Agent Based Simulation of Incentive Mechanisms on Photovoltaic Adoption

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Abstract. Sustainable energy policies are becoming of paramount importance for our future, shaping the environment around us, underpinning economic growth, and increasingly affecting the geopolitical considerations of governments world-wide. Renewable energy diffusion and energy efficiency measures are key for obtaining a transition toward low carbon energy systems.

A number of policy instruments have been devised to foster such a transition: feed-in-tariffs, tax exemptions, fiscal incentives, grants. The impact of such schemes on the actual adoption of renewable energy sources is affected by a number of economic and social factors.

In this paper, we propose a novel approach to model the diffusion of residential PV systems and assess the impact of incentives. We model the diffusion's environment using an agent-based model and we study the emergent, global behaviour emerging from the interactions among the agents. While economic factors are easily modelled, social ones are much more difficult to extract and assess. For this reason, in the model we have inserted a large number of social parameters that have been automatically tuned on the basis of past data. The Emilia-Romagna region of Italy has been used as a case study for our approach.

1 Introduction

Energy policies affect and are affected by a number of interconnected social, economical and environmental aspects. The transition toward a sustainable and low-carbon economy should be fostered by governments worldwide. Energy efficiency measures and renewable energy sources are two key enablers for such a transition. For this reason a number of policy instruments have been implemented to push stakeholders toward virtuous energy-aware behaviour: feed-in tarifs, tax exemption, investment grants, fiscal incentives. Stakeholders involved in energy policies have conflicting interests that should be taken into account to understand and forecast the impact of energy policy instruments.

We propose here the design and assessment of a predictive model that takes into account both economic and social drivers pushing stakeholders (households in particular) toward the adoption of photovoltaic plants. A large portion of the total installed PV power, in fact, comes from photovoltaic panels installed by private citizens and enterprises. For this reason, policy makers cannot directly

M. Gavanelli et al. (Eds.): AI*IA 2015, LNAI 9336, pp. 136–148, 2015.
DOI: 10.1007/978-3-319-24309-2_11

decide on the total photovoltaic power installed, but they have to foster the PV power generation through indirect means, usually in the form of incentives to the PV energy (i.e. feed-in-tariffs for the electricity generated by PV systems).

We propose an agent-based model[5,9,17] (ABM) that simulates the behavior of single households and government entities (*micro*-level) in order to evaluate and explain emergent phenomena (*macro*-level). We tackled the challenge of reproducing the household's decisions to install a PV system for their houses. We take into account both economic aspects (return on investment, income, interest on loans), territorial aspects (position, roof width, population distribution) and social aspects (imitation, network effect on knowledge diffusion). Since it is very difficult to a priori calibrate these parameters, we employ automatic parameter tuning techniques to tune these social aspects to meet an emerging behaviour that is taken from past data. Past data concern policy instruments present in the past and photovoltaic adoption[1].

2 Related Works

Many scholars have tried to model the diffusion of innovations. Their works had evidenced that the diffusion of innovation is a social process. Many proposed models are ABMs, where the agents are connected to form a *small-world* network. The information exchanged between entities in the network influences the diffusion of the innovation. In this direction [1] implemented a threshold model based on the so called "bandwagon effect". In this model the increase of the number of adopters generates new information about the innovation, which in turn produces high pressure on people who have not yet adopted the innovation. An important factor in this process is the estimation of the profitability of the innovation made by potential adopters. Since potential adopters may be unsure about the correctness of their profitability assessment, other people who have already adopted the innovation could influence their decision. The authors of [1] express the bandwagon assessment of innovation of a potential adopter as a function that involves the evaluation of profitability of the new technology and the amount of information received regarding the innovation, weighted by the amount of "trust" placed on such information.

Another approach used to predict the diffusion of an innovation has been proposed by [4]. In this model the price and the performance of the innovation influence people decisions. The potential adopter knows the price of innovation but he ignores its performance. The performance is based on the perception that the potential adopter has of the innovation. Over time, potential adopters receive information about the performance by word-of-mouth from other adopters and consequently the uncertainty about the innovation potential is reduced. The diffusion of residential PV systems could be modeled using the previously described models. The innovation is the PV technology and potential adopters are the households: models estimate the benefits deriving from the adoption of a PV system and a household decides whether to install or not a PV system.

[1] Data are available (in Italian) on http://www.gse.it

The authors of [18] proposed a two level threshold agent-based model that is specifically aimed at estimating the diffusion of PV systems. In this model agents represent households that choose whether or not to install a PV system. The low level component simulates electric consumption for each agent and provides the payback time of the investment. The high level component models the behaviour of agents toward PV adoption. Four factors affect the decision: payback period, household income, neighbourhood and advertisement. The adoption of a PV system by a household is determined by its "desire level", computed as the linear combination of the four factors. If the desire level of the household exceeds the threshold the household installs a PV system. [10] has proposed an ABM inspired by the work of [18]: the household's decision is again a linear combination of four factors but in the latter work these factors are weighted differently according to the social class of the household. Moreover in the [10] model agents are connected to form a small-world network in such a way that those who are in the same social class are more likely to be linked together.

Another factor that we may consider is the geographical location of buildings. [12] proposed a model that uses a geographic information system (GIS) along with an ABM to study the diffusion of PV systems. Including the real topology of the area under consideration allows to analyse the effects of solar exposure and population density on diffusion of PV systems. Agents who have a similar opinion on technology could influence each other.

3 The Simulated Model

Our model simulates the behaviour of households in presence of different incentive mechanisms, to predict the diffusion of PV systems. We focused mainly on families living in the Emilia-Romagna region (and especially considering the 2007-2013 period), but the process described below is valid for any region or country. In [3] [2] we proposed a preliminary agent-based model to simulate the impact of national and regional incentives on the installation of PV panels in the Emilia-Romagna region. The model we discuss in this paper largely improves the previous version, especially in the social interactions among the agents; our work was partially inspired by related works cited in Section 2, in particular by [10]. The simulation model was developed in Netlogo [15].

We define two kinds of agents: the households and the region. The households make the decision whether or not to install a PV system. Each household is described by a set of attributes: age class, education level, income, family size, consumption, roof area, budget, geographical coordinates and social class. We use these attributes to define the household behaviour and to build the social network. The region agent regulates the regional incentive; it defines the type of incentive offered, the amount of available budget and who is eligible to obtain the incentive. The regional incentives are provided by the region on top on the national ones given by the Italian government during the considered timespan, i.e. a feed-in tariff (see [3] for a detailed survey on the incentives).

The simulator is structured into two phases: 1) the configuration phase and 2) the evolution phase. In the *configuration phase*, the simulator sets up the virtual environment and creates the agent-based model. Firstly, it places the agents on the virtual environment recreating the actual population density. WE have used data on the buildings of the Emilia-Romagna region to obtain the positions and roof areas of houses. The simulator uses this information to assign a building and a roof to each household. Then the simulator builds the social network taking into account the physical distance between the household and the proximity between their attributes. The social network determines how the information about PV systems is exchanged.

In the *evolution phase* the simulator runs the model, recreating the behaviour of agents and updating the virtual environment. A simulation consists of a sequence of steps with a time frame of six months. The PV adoption by each household/agent is affected by the payback period of the investment, environmental sensitivity, the household's income and the communications with other households. We express these factor using a combination of four functions (which we refer to as *utility* function) to determine the "desire level" of a household. If the desire level exceeds a threshold the household installs the PV system.

3.1 Configuration Phase

In the configuration phase the simulator initializes the virtual world creating the starting conditions. The simulator loads the dataset containing the household's descriptions and places the families in the virtual world following the actual density distribution. The geographical coordinates and roof areas are obtained by associating each family to a building: buildings are sorted by their roof size and families with the highest income and the largest number of members are assigned to the biggest ones.

We acquired the buildings by analysing the Ersi shape-files provided by Emilia-Romagna region[2]. Those shape-files contain a polygon for each building detected by the region. Since our model requires only the positions of buildings and the areas of the roofs, it was necessary to process these files to extract the relevant information. We used QGIS [11], a free and open source Geographic Information System (GIS), to manipulate these shape-files and calculate the position and size of the houses.

Each household is described by a vector of attributes: age class, education level, income, family size, energy consumption and social class. The distribution of each attribute is obtained by analysing the Survey on Household Income and Wealth (SHIW) provided by Bank of Italy[3]. In addition each household establishes a budget for purchasing a PV system. The key idea is that to different household income classes correspond different spending powers. If a family has an income around the mean, the family will expect to pay the average PV system price. Conversely, if the family income is lower or higher than the average, the family will aim to spend less or more for a PV system.

[2] http://dati.emilia-romagna.it

[3] https://www.bancaditalia.it/statistiche/indcamp/bilfait/

To assign an income to each family we used a linear regression model based on a set of explanatory variables extracted from the data provided in SHIW, i.e. the number of earners and members of the family, age class, etc.

The Social Network. During the configuration phase the simulator initializes also the social network: for each family, a list of friends is provided. Since the families are geographically distributed on the region we use the extended version of the rank-based model proposed by [8] to get the small-world properties. In such a model the probability that a link between node u and node v exists is proportional to a ranking function which depends both on the geographical proximity of the nodes (physical neighbours) and on the attribute proximity of the nodes (how the nodes are similar w.r.t. their attributes). After we build a network using the extended rank-based method, we randomize it to add long-range links. These links drastically reduce the average path length because they connect distant parts of the network. The randomization process takes every edge and rewires it with an empirically obtained probability p.

Social Classes. An innovation has a very high price at the beginning due to the high costs of production. However the price decreases over time because of technological improvements, especially those in the production phase, that make manufacturing more efficient. Indeed, many technologies follow an S-shape curve that relates the investments made by the company with the performance of the technology [13][14]. In the first stage the performance improvement is slow because the technology still needs to be fully understood. Afterwards, as researchers and producers obtain a better knowledge of the technology, the improvement accelerates. However, when the technology reaches its natural limit of performance, the improvements tend to slow down.

Similarly the diffusion of innovations follows an S-curve. In the initial stage, the adoption is slow because the technology is poorly understood. When the knowledge about the technology has spread, the innovation enters the mass market and the rate of adoption increases. Finally the adoption rate decreases when the market has been fully saturated. [13] identifies five categories of different adopters: 1) innovators, 2) early adopters, 3) early majority, 4) late majority and 5) laggards. In Figure 1 the five different classes of adopters considered in order to model the technology adoption rate are shown (bell-shaped curve); in the Figure we also report the S-shaped curve which represents the innovation diffusion. During the configuration phase we adopt the model of [13] to group the households into social classes. Households that belong to the same social class have similar characteristics and behaviours. Since the utility function models the households' behaviours, the social class is reflected in different sets of weights which combine the four factors.

We consider each family as a point in three-dimensional space: age class, education level and income. We use the K-means clustering technique to subdivide these points in five social classes. The K-means is a prototype-based technique that attempts to find a user-specified number of clusters (k). Each cluster C_i with $i = 1, .., k$ is represented by its prototype c_i, defined as the centroid of the

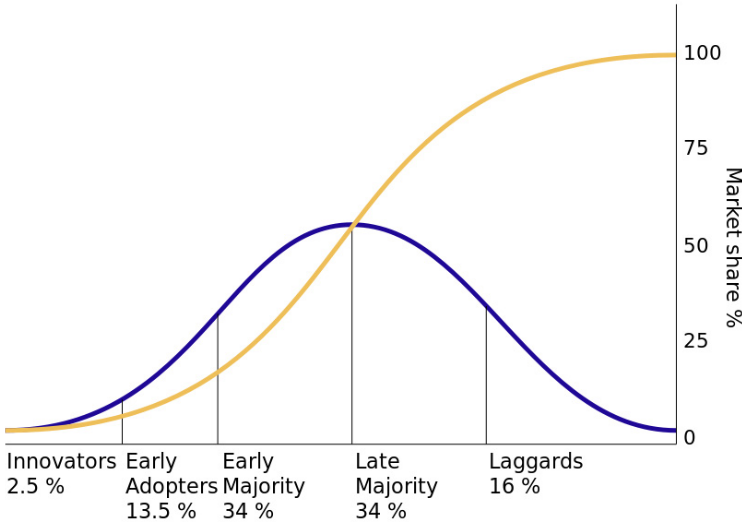

Fig. 1. Adopters Classes, source: http://en.wikipedia.org/wiki/Diffusion_of_innovations

group of points. The K-means algorithm attempts to minimise the total intra-cluster variance, repositioning the centroid at every step until the centroids do not change. It starts with a random set of centroids $c_1, .., c_k$ and then assigns each point x to the nearest centroid. After that, it calculates the new centroids by averaging the points in a cluster. The results of the clustering are shown in Figure 2. The five different colors in the figure represent the five different clusters identified on the base of the three parameters considered (age class, AGE, education level, EDL, and income, INC).

It is difficult to evaluate the goodness of a clustering because we do not know the class labels to be used as a reference. When the ground truth is unknown unsupervised techniques can be used to evaluate the clustering; these methods measure the goodness of a clustering structure without using external information. A common unsupervised method is the silhouette coefficient that relates the cohesion of a cluster with the separation between clusters [16]. The silhouette coefficient is defined for each sample i and it is composed of two scores: 1) the cohesion $a(i)$, the mean distance between the sample i and all other points in the same cluster; 2) the separation $b(i)$, the mean distance between the sample i and all other points in the next nearest cluster. The value of the silhouette coefficient can vary between -1 and 1. If the value is negative, the sample i is closer to the objects of another cluster than other objects of its cluster. Samples with a large $s(i)$ (almost 1) are very well clustered. An overall measure of the goodness of a cluster can be obtained by computing the average silhouette coefficient of all

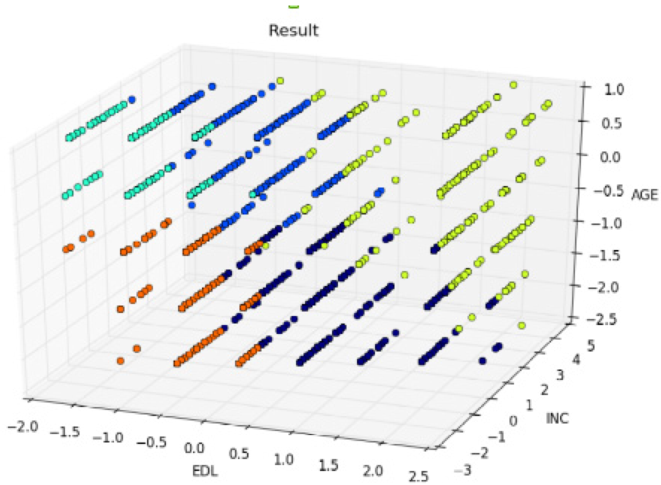

Fig. 2. Clustering Results

samples. Using K-means clustering we get a silhouette coefficient of 0.35, which is not an optimal value, but it is good enough for our purposes.

3.2 Evolution Phase

In the evolution phase the simulator recreates the behaviour of households for a period from the first half of 2007 to the second half of 2036; actually the PV systems are installed only during the 2007-2013 period but we have also to take into account the long lifetime of PV panels and the incentive durations. In each semester (from 2007 to 2013) households proceed to evaluate the adoption of PV system; in the remaining part of the simulation (from 2014 onwards) no new panels are installed. As previously mentioned the desire level for adoption of a PV system is estimated through the utility function described in the configuration phase that every agent computes according to its own characteristics. we remind that the utility function takes into account the income of the family, the payback period, the environmental benefits and the relationships with other families. These factors are weighted differently depending on the social group of the family. The weights for each group are determined by calibrating the model on real data over the 2007-2013 period.

The estimation of the ROE considers costs and gains for a 20 years period, which is the estimated lifetime of a PV system. We calculate the cash flow for each year as the difference between total earnings and total expenditure related to the PV. The expenses that are taken into consideration are the cost of the system, the maintenance costs and the loan interests. The sources of income are the electricity bill savings due to the self-consumption and sales to the grid operator. The national and regional incentives affect the gains and the expenses in different ways: for example earnings are related to the Italian national feed-in tariff and expenditures are influenced by the initial cost (modified by the investment grants offered by the regions) and loan interests (a target of several incentive mechanisms). A household solves the optimization problem to find the size of the system that provides the highest ROE.

We assume that families get advice from PV installers and they become well-informed about their options. Thus households install the PV system that maximise their reward in terms of production and saving.

The Utility Function. The core of our model is the utility function, or desire level, which is responsible for the agent decision to invest in a PV panel or not. The function is defined by the following equation:

$$\begin{aligned} U(v) = {} & w_{pp}(cls_v)u_{pp}(v) + w_{budget}(cls_v)u_{budget}(v) \\ & + w_{env}(cls_v)u_{env}(v) + w_{com}(cls_v)u_{com}(v) \end{aligned}$$

where cls_v is the class of agent v. The equation is a linear combination of four factors: the household payback time ($u_{pp}(v)$), the household budget ($u_{budget}(v)$), the neighbourhood influence ($u_{com}(v)$) and the environmental benefit of investing in a PV system ($u_{env}(v)$). These four factors are multiplied by four different weights $w_{pp}(cls_v)$, $w_{budget}(cls_v)$, $w_{com}(cls_v)$ and $w_{env}(cls_v)$, which depend on the class of the agent. The proper calibration of these parameters is a crucial aspect and it will be discussed in Section 4.

The partial utility $u_{pp}(v)$ estimates the expected payback period pp of an agent v. As the function value range is between 0 and 1, we map the actual payback period which could range between zero and twenty years to the range [0,1]; we subtract the $min(pp)$ considered, namely one year, and then divide the value obtained by $max(pp) - min(pp)$, where $max(pp)$ is 21 years, because 20 years is the expected useful life for PV systems. According to [10] we compute $u_{pp}(v)$ as:

$$u_{pp}(v) = \frac{21 - pp(v)}{20}$$

where $pp(v)$ is the payback period for the initial investment. The payback period requires the net present value (NPV) of the PV system: when the NPV value turns from negative to positive a household recovers from its initial investment. The NPV computation is based on the yearly cash flows. The regional and national incentives act on the payback utility factor because they reduce the payback period.

The household budget $u_{budget}(v)$ is given by:

$$u_{budget}(v) = 1/\frac{v_{equity}}{e^{v_{budget}}}$$

where v_{equity} is the initial investment obtained by subtracting any incentives that affect the PV panel installation price; v_{budget} is the budget available to the agent.

The $u_{env}(v)$ captures the sensitivity toward the environmental benefits related to the adoption of a PV system. It is calculated as the oil saved - clearly correlated to the amount of CO_2 produced - thanks to the PV panel. We use the conversion factor from MWh of energy to TOE (Tonne of Oil Equivalent) provided by the Italian Regulatory Authority for Electricity and Gas[4]. The ecological benefits are expressed as:

$$u_{env}(v) = \frac{1}{e^{oil_{notConsumed} - oil_{consumed}}}$$

Finally the partial utility $u_{com}(v)$ describes how the social interaction affects the agents behaviour. The neighbourhood of an agent is defined by the nodes it shares a link with. The communication factor is calculated as follows:

$$u_{com}(v) = \frac{1}{1 + e^{\frac{1}{2} L_{v,tot} L_{v,adopter}}}$$

with $L_{v,tot}$ the total number of links of agent v and $L_{v,adopter}$ the number of links shared with adopters.

4 Model Calibration

A critical aspect of our simulator is the correct calibration of the model parameters, since they have a great influence on the final outcome; a commonly known weak point of agent-based models is exactly the difficulty to find good parameters. The solution we chose to employ is to devise an automated fine-tuning process which allowed us to test numerous combinations of parameters and select those which provide better results. Our goal is to obtain a simulator able to reproduce the impact that real incentive strategies (along with economic and social aspects) have had on the PV adoption in the ER region; hence we use the real data from the period 2007-2013 to calibrate our model.Real data are taken from the GSE website that records every PV plant along with its power and geographical position. In practice we want to obtain a good fit between the observed trend of PV power installation and the simulated one.

The parameters we need to fine-tune are the weights of the utility function: $w_{pp}(cls_v)$, $w_{budget}(cls_v)$, $w_{com}(cls_v)$ and $w_{env}(cls_v)$. We chose to employ a Genetic Algorithm (GA) [6] to find the configuration of utility function weights which better fit the Emilia-Romagna PV power installation curve. In our model the parameters are correlated, i.e. if we increase the communication factor the remaining ones are necessarily affected, since the sum of all the weights is always equal to one (linear combination). Moreover since the choice is influenced also by the social interaction with the neighbours there is also a dependency among the weights of the different social classes: if we change the weights for the utility function of a node this may change the number of installed PV panels in the neighbourhood; this in turn would produce consequences on the whole network. To summarize, every slight change in the weights of each agent could have

[4] A TOE is defined as the amount of energy released by burning one tonne of oil, or 0.187 TOE for each MWh produced.

extremely great impacts on the final outcome and in such circumstances genetic algorithms have been proved to be very effective.

We defined a new set of parameters, $a_i, b_i, c_i \quad \forall i = 0, .., N-1$, where N is the number of clusters. Each parameter is a real number in the range [0,1]; the utility function weights are computed as a linear combination of these new parameters. The following equations define such relations:

$$\begin{aligned}
w_{budget}(cls) &= a_{cls} \\
w_{pp}(cls) &= (1 - w_{budget}(cls))b_{cls} \\
w_{env}(cls) &= (1 - (w_{budget}(cls) + w_{pp}(cls)))c_{cls} \\
w_{com}(cls) &= 1 - (w_{budget}(cls) + w_{pp}(cls) + w_{env}(cls))
\end{aligned}$$

The genetic algorithm starts generating a random initial population of parameters configurations (also called “individuals”). Then it proceeds to evaluate the entire population by running the model. After the evaluation phase, the GA selects the next generation of individuals. We use a strategy called *tournament selection* [7], which selects k individuals from the actual population using n tournaments of j individuals. Each tournament is composed of j random individuals and the individual with the highest fitness is selected for the next population.

Before the next evaluation the GA applies crossover and mutation on the offspring. The crossover randomly selects two individuals and generates one or more children from them. We use one-point crossover where a single crossover point on both parents' configuration is selected. The crossover method selects a random value from the two parents and then produces a new configuration by swapping the values beyond the crossover point. Finally the mutation randomly selects one individual and alters one or more values. The evolution process is repeated for 400 times.

4.1 Results

In Figure 3 we show the results of the fine-tuned simulator. We used a model composed by 2000 agents; each simulations requires around 20 seconds with a 2.40GHz Intel Pentium DualCore CPU e2220 with a 2GB RAM. The genetic algorithm uses a population of 50 individuals and the overall time required to calibrate the machine is around 40 hours.

The Figure shows the observed photovoltaic power installation trend in the Emilia-Romagna Region in the considered timespan (solid line) and the trend obtained through our fine-tuned simulator (dotted line). The year is displayed in the x-axis while the y-axis tells the yearly PV power growth in percentage. The figure clearly reveals that the installed PV power predicted by the agent-based model correctly follows the real trend. Both curves indicates that after an initial slow diffusion phase in the first years (2007-2009) there is a peak in the power capacity in 2011 - possibly due to the combination of high level of national incentives and more widespread knowledge of the technology (see [2] for more insight on the correlation between national incentives and PV diffusion in

ER). The summed square of residuals (SSE) of our forecast w.r.t. the real data is equal to 8.56 and the R-squared is 0.984, a very good value. There is still a not entirely negligible gap between the simulated results and the real data but we are currently working to refine the model; we are confident that better results could also be achieved through a more accurate fine-tuning of the model.

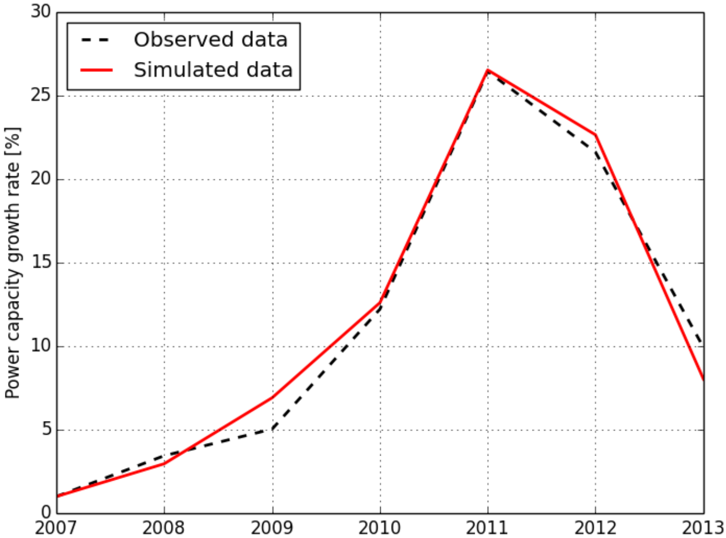

Fig. 3. Model Calibration Results

5 Conclusions

In this paper we proposed an agent-based model to simulate the diffusion of photovoltaic systems with the goal to assist policy makers in their decisions. With this model it is also possible to study the impact that different incentive mechanisms can have on the overall amount of PV power installed. Due to the difficult nature of the problem and especially since a key factor is given by the extremely complex nature of social interactions, an agent-based model was a natural way to cope with this problem. The main advantage of such type of model is the possibility to define the behaviour of each agent at a micro-level and observe the emergent trends at macro-level.

The agents in our model are the households which decide whether install a PV panel on their roof or not. The decision is taken w.r.t. to four factors: 1) economic sustainability, 2) economic return, 3) social interaction and 4) environmental benefits. How much these four factors influence the final decision (their weights) is the subject of another problem we considered in this paper. To understand which were the best weights we used a Genetic Algorithm, employing as a training set the data of the photovoltaic power installed in Emilia-Romagna region in the period 2007-2013.

The fine-tuning of the parameters provided us with a model able to correctly predicts the trend of the installed PV power within an acceptable margin of error. It is nevertheless possible to achieve even better results and this is a research direction we are currently exploring. Along with the model refinements other future research include the development of different parameters calibration techniques and experiments with others data sets. Future works will also try to scale-up the number of agents in the model to get closer to the real number of households in the Emilia-Romagna region (a few millions). We also plan to study more in detail the impact of the incentives on the overall PV installed power, integrating these results within a complete framework capable to aid policy makers in each phase of the decision process.

Acknowledgment. The research leading to these results has received funding from the European Union Seventh Framework Programme (FP7/2007-2013) under grant agreement n. 288147.

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