Energy storage for PV power plant dispatching

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Energy from the sun is weather-dependent. In modern electric grids that is a shortcoming; generation (and load) has to be regulated accordingly. This issue is a cornerstone for an effective transition to a renewable-based energy system. Weather forecast algorithms can predict photovoltaic production but, in real life conditions, their reliability is only partially effective with respect to the actual grid operation requirements. In the paper, Energy Storage Systems are adopted to compensate the mismatch between the injections of a photovoltaic power plant and the day-ahead market power schedule: the final goal is to achieve the full programmability of the photovoltaic resource on an hourly basis. In particular, the optimal design of the storage apparatus (nominal power and capacity) is defined according to the regulating performances required. Moreover, three weather forecast models are tested in order to evaluate the impact of weather prediction accuracy on the ESS design. Eventually, the payback time of the ESS application is assessed according to the main economic parameters (e.g., energy price, ESS cost, discount rate). The analyses are performed on data measured in a real life scenario.

Nomenclature

- *ANN*: Artificial Neural Network.
- *BCR*: Benefit/Cost Ratio of the investment.
- *DG*: Dispersed Generation.
- *ESS*: Energy Storage System.
- *FM*: Forecasting Method.
- *LRWF*: Linear Regression and Weather Forecast.
- *NNWF*: Neural Network and Weather Forecast.
- *PV*: Photovoltaic.
- *RES*: Renewable Energy Source.
- *SoC*: battery State of Charge.
- *SRC*, *SRP*: Storage Rated Capacity / Power.
- c^C: ESS CAPEX coefficient w.r.t. the energy capacity [€/kWh].
- c^P: ESS CAPEX coefficient w.r.t. the nominal power [€/kW].
- c^F: ESS deployment fixed costs [€].
- e_t^{UP}, e_t^{DW}: imbalances affecting the PV production at time *t*, exceeding the tolerance threshold.
- G_t: linear regression proportionality coefficient between the PV plant power production and the solar radiance, in the time slot *t*.
- *heq*: PV plant equivalent hour of operation at the nominal power.
- I_t: forecast of solar radiance for the time slot *t*.
- η^C, η^D: ESS charge and discharge efficiency.
- ρ_t^C, ρ_t^D: charge and discharge rates of the ESS at the hour *t*.
- $\rho_t^{C\text{-}MAX}$, $\rho_t^{D\text{-}MAX}$: maximum charge and discharge rates of the ESS according to the technical limits.
- $\rho_t^{C\text{-}REF}$, $\rho_t^{D\text{-}REF}$: ideal charge and discharge rates.
- $\rho_t^{C\text{-}TOL}$, $\rho_t^{D\text{-}TOL}$: maximum ESS injections, positive or negative, that cause no imbalances (e.g., to keep the SoC at the reference value), in the time slot *t*.
- p_t^E: estimated power production of the PV power plant in the time slot *t*.
- p_t^A: actual power production of the PV power plant in the time slot *t*.
- τ: tolerance admitted for the prediction.

1. Introduction

Renewable Energy Sources (RESs) are a key driver for a new, sustainable, energy ecosystem. Nevertheless, RESs introduce some drawbacks in the operation of electric networks, which must be properly addressed in order to avoid deteriorating power quality, reliability and supply efficiency [1, 2]. In particular, one of the main RESs issues is their unpredictability, which reduces the programmability of the energy flows on networks. The energy balance between load and generation has to be respected in real time, acting on the injections of some flexible power plants able to accept dispatching orders from the System Operator (i.e. conventional generators). Increasing cost in the selection of conventional power plants is being caused by the rising RES exploitation and the consequent production fluctuations, in order to respect the operational security margins of the system. Consequently, in the last few years, the improvement in dispatch capability of RES and their better coordination with the other production (and consumption) resources is of increasing interest. Today, in the liberalized markets, RES power plants are requested to dispatch their output power to meet the submitted power schedule, or they might face financial penalties. In order to achieve such a challenging target, Energy Storage System (ESS) is one of the most promising options.
The paper focuses on the Photovoltaic (PV) dispatching feasibility by the exploitation of energy production Forecasting Models (FMs) and ESSs. In particular, Section 2 reports an analysis of the literature, with a discussion about several issues relevant for the problem under study; Section 3 describes the approach proposed; Section 4 focuses on the forecast models adopted in the work; Section 5 illustrates the ESS design procedure developed; Section 6 reports the numerical applications performed on a real PV power plant; in particular, the performances of the FMs adopted are described. The results depicted in Section 6 are used in Section 7 to apply the ESS design procedure; the economic feasibility of the investment involving the ESS is assessed w.r.t. the main economic parameters in Section 8; finally, some conclusions are provided in Section 9.

2. Related Works

RES dispatching affects several areas, ranging from production prediction methods (typically based on weather forecast procedures) to regulatory issues, while technological aspects related to PV generation, ESS design and storage technologies have to be addressed, too.

Regarding forecasting, the RES production related to PV power plants has been addressed in several papers and projects. In particular, PV prediction requires the estimation of both the weather conditions (first of all the solar radiation) and the PV modules parameters (to evaluate the production efficiency).

In the literature, different methods have been proposed for the production estimation: in [3] ARIMA models, k-NN models, ANN and ANFIS models are used to assess the production based on a numerical prediction model and on historical data, in [4] Medium-Range Weather Forecasts and a detailed PV simulation model are exploited, while in [5] a Multi-Layer Perception network is used. Despite the accuracy of these methods in estimating PV production, the wide set of data about weather and PV plant that they require could be an issue, especially where small users (domestic users) are involved. For example, in [3], surface sensible and latent heat flux, surface downward shortwave and longwave radiation, top outgoing shortwave and longwave radiation, and temperature are used to estimate PV production up to 39 hours in advance. In [4], to refine the irradiance forecasts provided by the ECMWF model (e.g. by spatial averaging and temporal interpolation, improved clear sky forecasts and post processing with ground data) deriving site-specific hourly forecasts, additional data about the PV plant are needed, such as location, orientation and PV panels characteristics. Similarly, in order to evaluate the PV production of the next day, the Multi-Layer Perception model proposed in [5] processes global radiation (subdivided into direct, diffuse and ground-reflected radiations), pressure, nebulosity, ambient temperature, (peak) wind speed, wind direction, sunshine duration, relative humidity and rain precipitations.

In conclusion, nowadays, there are many models able to provide good PV production estimations, however they do not seem to be decisive: they typically require a wide set of information about the PV power plant technology, its installation site and the weather conditions acting on it [6]. Therefore, reliability for “on field” uses might not be as good as depicted in theoretical studies.

In order to guarantee the real feasibility of PV dispatching, ESSs are today identified as the most promising solution. In [7] a general overview about the applicability, advantages and disadvantages of various ESS technologies for large-scale RES integration is provided.

Typically, the literature has focused on ESSs coupled with wind power plants [8]: this is because wind farms have rated power up to hundreds of MW, i.e. they significantly impact on the energy flows on the main grid. Unfortunately, wind production is quite intermittent resulting in a complex (expensive) ESS design. PV production forecast is more effective; consequently, the use of ESSs for this application is increasingly considered a feasible option [9].

Today, coupling PV power plants with ESSs is being widely discussed, from both the regulatory point of view (incentive schemes and economic feasibility), and the technical point of view [10, 11, 12, 13, 14]. Focusing on the issues under analysis, [15] and [16] report a detailed energetic analysis of ESS design in order to obtain a constant-by-hours PV power reference that mitigates the stochastic nature of PV production. Nevertheless, no economic analyses are reported about costs, penalties, incentive schemes, and the payback time sensitivity w.r.t. these parameters.

Generally speaking, two main approaches can be defined: utility owned ESS (sited in strategic buses of the grid and managed to regulate the aggregated power flows of several loads and generators) and a non-utility ESS (e.g. ESS coupled with a single PV power plant). The second configuration, which is investigated in the present study, proves to be the most challenging owing to the economic feasibility of the application, in particular for small generators [17].

From the system standpoint (market regulation change), in Italy a novel resolution with regard to imbalance costs for generating plants, including renewables, has been released. Motivated by an impressive development of RES installation in recent years (from 2010 to 2013 PV and Wind generation increased from 7 to 25 GW [18]), in July 2012 the National Regulating Authority (Autorità per l’Energia Elettrica e il Gas, AEEG) introduced Resolution 281/2012/R/efr [19], that applies imbalance penalties also to RES producers. The paper adopts this resolution as a reference term for the economic analysis reported. Generally, all over the world energy authorities are pushing incentive schemes and mandatory targets in order to drive an ESS deployment; the final goal is to improve the electric grids capability to integrate RES without affecting efficiency and reliability levels [20, 21].

3. The approach proposed

As already stated, it is commonly understood that RES fluctuations are the main cause of the issues concerning the programmability of the energy flows on power systems. In perspective, the improvement of the forecasting accuracy of the load/generation power withdrawals/injections is one of the most promising services for the ESSs.

The paper proposes a parametric study devoted to evaluating in which conditions ESSs could be a feasible solution in order to obtain an effective PV dispatching. The study focuses on Low Voltage PV generators (i.e., in the Italian scenario, power plants with rated power lower than 100 kW [22]). In this scenario, the investments in complex weather forecasting tools could significantly affect the economics of the PV power plant; consequently, simplified Forecasting Models (FMs) have to be taken into account in order to identify the most cost-effective solution.

The main steps of the analysis are shown in Figure 1 and summarized below.

1. Three FMs have been developed: the Persistence Model, weather forecasts applied to a simple linear regression model of the PV power plant (LRWF model), weather forecasts applied to a PV power plant model based on a neural network (NNWF model). The goal of this first step is not to build up an innovative FM; the target is to collect realistic data (FMs implemented on medium-small size PV plants) for the following ESS design procedure.

2. An ESS (the mathematical model is described in Section 5) is used to reduce the error of the PV production FMs. In particular, time-dependent simulations are carried out over the whole time period under analysis, according to a fixed tolerance limit (10% of the predicted value, as stated by Italian rules). Eventually, suitable characteristics of the ESS are defined: power rating, energy capacity, service life, etc.
3. Results from step 2 (residual imbalances, energy losses in the ESS) are used, together with energy market data and the storage technological characteristics (e.g. energy price, ESS cost), to accomplish a cost/benefit analysis of the storage solution.

The procedure is iterated for different storage sizes, in order to perform a sensitivity analysis aimed at evaluating the impact of the ESS characteristics on the performance of the whole system, and on the economic feasibility of the investment. In particular, the purpose of the regulation is to limit the amount of PV production (energy) subject to penalties for imbalance. At the hour *t*, the imbalance affecting the PV production is evaluated (in percentage) as [23]:

$$100 \cdot \frac{\int_{hour\_i} p_t^A \, dt - \int_{hour\_i} p_t^E \, dt}{\int_{hour\_i} p_t^E \, dt} \tag{1}$$

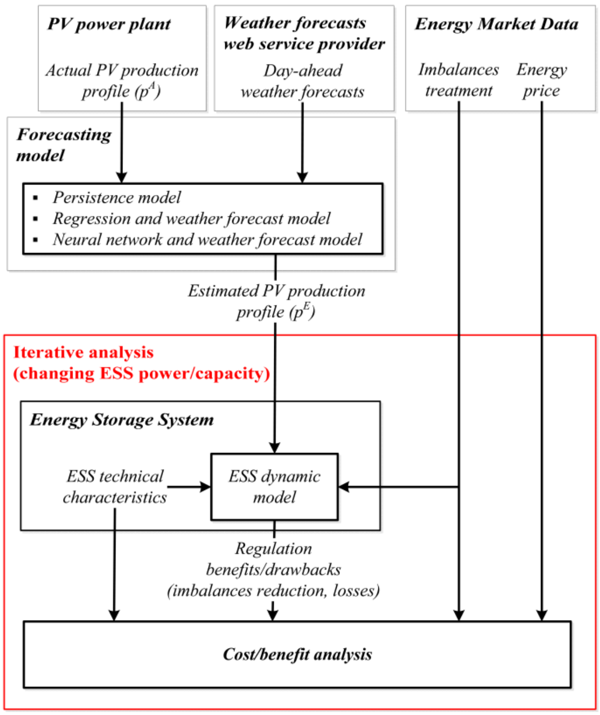

FIGURE 1. Flow-chart of the procedure adopted.

4. PV production forecast methodologies

In order to predict the injection profiles of a PV power plant, it is necessary to identify suitable FMs. As depicted in Section 2, several approaches are proposed in the literature to this purpose; the simpler ones exploit only historical data, others also use weather forecasts data. In this study, three forecasting methods are tested. All of them are compliant with the hypothesis of small PV plant involved: i.e. they do not require parameters which could be difficult to obtain (cost impacting) for final Low Voltage users.

4.1. Persistence model

The simplest method to predict the PV production is the so-called persistence model [24]; it is based on the assumption that weather conditions of today are the same as yesterday. This could seem like as a quite basic FM; nevertheless, it could be a possible option for small case applications (this approach has the advantage of introducing no incremental cost for the forecast).
According to the Persistence model, the power production estimated at the hour *t* (p_t^E) is assumed equal to that measured 24 hours before (p_{t-24}^A):

$$p_t^E = p_{t-24}^A \tag{2}$$

This method well represents the periodicity of weather conditions (day/night cycle); however, it is not able to take into account the unpredictability of weather phenomena.

4.2. Linear regression model based on weather forecasts

The second approach results from the consideration that, basically, FMs reliability is strongly correlated with the weather forecast reliability: the adoption of very detailed PV mathematical models could not be justified.
According to this assumption, and exploiting a standard commercial weather forecasting service, a very simple PV model has been developed. PV active power injections have been correlated with the solar radiance by a linear regression algorithm.
Actually, the Linear Regression and Weather Forecasts (LRWF) model is based on the following equation:

$$p_t^E = G_t \cdot I_t \tag{3}$$

In eq. (3):
- p_t^E is the estimated power production of the PV power plant in the time slot *t*;
- G_t is the proportionality coefficient representing the PV power plant model, as evaluated at time *t*;
- I_t is the value of forecasted solar radiance made available by the web service provider at time *t*.

In each time slot *t*, the proportionality coefficient G_t modeling the PV power plant behavior is evaluated according to the historical production and the past weather forecast data (e.g. on 50 past samples). G_t coefficient is determined by a linear regression algorithm (Levenberg-Marquardt algorithm [25]) that minimizes, on an iterative basis, the sum of the squares of the deviations between the estimated production values assessed by the fitting curve and the actual production values. Then, the day-ahead weather forecasts are applied in input to the LRWF model to obtain the PV production profile prediction.

4.3. PV Artificial Neural Network based on Weather Forecasts

The last approach adopted (Neural Network and Weather Forecasts model: NNWF model) exploits detailed weather forecast data coupled with a complex PV model based on an Artificial Neural Network (ANN). Radial basis model (GRNN type: Generalized Regression Neural Network) is chosen since this type of ANN has a sharp performance when a wide set of training data is available and it is often used for functions approximation. It has a radial basis layer and a special linear layer. The ANN is managed by the Matlab ANN Toolbox [26]: to increase the robustness of the approach, each input has been scaled to normalize the mean and standard deviation of the training set (zero mean and unity standard deviation).

The weather forecast data required by the procedure are 24 hours ex-ante predictions about: solar radiance [W/m^2], weather temperature [°C], wind intensity [km/h], wind direction [deg] and wind gust [km/h]. All this information is completed with the PV plant production.

In particular, the NNWF model adopts the first 15 days for the first ANN training. After this training phase, for the day i^{th} all the information collected in the previous *(1÷(i-1))* days are used in order to rerun the ANN training process and to elaborate the $(i+1)^{th}$ active power injections profile forecast.

5. Energy storage mathematical model for PV dispatching

In the architecture proposed, the ESS adjusts the production profile of a PV power plant to respect the forecasted injections profile. With this aim, the storage charge/discharge process must be suitably controlled, in order to:

– correct the prediction error affecting PV injections within a fixed tolerance;
– keep the energy stored in the ESS close to the reference value (e.g., in the simulations performed, $SoC^{REF}=0.5$).

The ESS control logic proposed is depicted in Figure 2.

At time *t*, the logic defines (with an hourly resolution) the charge/discharge power rates (ρ_t^C and ρ_t^D) that the ESS must perform to satisfy the above-mentioned requirements. According to the power rate assessed at time *t*, the State of Charge (SoC) of the battery at time *t+1* (SoC_{t+1}) is evaluated. If, at hour *t*, the mismatches between the actual PV production (p_t^A) and the estimated one (p_t^E) exceed the admitted tolerance (τ), the ESS has to be exploited in order to avoid financial penalties. If p_t^A is greater than p_t^E the ESS must store energy, while if p_t^A is lower than p_t^E the ESS must release energy. In Figure 2, e_t^{UP} and e_t^{DW} are the prediction errors to be corrected by absorbing/injecting energy from/to the network through the ESS. They can be expressed as:

$$\begin{cases} e_t^{UP} = max[p_t^A - p_t^E \cdot (1+\tau); 0] \\ e_t^{DW} = max[p_t^E \cdot (1-\tau) - p_t^A; 0] \end{cases} \tag{4}$$

On the contrary, if the forecasting error affecting the PV production is lower than the admitted tolerance (τ), no adjustments are required; the ESS control logic exploits the tolerance band in order to restore the reference SoC (SoC^{REF}):

– $\rho_t^{C\text{-}TOL}$ is the maximum power that the ESS can absorb from the grid at the hour *t* (to keep the SoC at the reference value) without causing the violation of the lower tolerance limit;
– $\rho_t^{D\text{-}TOL}$ is the maximum power that the ESS can inject without causing the violation of the upper tolerance limit.

According to the just mentioned formulas, $\rho_t^{C\text{-}TOL}$ and $\rho_t^{D\text{-}TOL}$ are defined as:

$$\begin{cases} \rho_t^{C-TOL} = max[p_t^A - p_t^E \cdot (1-\tau); 0] \\ \rho_t^{D-TOL} = max[p_t^E \cdot (1+\tau) - p_t^A; 0] \end{cases} \tag{5}$$

In Figure 2, $\rho_t^{C\text{-}REF}$ and $\rho_t^{D\text{-}REF}$ are the charge and discharge rates that allow the ESS, in one time step (an hour), to restore the reference SoC (SoC^{REF}). They are defined as:

$$\begin{cases} \rho_t^{C-REF} = max\left[(SoC^{REF} - SoC_t) \cdot \dfrac{SRC}{\eta^C}; 0\right] \\ \rho_t^{D-REF} = max[(SoC_t - SoC^{REF}) \cdot SRC \cdot \eta^D; 0] \end{cases} \tag{6}$$

In eq. (6), η^C and η^D are the charge and discharge efficiencies of the battery and SRC is the Storage Rated Capacity. $\rho_t^{C\text{-}REF}$ and $\rho_t^{D\text{-}REF}$ are "ideal" charge and discharge rates, because they not take into account the operational limits of the ESS, i.e. its rated power (Storage Rated Power, SRP) and the energy actually stored.

The maximum charge/discharge rates that the ESS can perform according to its technical limits, $\rho_t^{C\text{-}MAX}$ and $\rho_t^{D\text{-}MAX}$, are defined as:

$$\begin{cases} \rho_t^{C-MAX} = min\left[(1 - SoC_t) \cdot \dfrac{SRC}{\eta^C}; SRP\right] \\ \rho_t^{D-MAX} = min[SoC_t \cdot SRC \cdot \eta^D; SRP] \end{cases} \tag{7}$$

In eq. (7), the charge and discharge SRPs are assumed equal.

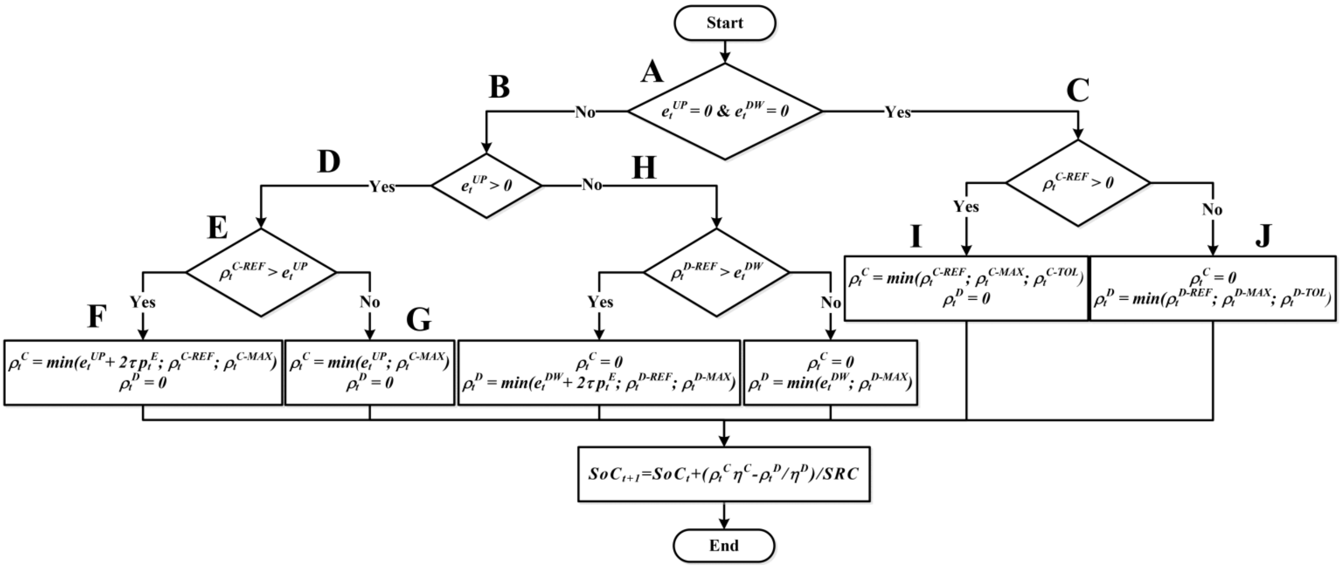

FIGURE 2. Control logic of the ESS.

At each time step t, the ESS control logic operates as follows.

1. The violation of the tolerance admitted for the forecasting error (τ) is assessed (A): if the error is greater than the tolerance, the logic operates to correct it (B), otherwise the ESS exchanges energy with the grid to restore SoC^{REF} (C).
2. In case (B), if the upper tolerance limit is violated (D), in order to avoid imbalance fees the ESS must absorb the energy production exceeding the limit (e_t^{UP}). To this purpose, a suitable charge rate (ρ_t^C) has to be defined.
3. Moreover, the logic evaluates whether the regulating action needed to compensate the prediction error is concordant with the energy required to restore SoC^{REF} (E).
4. If condition (E) is true, the algorithm assesses whether the energy required to correct the forecasting error is lower than the energy needed to reach SoC^{REF} ($\rho_t^{C\text{-}REF} > e_t^{UP}$). If so, $\rho_t^{C\text{-}REF}$ is the most binding requirement for the ESS charge rate at time t, consequently the control logic sets the charge rate ρ_t^C (F) at the value nearest to $\rho_t^{C\text{-}REF}$ that respects the operational limits of the ESS ($\rho_t^C \le \rho_t^{C\text{-}MAX}$). This action does not increase the estimation error affecting the PV production beyond the admitted tolerance (the lower tolerance bound must be taken into account: $\rho_t^C \le e_t^{UP} + 2\tau p_t^E$).
5. If $\rho_t^{C\text{-}REF}$ is lower than e_t^{UP}, the energy required by the ESS to compensate the error is smaller than, or even opposite to, the energy needed to restore SoC^{REF}. The control logic assigns priority to the correction of e_t^{UP} (G): ρ_t^C is set to the value nearest to e_t^{UP} compliant with the ESS operational limits ($\rho_t^{C\text{-}MAX}$).
6. Similar control actions are carried out if the lower tolerance limit is violated (H): in this case, the ESS has to inject energy in the grid in order to compensate the lack of PV production and to reduce the estimation error below τ.
7. If the forecasting error is smaller than τ (C), as already mentioned, the logic acts to restore SoC^{REF}.
8. If the current SoC (SoC_t) is lower than the ideal one ($\rho_t^{C\text{-}REF} > 0$), to restore SoC^{REF} the ESS must absorb energy from the main grid ($\rho^C > 0$; $\rho_t^D = 0$) (I). PV dispatching has always the priority; therefore the ESS charge rate is set to the value nearest to $\rho_t^{D\text{-}REF}$ compliant both with the admitted tolerance ($\rho_t^{D\text{-}TOL}$) and the operational limits of the apparatus ($\rho_t^{D\text{-}MAX}$). The same approach is used when the SoC_t is greater than the ideal one (J).

Once defined the charge and discharge ESS rates, ρ_t^C and ρ_t^D, the SoC of the ESS at the time $t+1$ (SoC_{t+1}) is computed as:

$$SoC_{t+1} = SoC_t + \frac{1}{SRC}\left(\eta^C \rho_t^C - \frac{\rho_t^D}{\eta^D}\right) \tag{8}$$

6. Numerical analysis: PV production forecast

With respect to the approach proposed in Section 3, numerical analyses are performed to evaluate the performance of the three FMs adopted.

The study is carried out on the data collected in the period September 2012 - April 2013 from a real PV plant (P_n = 96.33 kWp) located in Northern Italy (Mantua province). The weather forecasts data required by the LRWF and NNWF models have been acquired from a commercial web service [27] that provides 12-24-36 hours ex-ante predictions about solar radiance, weather temperature, wind intensity, wind direction and wind gust.

Applying the FMs described in Section 4 to the PV power plant under study, the results reported in Table 1 are obtained. In particular, the accuracy of the prediction is evaluated according to the following statistical indexes:

– MEAN and Standard Deviation (STD) of the forecasting error, in percentage w.r.t. the rated power of the PV plant;

– Mean Average Error (MAE) of the prediction, in percentage w.r.t. the PV rated power;
– Mean Average Percentage Error (MAPE) of the forecasted time series, evaluated, according to the theoretical definition, as a percentage of the actual PV production.

The indexes are evaluated on the samples in which the actual PV production is equal to, or greater than, 1% of the rated power of the PV plant (i.e. on daylight conditions). Table 1 clearly shows that the Persistence model gives the worst results, while the LRWF and the NNWF models allow a better estimation of the PV production (at the price of greater complexity: the need to acquire and to process weather forecast data). Concerning the LRWF model, we tested its performance on different training intervals. The best results (shown in Table 1) are obtained using 15 samples, i.e. the model proposed results more reliable if the linear regression is applied to a limited set of historical data. The best performances are obtained, for almost all the indexes considered, with the NNWF model. Actually, the results obtained are compliant with the literature data [6], which validates the procedures developed.

TABLE 1. Performance comparison of the models used for the PV production prediction.

	Persistence model	LRWF model	NNWF model
MEAN	1.59	0.57	0.70
STD	15.24	10.22	5.86
MAE	10.67	7.58	4.03
MAPE	100.37	68.18	35.47

Figure 3 reports the imbalances computed through eq. (1), for each FM, assuming a day-ahead prediction. The samples are divided into two sets: those measured in the hours in which the power production estimated is significant (greater than 10% of the PV rated power: blue), and those in which it is very low (in the latter case, a small difference between the actual and the estimated production in absolute value can cause great relative errors; red). The graph saturates at -100%, corresponding to the case in which the forecasted PV production is non-null, but the actual PV injections are equal to zero. Results in Figure 3 confirm the indications provided by Table 1. As a general observation, all the three FMs perform much better when the PV production is significant (blue bars), while they incur in greater errors when the estimated power is low (e.g., sunrise/sunset). From a practical point of view, this fact has limited impact on the performance of the forecasting process: the energy amounts involved during sunrise/sunset are usually very small, and consequently also the imbalances are small.

According to the requirements fixed by the Italian regulation (day-ahead prediction of the exchange profiles with a tolerated mismatch equal to 10% of the forecasted power) [19], the NNWF model is the FM with the best performance: about 27.5% of samples are estimated with accuracy better than 10%. This result is even more important considering that the error range ±10% includes the most of samples in which the PV injections are significant: 44.2% of the overall samples with forecasted production greater than 10% of the PV rated power are in this interval (versus 25.0% and 20.2%, respectively, of the Persistence and LRWF models).

Nevertheless, none of the FMs tested is fully compliant with the Italian prescription.

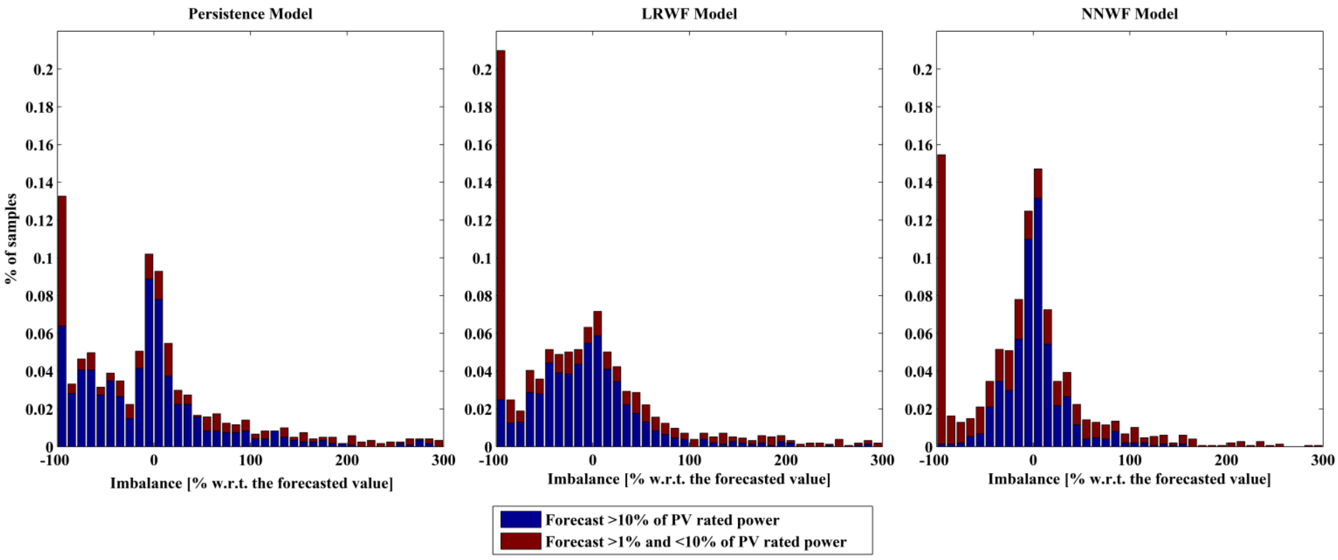

FIGURE 3. Imbalance with the models proposed for the PV production forecasting.

7. Numerical analysis: ESS design

The prediction error induced by the FMs is corrected by means of an ESS. The study focuses on the ESS coupling with the NNWF model (i.e. the FM with the best performance), iterated for different storage sizes, so as to perform a sensitivity analysis.

7.1.1. *Imbalances management*

The ESS could reduce the imbalance error affecting the PV production, adjusting the DG injection profiles according to the control law detailed in Section 5. A 10% tolerance is adopted: therefore, considering the energy imbalances in Figure 3, only the samples outside this tolerance band require an ESS regulation.

Table 2 reports the results obtained according to the storage size: the columns show the ESS power in percentage w.r.t. the size of the PV power plant, while the rows show the ESS capacity in percentage w.r.t. an equivalent hour of operation (heq) of the PV plant. Imbalances are reported as percentage of the yearly PV production. For example, an ESS with power equal to 10% of the generator size, and capacity 10% of one heq (i.e., with rated power 9.6 kW and capacity 9.6 kWh, assuming the 96.33 kW power plant under analysis) is able to reduce the yearly imbalances to about 6.50% of the total yearly production (compared to 15.96% in the case without ESS). In general, there is a strict correlation between ESS power and energy sizing. In particular, to achieve acceptable regulating performances, the ESS must have a suitable energy capacity (otherwise, in many cases it will not perform the regulation, since it is fully charged or discharged). However, also the power sizing is very important: if the ESS power is too low, it might not be able to solve completely imbalances when the forecasting error is big. In addition, a lower power sizing means longer times to restore the reference SoC.

TABLE 2. Percentage of PV production subject to imbalances, according to SRP and SRC.

Energy (% w.r.t. an equivalent hour of operation of the PV plant)	Power (% w.r.t. the power of the PV plant)									
	2	**4**	**6**	**8**	**10**	**12**	**14**	**16**	**18**	**20**
5	11.07	9.95	9.69	9.69	9.69	9.69	9.69	9.69	9.69	9.69
10	10.08	7.92	7.04	6.65	6.50	6.49	6.49	6.49	6.49	6.49
15	9.61	7.05	5.77	5.14	4.81	4.61	4.52	4.50	4.50	4.50
20	9.28	6.51	5.01	4.19	3.73	3.48	3.30	3.20	3.15	3.14
25	9.05	6.13	4.51	3.57	3.02	2.69	2.50	2.37	2.31	2.27
30	8.91	5.84	4.14	3.13	2.54	2.18	1.96	1.80	1.72	1.67
35	8.83	5.62	3.87	2.81	2.18	1.79	1.54	1.37	1.26	1.21
40	8.81	5.45	3.67	2.58	1.91	1.51	1.25	1.06	0.94	0.87
45	8.80	5.34	3.51	2.41	1.72	1.30	1.03	0.83	0.70	0.62
50	8.80	5.27	3.39	2.28	1.58	1.16	0.88	0.68	0.55	0.45
55	8.80	5.23	3.33	2.19	1.50	1.07	0.79	0.58	0.44	0.35
60	8.80	5.21	3.29	2.14	1.43	1.01	0.73	0.52	0.37	0.28
65	8.80	5.21	3.27	2.12	1.40	0.98	0.70	0.49	0.34	0.24
70	8.80	5.20	3.26	2.10	1.38	0.95	0.67	0.46	0.31	0.21
75	8.80	5.20	3.25	2.09	1.37	0.93	0.65	0.44	0.30	0.19
80	8.80	5.20	3.25	2.09	1.37	0.92	0.64	0.43	0.29	0.18
85	8.80	5.20	3.25	2.09	1.37	0.92	0.63	0.42	0.28	0.18
90	8.80	5.20	3.25	2.09	1.37	0.92	0.63	0.42	0.28	0.18
95	8.80	5.20	3.25	2.09	1.37	0.92	0.63	0.42	0.28	0.18
100	8.80	5.20	3.25	2.09	1.37	0.92	0.63	0.42	0.28	0.18

7.1.2. *Energy losses in the ESS*

The regulation performed by the storage in order to adjust DG injection profiles also has drawbacks: during the charge/discharge process, a share of the energy exchanged by the ESS is lost. In this study, an efficiency of the whole charge/discharge cycle equal to 90% is supposed [7].

Energy losses occurring in the ESS, in percentage w.r.t. the overall PV production, are shown in Table 3 (the results correspond to the same hypotheses adopted in Section 7.1.1). As one can observe, losses increase with an increase in storage size, i.e., as expected, with the percentage of imbalances that can be corrected. There is a direct proportionality between the two quantities: at the increasing of the energy that the ESS saves from the imbalance penalties, losses rise. This fact can be observed comparing the results in Table 2 and Table 3: by using an ESS with rated power 2% of the size of the PV power plant and capacity 5% of one heq, the imbalances reduction w.r.t. the scenario without ESS is about 4.89% of the PV production (imbalances without ESS are equal to 15.96, and with ESS to 11.07%) and the energy losses 0.33%. With a much greater ESS, for example rated power 20% and capacity one heq, the imbalances decrease to 0.18% (reduction of 15.78%), but losses increase to 1.13% of the PV production. Both quantities (imbalances and losses) reduce/increase by a factor of 3.2.

TABLE 3. Energy losses in percentage w.r.t. the PV production, according to SRP and SRC.

Energy (% w.r.t. an equivalent hour of operation of the PV plant)	Power (% w.r.t. the power of the PV plant)									
	2	**4**	**6**	**8**	**10**	**12**	**14**	**16**	**18**	**20**
5	0.33	0.40	0.42	0.42	0.42	0.42	0.42	0.42	0.42	0.42
10	0.40	0.54	0.60	0.63	0.64	0.64	0.64	0.64	0.64	0.64
15	0.44	0.61	0.70	0.74	0.76	0.78	0.79	0.79	0.79	0.79
20	0.47	0.6	0.76	0.81	0.84	0.86	0.88	0.88	0.89	0.89
25	0.49	0.69	0.80	0.86	0.90	0.92	0.93	0.94	0.95	0.95
30	0.50	0.71	0.83	0.90	0.94	0.96	0.98	0.99	1.00	1.00
35	0.51	0.73	0.85	0.93	0.97	1.00	1.02	1.03	1.04	1.04
40	0.51	0.75	0.87	0.95	1.00	1.02	1.04	1.06	1.06	1.07
45	0.51	0.76	0.88	0.97	1.01	1.04	1.06	1.08	1.08	1.09
50	0.51	0.76	0.89	0.98	1.03	1.06	1.08	1.09	1.10	1.11
55	0.51	0.77	0.90	0.98	1.03	1.06	1.08	1.10	1.11	1.12
60	0.51	0.77	0.90	0.99	1.04	1.07	1.09	1.11	1.12	1.12
65	0.51	0.77	0.91	0.99	1.04	1.07	1.09	1.11	1.12	1.13
70	0.51	0.77	0.91	0.99	1.04	1.08	1.10	1.11	1.12	1.13
75	0.51	0.77	0.91	0.99	1.05	1.08	1.10	1.11	1.12	1.13
80	0.51	0.77	0.91	0.99	1.05	1.08	1.10	1.11	1.12	1.13
85	0.51	0.77	0.91	0.99	1.05	1.08	1.10	1.12	1.13	1.13
90	0.51	0.77	0.91	0.99	1.05	1.08	1.10	1.12	1.13	1.13
95	0.51	0.77	0.91	0.99	1.05	1.08	1.10	1.12	1.13	1.13
100	0.51	0.77	0.91	0.99	1.05	1.08	1.10	1.12	1.13	1.13

7.1.3. *ESS cycling*

The rate of use has a huge impact on the service life of the ESS. In first approximation, the degradation of batteries can be considered proportional to the number of charge/discharge cycles that they carry out and to their depth (Depth of Discharge, DoD). The correlation between these factors and the ESS lifetime consumption is very difficult to be accurately assessed: it depends on the storage technology involved and on the modalities of use of the apparatus (e.g., most of charge/discharge cycles are partial, so they have different effects on the ESS's aging).

In this study, the service life of the ESS is assumed only dependent on the number of complete charge/discharge cycles that it performs. This quantity, assessed simulating the ESS operation according to the historical data measured on the real PV plant under analysis, is reported, on a yearly basis, in Table 4.

As expected, ESSs with smaller energy capacity are required to perform a greater number of cycles (they are more stressed): for example, an ESS with power 10% of PV size and capacity equal to 5% of one heq must perform about 757 cycles/year, while an ESS with the same power but capacity equal to one heq is charged/discharged only about 216 times. Moreover, the number of cycles that the storage apparatuses perform always increases with an increase in their rated power: this is because a greater power of the ESS allows a better exploitation of the energy capacity (faster charge/discharge cycles).

TABLE 4. Number of charge/discharge cycles per year, according to SRP and SRC.

Energy (% w.r.t. an equivalent hour of operation of the PV plant)	Power (% w.r.t. the power of the PV plant): 2	4	6	8	10	12	14	16	18	20
5	706	751	757	757	757	757	757	757	757	757
10	537	641	655	661	663	663	663	663	663	663
15	413	554	587	596	599	601	602	602	602	602
20	333	479	531	546	550	552	553	554	554	554
25	278	417	480	502	511	515	516	517	518	518
30	239	368	435	464	475	480	482	483	483	483
35	210	328	396	430	444	450	453	454	455	455
40	186	295	362	398	417	425	429	431	431	432
45	167	268	332	369	389	400	406	409	410	410
50	151	245	306	343	364	376	382	385	387	388
55	138	226	284	320	342	355	361	365	367	368
60	126	209	264	300	322	335	343	347	349	350
65	117	195	247	283	305	318	326	330	333	334
70	108	182	232	266	288	302	310	315	318	319
75	101	171	218	251	274	288	296	301	305	306
80	95	161	206	238	260	274	283	288	291	293
85	89	152	195	227	248	262	271	276	279	281
90	84	143	185	215	236	251	259	265	268	270
95	80	136	176	205	226	240	249	254	257	259
100	76	129	168	196	216	230	239	244	247	249

8. Economic analysis of the storage solution

In this section, a study of the economic feasibility of the solution based on the ESS is discussed. A cost/benefit analysis is performed in order to identify the best trade-off between the cost required for the ESS and its benefits for the user. The costs involved are the investment costs of the ESS (CAPEX) and the price of the energy lost during the charge/discharge cycles (OPEX). For simplicity, the maintenance costs of the ESS are assumed already included in the initial cost of investment and unrelated to the service life of the storage apparatus. The benefits of the ESS regulation are evaluated in terms of reduction of the yearly PV production subject to imbalance fees. All the quantities involved in the analysis (imbalances, losses, charge/discharge cycles) are evaluated as a function of the PV production by time-dependent simulations carried out on the data collected on the period September 2012 – April 2013. Then, they are projected on a yearly basis assuming a yearly PV production equal to 1200 h.

The cost/benefit analysis is carried out according to the assumptions described in the following.

The penalties for imbalance are evaluated with the same approach adopted in the Italian regulatory framework. The user must declare the production program of its power plant a day in advance. On the basis of this program and of the energy price on the Day-Ahead Market (c^E), the user is remunerated. However, the actual production of the DG plant (p_t^A) can be different w.r.t. the programmed one (p_t^E). If the gap between the actual PV production and the forecasted value exceeds the admitted tolerance (10% of p_t^E), an imbalance penalty (c^I) is applied to the amount of energy exceeding the tolerance limit. If p_t^A has been overestimated, the energy beyond the threshold is paid to the user c^E-c^I (this energy was not considered in the day-ahead program declared by the user), while if p_t^A has been underestimated, the energy not produced exceeding the lower tolerance limit must be refunded by the user at price c^E+c^I. In this study, the energy price (c^E) and the imbalance fee (c^I) are assumed constant and equal to, respectively, 10 c€/kWh and 50% of the energy price.

The CAPEX costs are evaluated as:

$$c^C \cdot SRC + c^P \cdot SRP + c^F \tag{9}$$

In eq. (9), c^C and c^P are the costs of the ESS per unit, respectively, of Storage Rated Capacity (SRC) and Storage Rated Power (SRP). The fixed costs needed for the installation of the ESS by the user's plant (site preparation, etc.) are represented by c^F. In the simulation performed, c^P has been fixed equal to 10% of c^C, while the fixed costs (c^F) are set to 500 €; in addition, a discount rate of 8% is introduced.
The cost per unit of SRC (c^C) is considered as parameter of the cost/benefit analysis: i.e. the feasibility of the investment is assessed according to the technological cost of the storage solution.
Moreover, the OPEX of the ESS investment are assumed proportional to the energy lost during the charge/discharge cycle. The overall efficiency of the ESS (inverter + batteries) is considered equal to 90%.

To provide accurate results, the energy/power ratio of the ESS is subject to maximum/minimum constraints: it must be included in the range 0.5 ÷ 7. Energy/power ratios lower than 0.5 or greater than 7 are also admitted, but in this case the ESS must be oversized in energy capacity (with ratios lower than 0.5) or in power (with ratios greater than 7) to fit the requirements.

The service life of the ESS is supposed only dependent on the number of complete charge/discharge cycles that the battery performs. The expected life of the ESS is fixed to 4.000 complete charge/discharge cycles (as already mentioned, the technology has a strong influence on this parameter, so this is only a first estimation). After this number of cycles, the ESS is no more able to provide the service required with acceptable performance (excessive degradation, with a consequent decrease in efficiency) and must be substituted (new investment). It is assumed that in no case the service life of the ESS can exceed 15 years. According to this hypothesis, and to the yearly number of charges/discharges in Table 4, the service life of the ESS studied in Section 6 (storage integrated with the NNWF model) is reported in Table 5.

TABLE 5. ESS life in years, according to SRP and SRC.

Energy (% w.r.t. an equivalent hour of operation of the PV plant)	Power (% w.r.t. the power of the PV plant) 2	4	6	8	10	12	14	16	18	20
5	5.09	4.16	3.98	3.98	3.98	3.98	3.98	3.98	3.98	3.98
10	8.30	6.14	5.54	5.30	5.21	5.20	5.20	5.20	5.20	5.20
15	11.34	8.18	7.18	6.76	6.54	6.41	6.34	6.33	6.33	6.33
20	14.28	10.17	8.82	8.21	7.90	7.74	7.61	7.54	7.50	7.50
25	15.00	12.13	10.46	9.68	9.27	9.05	8.92	8.83	8.77	8.75
30	15.00	14.03	12.04	11.12	10.64	10.37	10.20	10.10	10.04	10.01
35	15.00	15.00	13.65	12.55	12.00	11.68	11.47	11.34	11.27	11.23
40	15.00	15.00	15.00	14.03	13.38	13.03	12.80	12.63	12.54	12.48
45	15.00	15.00	15.00	15.00	14.79	14.38	14.13	13.94	13.83	13.75
50	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00
55	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00
60	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00
65	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00
70	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00
75	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00
80	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00
85	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00
90	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00
95	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00
100	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00	15.00

Figure 4 reports the results of the study: Figure 4.a, 4.b and 4.c show the best Benefit/Cost Ratio (BCR) that can be achieved with a given cost of the storage technology and a given value of imbalance penalties. The green line depicts the case with imbalance penalties equal to 50% of the energy price: this is the condition to which all the results in the subsequent plots are referred, from Figure 4.d to 4.i. In particular, Figure 4.d, 4.e and 4.f show, according to the ESS cost, the SRC that allows the achievement of the best BCR (black line). The plots also report the range of ESS sizes, in energy, allowing a given BCR (isolines). Figure 4.g, 4.h and 4.i show, with a similar approach, the correlation between SRP and BCR.

For example, let us consider to use the Persistence model to forecast the day-ahead the production profile of a PV power plant, e.g. sized 30 kW, coupled with an ESS in order to improve its programmability. Figure 4.a shows that, with the reference imbalance cost (50% of c^E), the investment would be feasible (BCR ≥ 1) if the cost per unit of SRC is lower than about 107 €/kWh. Assuming, e.g., the cost of ESS equal to 100 €/kWh, to maximize the BCR (at the value of 1.05, that can be read in Figure 4.a) the user must use an ESS with SRC about 31% of one heq of the PV power plant, i.e. 9.3 kWh (black line in Figure 4.d) and power 9.2% of the PV rated power, i.e. 2.76 kW (black line in Figure 4.g). In this configuration, the total cost of the ESS can be assessed by eq. (9) as: $100 \cdot 9.3 + 10 \cdot 2.76 + 0.5 = 958$ €. All SRCs and SRPs at the left of the green characteristics marked with the tag “1” in Figure 4.d and 4.g give a BCR greater than 1: e.g., SRCs included in the range 14.3 ÷ 84.5% and SRPs within the range 2.6 ÷ 35.7% allow a feasible investment.

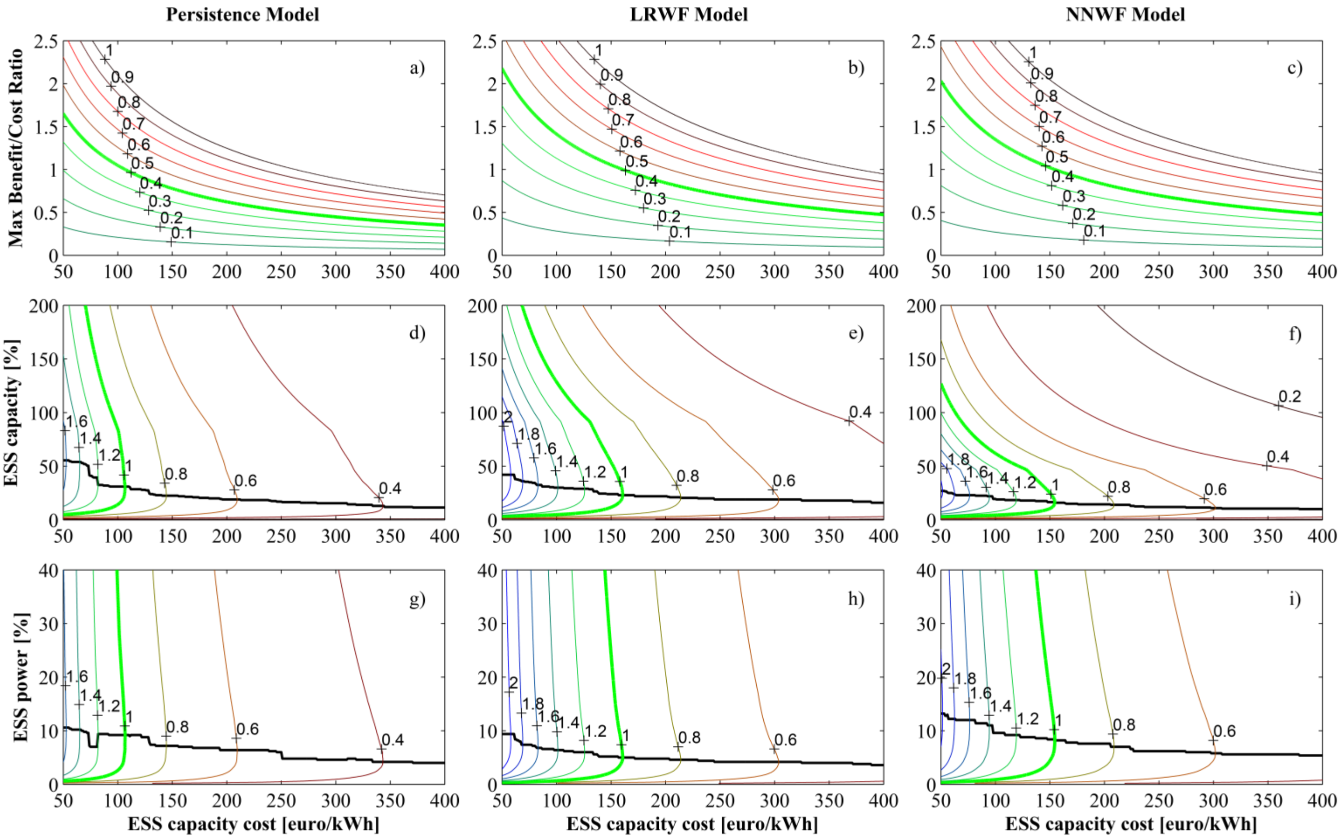

FIGURE 4. Results of the cost/benefit analysis.

Figure 4.a, 4.b and 4.c clearly depict that, under the assumptions of the study, the ESS becomes an effective solution to reduce RES imbalances with costs per unit of SRC lower than 107 €/kWh with the Persistence Model, 160 €/kWh with the LRWF model and 154 €/kWh with the NNWF model. The situation changes considerably at an increase in the imbalance penalties: with c^I equal to 80% of the energy price, the break-even cost of the ESS increases with all the three FMs proposed: respectively, 200, 289 and 286 €/kWh. This is an important fact considering that in the

future, with an increase in the share of RESs, the costs required to ensure the real-time balance of the power system are expected to increase (proportionately with the imbalance penalties applied to users). Nevertheless, for the feasibility of the investment a significant reduction in the cost of the storage technologies w.r.t. today's scenario is pivotal.
The results about the ESS sizing, in energy capacity and power, provide other useful indications. Looking at the plots concerning the SRC (4.d-4.f), it is possible to observe that, in general, the choice of a suitable SRC is essential for the success of the investment: in fact, the range of SRCs for which the investment is feasible is in many cases quite narrowed and changes according to the ESS cost. The situation changes slightly considering the SRP (4.g-4.i): in this case, the range of SRPs giving BCR ≥ 1 is wider and quite independent of the ESS cost. This fact was expected, as the cost of the storage apparatus is mainly related to the SRC. In fact, the cost per unit of SRC is much greater than the ESS cost per unit of SRP. In addition, the results highlight that the imbalance reduction service generally requires "energy intensive" ESSs, i.e. with high energy/power ratios. In particular, with the Persistence and LRWF models, the ratio between the optimal SRCs and SRPs (black line in Figures 4.d, 4.e, 4.g and 4.h) usually ranges from 3.5 to 5.5; whereas with the NNWF model, it is considerably lower: equal to about 2.
Another interesting fact is that if the ESS cost lowers, the adoption of bigger storage apparatuses is worthwhile for the user (the storage can be used to prevent greater imbalances). For example, with the Persistence model, with a capacity cost of 250 €/kWh, the size of the ESS ensuring the best BCR of the investment is 17% of one heq of the PV plant, while if the cost decreases to 150 €/kWh the optimal SRC rises, as already mentioned, to 31%.
It is important to point out that, in addition to the cost of the storage technology and the value of imbalance penalties, in perspective other factors will contribute to make more affordable the adoption of ESSs for a better RES programmability. In particular, the increasing of the charge/discharge cycles that the ESS can perform during its life has a direct effect on the investment feasibility (especially for small sized ESSs, which usually carry out more charge/discharge cycles and have a shorter service life; see Table 5).

9. Conclusion

In the paper, the possibility of achieving a fully-programmable production profile for a PV power plant is assessed. In particular, the study focuses on the evaluation of the technical and economic feasibility of using FMs and ESSs to improve the accuracy of the prediction.
The first part of the analysis deals with the FMs performance. An overview of the mathematical models able to estimate the PV production is provided, and three different FMs are applied to measured data. The results obtained are adopted in order to contribute to the second section of the work.
Actually, although the FMs allow a good estimation of the future production of the PV energy resource, they show an accuracy not fully compliant with the requirements of the liberalized markets regulation, e.g. Resolution 281/2012/R/efr in the Italian scenario.
Therefore, an ESS is coupled with the PV power plant to correct the residual prediction error. In the work, the ESS is designed, evaluating not only the technical parameters but also the economic variables. The purpose of the approach is to provide useful indications for the optimal (maximum Benefit/Cost Ratio) sizing of the ESS.
Eventually, a sensitivity analysis is carried out to evaluate how the design procedure is affected by variations in the economic parameters (such as energy costs, imbalance penalties and discount rate).
The analyses demonstrate that, in the current scenario, the adoption of ESSs for RES imbalances reduction is hardly cost-effective. However, in the future, the expected ESS costs reduction and rise in imbalance costs will make the investment more viable. Proper incentive schemes could be very useful to speed up the process.

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