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A Dynamic Behavioral Model of the Long-Term Development of Solar Photovoltaic Generation driven by Feed-in Tariffs

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ABSTRACT

This work aims to assess the impact of renewable energy incentives, particularly that of the feed-in tariff (FiT), on the long-term development of solar photovoltaics (PVs). With this aim, the paper introduces a dynamic model based on nonlinear delay differential algebraic equations to simulate the evolution of the PV capacity and its commitment in the power grid. The model assumes the FiT budget, the PV cost and willingness of the public to install PVs as the main drivers for solar PV installations. In particular, the *learning-by-doing* concept to model the PV cost and consequently the PV deployment is proposed for the first time in this paper. The accuracy of the model is validated against historical data of two of the biggest PV markets in the world driven by FiT, namely, Italy during 2008-2014, and Germany during 2000-2014. A sensitivity analysis based on the Italian PV market is carried out to identify the impact of the parameters of the proposed model. Results indicate that the proposed model is a valuable tool that can help policymakers in the decision-making process, such as the definition of the FiT price and the duration of the incentives.

1. Introduction

1.1. Background and Motivation

Due to extremely favorable incentives policies and installation cost reduction, the solar photovoltaic (PV) market has seen a significant increase over the past two decades. As a matter of fact, PV generation is one of the leading technologies to achieve the target for high shares of renewable energy sources set by the European Union and combat the global climate change [1].

The most common incentive mechanism in Europe has been the so called feed-in tariff (FiT) [2, 3]. A FiT program is an incentive plan that provides investors with a set payment for electricity generated from renewable energy sources fed into the power grid [4]. It is typically introduced as a booster in the early stages of solar PV development. The latest reports on the global status of renewables integration explicitly indicate that FiT is a highly adopted policy to support PV development. For example, reference [5] suggests that "*Government policies continued to propel most of the global market in 2020, with feed-in tariffs (FITs) and tenders the leading policy drivers of the centralised market, and FITs and incentivised self-consumption or net metering the primary drivers of the distributed market*". The relevance of FiT is also supported by the recent literature [6, 7].

In Europe, two of the main PV markets have been Italy and Germany. Indeed, these two markets alone accounted for 60% of the global PV market in 2010 [8]. According to the latest PV data from IRENA [9], Germany and Italy are the leading countries in Europe when it comes to the total cumulative installed PV capacity, with 58,461 MW and 22,698 MW, respectively.

While FiT has provided a good platform for increasing the number of PV installations, it has also put a massive burden on the national budgets. This is because governments put in place extremely favorable and generous FiT schemes. However, generous FiT prices may lead to economic instability and eventually to the collapse of the scheme. Hence, defining appropriate policies is of utmost importance [10]. Understanding the coupling between incentives and the actual installed capacity of PV panels is considered key for the design of policies under different scenarios [11]. A powerful way to understand the long-term behavior of incentive policies and capture the interactions among their variable components, is to construct proper dynamic models and simulate their response over different scenarios.

Reference [12] states that, in practice, "*national or regional installation of solar PV systems depends on factors such as solar PV cost, FiT price, and the installation subsidies provided*." Motivated by this statement, this paper relates the number of PV installations to the above factors by constructing a proper dynamic model. In particular, the proposed model uses the *learning-by-doing* concept to realistically account for PV technology cost reductions due to gained experience [13].

1.2. Literature Review

There has been significant work on the impact of energy policies on the long-term development of renewable energies. For example, the authors in [10] propose a dynamic model to study the impact of incentive policies on power system reliability, costs and environment in Spain. However, the analysis is country-specific (only Spain considered in the

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case study) and the model does not directly account for PV cost reductions. In the same vein, references [12] and [14] use the system dynamics approach to simulate Taiwan's and China's PV development, respectively, under different policy incentives, but use an oversimplified method for the PV technology cost reduction. It must be noted that the above three references rely on a specific commercial software tool (utilized as a "black-box") to implement the dynamic models and perform the relevant analyses. This is considered a disadvantage compared to the dynamic model proposed in this work, which can be implemented in any software tool able to integrate a set of differential equations. The work in [15] proposes a generic dynamic model to study the viability conditions of the FiT schemes but neglects the PV cost and uses a simple constant penetration rate for the contribution of renewable energies in the energy mix. Finally, the work in [16] combines the system dynamics method with the Monte Carlo simulation to consider various uncertainties of renewable energy technologies over the long-term. However, it does not consider the FiT effect (e.g. impact of FiT price) and focuses in a single market (Korean PV power generation).

The aforementioned works give insights into the dynamic evolution of solar PV systems for specific countries and/or for specific aspects of the system. However, to the best of our knowledge, a comprehensive and general dynamic model able to capture the dynamic evolution of solar PV capacity for different countries is missing. This paper attempts to fill this gap. With this aim, the paper builds on the above works and proposes a generic dynamic model formulated as a set of nonlinear delay differential algebraic equations that can capture the solar PV evolution of different countries. In this work, Italy and Germany are chosen as two of the main PV markets driven by FiT in Europe to validate the model's accuracy. The main assumption of the model is that the cost of PV systems, the budget of the policy and willingness of public to install PVs are the main drivers for the evolution of the PV installations.

The paper provides the following contributions with respect to the state of art:

- A simple yet accurate dynamic model for the long-term development of solar PV generation.
- The utilization of the *learning-by-doing* concept, FiT price and willingness of people to install PVs to reproduce the evolution of PV installations. In particular, the *learning-by-doing* concept to model the PV development is proposed for the first time in this paper to better represent the PV technology cost reductions.
- A thorough validation of the proposed model through the Italian and German cases. The ability to fit different cases is a feature of the proposed model. In fact, other models proposed in the literature only fit a single PV market.

The remainder of the paper is organized as follows. Section 2 presents the background of FiT schemes in Italy and Germany. Section 3 presents the proposed dynamic model. The model validation and sensitivity analysis are given in Section 4 and Section 5, respectively. Finally, Section 6 states the main conclusions of this work and discusses relevant policy implications.

2. FiT Evolution in Italy and Germany

2.1. Italy

The solar PV capacity in Italy experienced an unexpected and exponential growth between 2008 and 2012 [17]. The main driver of the increase was the favorable and generous FiT applied by the Italian government through the so called energy bill [18, 19]. The first energy bill was introduced in 2005 and lasted until 2007. While it included a very high FiT price, namely, 490 EUR/MWh, this energy bill also had a cap of 100 MW. The capacity cap and the excessive bureaucratization regarding the procedures for the installations were a huge barrier to incentivize the investors [18].

In 2008, the Italian government introduced the second energy bill. This bill remained in place until 2010. It foresaw a 2% decrease of the FiT price and removed the administrative procedure and the cap on the overall PV capacity. Despite the decrease of the FiT price, the bill had a positive impact with 432 MW additions taking place in 2008. This deployment led to an aggregate cost of 110 MEUR. The solar PV capacity tripled in 2009 with a capacity of 1,114.4 MW and an annual cost of 303 MEUR [18]. At this point, the Italian government realized that the incentive cost was creating a considerable burden on the national budget. Thus, the government introduced the third energy bill where it foresaw a cut of the FiT price. Despite the new changes, the rush in the PV investment continued, and 3.74 GW were added. In terms of costs, 800 MEUR were paid in 2009 [18]. Furthermore, it is relevant to mention that this bill set an aggregate cap of 23 GW and 6,700 MEUR for the installed capacity and incentive cost, respectively.

In 2012, the Italian government revised the energy bill again and significantly decreased the FiT price. Finally, on the 7th of July 2013, the assigned annual incentive budget of 6,700 MEUR was reached thus leading to the removal of the FiT [2].

2.2. Germany

In 2010, Germany was the world's largest market for PVs with approximately 17.3 GW of installed capacity [20]. The growth was directly related to the so called renewable energy sources act in 2000 that introduced the FiT mechanism [21]. The act restored a secure climate for investment as it guaranteed a fixed price for PV-generated electricity for a period of 20 years. In other words, it provided long-term financial security for investors and made the PV technology economically viable [8].

The German FiT mechanism for solar PV power is regarded by many as a highly effective policy instrument that led to a significant diffusion and development of PV technology [22]. Since its implementation in 2000, the installed capacity of renewable energy technologies increased remarkably, more than eightfold between 2000 and 2015 [23].

The initial plan was to review the FiT scheme every year to take into account technological and price developments [24]. For example, the amending law of 2004 stated that the FiT price for PV and other renewable technologies should be increased to reflect the cost situation of the technologies [15]. Then the modification of the renewable act in 2009 established an increase in the reduction of FiT from 5% to 10% [8]. The renewable act was further amended in 2012 and decided to reduce FiT by 1% per month, and set a 52 GW PV capacity threshold [21]. The German government moved away from the FiT approach in 2014, and introduced pilot auctions for solar energy [25].

Finally, we illustrate the FiT policy changes (e.g., the evolution of FiT price and fund (reviewed every certain year)) of both Italy and Germany in Tab. 4 and Tab. 6, respectively.

3. Proposed Model

This section presents the proposed dynamic model. The objective of the model is to simulate and reproduce long-term variation of indices such as the number of solar PV installations and solar PV generation capacity. This model properly accounts for the dynamic coupling between different variables of the system, for example, between the FiT price and the number of PV installations.

The remainder of this section describes the mathematical formulation of the proposed solar PV energy policy model. For clarity, the description of all variables is given in Table 2 of Appendix A.

3.1. PV Installation Costs

In this work, we use the *learning-by-doing* concept to model solar PV system costs [26]. It is well-known that, as the cumulative output of a product increases, its cost decreases due to gained experience. For example, the experience earned from the solar PV panel unit production process accumulates and, over time, leads to a cheaper production of future units. In mathematical terms, this can be expressed as [27]:

$$c(t) = c_0 \cdot \left(\frac{n(t)}{n_0} \right)^{-\beta} , \tag{1}$$

where $c(t)$ is the cost of installing a MW unit (EUR/MW); c_0 is the initial cost at $t = 0$; n_0 and $n(t)$ are the initial and cumulative MW installed to the system, respectively; and β is the learning parameter. Eq. (1) means that production costs will decrease exponentially and tend to zero in the long run [20].

The rate of the cost reduction can be quantified by referring to the learning rate (expressed as a percentage), which is calculated as follows:

$$LR = 1 - 2^{-\beta} . \tag{2}$$

For example, a value of $\beta = 0.322$ means that doubling solar PV installations will lead to approximately 20% reduction of the PV panel production cost.

3.2. Cumulative PV Installations

As mentioned above, this study assumes three main factors that decide the number of PV installations, namely, FiT budget, PV cost and willingness of the people to install PVs. The factors represent economic indicators that motivate people to install solar PVs. In this context, the cumulative PV installations are calculated through the following differential equation:

$$T_n \cdot \frac{dn(t)}{dt} = \frac{w(t) \cdot y(t)}{c(t)} , \tag{3}$$

where $y(t)$ is the cumulative revenue of the FiT scheme (EUR) (see Eq. (10) below); and $w(t)$ represents the willingness of people to install PVs (see Eq. (6)). Eq. (3) allows relating FiT policy parameters (e.g., FiT price through $w(t)$, see Eq. (6) below) to the actual PV deployment (i.e., $n(t)$).

3.3. Feed-in Tariff Price Dynamics

The evolution of the FiT price is described by the following equation:

$$f(t) = \alpha(t - \tau) , \tag{4}$$

where $f(t)$ represents the FiT price (equal to the delayed value of $\alpha(t)$); τ is a time delay that models the time that has elapsed when the FiT starts decreasing; and $\alpha(t)$ is a proper decreasing function, defined as follows:

$$T_\alpha \cdot \frac{d\alpha(t)}{dt} = \alpha(t - \tau) - \alpha_0 , \tag{5}$$

with T_α being its time constant and α_0 representing an input disturbance. To model the decrease of the FiT price by the governments over time, we assume that the value of α_0 is 20% greater than the initial value of $\alpha(t)$, say $\alpha(t_0)$. Therefore, there will be a negative balance in Eq. (5) which means that $\alpha(t)$ will start decreasing after a time that is equal to the delay τ. Note that in practice, the governments cannot decrease the FiT price indefinitely. Hence, in order to prevent that Eq. (5) becomes lower than a certain minimum value, we implement a limit on the value of $f(t)$ and $\alpha(t)$, respectively (see Eqs. (15)-(16) in Appendix B).

3.4. Willingness of People to Install PVs

People's willingness is a crucial factor to increase the solar PV capacity [12, 28]. It is well-known that people are more willing to do something if the incentive is high. For this reason, we assume that the willingness of people to install PVs is proportional to the FiT price, as follows:

$$w(t) = \frac{f(t)}{f_0} , \tag{6}$$

where f_0 is the initial FiT price. Thus, the model assumes that people's behavior to install PVs follows a strategy that is based on pure economic return. Furthermore, it is assumed that when $f(t)$ hits the lower limit, say $f^{\min}$, $w(t)$ will still decrease. This implies that even though the FiT price is constant, people's willingness will continue to decrease since the FiT price is too low.

The assumption that the willingness of people to install PVs is proportional to the FiT price (Eq. (6)) is widely accepted in the literature, e.g. [12]. Different from [12], where the willingness of people to install PVs directly depends on other factors such as total cost of PV installations, in this work, the willingness of people is modelled as a proper decreasing function based on FiT price. However, note that we explicitly model the total cost of PVs through Eq. (1) and its impact on PV installations in Eq. (3). Therefore, it can be concluded that our model offers new ways to relate/model the willingness of people as well as the cost of PV installations and their impact on total PV installations.

3.5. Contribution of Solar PVs in the Energy Mix

The contribution of solar PVs in the energy mix (i.e., PV installed capacity being effectively utilized) is modeled through the following algebraic equation [8]:

$$e_z(t) = n(t) \cdot I \cdot PR\,, \tag{7}$$

where $e_z(t)$ represents the energy produced by PV generation (MWh); I is the reference PV yield (MWh/MW) e.g., in a year; PR is the performance ratio (e.g., 85%).

In general, it is useful to estimate the cumulative solar PV generation. With this aim, the following differential equation is introduced:

$$T_z \cdot \frac{dz(t)}{dt} = n(t) \cdot I \cdot PR\,, \tag{8}$$

where $\frac{d}{dt}$ denotes the time derivative; $z(t)$ represents the cumulative PV generation and T_z represents its time constant.

3.6. Cumulative Expenses to Support Solar PV Generation

As mentioned above, under the FiT program, investors are paid using a fixed price ($f(t)$) for the electricity generated and fed into the grid from the solar power plant. The cumulative expenses to support solar PV generation can be predicted using the following differential equation [15]:

$$T_x \cdot \frac{dx(t)}{dt} = f(t) \cdot e_z(t)\,, \tag{9}$$

where $x(t)$ represents the cumulative expenses to support the solar PV production and T_x represents its time constant.

3.7. Cumulative Revenue of the FiT Fund

Incentives such as FiT are generally paid by the consumers through a surcharge on the electricity bill [23]. In this context, the cumulative revenue of the FiT fund can be modeled through the following differential equation [15]:

$$T_y \cdot \frac{dy(t)}{dt} = \lambda \cdot LP \cdot e_L \cdot u\,, \tag{10}$$

where T_y represents the time constant of $y(t)$; λ represents the electricity price; LP is the constant levy given as a percentage of the electricity price; e_L is the total energy consumption (assumed constant in this work unless stated otherwise); and $u = 1$ if:

$$y(t) > x(t)\,,\ \forall t\,, \tag{11}$$

holds. Otherwise $u = 0$. Equation (11) represents the viability condition of the FiT scheme [15]. In other words, the condition for the FiT viability is that the cumulative revenue of the FiT fund ($y(t)$) should be greater at any time than the cumulative expenses $x(t)$.

3.8. Variable Limits

In practice, there are limits on certain variables of the system. For example, the FiT budget is not infinite, and the FiT price cannot decrease indefinitely. Appendix B presents the implementation of the limiters for the variables of the proposed model.

4. Model Validation

The accuracy of the model is validated based on two of the most important PV markets in Europe and globally, namely, Italy for the period 2008-2014 and Germany for the period 2000-2014. With this aim, simulation results produced with the proposed model are compared against historical data. Six key and highly uncertain variables of the model are selected for illustration. These are: (1) cumulative PV capacity; (2) cumulative PV generation; (3) PV cost; (4) cumulative FiT budget; (5) FiT price; and (6) people's willingness.

It is worth mentioning that the model can be conveniently extended to any other PV market, assuming the parameters of the market are known with acceptable accuracy. As a matter of fact, the PVs development in different countries (including Greece and the Netherlands) shows a similar trend as in Germany and Italy, that is, slow growth at the beginning (i.e., high "inertia" due to, for example, PV high cost), then followed by a steady increase (e.g., good incentives and PV cost reductions) and then a saturation due to the high burden on government budget (e.g., FiT price decreases significantly compared to the early stage). The global PV market is likely to follow a similar trend to the one described above, which is currently in the steady increase phase due to good government incentives and solar PV cost reductions). Therefore, a potential application of the proposed model is the global PV market.

For completeness and reproducibility of the results, the input data of the model are given in Appendix A. In particular, the parameter values and historical data are given in Tables 3-4 for Italy, and in Tables 5-6 for Germany. It is relevant to note that some of the parameters can be obtained by conducting surveys [29]. All simulations in this work are performed using the software tool Dome, that is designed for the transient analysis of nonlinear dynamic systems [30].

4.1. Solar PV Development in Italy 2008-2014

Figures 1-5 compare the historical PV installed capacity, generation, fund, costs, and FiT price values with their respective simulated values, while Fig. 6 shows the evolution of the willingness of the people.

Results indicate that, if the parameters are properly chosen, the model can accurately reproduce the historical data. In particular, the model is able to predict the relatively slow response of the installed PV capacity (with a rate of change of approximately 3000 MW/Year) to the policy during the first years (see Fig. 1). This slow response implies that during the first years there is a high "inertia" mainly due to high initial PV costs (Fig. 4), even though the willingness of the people to install PVs is high (Fig. 6). Note that the current model does not account for other factors that may impact the PV installation in the first years, e.g. large development times and/or administrative procedures.

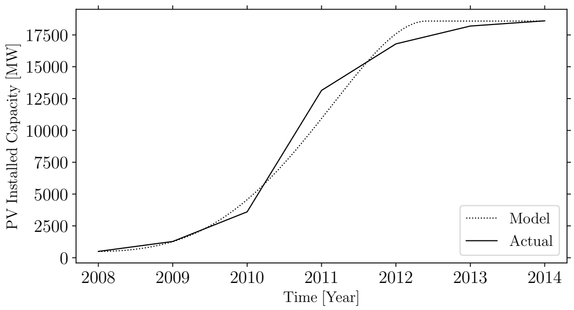

Figure 1: Italian case: Cumulative solar PV installations.

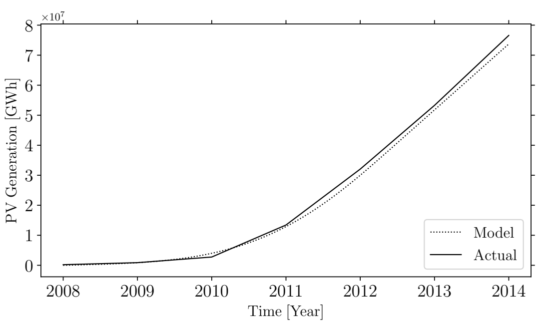

Figure 2: Italian case: Cumulative solar PV generation.

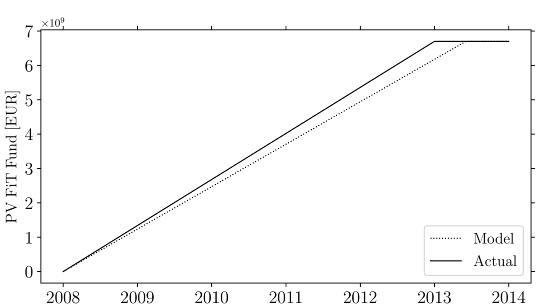

Figure 3: Italian case: Cumulative FiT fund.

It is also worth observing that the model almost perfectly matches the cumulative solar PV generation over the years (Fig. 2) and forecasts reasonably well the FiT fund (Fig. 3). The validation of the learning-by-doing model against real data from the Italian market (Eq. (1)) is shown in Fig. 4. In particular, it can be observed that in the first few years the model predicts that the cost reductions take place sooner, while in the last two years the model overestimates the PV costs (Fig. 4). However, it appears that these differences in the cost predictions do not significantly impact the PV installed capacity (Fig. 1).

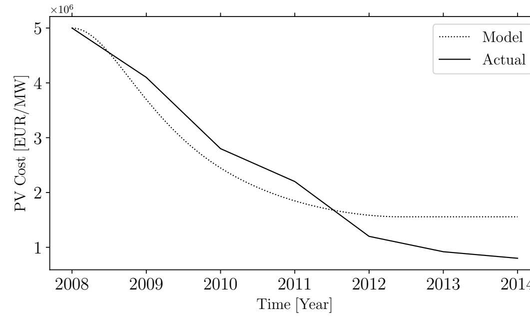

Figure 4: Italian case: Solar PV cost.

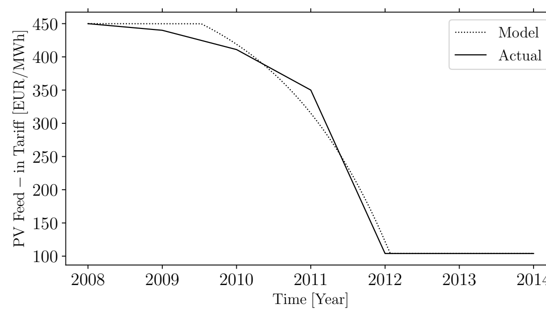

Figure 5: Italian case: Solar PV feed-in tariff price.

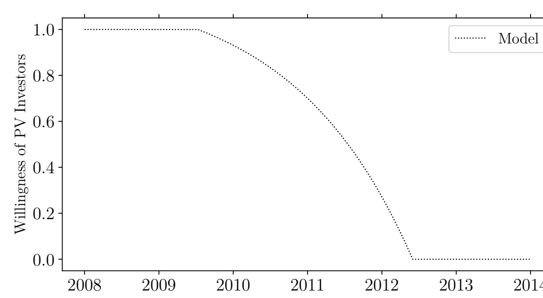

Figure 6: Italian case: Willingness of people to install solar PVs.

With regard to the FiT price, Fig. 5 shows that the model captures very well its evolution in the considered period of analysis. Therefore, the use of Eq. (4) appears to be useful in predicting the change of FiT price over time. The willingness of the people to install solar PVs is shown in Fig. 6. As expected, evolution of the willingness is proportional to the FiT price (Fig. 5). However, it is interesting to note that people's willingness reaches the limit ($2 \cdot 10^{-5}$ considered in this paper) at around 2012 when the FiT price was fixed and the lowest of the policy. These results explain the small increase of the solar PV installations after 2013 (see Fig. 1). Thus, keeping high FiT prices is crucial for the willingness of people to install PVs.

4.2. Solar PV Development in Germany 2000-2014

This second example validates the model against historical data of the solar PV systems in Germany in the period 2000-2014. This is needed to check if the model is general enough to reproduce different PV markets. With this aim, and similar to the Italian case, Figs. 7-11 show the comparison between historical values and simulated ones. Moreover, Fig. 12 shows the evolution of the willingness of the people to install PVs.

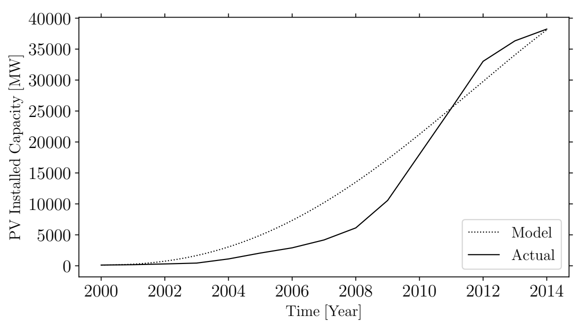

Figure 7: German case: Cumulative solar PV installed.

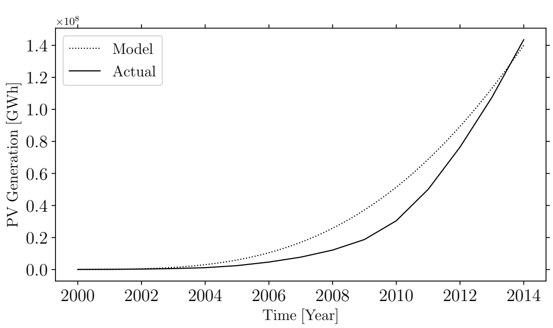

Figure 8: German case: Cumulative solar PV generation.

In general, the proposed model is able to represent the development of the PV market in Germany between 2000-2014. However, compared to the Italian case, the differences between historical and simulated values are slightly more evident. Specifically, while the model is able to accurately reproduce the historical data of the PV installations (Fig. 7) and generation (Fig. 8), PV costs (Fig. 9), FiT budget (Fig. 10) and FiT price (Fig. 11) are predicted with less accuracy.

The main reason for these deviations is that several parameters, e.g., the electricity price λ and the levy constant

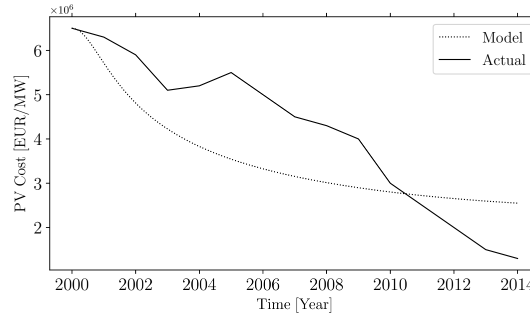

Figure 9: German case: Solar PV cost.

LP, are time-dependent and change significantly over the years. This is however unpredictable and cannot be properly modelled *a priori*. For example, at the beginning, the electricity price λ and the levy constant were small [23]. The government then realised that to further incentivize the PV market, they needed to increase the burden on the consumer electricity bill. As a result, the FiT budget does not increase linearly, as predicted by the proposed model (see Fig. 10). Note that assuming constant parameters is a common approach in the literature. For example, reference [15] uses a simple constant penetration rate for the contribution of renewable energies in the energy mix. While a reason why the PV cost does not follow the *learning-by-doing* concept (Eq. (1)) is due to PV material scarcity in the PV production facilities. For example, reference [31] states: "*Unexpected demand growth, driven by rapid increase of support schemes across the globe, resulted in demand increases that exceeded production capacity, and thus created scarcity rents*". It is relevant to note, however, that while the proposed model cannot anticipate the changes in the policy, it provides a tool to estimate what happens if some of the parameters are varied. This feature is discussed in detail in Section 5.

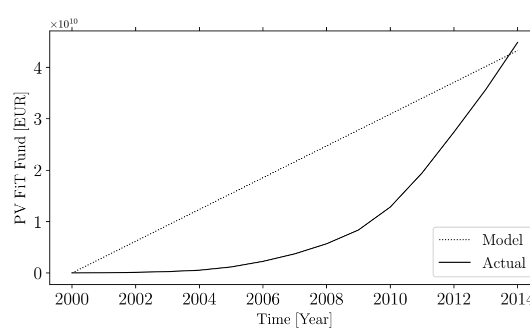

Figure 10: German case: Cumulative FiT fund.

Fig. 12 shows the evolution of the willingness of the public to install PV panels. While the willingness has generally the same trend as the FiT price (Fig. 11), its behavior changes when it reaches its lowest value. Specifically, Fig. 12 shows that at the end of the period of analysis (i.e., the year 2014), the willingness has a value of more than 0.4.

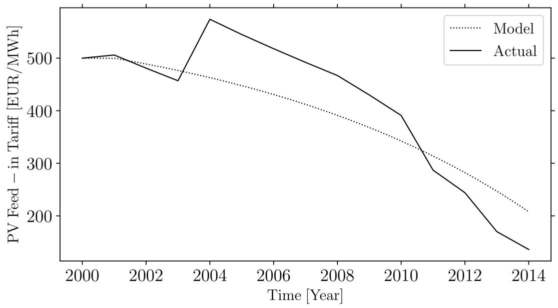

Figure 11: German case: Solar PV feed-in tariff price.

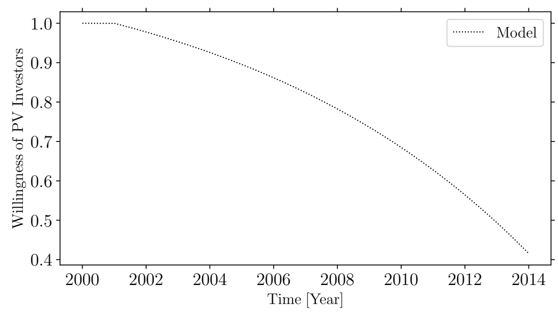

Figure 12: German case: Willingness of people to install solar PVs.

This value is significantly higher compared to that obtained in Italy ($2 \cdot 10^{-5}$). This means that, compared to Italy, the willingness of people in Germany was relatively high. These results can explain the development of solar PV installations in Germany, where there is still a strong increase in the number of PVs installed [32]. In contrast, Italy's PV market has seen a prolonged rise in the number of PVs after 2014 [33].

To better analyze the accuracy of the proposed model, similar to [10], we use the coefficient of determination R^2 as a metric. In particular, the higher R^2 is, the better the model fits the actual data. The limit case is $R^2 = 1$, for which the model exactly matches the actual data. Table 1 summarizes the results for the German and Italian cases. As expected, for the Italian case, all R^2 are close to 1, which indicates a good match between model and actual data. While the German case has idiosyncrasies that cannot be fully captured (in particular, the FiT fund), the proposed model is still able to give the correct trend in all cases.

Furthermore, to compare the model's performance to that of other complex methods from the literature, we show in Tab. 1 the same metric for the cumulative PVs installations for the Spain and Taiwan cases , see [10], [12], respectively. Note that neither of these shows other variables considered in our work (e.g., cumulative solar PV production and/or the PV cost). As it can be seen, the proposed model appears to have similar performance compared to other more complex models proposed in the literature. Therefore, it is fair to say that, overall, the proposed model passes the validation test.

5. Sensitivity Analysis

This section presents a sensitivity analysis of the model using the Italian case for the period 2008-2014. The goal is to show the effect of varying different parameters of the proposed model. This goal is adequately attained by discussing only one PV market. Of course, the same analysis could also be repeated for the German case (and possibly for others, too), without however contributing any additional insights. Using adequate parameters is, in fact, crucial to obtain a reliable prediction of the evolution of the PV technology [15]. Unless stated otherwise, for all scenarios, we show two variables of the system, namely, the cumulative solar PV capacity and generation.

5.1. Results and Discussion

5.1.1. Effect of Different Cost Modelling

This section compares different PV cost modelling and their impact on the PV capacity and generation. As discussed in Section 3, we have proposed the utilization of the learning-by-doing model, which is based on Eq. (1). While this model is heuristic, we show in this section that it is actually quite accurate. For illustration, we compare the proposed learning-by-doing and a simple linear cost modelling and show their effect on the evolution of the PV capacity and generation.

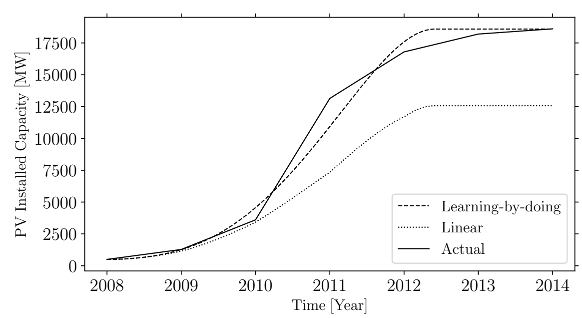

Figure 13: Italian case: Cumulative solar PV installed.

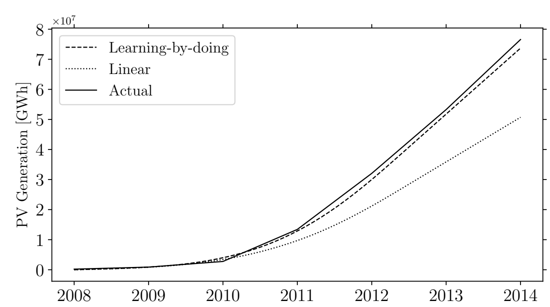

Figure 14: Italian case: Cumulative solar PV generation.

Figures 13-14 show the evolution of the PV capacity and generation during the period 2008-2014 for different PV cost

Table 1
Coefficient of determination R^2 for the German and Italian cases.

Item	R^2 (German)	R^2 (Italian)	R^2 (Spain)	R^2 (Taiwan)
Cumulative PV installations	0.932	0.983	0.971	0.990
Cumulative solar PV production	0.940	0.996		
PV cost	0.550	0.904		
FiT price	0.770	0.989		
Cumulative FiT fund	0.167	0.985		

modelling. The learning-by-doing approach leads to a better forecast compared to the linear one, i.e., the linear cost modelling leads to an underestimate of the PV capacity. These results support the utilization of Eq. (1).

5.1.2. Effect of β

In this section, we compare the effect of different learning coefficients β in the evolution of the PV technology. Such analysis is relevant because the value of the parameter β is not always obvious [34]. For example, different values of β are indicated for Germany in [12] and [8]. For this reason, the sensitivity analysis is carried out using three values of β, namely, 0.2, 0.322, and 0.4 [8].

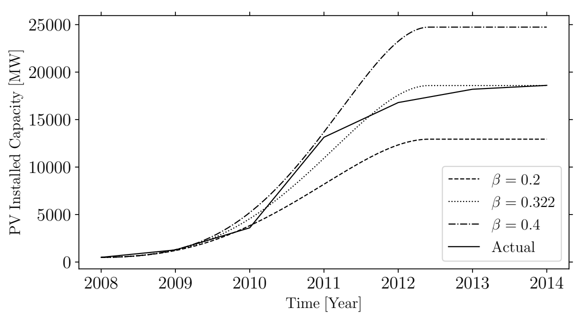

Figure 15: Italian case: Cumulative solar PV installed.

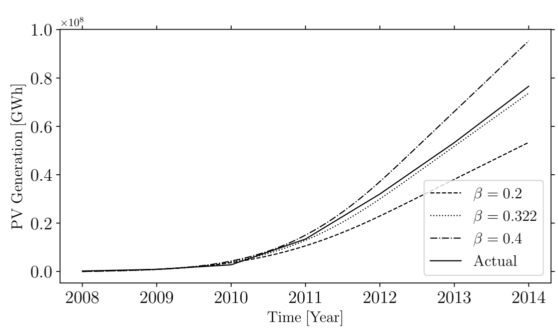

Figure 16: Italian case: Cumulative solar PV generation.

Figures 15-16 show that results are sensitive to the value of the learning parameter β. Moreover, it can be seen that larger values of β lead to higher PV installed capacity and generation. This was to be expected. Larger values of β mean a higher accumulation of experience as well as a faster decrease of the PV system costs.

5.1.3. Effect of Load Consumption

Another relevant but uncertain parameter of the model is the load power consumption. Three scenarios are assumed namely, 1% consumption increase per year, constant load consumption, and 1% decrease per year. The results of the sensitivity analysis are shown in Figs. 17-18.

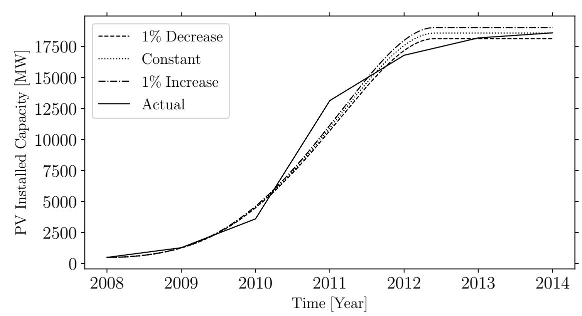

Figure 17: Italian case: Cumulative solar PV installed.

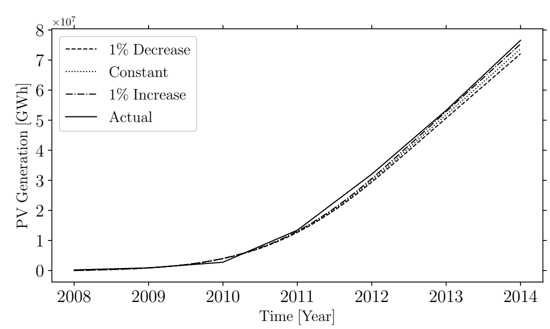

Figure 18: Italian case: Cumulative solar PV generation.

These figures show that different levels of load power consumption lead to similar trends in the evolution of PV capacity. It appears, thus, that the load power consumption is not a highly sensitive parameter of the model. However, it is worth observing that the higher the load consumption, the bigger the increase of the PV capacity and generation. In other words, the increase of e_L impacts positively on the development of the PV market.

5.1.4. *Effect of Levy*

In this section, we perform a sensitivity analysis with respect to different levy constant values LP. This parameter defines the level of financial support from the governments to support the development of different energy technologies (see Eq. (10)). It has been observed that over time this parameter changes significantly (i.e., very uncertain) [23]. With this aim, three scenarios are considered, namely, $LP = 10\%$, $LP = 15\%$, and $LP = 20\%$, respectively. These values are realistic and are consistent with what happened in Italy [18].

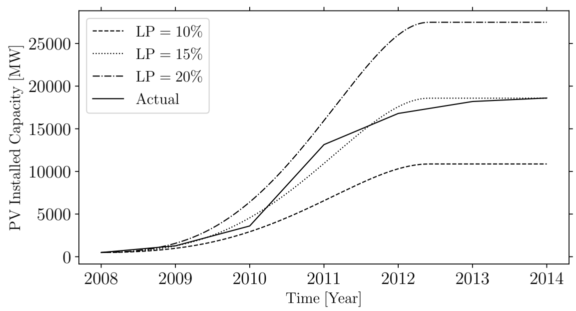

Figure 19: Italian case: Cumulative solar PV installed.

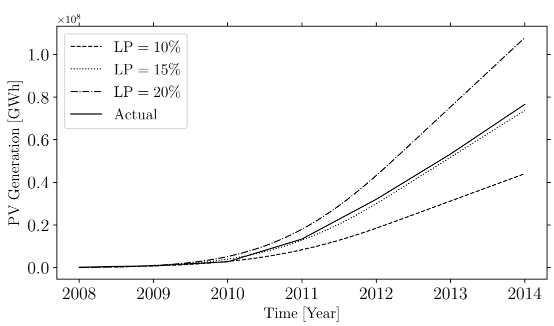

Figure 20: Italian case: Cumulative solar PV generation.

Figures 19-20 show that the levy constant is a highly sensitive parameter. This was to be expected as this parameter defines the amount of money (budget) that the government puts in place to support the PV technology. Results confirm the previous conclusion that government financial support is crucial for successfully integrating and fostering the solar PV market.

5.1.5. *Effect of the Electricity Price*

This section discusses the impact of the electricity price λ on the evolution of the PV market. Similar to the previous sections, a sensitivity analysis is carried out considering three values of λ, namely, 100, 200, and 300 EUR/MWh, respectively.

Figures 19-20 show that with the increase of λ there is an increase in the solar PV installations and generation. This has also to be expected because increasing λ means that there

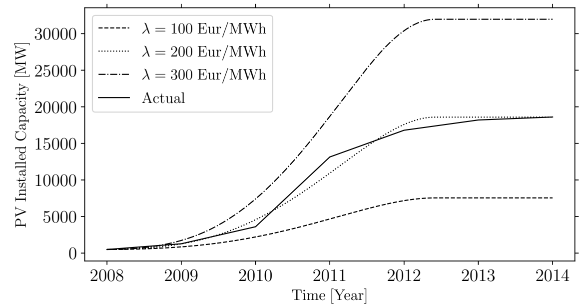

Figure 21: Italian case: Cumulative solar PV installed.

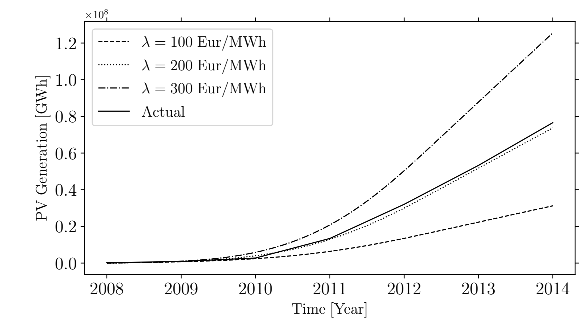

Figure 22: Italian case: Cumulative solar PV generation.

is more money to support the development of the PV market (Eq. (10)). It can be concluded that the electricity price λ is a highly sensitive parameter of the model.

5.1.6. *Effect of $y^{\max}$*

The Italian government closed the FiT program in July 2013 when the budget limit was reached (i.e., 6,700 MEUR) [19]. It is relevant to study the impact of such a cap on the evolution of the PV market. In the proposed model, this information is given by $y^{\max}$. With this aim, we vary the value of $y^{\max}$ and observe its impact on the PV capacity and generation. Three values are used, namely, 4,700, 6,700, and 8,700 MEUR, respectively.

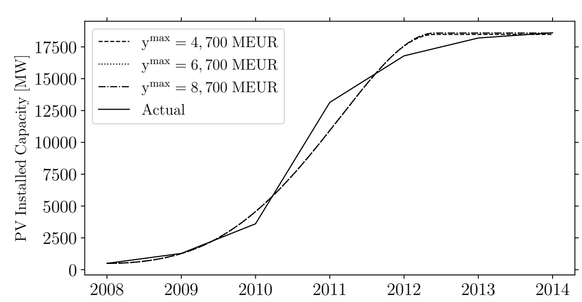

Figure 23: Italian case: Cumulative solar PV installed.

Figures 23-26 show the results. Interestingly, there are

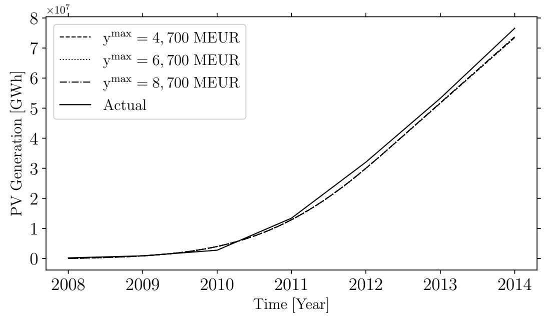

Figure 24: Italian case: Cumulative solar PV generation.

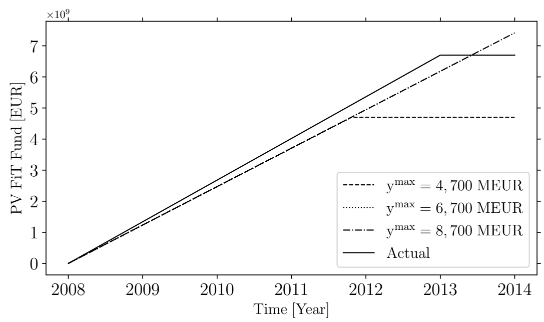

Figure 25: Italian case: Cumulative FiT fund.

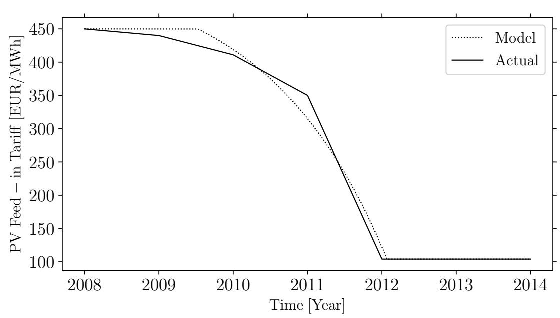

Figure 26: Italian case: Solar PV FiT.

no significant differences with respect to the PV installed capacity and generation. This can be explained by the fact that in 2012 the FiT price is too low (104 EUR/MWh) to incentivize people to install solar PVs (see Fig. 26). This affects negatively the people's willingness, which hits the lower limit considered, i.e., $2 \cdot 10^{-5}$, as shown in Fig. 6. It descends that keeping high FiT prices is vital if an energy policy is to be successful. By doing that, governments can increase the willingness of people to install solar PVs. However, high FiT rates may lead to economic instability [35]. Therefore governments should find a trade-off between compensation for investors and a reasonable burden for the energy consumers [15].

5.1.7. *Effect of* T_n

Since we are using a dynamic model based on differential equations, it is relevant to perform a sensitivity analysis with respect to the time constants of the main state variables of the system, namely, T_n, T_α and T_y. In this first scenario, we discuss the effect of the time constant of the cumulative solar PV capacity, T_n.

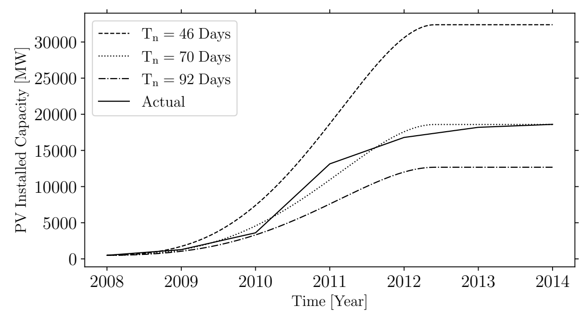

Figure 27: Italian case: Cumulative solar PV installed.

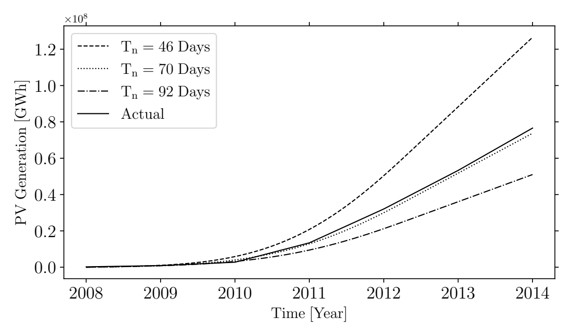

Figure 28: Italian case: Cumulative solar PV generation.

Figures 27-28 plot the relevant results. It can be seen that T_n is a highly sensitive parameter of the system and greatly impacts the number of PV installations and the cumulative PV generation. For example, decreasing T_n from 70 days (which is the base case) to 46 days leads to an increase of more than 1 GW installed capacity.

5.1.8. *Effect of* T_α

Another relevant time constant of the model is T_α, which defines the dynamics of the FiT price and willingness of the people (Eq. (5)). In this context, and similar to the previous scenario, a sensitivity analysis is performed and the relevant results are shown in Figs. 29-30.

Both figures indicate that the evolution of the PV capacity and generation over the years is highly sensitive to T_α.

5.1.9. *Effect of* T_y

This scenario discusses the sensitivity analysis with respect to the time constant of the FiT budget, T_y (Eq. (10)). Figures 31-32 show relevant results.

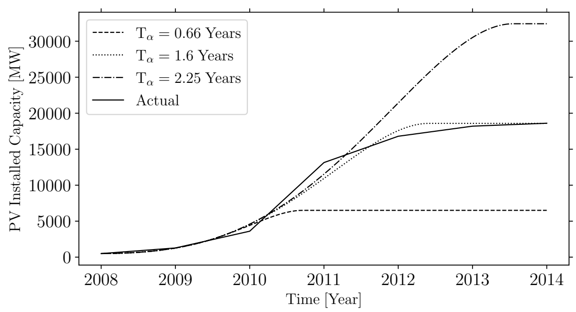

Figure 29: Italian case: Cumulative solar PV installed.

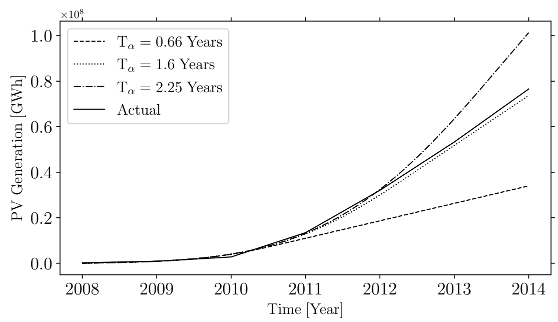

Figure 30: Italian case: Cumulative solar PV generation.

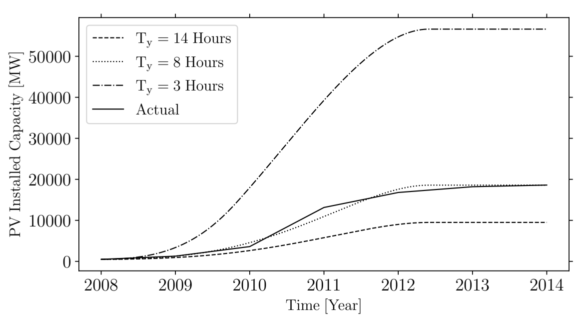

Figure 31: Italian case: Cumulative solar PV installed.

Decreasing the time constant T_y from 8 hours (base case) to 3 hours leads to an increase with more than 3 GW of PV installed capacity (see Fig. 31).

6. Conclusions

The last two decades saw an unprecedented increase in solar PV installations in Italy and Germany. The main driving force was extremely generous FiT applied by the respective governments that encouraged the public to invest in PV systems. While FiT is an excellent mechanism to incentivize investors, it led to a severe impact on system costs and economic instability (tens of thousands of MEUR to be paid by the energy consumers). An accurate dynamic model appears thus as a relevant tool to predict and prevent the collapse of

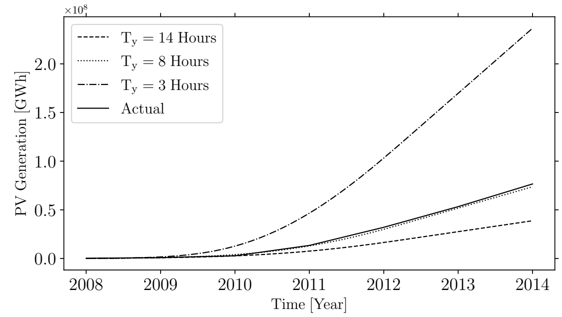

Figure 32: Italian case: Cumulative solar PV generation.

these schemes and help choose a trade-off between a good compensation for investors and a reasonable burden for the energy consumers [15].

Motivated by the discussion above, this paper presents a long-term dynamic model to assess such energy policies promoting solar PV through FiT schemes.

The proposed model appears to be general enough to reproduce with good accuracy the long-term development of the solar PV market in both countries (see Figs. 1-12). Moreover, this model provides valuable information to policymakers by relating, for example, FiT policy parameters (e.g., FiT price) to actual PV deployment. Therefore, we believe that the model is a useful tool for policy-making institutions to capture the long-term behavior of an energy technology such as that of PVs. This is facilitated by the fact that one can easily implement the proposed model (Eqs. (1)-(17)) and reproduce the results in any of the many software packages designed to integrate a set of differential equations. This is an advantage compared to other complex methods presented in the literature that require specific software tools [14, 10, 12]. A simple yet accurate model, in fact, is much more likely to be implemented and used in practice by policymakers.

The development of the PV markets in Italy and Germany is directly related to FiT levels. For example, low tariffs in Italy contributed to discouraging people from installing solar PVs (i.e., very low willingness). When comparing the two countries considered in this work, the model validation test showed that people in Germany had a much higher willingness (18,000 times higher than people in Italy according to this work) at the end of the period of analysis. These results support the idea that despite declining investment costs, incentive policies are still required to increase the share of alternative technologies such as solar PV [10]. This is especially the case of Italy, where the FiT scheme was replaced with other policy mechanisms [19].

The parametric sensitivity analysis of the model in Section 5 for the solar PV market in Italy revealed that:

- The learning-by-doing approach is accurate enough to predict the evolution of the PV cost and capacity.
- The learning parameter β, the levy constant LP, the electricity price λ as well as the time constants of the

Table 2
Variables.

Variable	Description	Unit	Reference
$e_z(t)$	PV production	MWh	[8]
$z(t)$	Cumulative solar PV production	MWh	[8]
$c(t)$	PV cost	EUR/MW	[27]
$n(t)$	Cumulative PV installations	MW	This work
$f(t)$	FiT price	EUR/MWh	This work
$w(t)$	Willingness of people to install PVs	-	This work
$\alpha(t)$	Function that models FiT price evolution	EUR/MWh	This work
$x(t)$	Cumulative expenses to support PV production	EUR	[15]
$y(t)$	Cumulative revenue of the FiT fund	EUR	[15]

state variables of the system are highly sensitive parameters of the model and as such they have to be carefully chosen in order to obtain a realistic prediction of the PV capacity.

- The sensitivity of the parameters of the load consumption and the system total budget do not change significantly the effect of the incentives.

We see many directions for future work. For instance, the proposed model is general and, we believe, can be applied to other technologies. Thus, validating the model against other energy technologies, such as wind power and electric vehicles, is a promising direction. Furthermore, we are aware of a few limitations (e.g., some parameters are tuned by trial-and-error) of the proposed model and recognize that there is still room for improvement in terms of accuracy for some variables. Finally, a promising approach to capturing certain aspects of people's long-term behaviour (e.g., their willingness) is through fractional calculus, i.e., representing the dynamics of people's behavior with properly defined fractional-order differential equations [36, 37].

A. Appendix

This appendix provides all the information concerning the variables (Tab. 2), parameters and data of the model used in the simulations of the two real-world cases considered in the paper, namely, Italy (Tabs. 3-4) and Germany (Tabs. 5-6).

B. Appendix

This section provides the limits of the relevant variables of the model.

Limit on $e_z(t)$:

$$e_z(t) \leq e_G \ , \tag{12}$$

where e_G represents the total energy generation (assumed to be constant in this work).

Limits on $y(t)$:

$$\begin{array}{ll} \text{if } y(t) \geq n^{\max} & : y(t) = y^{\max} \\ \text{if } y(t) \leq y^{\min} & : y(t) = y^{\min} \\ \text{otherwise} & : \text{Eq. (3)} \, , \end{array} \tag{13}$$

where $y^{\min}$ and $y^{\max}$ represent the minimum and maximum FiT fund, respectively.

Limits on $n(t)$:

$$\begin{array}{ll} \text{if } n(t) \geq n^{\max} & : n(t) = n^{\max} \\ \text{if } n(t) \leq n^{\min} & : n(t) = n^{\min} \\ \text{otherwise} & : \text{Eq. (3)} \, , \end{array} \tag{14}$$

where $n^{\min}$ and $n^{\max}$ represent the minimum and maximum PV installed capacity, respectively.

Limits on $f(t)$:

$$\begin{array}{ll} \text{if } f(t) \geq f^{\max} & : f(t) = f^{\max} \\ \text{if } f(t) \leq f^{\min} & : f(t) = f^{\min} \\ \text{otherwise} & : \text{Eq. (4)} \, , \end{array} \tag{15}$$

where $f^{\min}$ and $f^{\max}$ represent the minimum and maximum FiT price, respectively.

Limits on $\alpha(t)$:

$$\begin{array}{ll} \text{if } \alpha(t) \geq \alpha^{\max} & : \alpha(t) = \alpha^{\max} \\ \text{if } \alpha(t) \leq \alpha^{\min} & : \alpha(t) = \alpha^{\min} \\ \text{otherwise} & : \text{Eq. (5)} \, , \end{array} \tag{16}$$

where $\alpha^{\min}$ and $\alpha^{\max}$ represent the minimum and maximum value of $\alpha(t)$, respectively.

Limits on $w(t)$

$$\begin{array}{ll} \text{if } w(t) \geq w^{\max} & : w(t) = w^{\max} \\ \text{if } w(t) \leq w^{\min} & : w(t) = w^{\min} \\ \text{otherwise} & : \text{Eq. (6)} \, , \end{array} \tag{17}$$

where $w^{\min}$ and $w^{\max}$ represent the minimum and maximum value of $w(t)$, respectively.

Table 3
Italian case: Parameter values. These data are based on this work and [8, 33, 38].

Parameter	Description	Unit	Value
Period of analysis	2008-2014	Year	6
e_G	Total energy generation	MWh	40,000
e_L	Total energy consumption	MWh	39,200
I	Reference PV yield	MWh/MW	1,250,000
PR	Performance ratio	%	85
β	Learning coefficient		0.322
c_0	PV initial cost	MEUR/MW	5
n_0	Initial PV MW installed	MW	496
$n^{\max}$	Maximum cumulative PV installations	MW	103,000
$n^{\min}$	Minimum cumulative PV installations	MW	496
$y^{\max}$	Maximum PV fund	MEUR	6,700
$y^{\min}$	Minimum PV fund	MEUR	0
$\alpha^{\max}$	Maximum value of $\alpha(t)$	EUR/MWh	450
$\alpha^{\min}$	Minimum value of $\alpha(t)$	EUR/MWh	0.01
$\alpha(t_0)$	Initial value of $\alpha(t)$	EUR/MWh	450
α_0	Disturbance of $\alpha(t)$	EUR/MWh	$1.2\alpha(t_0)$
$w^{\max}$	Maximum value of $w(t)$		1
$w^{\min}$	Minimum value of $w(t)$		$2 \cdot 10^{-5}$
T_z	Time constant of Eq. (8)	h	0.25
T_n	Time constant of Eq. (3)	h	1,667
T_α	Time constant of Eq. (5)	h	14,139
T_x	Time constant of Eq. (9)	h	8
T_y	Time constant of Eq. (10)	h	8
λ	Electricity price	EUR/MWh	200
LP	Levy constant	%	15
f_0	Initial FiT price	EUR/MWh	450
τ	Time delay of variable $\alpha(t)$	h	13,333

Table 4
Italian case: PV historical data. These data are based on this work and [33, 39, 40].

Year	Capacity MW	Generation GWh	Cost MEUR/MW	Fund MEUR	FiT price EUR/MWh
2008	496	200	5	0	450
2009	1,277	877	4.1	1,340	440
2010	3,605	2,751	2.8	2,680	411
2011	13,141	13,419	2.2	4,020	350
2012	16,796	32,050	1.2	5,360	250
2013	18,197	53,279	0.920	6,700	104
2014	18,606	76,578	0.8	6,700	104

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CRediT authorship contribution statement

Taulant Kërçi: Conceptualization, Methodology, Software, Validation, Original draft preparation, Writing- Reviewing and Editing. **Georgios Tzounas:** Software, Writing-Reviewing and Editing. **Federico Milano:** Supervision, Conceptualization, Methodology, Writing- Reviewing and Editing.

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[2] V. Di Dio, S. Favuzza, D. La Cascia, F. Massaro, G. Zizzo, The evolution of the FIT mechanism in Italy for PV systems: A criti-

Table 5
German case: Parameter values. These data are based on this work and [12, 41, 32].

Parameter	Description	Unit	Value
Period of analysis	2000-2014	Year	14
e_G	Total energy generation	MWh	60,000
e_L	Total energy consumption	MWh	58,800
I	Reference PV yield	MWh/MW	875,000
PR	Performance ratio	%	85
β	Learning coefficient		0.322
c_0	PV initial cost	MEUR/MW	6.5
n_0	Initial PV MW installed	MW	114
$n^{\max}$	Maximum cumulative PV installations	MW	200,000
$n^{\min}$	Minimum cumulative PV installations	MW	114
$y^{\max}$	Maximum PV fund	MEUR	-
$y^{\min}$	Minimum PV fund	MEUR	0
$\alpha^{\max}$	Maximum value of $\alpha(t)$	EUR/MWh	500
$\alpha^{\min}$	Minimum value of $\alpha(t)$	EUR/MWh	0.01
$\alpha(t_0)$	Initial value of $\alpha(t)$	EUR/MWh	500
α_0	Disturbance of $\alpha(t)$	EUR/MWh	$1.2\alpha(t_0)$
$w^{\max}$	Maximum value of $w(t)$		1
$w^{\min}$	Minimum value of $w(t)$		$2 \cdot 10^{-5}$
T_z	Time constant of Eq. (8)	h	0.28
T_n	Time constant of Eq. (3)	h	15,972
T_α	Time constant of Eq. (5)	h	83,333
T_x	Time constant of Eq. (9)	h	8
T_y	Time constant of Eq. (10)	h	5
λ	Electricity price	EUR/MWh	150
LP	Levy constant	%	5
f_0	Initial FiT price	EUR/MWh	500
τ	Time delay of variable $\alpha(t)$	h	8,760

Table 6
German case: PV historical data. These data are based on this work and [41, 23, 42].

Year	Capacity MW	Generation GWh	Cost MEUR/MW	Fund MEUR	FiT price EUR/MWh
2000	114	60	6.5	14	500
2001	176	136	5.0	51	506
2002	296	292	5.0	129	481
2003	435	611	5.0	274	457
2004	1,105	1,168	5.0	540	574
2005	2,056	2,450	5.0	1,176	545
2006	2,899	4,670	5.0	2,266	518
2007	4,170	7,745	5.0	3,729	492
2008	6,120	12,165	5.0	5,689	467
2009	10,556	18,748	4.1	8,365	430
2010	17,994	30,477	2.8	12,830	391
2011	25,429	50,076	2.2	19,468	287
2012	33,033	76,456	1.2	27,407	244
2013	36,337	107,466	0.92	35,683	170
2014	38,236	143,522	0.8	44,849	136

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