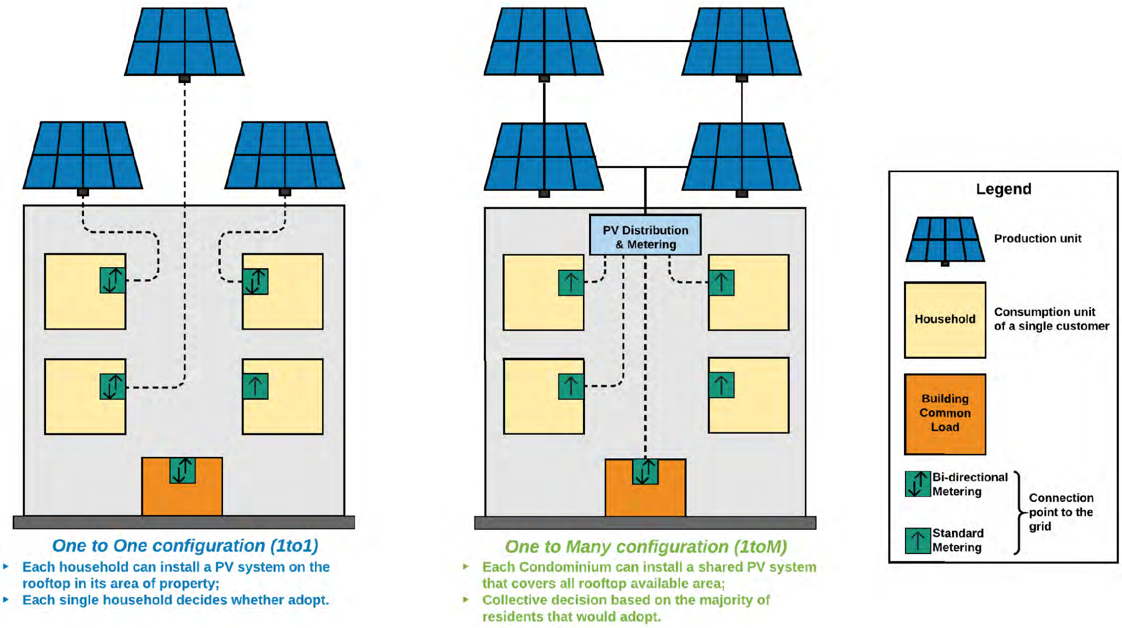


FIGURE 8. A simplified illustration of the scenarios under study with a short description of each of them. It represents the application of the scenarios in the buildings, like a Condominium, but also applied in single-family homes, which are however few in the urban context.

system is based on a collective decision process in which the adoption occurs if the majority of the residents wants to adopt. For those who do not want to adopt or cannot, i.e. tenants, they will not participate in the investment and they will not receive the related benefits. Moreover, we assumed that the financial revenues of the investment are equally distributed among the residents. The on-site generated electricity is primarily self-consumed by the households while any surplus/deficit is exchanged with the grid.

This configuration is actually not feasible in Italy because of the one-to-one constraint. In fact, the aim of this scenario is to explore the PV diffusion in a hypothetical future in which it will be possible to set *one-to-many configuration* (e.g. the Citizen Energy Community, as proposed by RED II) and benefit from a Net-Billing scheme at the Condominium scale overcoming all the constraints imposed by the current regulatory framework.

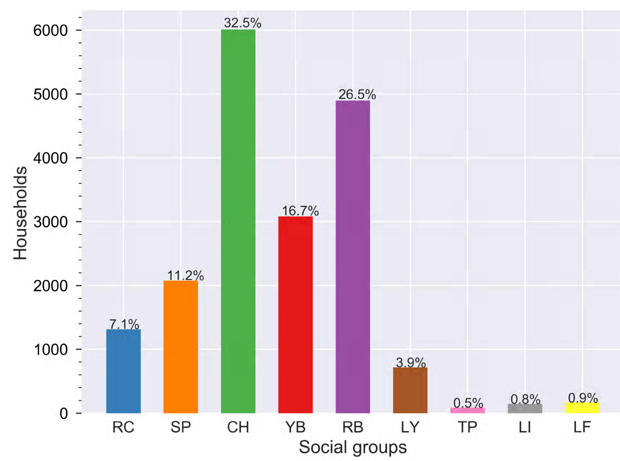


FIGURE 9. Households distribution in the city district with respect to the social groups.

C. DISTRICT DESCRIPTION

The *San Salvario* district includes nearly 18, 720 households distributed over nearly 1, 290 buildings and a total district land area of 2.47 km^2. The area has been chosen for the high presence of condominiums. The high presence of multiple-property buildings gives us the possibility to highlight the different impact of the regulatory schemes on the diffusion of PV systems.

Fig. 9 show the distribution of the social groups within the district. From the plot, it is possible to see that about a third of the households belong to the CH group and about the half belong to the RB, YB and SP groups. The remaining part is mostly composed by RC and LY, with a very small part by (less than one percent) TP, LI and LF groups. This particular social groups distribution has a strong impact concerning the electricity load profiles. In fact, as shown in Fig. 10, the CH and YB groups exhibit a typical single night peak demand. As a consequence, we expect that the majority of the households cannot exploit well the PV production caused by the meaningful mismatch in time between load and PV production profiles.

D. MODEL SETTINGS

Table 2 reports the fundamental parameters and their related values used to initialize both scenario simulations. In order

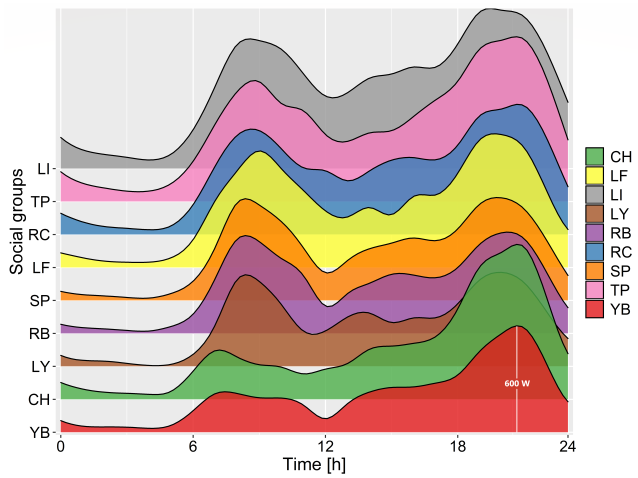


FIGURE 10. Yearly mean of the daily load profiles regarding the social groups. They are listed from low profiles to high profiles based on peaks power.

TABLE 2. Model's parameters.

Model parameter	Symbol	Value
Behavioral threshold (TPB)	b_{thsd}	0.72
Weight of Behavioral Intention (TPB)	w_{bi}	0.6
Re-wiring parameter (SWN)	rw	0.1
Radius of neighborhood [m] (SWN)	r	50
Number of interactions at each time step (RA)	ϕ	2
Speed convergence parameter (RA)	μ	0.05

to choose realistic values, a parametric analysis is performed over a simplified population and city environment as reported in Appendix C.

Besides the parameters reported in Table 2 there is the need to set citizens opinions and uncertainties over opinion. The citizen opinions are initialized accordingly with [29], [52]. The main assumption is that in a low market penetration people do not have strong opinions, either positive or negative, but are mostly neutral toward technology adoption. Meanwhile, uncertainties over the opinions are chosen assuming that there is high uncertainty over neutral opinions, according to the following expression: $unc = -2(opi^2 - 1)$.

VI. RESULTS

In this section, we present the results of the case study in which we investigate the rooftop PV diffusion in a city district under two different policy scenarios. The selected urban district (San Salvario) is one the most densely populated area of the city of Torino (Italy). The results of the simulation are diffusion curves, the spread of PV adoption in the social groups over time and thematic maps showing, on a spatio-temporal scale, the evolution of kW installed, self-consumption and self-sufficiency ratios for each census block.

A. DIFFUSION CURVES

The diffusion curves of rooftop PV in city buildings are shown in Fig. 11, for both scenarios. The graphs show the cumulative installed power that has been normalized with regard to the maximum potential capacity, which is 16.2 MW for the considered district.

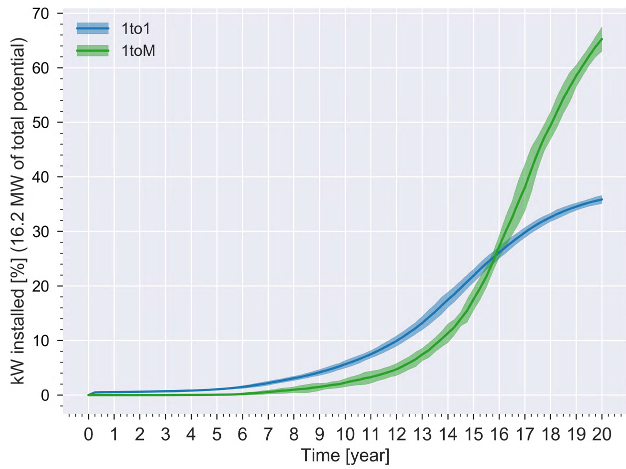
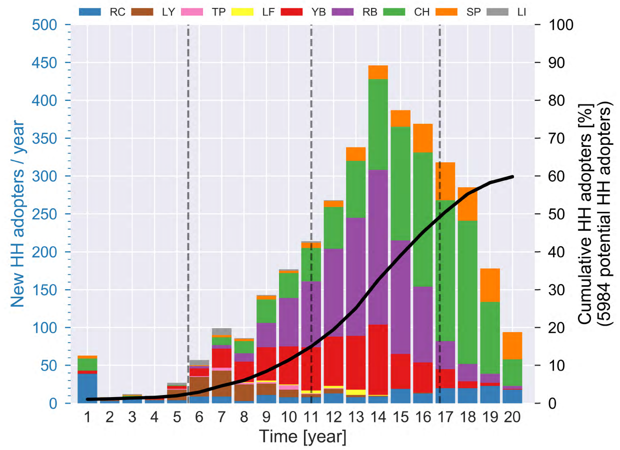


FIGURE 11. Residential PV systems diffusion curves in the city district concerning the scenarios 1to1 (blue) and 1toM (green). These are obtained from the statistical elaboration of 100 runs for each scenario. Each curve is represented with the mean value (solid line) and the confidence interval of 95.45%.

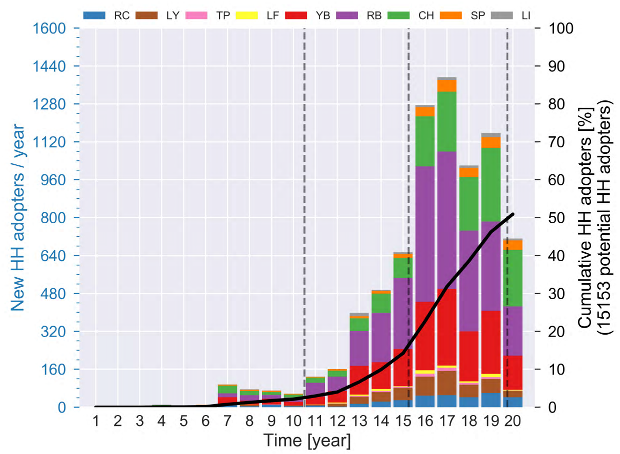
The PV penetration in the city district at the end of our simulation windows (20 years) is 35% for the one-to-one (*1to1*) scenario and 65% for the one-to-many (*1toM*) scenario. The installed capacity increases by a factor of about 1.80, i.e., from 5.90 MW in the 1to1 scenario to 10.64 MW in the 1toM scenario. Both curves do not reach the saturation level, even though in the 1to1 scenario is visible the knee preceding the plateau. Therefore, the value achieved at the end of the simulation window represents the maximum attainable PV power capacity under the 1to1 policy scenario. On the other side, the PV penetration in the 1toM scenario is much higher than the 1to1 scenario and it might further increase on a longer period, even though is not possible to determine exactly what would be its saturation value.

To explain why the installed PV power capacity in the 1to1 scenario is just 35% of the full potential we should analyze the reasons that hinder the households (HHs) to adopt. There are feasibility issues and socio-economical causes. The feasibility issues considered in our model are the ability of HHs to own the PV system, which is denied to tenants, and the availability of rooftop surface on the building. Instead, the socio-economical causes are related to HHs behavior and their adoption curve.

The feasibility issue account for the 68% of the HHs in the 1to1 scenario and for a 18.4% in the 1toM scenario. The increase of the feasibility for of 49.6% HHs in the 1toM scenario is due to rooftop availability in the shared configuration. The remaining 14.5% are the tenants that cannot own



(a) 1to1 scenario.



(b) 1toM scenario.

FIGURE 12. The graphs show for both scenarios: cumulative adoption curve normalized to the potential HH adopters; yearly new HH adopters aggregated by social groups. The dashed lines split the time into the typical ranges of the adoption categories by Rogers [10].

a PV system and they are excluded from the decision in the condominium.

The HH's behavior exhibit in both scenarios can be analyzed by looking at the adoption curves shown in Fig. 12a and Fig. 12b for the 1to1 and 1toM scenarios, respectively. The graphs present both the cumulative (solid line) and the differential curves (bars). The bars show the number of new HH adopters per each year, aggregated by their social groups, during the whole simulation period. Whereas, the solid lines show the cumulative number of adopters normalized to the number of HHs that have the feasibility to install the PV systems.

By using the cumulative plot, it is possible to classify the adopters using Roger's rages as: Innovators (*IA*), the ones up to the 2.5% of the potential; Early Adopters (*EA*), between 2.5% and 16%; Early Majority (*EM*), between 16% and 50%; Late Majority (*LA*) between 50% and 84% and Laggards (*LG*) above 84% of the potential. In Fig. 12a and Fig. 12b these ranges are indicated by vertical dotted lines.

The adoption curve of the 1toM scenario is delayed respect to the 1to1 one. In the 1to1 scenario, the EA period starts at the 5th year and by the 17th year half of the potential HHs already adopted; whereas in the 1toM scenario, the EA period starts later (11th year), then the number of adopter reaches quickly the 50% by the 20th year.

Analyzing further the adoption curves, it is possible to understand how adoption spreads among social groups and who are the HHs promoting or delaying the technology penetration. By looking at Fig. 12a of 1to1 scenario, the Innovator range is populated mainly by householders belonging to *RC* (Ruling Class) and *CH* (Clerks' HHs). The Early Adopters are represented by *LI* (Low-Income Italian), *LY* (Lonely old ladies and Young unemployed) social groups since; moreover, in this range starts the adoption by some HHs of the *YB* (Young Blue-collars) social group. However, the majority of the YB behave as Early Majority adopters, as well as *RB* (Retired Blue-collars), *TP* (Traditional Provincial) and *LF* (Low-income HHs with Foreigners) households. Finally, the HHs that show a more conservative behavior, i.e. Late Majority adopters, belong to *CH* and *SP* (Silver Pensioners) social groups. A peculiar behavior is exhibited by the *CH* as their adoption rate is almost constant along the whole time frame showing a behavior not classifiable in a specific range.

On the other side in the 1toM scenario (see Fig. 12b) it is not possible to associate a specific social group with an adopter range because all the social groups show similar adoption behavior. This phenomenon is explained recalling that the choice of whether adopt is collective in nature, i.e. the adoption in a condominium requires the agreement of the majority of the HHs. Moreover, the adoption mechanism is responsible for the time shift between the two adoption curves. In fact, in the 1toM scenario, the collective decision delays the adoption curve. Many of the HHs belonging to LI, LY, TP and YB social groups have advantageous economic conditions and are individually favorable to adopt earlier than the 11th year but are hindered by the RB and CH groups. In fact, they have a low attitude to adopt but represent the HHs majority (59%).

B. THEMATIC MAPS

The analysis of the thematic maps is fundamental to understand the spatial diffusion over the district at census' section level. Such maps can be used to highlight the presence of probable bottleneck or strengths in the diffusion. Moreover, it is possible to analyze the spatio-temporal diffusion through animated maps over time. The thematic maps of San Salvario's district for the scenarios 1to1 and 1toM are reported in Fig. 13.

The PV penetration is expressed in terms of percentage of kW installed over the census block potential, at the 20th year of the simulation. The time evolution of the thematic maps, showing how the PV adoption spreads over the districts, is available as supplementary material. In the 1to1 scenario the PV share distribution is flat (see Fig. 13), if we exclude 30% of the census blocks whose share is lower than 10%,

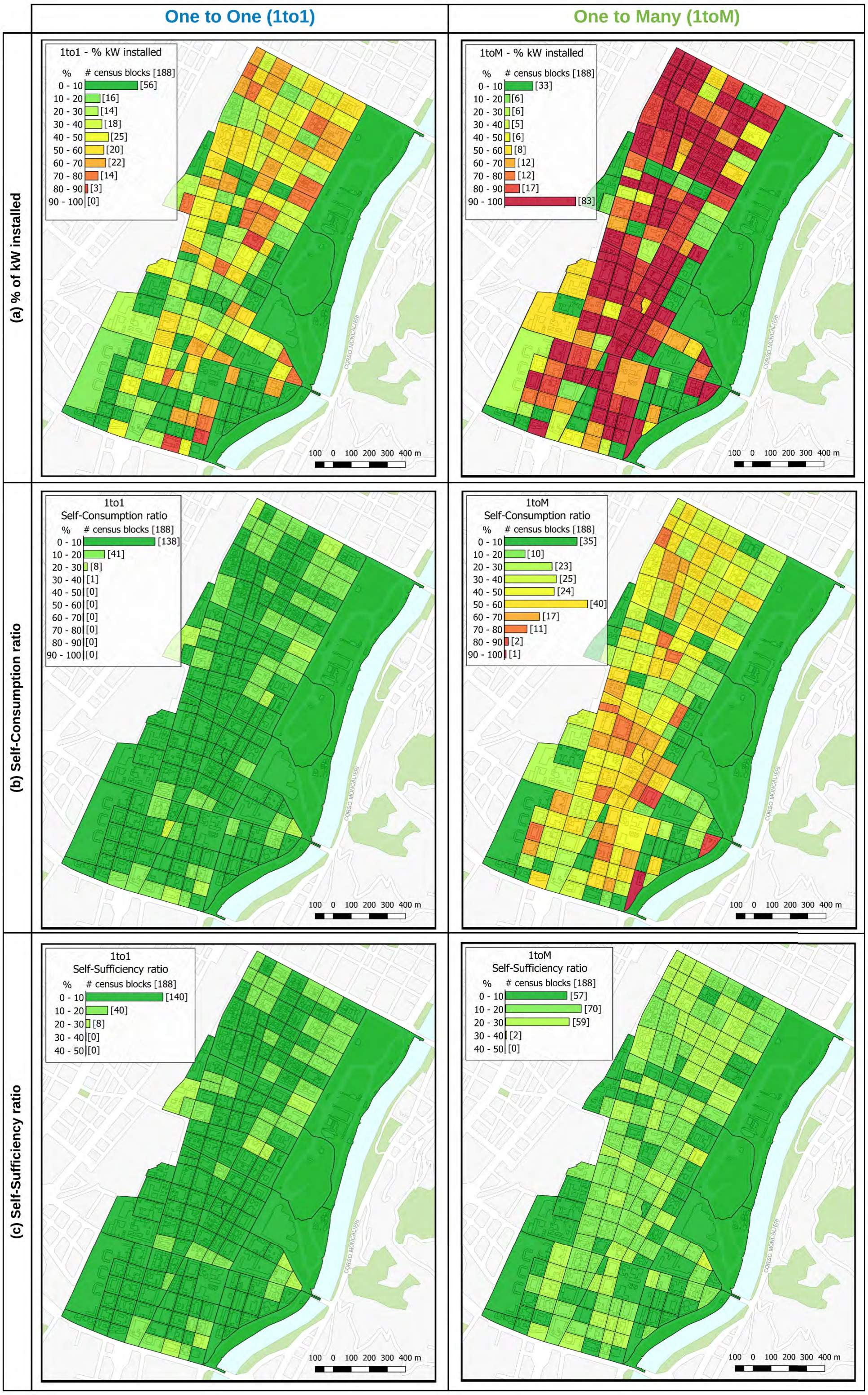
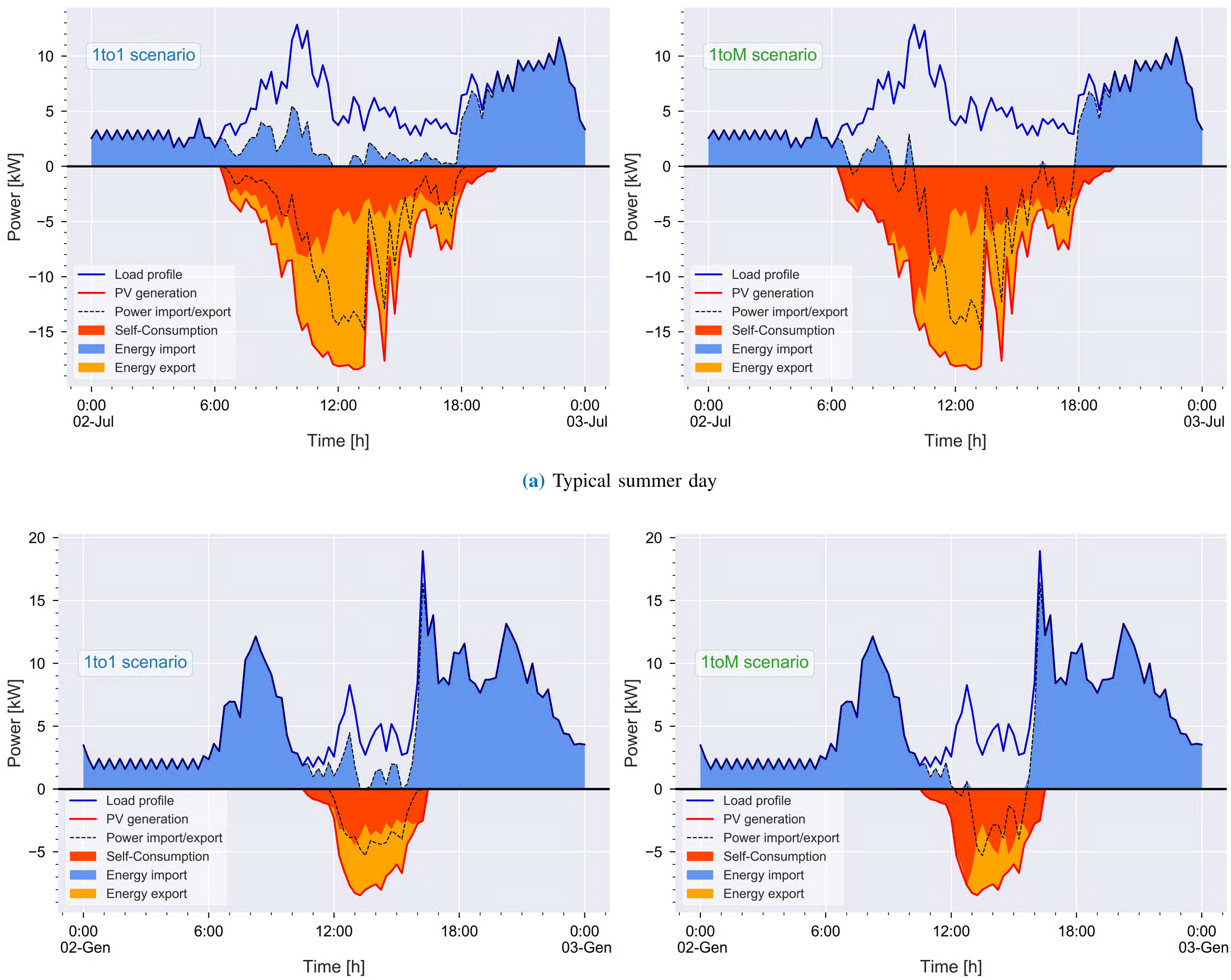


FIGURE 13. **Thematic maps of the scenarios 1to1 and 1toM, regarding the final step (20th year) of the simulation. The spatial distributions were calculated for each census's section: (a) the *% of kW installed* respect to the maximum potential; (b) the average of *Self-Consumption ratio*; (c) the average of *Self-sufficiency ratio*. The parameters are subdivided into classes in the domain range and colored based on the magnitude value of each class (from green to red). Note that it was considered the whole PV potential for each census block and the total potential electrical demand of all agents that could feasibly adopt a PV system (therefore, the buildings with zero PV area were excluded).**



(a) Typical summer day

(b) Typical winter day

FIGURE 14. Comparison of the scenarios in an example Condominium of 20 residents, assuming same load and PV generation profiles in two typical days (Fig. 14a summer and Fig. 14b winter): in scenario 1to1, each household installs a rooftop PV system of 1 kWp for a total of 20 kWp in the whole Condominium; in scenario 1toM, the residents install a single shared rooftop PV system of 20 kWp. The comparison shows the clear advantage of the 1toM configuration, in which the local generation is efficiently exploited because is primarily shared among residents, thus increasing the self-consumption. Conversely, in 1to1 configuration the local generation is never shared; therefore, at the level of Condominium, power import and export comes at the same time and the self-consumption is low. Furthermore, the resulting load profiles also exhibit the typical Duck Curve that shows the timing imbalance between peak demand and renewable energy production.

and quite homogeneously distributed over the whole district. Besides, just 2% of the blocks reach a penetration above 80%. On the other side, in the 1toM scenario, the majority of the census blocks reach the 100% of installed PV, with a jeopardize spatial distribution of the remaining census blocks that have lower PV share. Moreover, in this case, there is an 18% of blocks with a PV share lower than 10%. Other useful indicators are the rates of self-consumption and self-sufficiency. In the 1toM scenario, the generated electricity in most of the blocks is self-consumed for more than 50%, with self-sufficiency above 20%. On the contrary, the majority of the blocks in the 1to1 scenario have self-consumption and self-sufficiency levels below 10%.

The great potentiality of the thematic map is the capability of localizing easily the census block with evident issues hindering the PV technology diffusion and subsequently analyze them in detail understand what is the problem. In fact, we can analyze how the electricity generated by PV systems are used at the blocks level or within the condominium. As an example, we can analyze the daily net power import and export profiles of a sample Condominium of both scenarios, illustrated in Fig. 14 in a typical day of summer and in a winter one. It can be noticed that for the 1to1 scenario, at a given time, there is the presence of power imported and exported simultaneously, rather than the 1toM scenario where often the electricity is weather imported or exported. This difference is due to those households that export to the grid part of their excess of generated electricity without sharing it with their neighbors, which at that time are importing it from the grid. For these reasons, in 1to1 the rooftop solar area of the building is not exploited efficiently and is not cost-effectively. On the other hand, in 1toM the PV production is firstly shared among the residents and then, eventually, is sold to the grid. Normally, in 1toM there is no simultaneous presence of power import and export, except for those cases in which part of the HHs do not participate to the energy community and import the electricity from the grid. Nevertheless, the amount of imported electricity is significantly lower than the 1to1 scenario because of the high Self-Consumption, especially in the summer season when the effects are more pronounced. Moreover, notwithstanding the almost halved PV production during the winter season (see Fig. 14b) with respect to the summer one, the 1toM scenario gives the opportunity to improve the self-consumption anyway.

VII. CONCLUSION

In this work, the diffusion of residential rooftop PV systems in a city district was studied by means of a co-simulation platform. The goal of the co-simulation is to quantitatively assess the impact of regulatory schemes on the adoption of roof-top PV. In particular, we have studied a 'one-to-one' business as usual regulatory scheme and a 'one-to-many' configuration that enables the citizen energy communities. To do so we integrated into the platform geo-referenced data (i.e., technical, environmental, economic and social quantitative parameters or indicators) of city buildings and households. An agent-based model simulates the human decision-making process. The model takes into account the complexity and heterogeneity of the real-world in terms of the geographical distribution of buildings, social structure and peer interaction. The households are thus the agents who act, interact among them, and finally decide whether to adopt rooftop PV or not.

A real city district is used to simulate two different energy policy scenarios depicting the transition from the single user - single PV plant case (*one-to-one configuration*) to paradigms in which a shared PV system is used by a community of users (*one-to-many configuration*). The PV diffusion curves under the two different scenarios, as the cumulative percentage of kW installed over time with respect to the maximum potentiality of the system, show the huge impact that the underlying regulatory framework has on the exploitation of the available PV potential in the district. In addition, thematic maps of the percentage of kW installed, self-consumption ratio and self-sufficiency ratio have been constructed over the census section maps. As suggested by the European Renewable Energy Directive (RED II), national policies and regulations should be oriented toward the establishment of Citizen Energy Communities (CEC). Energy community buildings with shared rooftop go into this direction. Indeed, the possibility to spread the auto-generated solar electricity over the load profile of the entire residents of Condominium results in self-consumption rates greater than 50% and self-sufficiency ratios above 20% for most of the simulated buildings.

The use-case of this work is a city district that includes 18,720 households distributed over 1,290 building blocks and a surface area of 2.47 square kilometers was used to test the proposed ABM framework. Results show how the establishment of 'prosumers' within Condominiums (i.e., energy community buildings) is key to yield high diffusion rates. The installed capacity increases by 80% by switching from the *one-to-one configuration* to the *one-to-many* paradigm, i.e., from 5.90 MW of rooftop PV installed on single-family households and/or single PV owners to 10.64 MW in energy community buildings. Moreover, the possibility to spread the auto-generated solar electricity over the load profile of the entire population of a Condominium results in self-consumption rates greater than 50% and self-sufficiency ratios above 20% for the majority of the simulated buildings.

The ABM methodology is a powerful tool to simulate the decision-making process of consumers with respect to the adoption of new energy technology in a complex system and explore what could happen when varying environmental parameters. Moreover, the ABM framework takes into account the role of the social influence and social interactions among agents in combination with economic and technical constraints or drivers.

The main limitation of the present work is most likely in the calibration of the ABM model, i.e., the fine-tuning of those empirical and user-defined parameters that govern the shape and rate of diffusion of energy technology. In the present work, we have extensively relied on the existing literature on ABM applied to energy technology diffusion to derive sensible values. Future work should aim to use past diffusion trends of a given technology, available for a given time window and geographical area, in order to calibrate the ABM model parameters. Concerning the specific case of rooftop PV, past rates of rooftop PV adoption on city buildings are either unavailable as open data, or unusable since they incorporate a variety of supporting schemes changed multiple times [88].

The developed ABM co-simulation platform allowed a fine-grained understanding of the emergent patterns and spatio-temporal evolution of rooftop PV diffusion in a city district under different regulatory schemes. We tested the platform in a specific context (city district), however, the approach can be extended and generalized to different geographical areas. In the Appendix, we describe in detail the methodology for preparing the required data inputs for assessing a specific territory. In addition, the presented co-simulation platform, thanks to its modularity and flexibility, could simulate the adoption of other building-integrated energy technologies (such as energy storage systems and micro-cogeneration power units) by integrating or substituting in a plug-an-play fashion the module(s) of the technology under investigation. The main limitation of the present work most certainly lies in the initialization of some user-defined parameters. Especially, by means of a survey data on the willingness by households to adopt green technology (e.g., photovoltaics), the initial agents' opinion could be better initialized. In general, the more empirical data is fed to the ABM to describe the social layer, the more realistic are the obtained simulations. Thanks to high-performance computing, data science techniques, and the increasing availability of granular city-data coming from Information and Communication Technologies and Internet of Things solutions for the smart city more robust and powerful ABM simulation could be produced in the future. The application of ABM to the energy sector could support city-planners, local and national policy-makers, utilities and citizens in the decision-making process towards communities that make a smart, efficient and rational management and use of energy.

APPENDIX A INVESTMENT EVALUATION

The investment evaluation is made by calculating the payback period (*pp*). The investment strongly depends on the scenario under study due to the different subsidies that are in place.

For the sake of simplicity, a general framework of *pp* is provided. We consider the baseline scenario with the current energy policies in Italy. An agent, that would adopt, chooses the size of the rooftop PV system (the power, P, expressed as kW peak [kWp]) so that the yearly production of the PV system E_{PV} [kWh/y] is equal to the yearly electricity consumption of the household E_{load} [kWh/y]. The economic assessment is made on a yearly base and it is supposed that E_{load} does not change during the years. Thus, the yearly load profile is considered as a time-invariant (static) value. Meanwhile, the yearly productivity E_{PV} decreases over time due to degradation of the solar cells.

The power of PV system P is calculated from the definition of the productivity E_{PV}

$$E_{PV} = A_{PV} \cdot \eta_{STC} \cdot G_t \cdot PR = P \cdot Y_R \cdot PR, \tag{14}$$

where: A_{PV}, total solar panel area [m]^2; η_{STC}, efficiency of PV modules at Standard Test Condition; G_t, yearly global in-plane irradiation [kWh/(m^{2}y)]; PR, Performance Ratio, also known as balance of plant, that includes the different losses of the whole PV system; Y_R, Reference Yield or peak solar hours, calculated as G_t/G_{STC} [h/y] where G_{STC} is the reference solar irradiation at STC equal to 1 kW/m^2

The total investment $I(t_I)$ is calculated as (15). The year of investment t_I is referred to the time t of the model. In $t = 0$ (model initialization) it is assumed an initial turnkey cost c_0 [€/kWp] of rooftop PV system and a yearly cost reduction trend τ_c.

$$I(t_I) = P \cdot c_0 \cdot (1 - \tau_c)^{t_I} \tag{15}$$

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 a time $y = t - t_I$, so referred to the year t_I of installation, the initial productivity at $y = 0$ is equal to E_{PV_0}. The productivity $E_{PV}(y)$ is obtained from the (16).

$$E_{PV}(y) = E_{PV_0} \cdot (1 - \tau_{PV})^y \tag{16}$$

A part of the yearly electricity produced by PV modules is self-consumed $E_{selfcons}(y)$ [kWh/y], and it can be calculated as

$$E_{selfcons}(y) = E_{PV}(y) \cdot sc, \tag{17}$$

where sc is the ratio of self-consumption of a household. Self-consumption is evaluated thanks to the knowledge of both load and production profiles during a whole year with a resolution of 15 minutes [74]. It is defined as the ratio of self-consumed energy with respect to the energy produced by PV over 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 (18).

$$E_{export}(y) = E_{PV}(y) - E_{selfcons}(y) \tag{18}$$

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 (19).

$$E_{import}(y) = E_{load} - E_{selfcons}(y) \tag{19}$$

The evaluation of the payback period is made by calculating the net present value $npv(y)$, as already explained in Section IV-B6. The formulation is reported here for clear understanding.

$$\begin{aligned} npv(y) &= -I + \sum_{y=1}^{N} \frac{R(y)}{(1 + WACC)^y}, \\ npv(y) &= 0 \rightarrow y = pp, \end{aligned} \tag{20}$$

where the I [€] is the total investment made at time t_I, $WACC$ is the Weighted Average Cost of Capital, N is the final year of the npv calculation (maximum PV lifetime) and $R(y)$ [€] is the net cash flow at time y. $R(y)$ is generally composed by

$$R(y) = R^+(y) + R^-(y). \tag{21}$$

$R^+(y)$ represents the positive cash flow [€], and it is generally composed by the yearly savings S achieved thanks to the electricity produced and not bought from the grid; the revenue represented by currently fiscal detraction R_{taxr}; the revenue from the particular tariff mechanism adopted R_i. 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 [81], [85], [89], which are:

- Sale to energy service utility (Ritiro Dedicato - RID), that is a simplified mechanism available to producers for the marketing of electricity produced and fed into the network. It consists in selling to the GSE the electricity injected into the grid by the PV system, 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;
- Net-Billing scheme (Scambio Sul Posto - SSP), 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 a tariff depends on what permits to obtain the best return on the investment, thus the smallest payback period.

The mathematical definitions for the positive cash flow are reported in the following equations:

$$R^{+}(y) = S(y) + R_{taxr}(y) + R_i(y), \text{ with } i = RID, SSP, \quad (22)$$

$$S(y) = E_{selfcons}(y) \cdot e_{price}, \quad (23)$$

$$R_{taxr}(y) = \left(y \leq 10 \rightarrow \frac{I(t_I) \cdot taxr}{10} \right) \wedge (y > 10 \rightarrow 0), \quad (24)$$

$$R_{RID}(y) = E_{export}(y) \cdot e_{sell}, \quad (25)$$

$$\begin{aligned} R_{SSP}(y) = {} & \min(O_E, C_{Ei}) + CU_{sf} \\ & \cdot \min(E_{export}, E_{import}) \\ & + (E_{export}(y) > E_{import}(y) \rightarrow C_{Ei} - O_E) \\ & \wedge (E_{export}(y) \leq E_{import}(y) \rightarrow 0), \end{aligned} \quad (26)$$

$$O_E(y) = E_{import}(y) \cdot PUN, \quad (27)$$

$$C_{Ei}(y) = E_{export}(y) \cdot MGP, \quad (28)$$

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]; $taxr$ - tax relief, which is spread over 10 years; E_{export} - electricity fed into the grid and sold [kWh/y]; e_{sell} - price of electricity fed into the grid [€/kWh]; E_{import} - electricity purchased from the grid [kWh/y]; PUN - Italian index of electricity market price (Prezzo Unico Nazionale); MGP - zonal price that is formed on the market of the day before (Prezzo del Mercato del Giorno Prima); CU_{sf} - yearly contribution calculated by the GSE to valorize 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 (Corrispettivo Unitario di Scambio Forfettario).

$R^{-}(t)$ 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 is

$$R^{-}(y) = I(y + t_I) \cdot OeM, \quad (29)$$

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

APPENDIX B
CHARACTERIZATION OF HOUSEHOLDS HETEROGENEITY

Consumers investments in new technology are related not only on economic aspects but also to specifics attitudes toward a technology's attributes and social aspects [10]. Moreover, the beliefs of people are dependent on background factors of individual, social and demographic nature. 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, the ABM framework exploits census and social clustering data.

TABLE 3. List of census variables used in the ABM framework [77].

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

A. CENSUS VARIABLES

The last census data of Italy (2011) is available from the portal of [77] and it contains the census variables. After having examined of whole variables we selected twenty to generate the households in the model. The selected census variables are listed in Table 3 by reporting the field code and a brief description per each variable.

B. SOCIAL GROUPING

A social structure of the households has been implemented in the model. Different social groups have been incorporated in the model by referring to the new social clustering of Italy proposed by Istat and published in the Annual Report 2017 [80]. Each group is representative of households displaying similarities in their socio-economic, demographic behavior and consumption patterns. Thus, each group has shared values and attitudes toward work, family type, leisure, money, and consumption. The Istat 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 are defined following a classification method of a hierarchical type [80]. The social groups identified by Istat are the following, classified by the highest income equivalent to the lowest:

1) Ruling class (RC);
2) Silver Pensioners (SP);
3) Clerks' households (CH);

TABLE 4. Statistics, characteristics and own assumptions made for each social group.

Data \ 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[a]	1.694	1.323	1.135	0.965	0.934	0.804	0.758	0.707	0.606
Gini coefficient	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 [%]	7.6	12.7	12.8	24.5	26.9	53.9	38.7	43.7	54.5
Fifth highest equivalent household expenditure [%]	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
$W_{if,k}$[b]	0.516	0.351	0.270	0.225	0.151	0.107	0.055	0.057	0.052
$W_{att,k}$[c]	0.611	0.518	0.465	0.408	0.306	0.171	0.117	0.116	0.084
$W_{sn,k}$[c]	0.331	0.360	0.392	0.304	0.340	0.270	0.350	0.308	0.345
$W_{pbc,k}$[c]	0.058	0.121	0.143	0.288	0.353	0.559	0.533	0.576	0.571
Mean household members type[d]	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 workers with kid

[a] In 2017, the mean income of household in Italy is 29,988 €(with standard deviation equal to 2,500 €); [b] Calculated taking into account the fifth highest household expenditure; [c] Weights of att, sn and pbc were derived from the fifth household income, the distribution of group per type of municipality and from the risk of poverty and social exclusion, respectively. Each weight is normalized between groups and finally normalized between the components of the TPB to obtain the sum of the weights equal to 1; [d] The type of household members was used for the estimation of the load profile for each group.

4) Young blue-collars (YB);
5) Retired blue-collars' households (RB);
6) Lonely old ladies and young unemployed (LY);
7) Traditional provincial households (TP);
8) Low-income Italian households (LI);
9) Low-income households with foreigners (LF).

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 (the member of the household that is the breadwinner). Citizenship of the household members occurs 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 [80]. In the Annual Report 2017 of Istat [90], a brief and salient description of the social groups is reported.

Thanks to the correlation of features and statistical data provided by each social group and with those of the census sections (georeferenced) it was possible to generate the households in the environment of the ABM. Each agent is assigned to a social group and some other attributes are derived by related data, e.g. the income value per each household, the number of components, the level of innovation, the weights for the attributes of Theory of Planned Behavior. In Table 4 we reported an overview of each group related to all statistics and characteristics used and also the own assumptions made for the purpose of the developed ABM framework.

TABLE 5. Level of Innovativeness was assumed for each social group based on what is already done in literature with other social clustering models and taking into account the Diffusion of Innovations by Rogers [10].

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

C. INNOVATIVENESS

The level of innovativeness represents 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 defined in the model as a static attribute, and the household acknowledges it from the social group of belonging. The Istat social groups' data do not offer this type of information per each group. Therefore, the innovativeness is assumed by taking into account other similar social clustering used in the literature [51], [53] and following the framework of Diffusion of Innovation theory proposed by Rogers [10]. The assumptions were shown in Table 5.

D. WEALTH SIMILARITY IN SOCIAL NETWORK

In our model, the agents' selection to form the social network is based on wealth similarity. The locals are obtained by selecting, from the neighbors' list, the agents within social groups that have wealth similar condition, thus considering the social groups that have a similar equivalent level of income. More is similar to the wealth condition, and more is the probability of remaining as locals, as shown in Table 6.

TABLE 6. Interaction probability table among 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

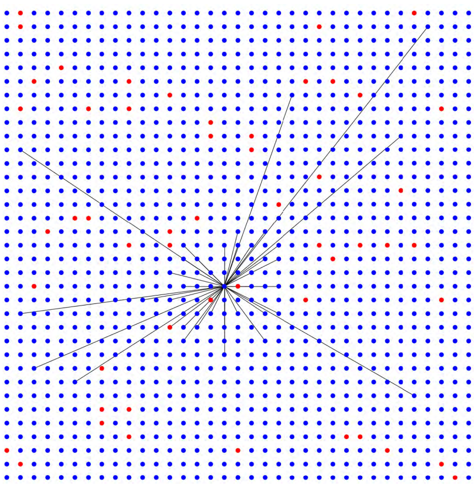


FIGURE 15. Map of the 'dummy city' *sc35*. It is constituted by 35 × 35 agents in a square lattice with one meter between them. In red the already PV adopters are shown. Moreover, the map shows an example of an agent's Small-World Network.

APPENDIX C
PARAMETRIC ANALYSIS ON *SC35*

The parametric analysis has been done to test the functionality of the model and to analyze the resulting diffusion curves. Such analysis is needed to explain the behavior of each parameter in the diffusion process. The analysis has been conducted on a 'dummy city' called *sc35*. The *sc35* aims to have an agents' data-set as homogeneous as possible to learn the behavior of the model and its functionality. It consists of a square lattice of points 35 × 35 spaced a meter, as shown in Fig. 15. Each point represents an agent, and it is defined by attributes randomly chosen from the empirical distributions applied in the real application.

The hypothesis of adoption is based on choosing a sized PV system that covers the yearly household electricity consumption and on the investment evaluation described in the main text. Finally, all the experiments are simulated for 80 steps equivalent to 20 years. The time domain is not calibrated, thus the reference time is arbitrarily chosen as a quarter of a year. We did several experiments to probe the suitable range of the values of parameters. The simulations and the chosen values are listed in Table 7. Test T13 (blue) was considered the baseline. The other tests were made changing just one parameter (red) respect to baseline.

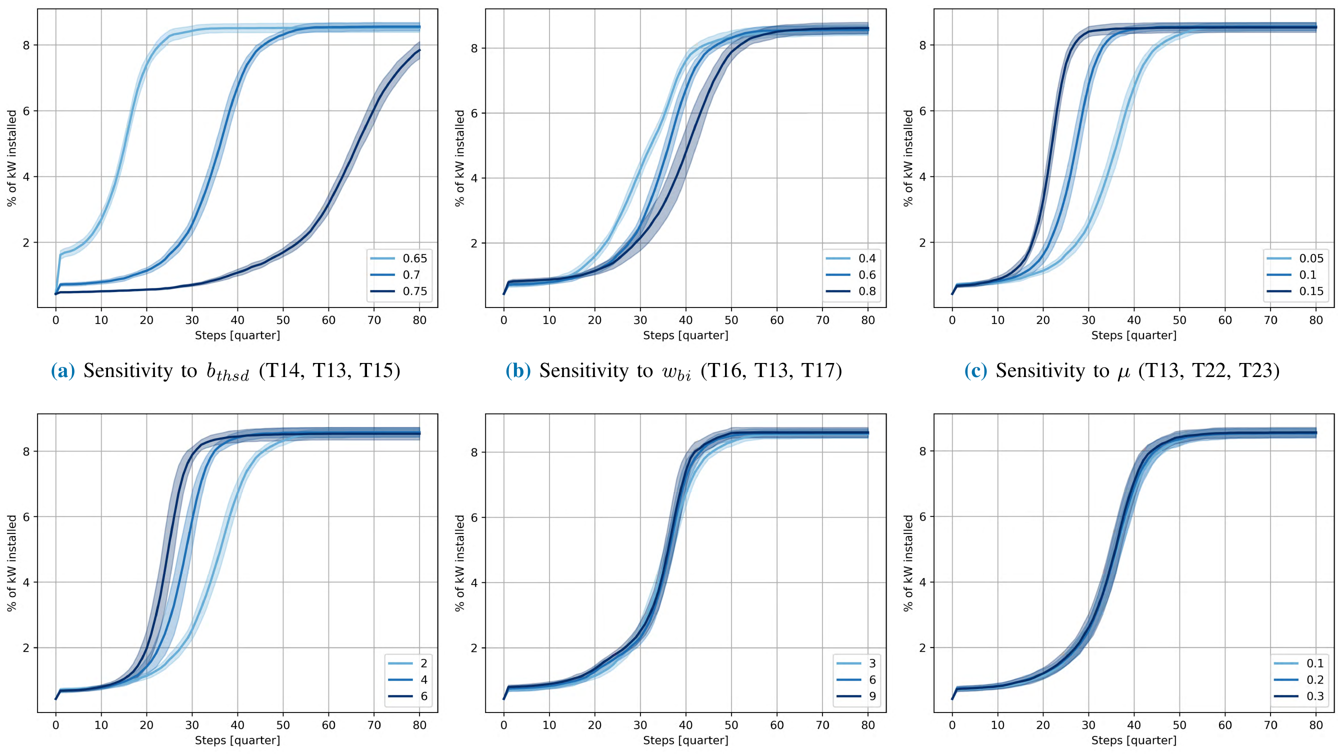
TABLE 7. List of the test performed in ***sc35*** with the chosen parameters. The T13 (blue) is the baseline with reasonable values of the parameters.

Test	b_{thsd}	w_{bi}	rw	r	μ	ϕ
T13 (base)	0.7	0.6	0.1	3	0.05	2
T14	0.65	0.6	0.1	3	0.05	2
T15	0.75	0.6	0.1	3	0.05	2
T16	0.7	0.4	0.1	3	0.05	2
T17	0.7	0.8	0.1	3	0.05	2
T18	0.7	0.6	0.2	3	0.05	2
T19	0.7	0.6	0.3	3	0.05	2
T20	0.7	0.6	0.1	6	0.5	2
T21	0.7	0.6	0.1	9	0.5	2
T22	0.7	0.6	0.1	3	0.1	2
T23	0.7	0.6	0.1	3	0.15	2
T24	0.7	0.6	0.1	3	0.05	4
T25	0.7	0.6	0.1	3	0.05	6

The general result of the parametric sweep shows that the obtained diffusion curves follow the classical S-shape curve, as shown in Fig. 16. Therefore, it can be distinguished three different phases of diffusion over time: *phase-1)* slowly initial increment due to the adoption of the people defined as innovators; *phase-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 inflection; *phase-3)* the growth of the curve slowing-down going to reach the saturation level. As a general result, it can be seen that each experimental test starts from the same point in phase-1, because of the same initialization of the model for all the experiments. Furthermore, in phase-3 each experimental test will reach the saturation level in the long run, which is equal for all the experiments because the model inputs were not changed.

A. TPB PARAMETERS SENSITIVITY: b_{thsd} AND w_{bi}

The parameters b_{thsd} and w_{bi} are related to the mathematical model of TPB [28]. As shown in the plot on Fig. 16a, b_{thsd} substantially impacts in the diffusion curve that undergoes to a shift of phase-2 along the time-axis. This because the lower is the value of the threshold's behavior over which an agent adopts, and more is the number of agents that will adopt at a given step. Therefore, the knee point of the curve in phase-1 is more defined and occurs earlier. Note that at the initial step,



(a) Sensitivity to b_{thsd} (T14, T13, T15)

(b) Sensitivity to w_{bi} (T16, T13, T17)

(c) Sensitivity to μ (T13, T22, T23)

(d) Sensitivity to ϕ (T13, T24, T25)

(e) Sensitivity to r [m] (T13, T20, T21)

(f) Sensitivity to rw (T13, T18, T19)

FIGURE 16. Parametric analysis on 'dummy city' ***sc35***.

there is a rung in the curve that is more accentuated in the case of lower values of the threshold. This behavior occurs to step 0 of the model in which assumes an initial number of adopters in the system that are not affected by the calculation of TPB. Thus, they are not in relation to the threshold value. Finally, because of curve shifting, the saturation points of phase-3 of diffusion are reached at different times. On the other hand, looking at the plot in Fig. 16b, 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 Behavioral Control *pbc* with respect to the Behavioral Intention *bi*. 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. Therefore, the behavior 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*.

B. RA PARAMETERS SENSITIVITY: μ AND ϕ

The parameters μ and ϕ modify the opinion dynamics, which is modeled by RA algorithm [37]. As shown in the plot in Fig. 16c, μ changes the slope of the inflection 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 and the higher is the speed of opinions' clustering. Concerning positive opinions, high μ makes high the Attitude Towards the Behavior *att* over time. The same behavior happens with the parameter ϕ, as shown in Fig. 16d, 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 opinion dynamics. Finally, because of the changing of the slope in phase-2, the saturation points of phase-3 of diffusion are reached at different times.

C. SWN PARAMETERS SENSITIVITY: R AND RW

The parameters r [m] and *rw* modify the creation of the agents' social networks, based on Small-World Network [36]. As shown in both plots in 16e and 16f, these parameters do not modify the emergent behavior pattern of the system, but actually, it is not always so. In fact, this happens due to the high spatial homogeneity of the *sc35*'s data set. In the dummy city, even if with higher radius and rewiring values, the emergent diffusion curves do not change so much between them. On the contrary, these parameters can strongly affect the diffusion curve in the real urban context, due to the high spatial heterogeneity and clustering of the agents. Moreover, as the diffusion curve describes an emergent behavior of the entire population, modifying these parameters, the differences could be evident by observation of the spatial domain, in which the local states of the agents are more relevant.

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