Modeling the Diffusion of Residential Photovoltaic Systems in Italy: An Agent-Based Simulation

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OVERVIEW

With the support of a governmental program (*Conto Energia* - CE) and favorable irradiation levels, the Italian PV market experienced a remarkable growth over the last few years, making it one of the most interesting PV markets in the world. Electricity generated by photovoltaic (PV) systems increased from 35 GWh in 2006 to 10,796 GWh in 2011, an astounding increment (Gestore Servizi Energetici, 2012b).

The diffusion of PV systems across the country has followed a rather peculiar path. The number of installed PV systems is much higher in the north, although the irradiation level is comparably lower. In addition, most of the installed systems in the north belong to consumers/homeowners and have a small nominal power. According to recent statistics, in 2011 small PV systems up to 20 kW accounted for 88% of all PV systems. However, they contributed to only 15.5% of Italy's total installed PV power. Furthermore, the share of small PV systems has fallen constantly (from 66% in 2006 to 15.5% in 2011) due to the installation of large PV farms (mostly located in central and southern Italy), a trend that strongly contributed to the PV boom in Italy (Gestore Servizi Energetici, 2012a). As a result, the geographical distribution, size and electricity generation of PV systems in Italy is rather uneven across the country.

It remains relevant to investigate whether the residential PV market will growth further, or whether the Italian PV market will be dominated by large PV farms. Hence, the objective of this paper is to simulate the additional future diffusion of residential PV systems via an agent-based model.

METHODOLOGY

Agent-based models (ABM) have been widely used to simulate the diffusion of innovations (Kiesling et al., 2012; Rogers, 1962), also for the case of PV systems (Zhao et al., 2011). ABMs provide a framework to explicitly model the adoption decision process of each member of a heterogeneous social system based on their individual preferences, behavioral rules, and interaction/communication within a social network.

In our model, we consider small grid-connected PV systems from 1 to 20 kW power. Furthermore, it is assumed that PV systems are installed on the roof of single- or two-family houses and only crystalline silicon solar cells are modeled (silicon solar cells have a 93% share of the Italian market in 2011). The decision to adopt the PV technology takes place once the utility of the potential adopter surpasses a certain threshold. The threshold is determined by comparing the simulation results to the actual diffusion of the PV system during the calibration of the model. The model simulates the diffusion process on a yearly basis over 20 years, starting in 2006. The simulation period between the years 2006–2011 is used for the calibration of the model to the actual diffusion of PV systems in Italy.

We explicitly model the geographical distribution of the agents, in order to account for the regional differences that have strongly influenced the PV diffusion in Italy. The investment in a PV system is ultimately dependent on (1) the payback period of the PV system, (2) the environmental benefit achieved by investing in a PV system, (3) the households income, and (4) the influence of communication with other agents. For the estimation of the payback period, the model considers investment costs, local irradiation levels, feed-in tariffs, earnings from using self-produced electricity vs. buying electricity from the grid, as well as various administrative fees and maintenance costs. The environmental benefit of the PV system could be estimated as the amount of CO_2 saved, but instead a proxy value is used (the expected total level of electricity produced with the PV system). The level of the household income is associated with the specific economic conditions of the region where the agent is located, as well as the agent's socio-economic group (age group, level of education, household type). Finally, the influence of communication is measured by the number of links with other households that have already adopted a PV system. It is assumed that each adopter communicates predominantly but not uniquely with other households that belong to the same socio-economic group. Furthermore, the likelihood that socio-economic groups interact with each other varies across the categories considered.

An important addition of the model to the current literature is the inclusion of adaptive Sinus-Milieu (SM) categories to subdivide the agent population across different socio-economic groups that have different attitudes toward adoptions and innovations. The SM paradigm is most relevant in the distribution of the households income and in the determination of a group-specific social communication networks. In each simulation step, the program updates the social system and the communication network dynamically.

RESULTS

Three simulation scenarios have been tested to consider the sensitivity and validity of the model: a baseline scenario with the most likely development of the PV market, a scenario with different PV investment costs, and a policy-driven scenario with varying levels of future governmental support.

The calibration of the model shows a good fit for the PV diffusion at the national level with respect to the number of adopters, the rate of adoption and the installed PV power.

In the base scenario, the model simulates a relative small number of new adopters per year after 2012, suggesting that the major expansion of the PV market for small photovoltaic systems has already taken place. Furthermore, the results of the baseline scenario indicate that economic considerations and profitability are the driving elements of the PV system diffusion process. Communication aspects, in contrast, hardly have an impact on the adoption rate.

CONCLUSIONS

Both a reduction in investment costs or an increase in the PV support scheme positively influence the diffusion process of small PV systems. However, bearing in mind the model's structure and underlying assumptions, the simulations suggest that governmental incentives have a stronger influence on the diffusion process than the PV investment costs. The reason for this outcome is that PV investment prices are assumed to depend on increased global production and the imputed learning rates of PV experience curves, while PV incentives can be used more freely and, therefore, accelerate the diffusion process at a faster rate.

References

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