SIMULATION OF INCENTIVE MECHANISMS FOR RENEWABLE ENERGY POLICIES

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ABSTRACT

Designing sustainable energy policies has a strong impact on economy, society and environment. Beside a planning activity, policy makers are called to design a number of implementation instruments to enforce their plans. They encompass subsidies, fiscal incentives, feed in tariffs to name a few. Understanding the impact of these instruments on the energy market is essential to select the most efficient one. We propose in this paper a multi-agent simulator that mimics the adoption of photovoltaic as a consequence of a number of implementation instruments. The simulator mainly considers economic evaluations in the agent decision-making procedure, but we are aware also social aspects play an important role and they are subject of current research.

INTRODUCTION

Following the strategy outlined in [Europe, 2020], the EU growth strategy for the coming decade - the EU is strongly committed to reducing its greenhouse gas emissions by at least 20% by 2020, relative to 1990 levels, increasing the share of renewable energy sources in final energy consumption to 20% and increasing energy efficiency in Europe by 20%. To drive progress and set the EU on a pathway towards meeting these targets, every country and every region should be committed to providing its own contribution to these objectives.

Therefore, national and regional energy policies need to take account of these guidelines and be designed to meet these ambitious objectives. With a view to achieve the 20% renewable energy target in the EU by 2020, the Renewable Energy Directive establishes legally binding individual targets for the share of renewable energy in final energy consumption for each Member State. E.g., Italy is supposed to reach a 17% renewable energy share, UK 15% and Austria 30%.

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To achieve these objectives, each country and, in some cases, regions are implementing a number of actions focused on the promotion and wide adoption of energy production from renewable energy sources. An important class of such energy policy instruments are incentives. There are a number of incentive mechanisms used in various EU member countries and some of these will be outlined in next Section. Examples of such incentives include investment grants (incentives to construct energy plants), feed-in tariffs (money given to produce and/or self-consume renewable energy), and fiscal incentives (low interest loans and many others). However, the effectiveness of these mechanisms is not clear. By analysing past data one conclusion that has emerged is that there is some evidence that a greater effect at lower cost may be achieved by a stable feed-in tariff regime that is sustained over a significant period. As a result of this, many countries have adopted feed-in tariffs as the basic incentive mechanism. In addition, certain regions have implemented other incentive mechanisms to further support renewable energy adoption. In this paper we focus on the Italian context, by considering national mechanisms and comparing different regional instruments implemented in the Emilia-Romagna region of Italy.

This paper has a particular emphasis on renewable energy sources and, specifically on photovoltaic (referred to as PV) power generation. We have analysed a number of incentive mechanisms for promoting the adoption of PV in Emilia-Romagna and simulated them from an economic perspective in order to understand their efficiency. We have utilised agent-based simulation [Troitzsch et al., 1999], [Matthews et al., 2007], [Gilbert, 2010], where agents represent the key players involved in the decision-making process. The hypothesis is that for modelling complex systems, agent-based simulation is a suitable approach to understand such systems in a more natural way. We are aware that not only economic aspects should be considered. We have analysed two social aspects, but recognise that the one we propose is far from being a social simulator.

We have developed an agent-based simulator in Netlogo [Sklar, 2011] implementing both national and regional incentives and have compared the efficacy of regional incentives regarding PV adoption. We have considered feed-in tariffs as national incentives (Italian incentives derived from the *Quarto Conto Energia*, Fourth Feed-In-Scheme [Ministerial Decree, 2011]. In addition to these national incentives, we have considered four alternative regional incentives, namely investment grants, fiscal incentives, interest funds and guarantee funds. We will explain these incentives in detail and will show the results of the economic simulator.

From an economic perspective, it could be concluded from this study that the interest fund is the most efficient, followed by fiscal incentives and guarantee fund which appear to have a similar impact. The least effective instrument is the investment grant, the only mechanism so far implemented by the Emilia-Romagna region to foster PV adoption.

INCENTIVES TO RENEWABLES

We have surveyed the types of incentives utilised to promote renewable energy in the EU and around the world. A number of categories have been identified:

Feed-in tariffs A feed-in tariff is a fixed and guaranteed price paid to the eligible producers of electricity from renewable sources, for the power they feed into the grid.

Premium In a feed-in premium system, a guaranteed premium is paid in addition to the income producers receive for the electricity from renewable sources that is being sold on the electricity market.

Quota obligation Quota obligations create a market in the provision of renewable electricity. The government creates a demand through imposing an obligation on consumers or suppliers to source a certain percentage of their electricity from renewable sources.

Investment Grant grants for renewable generation are often devised to stimulate the take-up of less mature technologies such as PV.

Tax exemptions Some countries provide tax incentives related to investments (including income tax deductions or credits for some fraction of the capital investment made in renewable energy projects, or accelerated depreciation). Other approaches are production tax incentives that provide income tax deduction or credits at a set rate per unit of produced renewable electricity, thereby reducing operational costs.

Fiscal Incentives This category includes soft loans, i.e., loans with a rate below the market rate of interest. Soft loans may also provide other concessions to borrowers, including longer repayment periods or interest holidays.

Compulsion A more radical approach would involve compulsion. Whilst no examples have been identified in the renewable generation market, similar situations have been noted: in some urban parts of Scandinavia it is a legal obligation for newly constructed homes to be connected to the local heat network.

Green Power marketing Under this arrangement, electricity customers can choose to buy electricity which is sourced partially or wholly from renewable sources. Typically they pay a premium compared to other available tariffs. Sometimes standards need to be set to ensure that sufficient and appropriate renewable generation is supporting the product.

The various categories listed above are not necessarily mutually exclusive so that more than one policy instrument may be in use at the same time.

These various incentive schemes can also generally be characterised as either

- **Production-based incentives** where the benefit of the scheme is related to the amount of energy generated. This includes feed-in tariffs and quota obligations. The features of such arrangements may include:

Technological differentiation as different renewable technologies are at varying levels of development and cost levels in relation to existing market prices there is a risk of "free riding" (i.e., a potential ongoing windfall benefit) for technologies that are close to being economic in the absence of subsidy if only one support level is provided to all technologies. Thus increasingly technological differentiation has been introduced into the support mechanisms used.

Inflation adjustment the level of support (i.e. feed-in tariff price) may vary in line with inflation.

Digression the level and availability of support may be varied according to take-up. Thus if such take-up is large then the support may be curtailed. Whilst this sometimes happens by unexpected Government decisions, arrangements are increasingly being established during the design of the incentive mechanism.

Own-use arrangements for feed-in tariffs there may be differences in the rate paid for electricity used on the premises where the electricity is generated rather than that feed into the distribution network. This also raises questions in regard to metering or the assumptions made about the proportion of the electricity generated used for each purpose.

- **Investment-based incentives** these schemes tend to provide support for the initial investment irrespective of the amount of electricity that is actually generated. Examples of such arrangements include:-

loans (interest free or at rates below the market level)

loan guarantees (where the repayment of the loan may be guaranteed by a national or regional government) which has the effect of facilitating both the availability of loan finance and reducing its cost

tax benefits such as VAT exemption or reduction or reduced corporate taxation via accelerated depreciation or improved capital allowances, although this will only provide advantages to profit making companies.

In Italy a national feed-in tariff for PV is in place and this paper considers the following mechanisms that could be implemented in the Emilia-Romagna region to provide a further incentive for the installation of PV:

1. Investment Grants: incentives are given as a grant, and no money is returned to the Region. The grants that are provided represent a proportion of the total plant cost. The financial requirement on the Region would be front-loaded as funds would need to be pro-

vided in advance of equipment installation.
2. Fiscal Incentives: incentives are given as soft loans, including longer repayment periods or interest holidays. Again the financial requirement on the Region would be front-loaded as funds would need to be provided in advance of equipment installation. In this case the loan would usually, eventually be paid back to the Region.
3. Interest funds: incentives are given as a grant to pay all or part of the interest on bank loans taken out in order to purchase PV equipment. Again no money is returned to the Region. In this case the financial burden on the Region would be spread over the lifetime of the loans which are likely to be a number of years.
4. Guarantee fund: the Region provides a guarantee to the bank providing the loan to the investor who is purchasing PV equipment, that the loan will be repaid. This provides security to the bank which is therefore more likely to approve the loan request and to charge a lower interest rate than would otherwise be the case. There would be little or no immediate financial burden on the Region and the overall cost over the longer term would depend on the level of default of the investors which in turn would depend on the credit worthiness of the investors that the Region chooses to support.

The approach so far used by the Emilia-Romagna Region to provide a further incentive for the installation of PV has been by means of investments grants.

ECONOMIC SIMULATOR

In order to establish a relationship between the subsidies of the Region and the total installed MW of electrical power from photovoltaic, we developed an agent-based simulation model. This simulator mainly takes into consideration economic aspects, and only marginally recognises potential other ones. This results from the fact that these economic aspects are better understood, and that for many people installing a PV plant is primarily a type of investment, as advertised and reported in major economic newspapers in Italy.

The simulator considers two types of agents: the Region, and House owners.

The Region provides incentives to house owners, and each year there is a certain amount of money that is available to the Region to fund such incentives. At the start of the period there are some initial funds and each year the Region receives a further constant budget to foster installation of PV plants. Moreover, depending on the adopted funding scheme, the Region may receive the repayment of loans or other charges from house owners which can be recirculated to other house owners.

House owner agents may install PV panels on top of their roof, depending on a number of parameters, including

- *Surface of the roof* A^r, in square meters
- *Budget* B
- *Energy consumption*, in kWh per year
- *Objective*: the percentage of energy consumption that the agent wants to be covered by PV
- *Increase of Energy Requirements*: on average the energy consumption of a family increases with time; this parameter represents the percentage increase in energy requirements in a year.
- *Obstinacy*: a parameter indicating the inclination toward green economy of the agent.

As previously menioned, most of these parameters are economic, reflecting the fact that for many people the installation of PV panels is mainly an economic issue. The only non-economic parameter is the *obstinacy* in pursuing the installation of the PV plant: in case for some reason the PV installation is not advisable (from a strictly economic viewpoint), the agent could still want to install it for other reasons, not detailed in this simulator, and roughly accounted for by this parameter.

As a first step, the house owner agent performs a feasibility study (that in real life is usually done by an installer of PV panels). The agent considers various global parameters like:

- Price of electricity. Depends also on the (yearly) energy consumption of the agent.
- Yearly increase of energy prices
- Average cost of a PV plant, in €/kWp (cost per peak power producible by the plant)
- Subsidies
- Interest rate of treasury bills (as a comparison)
- Energy minimal buying price for the grid manager.

Once these parameters are given as input by the user, the simulator determines the local parameters of a set of agents, either selecting randomly their values, or by using historical data (when available).

Once all the parameters are known to the model, it can compute the feasibility of the plant, in particular its size A^{pv} (m^2) and its cost C^{pv} (€). These values are compared with the available surface of the roof A^r and the agent's budget B; four cases can occur:

	$A^{pv} \leq A^r$	$A^{pv} > A^r$
$C^{pv} \leq B$	Consider Increase	Consider Decrease
$C^{pv} > B$	Consider Loan	Forgo

If none of the two feasibility conditions is satisfied, the agent decides against purchasing PV (Forgo) and terminates. Otherwise, resizing the plant, or asking for a loan is considered. If only one of the conditions is satisfied, the agent behaves according to its obstinacy: the parameter *Obstinacy* is utilised as a probability that the agent insists in pursuing the installation of the plant, notwithstanding adverse circumstances. The *Obstinacy* is compared to a randomly generated number, and if the test succeeds the agent considers asking for a loan (if the budget is not enough) or installing a smaller plant (if the available area is not enough).

In the case where both feasibility conditions are satisfied, the agent definitely installs the plant, and, moreover, considers increasing the size of the plant. In the fourth feed-in scheme, if in a year the total produced energy is higher than the energy that the household consumes, the difference is paid at a much lower rate, so again the agent will consider upgrading the plant with a probability given by its *Obstinacy*.

Finally, the simulator adopts a very preliminary model to account for social aspects. In human societies, the behaviour of a person is influenced by the per-

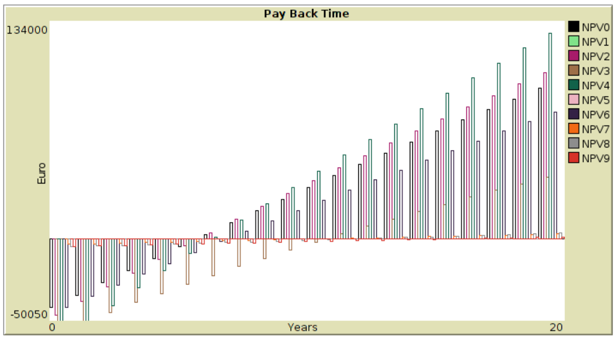

Fig. 1: Screenshot of the simulator, showing PBT and NPV of investments in the course of time, based on when the plant was built, ranging from first term of 2012 (NPV0) to second term of 2016 (NPV9).

sons near to him/her: neighbours, relatives, colleagues, friends, etc. In this simulator, each agent lives in a bi-dimensional world, and it is influenced by the agents that live within a predefined range. In particular, the *Obstinacy* of an agent is increased proportionally to the number of agents in its influence range that have installed PV panels.

The output of the simulator provides several data items including economic data for the agents (such as the Payback Time (PBT), the Return On Equity and the Net Present Value (NPV) of the investment, plotted in Figure 1), the total cost of subsidies provided by the Region, and the total power of installed PV plants.

EXPERIMENTAL EVALUATION

Our goal has been to understand the relationship between the capacity of PV that is installed and the budget available for regional incentives. We have treated all regional incentives as if they were independent from each other, i.e., we run simulations using one type of regional incentive at a time (on top of the national ones).

A large number of simulations have been undertaken (300) for each value of the regional budget from zero to €40 million, in steps of €1 million, and for each type of incentive, resulting in a total of 48,000 simulations. For each simulation the total installed power in kW of photovoltaic plants was recorded.

Of course, an individual simulation does not, of itself, provide much useful information and some statistics should be extracted from a significant number of such simulations to obtain a better insight. In order to derive a model of the relationship between the installed power and the available budget, we averaged the results of all the simulations with the same amount of budget, obtaining a point for each value in the range from 0M€ to 40M€ (Figures 2, 3, 4 and 5).

Using these results, machine learning was utilised to learn functions establishing the relationship between the available budget and the installed power. One function was determined for each incentive type. Various regression algorithms were used: linear models [Rousseeuw and Leroy, 1987], polynomial models [Stigler, 1974], [Gergonne, 1815] and local regression [Cleveland, 1981] (LOESS).

For each type of incentive we chose the best regression model using statistical analysis to evaluate which fitted best our data - when two or more models offered similar results, we used the simplest one.

The statistical analysis was carried out using *R* [Ihaka and Gentleman, 1996]. We evaluated the goodness of fit of regression models through numerical analysis, e.g. computing the coefficient of determination, evaluating the statistical significance (F-test) [Fisher, 1925], [Box, 1953], and graphical analysis, e.g. residuals scatter plots or normal probability plots.

The coefficient of determination R^2 is a number between 0 and 1, used to describe how well a regression line fits a set of data; the higher R^2, the better the data fit [Steel and Torrie, 1960], [Draper and Smith, 1998].

The graphical analysis was made taking into account that if the model fit to the data were correct, the residuals would approximate the random errors that make the relationship between the explanatory variables and the response variable a statistical relationship. Therefore, if the residuals appear to behave randomly, it suggests that the model fits the data well. On the other hand, if non-random structure is evident in the residuals, it is a clear sign that the model fits the data poorly [NIST/SEMATECH, 2012].

We can examine now the behaviour of the four types of incentives, namely the investment grant, the interest fund, the fiscal incentive and the guarantee fund.

Investment Grants

With an investment grant the installed power rises according to the budget increase, exhibiting an almost linear relation for budget smaller than 30M€ and a ratio decrease for bigger values. This is probably caused by the fact that once we meet the requests from most of the agents in the simulation with a budget big enough, further increases are less and less effective.

In Fig. 2 the linear, quadratic, 10th degree polynomial and LOESS models are compared with the points obtained through our simulations. Except the linear one, the other models fit the data quite well, without great differences.

In Table I we can see the numerical results used to evaluate the goodness of fit of our regression models. We reported the values for linear, quadratic, cubic and tenth degree polynomial model; since the LOESS model is not parametrical, we cannot compute those values for this model and rely on a graphical evaluation of the goodness of fit. DF stands for Degrees of Freedom (numerator and denominator).

Regression	R^2	*F-Test*	*p-value*
Linear	0.7601	186.9 on 1 and 39 DF	$< 2.2 \cdot 10^{-16}$
Quadratic	0.907	282.7 on 2 and 38 DF	$< 2.2 \cdot 10^{-16}$
Cubic	0.9074	186.3 on 3 and 37 DF	$< 2.2 \cdot 10^{-16}$
10^{th} Poly	0.9429	82.51 on 10 and 30 DF	$< 2.2 \cdot 10^{-16}$

TABLE I: Investment Grant, Regression results

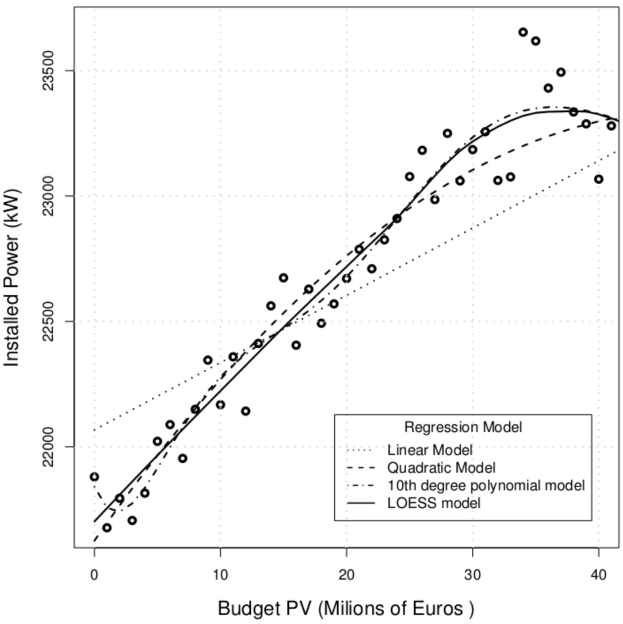

Fig. 2: Regression Models, Investment Grant

Interest Fund

With interest fund incentives, the function relating budget and installed power shows a surge in the installed power for low budget values (up to about 3M€) but after that new budget increases do not translate into further increases in the amount of PV installed; this behaviour is probably due to the fact that this kind of incentive is by far the one requiring the least amount of money, so it is relatively easier to fulfill all simulated agents who would like to benefit from it.

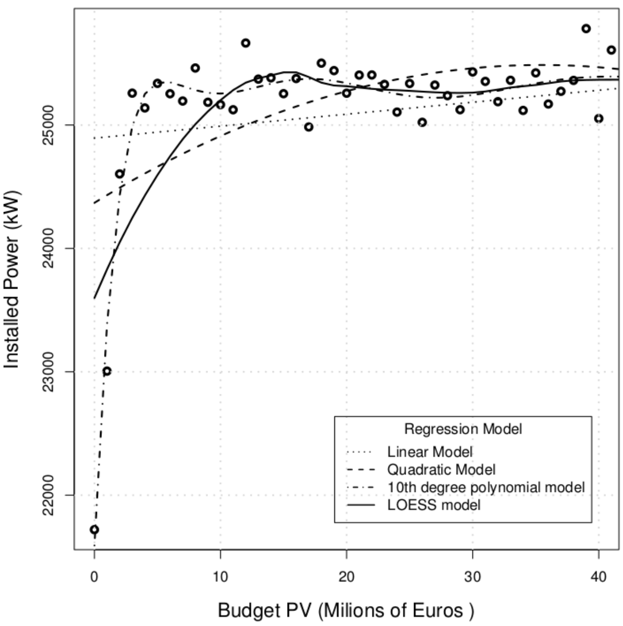

Fig. 3: Regression Models, Interest Fund

Fig. 3 shows that the tenth degree polynomial regression provides the best fit to our data. Table II shows the numerical results used to evaluate the goodness of fit.

Regression	R^2	*F-Test*	*p-value*
Linear	0.09055	5.874 on 1 and 39 DF	0.01845
Quadratic	0.2789	11.22 on 2 and 38 DF	$7.621 \cdot 10^{-5}$
Cubic	0.412	13.31 on 3 and 37 DF	$1.074 \cdot 10^{-6}$
10^{th} Poly	0.9012	45.61 on 10 and 30 DF	$< 2.2 \cdot 10^{-16}$

TABLE II: Interest Fund, Regression results

Fiscal Incentives

For fiscal incentives the function learned is similar to that for investment funds (Fig. 2), but with this incentive, compared to the previous one, the rise of the installed power for lower budgets is faster and the curve's slope declines more slowly.

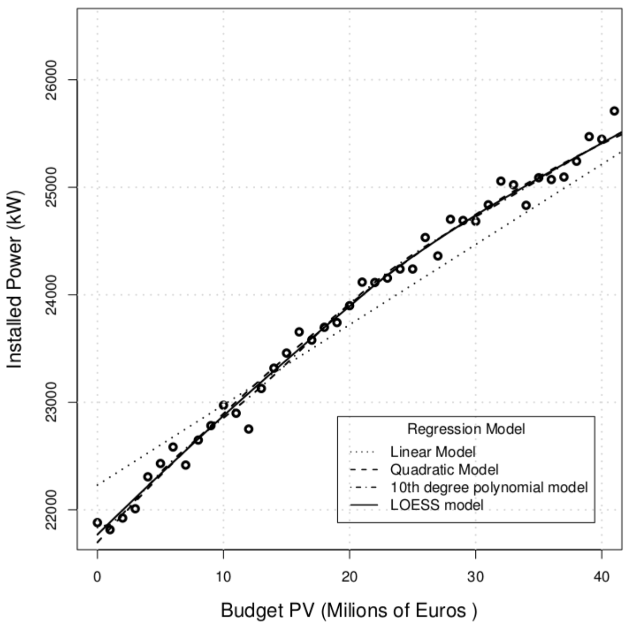

Fig. 4: Regression Models, Fiscal Incentives

The regression models used, except for the linear one, fit the data very well (Fig. 4). Again we preferred a quadratic model for the regression, for its simplicity and at the same time goodness of fit and statistical significance. Table III displays the results of the numerical analysis.

Regression	R^2	*F-Test*	*p-value*
Linear	0.9486	1089 on 1 and 39 DF	$< 2.2 \cdot 10^{-16}$
Quadratic	0.9831	1683 on 2 and 38 DF	$< 2.2 \cdot 10^{-16}$
Cubic	0.9838	1155 on 3 and 37 DF	$< 2.2 \cdot 10^{-16}$
10^{th} Poly	0.9849	327.1 on 10 and 30 DF	$< 2.2 \cdot 10^{-16}$

TABLE III: Fiscal Incentives, Regression results

Guarantee Fund

Finally, the last type of regional incentives is considered, the guarantee fund. From Figure 5, we can again note a trend characterized by an initial increase in installed power in response to the rise of available budget, represented by an almost linear curve up to about 15M€. Then the installed power stabilises after a certain budget level (about 20M€), probably because also in this case – as with the interest fund – it is possible to satisfy a large fraction of the requests made by simulated agents with budgets smaller than the investment grant and fiscal incentives. The stabilization appears here for higher levels of budget with respect to the interest fund. This could be explained by the fact that the interest fund needs less money than guarantee fund to satisfy the same number of agents.

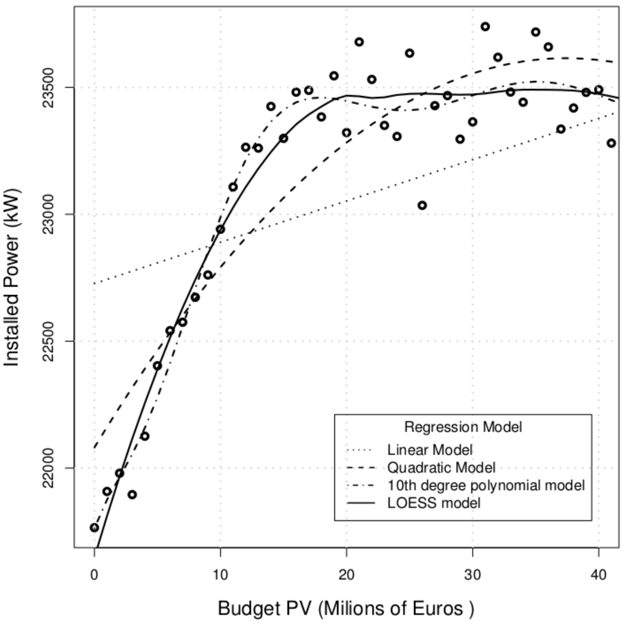

Fig. 5: Regression Models, Guarantee Fund

In Fig. 5 we can see that the linear and quadratic models do not perform very well, while the tenth degree polynomial and LOESS model offer better results, with the latter having a slightly better fit.

The numerical analysis reveals that both these models have a good statistical significance, but eventually we opted for a local regression model because it was less sensitive to outliers - at least with guarantee fund incentives.

Again, in Table IV the numerical values used to evaluate the goodness of fit are shown.

Regression	R^2	*F-Test*	*p-value*
Linear	0.3737	35.21 on 1 and 39 DF	$1.667 \cdot 10^{-07}$
Quadratic	0.7941	111.9 on 2 and 38 DF	$< 2.2 \cdot 10^{-16}$
Cubic	0.9059	183 on 3 and 37 DF	$< 2.2 \cdot 10^{-16}$
10^{th} Poly	0.937	74.39 on 10 and 30 DF	$< 2.2 \cdot 10^{-16}$

TABLE IV: Guarantee Fund, Regression results

Comparison

In Figure 6 all the four incentives are compared. It can be noted that the interest fund is the best type of incentive for almost the whole budget range that has been considered (this range is consistent with the

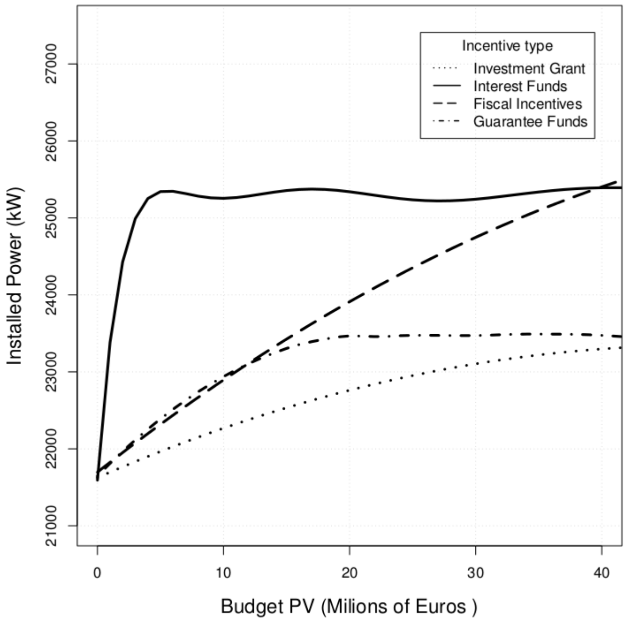

Fig. 6: Comparison among incentives

funds provided by the region in reality), with a slight advantage for fiscal incentives for budgets larger than 40M€. The guarantee fund and fiscal incentives present a similar behaviour for lower levels of funding, but with higher budget values fiscal incentives behave clearly better; overall, the investment fund (the only one implemented so far by the Emilia-Romagna region) turned out to be the least effective type of incentive in enhancing the installation of photovoltaic plants.

DISCUSSION AND FUTURE WORK

This paper represents a first step toward the understanding of the efficiency of different incentive mechanisms adopted as energy policies implementation instruments.

A number of research avenues are still open that we try to describe below.

Simulator extensions. The simulator has been developed in such a way that it simulates a single incentive mechanism and observes the results. We could in principle simulate combinations of instruments instead of single mechanisms. This extension would possibly highlight their interactions. Second, we could include auction mechanisms for the distribution of the regional budget taking into account fairness and truthfulness. Third, other agent types beside house owners should be considered.

The social aspect of the simulator is extremely important. All the social drivers that affect the decision making of an agent should be incorporated, even if it is extremely difficult to "measure" them. Up to now the simulator takes into account the environmental sensitivity that is basically randomly set and the network structure linking agents enables us to simulate emulation behaviours. Therefore the probability that an agent installs a PV plant is higher if its neighbors have already installed it. More complex social interactions could be considered as well.

Simulator validation. We are currently validating the simulator on a set of real data taken from the GSE web site [GSE, 2012]. Basically the data are about existing PV plants divided by region of Italy and time of installation. This is an extremely interesting set of data to validate the results of the simulator.

Concerning the validation, an important aspect concerns scalability. It is clear that we cannot have a simulation with 4.5M agents (that is equivalent to the population of the Emilia-Romagna region) nor 1.8M agents representing families in the Emilia-Romagna region. We therefore have to understand if results that we obtain for thousands of agents, that is the maximum number we can simulate can be "linearly" scaled for larger numbers. In addition, we are looking for a kind of asymptotic behaviour that could establish a minimum number of agents that can be projected to the Emilia-Romagna population in a realistic way.

Feedback on policy modeling These results are interesting if they could provide a feedback to the policy maker who could adjust the implementation strategy of his/her policies. We have defined a number of potential interactions mechanisms, described in [Gavanelli et al., 2012], between the optimization component [Gavanelli et al., 2013] and a simulator. We are now integrating the functions derived by this work linking the budget with the installed power into the optimization model for defining a regional plan. In this way, beside the regional plan, we are able to provide the best possible implementation schema to achieve it as described in [Milano, 2013].

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