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Imbalance Charge Reduction in the Intra-Day Market using Short-Term Forecasting of Photovoltaic Generation

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Abstract: The growing integration of photovoltaic power into electricity markets poses new challenges, particularly in terms of system balancing and forecasting accuracy. However, due to the strong dependence of PV output on weather conditions, forecasting the actual energy injected into the grid has become increasingly complex. Therefore, within intraday trading across Europe, short-term forecasting accuracy is crucial to reduce imbalances and improve market performance. While forecast performance is traditionally assessed using metrics such as RMSE or MAE, under the assumption that lower errors yield higher economic benefits, this relationship is not always linear. A thorough understanding of market conditions and the link between forecast deviations and imbalance penalties is essential. In this context, this study proposes a methodology to evaluate, analyze and, if necessary, reduce the charge imbalance in the Intra-Day market, using a short-term photovoltaic power forecasting model based on a hybrid physical–artificial neural network approach. The analysis focuses on the Italian electricity market, particularly the MI-XBID continuous trading session, where participants adjust their energy positions through continuous intraday trading. The results demonstrate that improved forecasting help in reducing charge imbalance-related costs and enhancing market efficiency. Furthermore, the evaluation of charge imbalances can serve as a key input for assessing the improvement that can be achieved by integrating a storage system with suitable sizing and charge/discharge control logic. By enhancing the efficiency and reliability of renewable energy integration, the proposed approach contributes to the broader goals of sustainable development and energy transition.

Keywords: intra-day market; photovoltaic; forecasting; Hybrid Artificial Neural Network; storage system.

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1. Introduction

Renewable energy has come a long way, with the most notable improvements in the solar PV and wind sectors where reduced production and installation costs are being achieved. These dynamics persist, fostering investment from both public and private actors, and contributing to cost reduction and improved productivity levels [1]. Specifically, in Italy, the national transmission system operator (TSO) reported an electrical consumption incremented of 2.2% in 2024 and the new installed capacity in 2024 was 7.5 GW; solar and wind power generation have reached overall 50 GW [2]. In this way, RESs for the first time have exceeded 40% coverage of needs, balancing the contribution of fossil sources. This growth is primarily driven by the positive contribution of hydroelectric and PV production. This paper focus on non-programmable RES (NP-RES), in particular PV since it is one of the most affordable, widespread and rapidly evolving solutions for sustainable power generation.

However, this growing integration of NP-RESs into the grid, entails an increased risk of instability in the electricity system, primarily due to potential imbalances between electricity production and consumption. In this context, system integration has become a key topic in public policy discussions, with particular focus on forecasting errors. Inaccurate PV power forecasts, in fact, can lead to power imbalances, compromising grid stability, disrupting market efficiency, and complicating real-time load management.

In response to these emerging challenges, the European regulatory framework has evolved to enhance market efficiency and flexibility. Among the key developments is Regulation (EU) 2015/1222 (CACM), which established the Single Intra-Day Coupling (SIDC) to facilitate more dynamic and integrated intraday electricity trading across member states. This Regulation introduced continuous trading in intraday markets (IDM) with closure at least one hour before delivery (H-1), contingent upon the availability of sufficient cross-border transmission capacity. The SIDC was implemented through the Cross-Border Intraday (XBID) project, operational in central Europe since 2018. Italy joined the SIDC in September 2021, aligning its IDM with the European framework. This integration allowed Italian market participants to access continuous cross-border trading until H-1 and led to a reorganization of the national IDM [3].

Therefore, the recent widespread deployment of NP-RES power plants has shifted the focus from day-ahead markets (DAM), where prices are driven by the marginal costs of power plants, to IDM, where prices are instead shaped by network conditions and system imbalances. Therefore, dispatching users, and in particular wholesalers, must develop strategies and tools to mitigate the risks associated with the variability of scheduled and injected electricity, as well as potential power imbalances. In this context, more precise forecasting methods of PV power have been investigated and used by more and more load-serving entities and balancing authorities to optimize their market and system operations [4]. A wide range of approaches has been proposed in research for forecasting PV production, including regression methods, artificial intelligence techniques, numerical weather prediction models, local sensing, and hybrid systems [5–13].

The most recent work of review [13] analyses different PV forecasting models, which are categorized into physical, persistence, statistical, machine learning (ML) and hybrid models. Authors have considered different forecasting horizons and have evaluated the different PV forecasting models using various performance metrics. They suggest that deep neural networks with ensemble techniques or hybrid techniques supersedes the traditional approaches of PV power forecasting in terms of efficiency and accuracy.

In [9] authors focus their attention on ML methods. They have considered very short-, short-, and long-term forecasts in a PV system. The performance of forecasting has been evaluated according to a different type of input parameter and time-step resolution. Lastly, the crucial aspects of a conventional and hybrid model of ML and ANNs have been reviewed comprehensively. The authors concluded that hybrid models perform better in forecasting, achieving substantially higher accuracy. A similar conclusion has been also reached in [12].

In [10] the authors have evaluated and compared the accuracy of two prediction models: the ML model most applied through ANNs and DL models with Long-Short Term Memory (LSTM) networks. They have considered three short-term prediction horizons (1, 15 and 60 min), concluding that better overall prediction accuracy skill for the LSTM models, except for the 60 min prediction horizon where the authors found the accuracy of the two methods to be comparable. This shows how ANNs and DL networks can both be used for PV power forecast with a forecast horizon of one hour without losing in performance. However, the choice between these two architectures depends on the specific application needs. Notably, ML methods, especially ANNs, are widely applied in industrial settings to develop data-driven models of nonlinear systems or plants [14] due to their ability to approximate with the desired accuracy any nonlinear function based on a suitable set of experimental data [5].

As clearly evidenced in the reviewed literature when dealing with PV power forecasting, algorithms and methods are typically evaluated and compared using standard error metrics such as the Root Mean Square Error (RMSE) and the Mean Absolute Error (MAE). However, from the perspective of market bidding strategies, a relevant question arises: Do more accurate forecasting models, measured through metrics such as RMSE, MAE, and others, necessarily lead to greater economic benefits for market participants? While the answer may appear intuitive, the relationship is not as straightforward, as it requires a careful analysis of how forecasting errors correlate with imbalance penalties [15]. This question has been addressed by only a limited number of studies. Specifically, in [4] the authors have highlighted the role of power forecasting models in smart micro-grid (SMG), they have introduced a profit forecasting technique as a key driver of SMG deployment success and presented the liberalized electricity market based on blockchain technologies as a new paradigm promoted by SMG with specific regard to regulations and standards.

In [16] the forecasting of the power output of a PV system located in Apulia South East of Italy at different forecasting horizons has been presented. An analysis has been carried out to evaluate the imbalance penalties associated with three forecasting models. This study dates back to 2015, a period in which the regulatory context differed substantially from today's framework.

In [15] the authors determine the value of PV power forecasting in the Iberian (Spain and Portugal) electricity market under actual conditions (years 2009–2010). While, [17] investigated the expected cost of issuing inaccurate forecasts in the Scandinavian energy markets,

To the best of the authors' knowledge, forecasting in the context of the MI-XBID continuous trading session, particularly relevant in the Italian electricity market, has not been further investigated in recent literature. The present study seeks to address this gap by providing a methodology that allows to reduce charge imbalances in the IDM, which uses a hybrid neural network model, called Hybrid Physical-Artificial Neural Network (HPANN), to short-term forecast the power output of PV plants, with a forecast horizon of 1 hour. The ultimate goal is to contribute to a more balanced and efficient IDM, where improved forecast accuracy enables better integration of variable NP-RES within the XBID framework. In order to reduce imbalances and thus avoid penalties, the use of a battery with a suitable capacity value and a control charge/discharge strategy is introduced and analyzed. By addressing the challenges of integrating NP-RESs into short-term energy markets, the proposed approach supports a more sustainable, flexible, and decarbonized electricity system, in line with the objectives of the energy transition.

The paper is structured as follows. Section I presents a preliminary analysis of the problem, along with a review of the main soft computing methodologies used for photovoltaic (PV) power forecasting. Section II describes the dataset and the preprocessing techniques applied to improve data quality. Section III explains the rationale behind the choice of the HPANN and outlines the hybrid model adopted for forecasting PV power generation. Section IV provides a detailed overview of the electricity market structure and regulatory framework, with particular reference to the Italian context. Section V introduces the methodology for evaluating and mitigating charge imbalances. Finally, Section VI presents the conclusions of the study.

2. Dataset Description

The data used in this study are from the EURAC PV system [18], which was installed at the airport of Bolzano/Italy in 2010. Table 1 summarize the main characteristics of the PV power system.

Table 1. Main characteristics of the EURAC PV system.

PV cell technology	Polycrystalline
PV nominal power	4.20 kWp
Tilt angle	30°
Azimuth angle	8.5°

A weather station is installed in close proximity to the test side to record various meteorological parameters. All data have been recorded for a period of 8 years, spanning from February 2011 to January 2019, with a time resolution of 15 minutes.

The available measured quantities are:

- ambient temperature (T_{amb}, [°C]);

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- module temperature (T_{mod}, [°C]);
- irradiance on the plane of array (G_{POA}, [W/m²]);
- wind speed (ω, [m/s];
- wind direction (dir, [°]);
- DC power (P_{DC}, [W]);
- AC power (P_{AC}, [W]).

To ensure the reliability of the data and the effectiveness of the model, various pre-processing techniques were applied to address missing entries, temporal inconsistencies, resolution differences, and feature scaling.

- Treatment of Missing Data: Only days with a percentage of 80% of available data have been considered, obtaining a subset of 2802 days. Gaps in the dataset, caused by sensor issues or environmental factors, were filled using linear interpolation, preserving the continuity and underlying patterns of the time series.
- Temporal Alignment: Ground-based sensor data were synchronized into a consistent 15 minutes interval using timestamp-based interpolation and merging. Solar radiation and power data have been compared to the CSM generated data for synchronization.
- Feature Scaling: Min-Max normalization (scaling values between 0 and 1) was applied to prevent features with larger numerical ranges from overshadowing those with smaller ranges.

3. Hybrid Model to Forecast the PV Power Generation

In this paper a HPANN, based on an ANN and clear sky solar radiation curves, has been used for PV production forecast. The choice of using an ANN can be justified by several factors that make it an effective and practical solution compared to other ML algorithms when it comes to forecasting PV power generation with a short-term horizon of one hour, particularly in the context of reducing imbalance s in the MI-XBID. Some reason are [10, 13]: its ability to model complex non-linearities; robustness and adaptability (ANNs can be designed to operate under different operating and environmental conditions, making them flexible to variations in input data); computational efficiency (traditional ANNs require far fewer computational resources than other DL algorithms); simplified implementation (the relatively simple structure of ANNs facilitates their implementation and maintenance, making them a practical choice for industrial applications where simplicity and reliability are crucial); better performance with limited data (ANNs typically require fewer training samples than DL to achieve convergence; this is particularly useful when historical data is sparse or noisy, common challenges in PV forecasting). For these reasons, using an ANNs for the forecast of PV power generation is a choice that balances accuracy, computational efficiency and simplicity of implementation, making it a practical and effective solution for applications in the continuous intra-day electricity market. The MI-XBID market, in fact, requires adjustments to energy bids close to the time of delivery to mitigate imbalances. The lightweight nature of ANNs makes them more practical for integration into energy trading platforms that require fast computation and regular model retraining. Moreover, the Clear Sky solar radiation Model (CSM), is considered as input for the ANN. This type of model estimates the amount of solar radiation reaching the Earth's surface under cloud-free conditions, based on factors such as solar elevation angle, site altitude, aerosol content, water vapor, and other atmospheric parameters. CSMs are also relatively simple to implement, making them a practical tool for the forecasting of solar radiation and PV power since it serves as a reference to assess the daily variability of solar radiation. It represents its theoretical upper limit and helps in improving the forecasting performance. A hybrid approach like a ANN combined with physical model could perform better and give precise and reliable predictions for both constant and varying weather conditions in different time horizons [10, 13].

In this section the design of the hybrid ANN-based model used to forecast the PV power with a horizon of one hour is described in details. Input data with a 15-minute resolution were used for the ANN, while the output was aggregated to an hourly resolution to match the time scale of the Italian electricity market. The environmental parameters, i.e. module temperature, T_{mod} and the AC power measured in the previous hours, P_{AC} have been used as inputs. In particular, the one-hour-ahead PV power forecast was carried out using historical data of P_{AC} and T_{mod} from the previous 15-minutes eight values (2 hour). Moreover, to improve the performance of the MLP NN, a hybrid method called Hybrid Physical Artificial Neural Network (HPANN) based on an ANN and the CSM has been considered [19, 20]. As previously described, Clear sky models provide estimates of ground-level solar irradiance under cloud-free atmospheric conditions [20].

The designed MLP neural network consists of a two hidden layer comprising 20 and 10 neurons [19]. Training performance is quantified using the Mean Squared Error (MSE) metric. A maximum of 500 training epochs is allowed, with early stopping based on a validation check criterion set to 10 consecutive failures. Both the hidden and output layers employ a radial basis activation function. The learning process is governed by the Levenberg-Marquardt backpropagation algorithm, which also handles weight and bias updates through its optimization strategy. The selection of key hyperparameters, such as training duration, hidden layer size, number of neurons in the hidden layer, and learning rate, was performed through empirical tuning based on trial-and-error experimentation. All network modeling and training procedures were implemented using the MATLAB® environment.

Among the available data, those relating to the first seven years of measurement were used for network training, while the data relating to the last year (2018) was used for the test. Only data from sunrise to sunset were considered. This means that power values equal to zero were excluded from the analysis. This step is crucial because including zero values would artificially reduce the error between the measured and predicted data. In fact, during nighttime hours, both measured and predicted power values would be zero due to the nature of PV power, resulting in a null error.

4. Electricity Market Structure and Regulatory Framework

To understand the dynamics of power imbalances and their management, it is essential to first examine the structure and functioning of electricity markets, as well as the relevant regulatory frameworks that govern them. This imbalance can be either positive, when more electricity is injected or less is withdrawn than scheduled, or negative, when less electricity is injected or more is withdrawn than planned. Electricity injection/withdrawal schedules are traded in the sessions of the markets organized by market operators, which are the DAM and the IDM. The number and timing of the IDMs change from one country to another. The IDM is an energy market that begins after the closure of the DAM. It represents the second phase of the spot electricity market and is primarily used by operators who participated in the DAM to modify their injection or withdrawal schedules through buy and sell offers, which can be submitted up to shortly before the physical delivery of electricity [3]. Within MI-XBID operators can submit buy and sell offers continuously from 3:30 PM the day before, until one hour before the actual delivery, except during auction sessions where continuous trading stops 50 minutes before the auction closes [3].

4.1. Case Study: The Italian Electricity Market

Two types of imbalances can be considered [21, 22]:

- Nodal imbalance: imbalance is computed based on effective behavior of each node (single imbalance). TERNA (Italian TSO) calculates the nodal marginal prices based on the offers of the balancing market (MB).
- Zonal imbalance: imbalance is computed based on the zonal imbalance. The difference between the effective and planned production or consumption is compared with the zonal imbalance. The later refers to the opposite sign (the energy bought by TERNA is count as negative, while the one

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sold is positive) of the total electricity procured by TERNA for balancing purposes, in the market for dispatching services, with reference to the time period and a macro area issued.

The Italian electricity market operates under the zonal imbalance mechanism. Then economic penalization takes into account the global imbalance, which can be either positive or negative.

- Positive zonal imbalance: it refers to periods where energy is in excess, which occurs when energy production is larger than planned or energy consumption is lower than planned. In this case, TERNA calls the programmable plants to lower their production, and therefore:
  - TERNA gets MB prices from producers that reduce their production.
  - TERNA pays imbalance price to imbalance operators.
- Negative zonal imbalance: it refers to periods where energy is lacking, which occurs when energy production is lower than planned or energy consumption is higher than planned. In this case, TERNA calls the programmable plants to increase their production.
  - TERNA pays MB prices to conventional plants that increase their production.
  - TERNA gets imbalance price from imbalance operators.

Imbalances are financially settled to hold operators accountable for adhering to their production or consumption schedules and to cover the costs incurred by Terna in rebalancing the system.

Each dispatching user is required to submit a schedule regarding their energy injections into the grid (for plants with a capacity below 10 MVA, the schedule is submitted in aggregated form). This schedule is traded on the DAM, can be modified on the IDM, and may be further adjusted on the Dispatching Services Market (MSD), though this last modification applies only to units authorized to participate in the MSD and therefore excludes RESs.

At the end of the market processes, the final schedule is referred to as the "Modified and Corrected Binding Schedule" (in Italian, PVMC – *Programma Vincolante Modificato e Corretto*); this is the schedule that the dispatching user is obligated to follow. The difference, calculated on an hourly basis in the case of NP-RES, between the actual injected energy and the PVMC is known as the imbalance. This imbalance, measured in MWh, can be either positive or negative. In other words, imbalances arise after all markets have closed, once real-time operation has occurred. If the production unit injects more energy than indicated in the PVMC (positive imbalance), the total value of the imbalanced energy is positive, meaning the producer is selling more electricity than planned. Conversely, if the injected energy is lower than that specified in the PVMC (negative imbalance), the total value of the imbalanced energy is negative, indicating that the producer is effectively repurchasing part of the electricity already sold.

Since imbalanced energy is not traded on the markets, it does not necessarily have the same unit value as the scheduled energy. As a result, higher costs or revenues may arise compared to a scenario where, with the same injections, no imbalances occur. The product of the imbalance and the unit price of the imbalanced energy is referred to as the imbalance settlement amount.

The unit imbalance settlement price depends on the sign of the production unit's imbalance relative to the sign of the aggregate zonal imbalance. Imbalances with opposite signs between the production unit's imbalance and the aggregate zonal imbalance are always settled at the DAM price. In particular, the rules for valuing imbalances vary depending on the nature of the unit. For enabled units (EUs), a so-called *dual pricing* system is applied. Under this mechanism, the price paid (or received) by the unit for its imbalance depends both on the overall imbalance sign of the macro-zone in which the unit is located and on the sign of the imbalance of the individual unit itself, as outlined in Table 2. The relevant time interval for the calculation of imbalances is 15 minutes, in alignment with the settlement period of the MB in which these units participate.

Table 2. Imbalance Prices for Enabled Units.

	Positive EU Imbalance	**Negative EU Imbalance**
Positive macro-zonal imbalance	EU receives $\mathrm{Min}(P_{DAM}, \min P_{MB\downarrow})$	EU pays P_{DAM}

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Negative macro-zonal imbalance	EU receives P_{DAM}	EU pays Max(P_{DAM}, max $P_{MB\uparrow}$)

where:

- P_{DAM} is the valuation price of electricity sale offers (hereafter: zonal price) accepted in the zone where the EU is located, referring to the same relevant time interval;
- min $P_{MB\downarrow}$ is the lowest price among the purchase offers (downward offers) accepted on the MB during the same relevant time interval in the macro-zone where the enabled unit is located, including also the offers accepted for the secondary frequency regulation service;
- max $P_{MB\uparrow}$ is the highest price among the sale offers (upward offers) accepted on the MB during the same relevant time interval in the macro-zone where the enabled unit is located, including also the offers accepted for the secondary frequency regulation service.

For non-enabled units (NEUs), a *single pricing* mechanism is applied. Under this system, the price paid (or received) by the unit for its imbalance depends exclusively on the overall imbalance sign of the macro-zone in which the unit is located, as described in Table 3. The relevant time interval is one hour, in accordance with the measurement system used for injections and withdrawals by these units.

Table 3. Imbalance Prices for Non-Enabled Units.

	Positive EU Imbalance	**Negative EU Imbalance**
Positive macro-zonal imbalance	NEU receives Min(P_{DAM}, average $P_{MB\downarrow}$)	NEU pays Min(P_{DAM}, average $P_{MB\downarrow}$)
Negative macro-zonal imbalance	NEU receives Max(P_{DAM}, average $P_{MB\uparrow}$)	UNAB pays Max(P_{DAM}, average $P_{MB\uparrow}$)

where:

- average $P_{MB\downarrow}$ refers to the weighted average of the prices of purchase offers (downward offers) accepted on the MB during the same relevant time interval in the macro-zone where the non-enabled unit is located. The weighting is based on the accepted quantities, and the average also includes offers accepted for the secondary frequency regulation service.
- average $P_{MB\uparrow}$ refers to the weighted average of the prices of sale offers (upward offers) accepted on the MB during the same relevant time interval in the macro-zone where the non-enabled unit is located. The weighting is based on the accepted quantities, and the average also includes offers accepted for the secondary frequency regulation service.

Renewable energy producers, in addition to the single pricing scheme, may access an equalization mechanism that distributes costs across a portfolio of units, rather than bearing their individual imbalance cost.

In general, all forms of non-dispatchable electricity generation are characterized by a degree of forecastability of their grid injections, albeit with varying levels of accuracy depending on the specific energy source.

The regulatory authority has established that dispatching users (UdD) may select, on an annual basis and for each dispatching point under their responsibility, between two different imbalance settlement mechanisms. This choice must be communicated to Terna and is valid for the entire calendar year.

- Option I – Standard Single-Pricing Scheme (No Tolerance Band): Under the first option, the imbalance settlement for a non-enabled production unit is calculated according to a "no-band" model. This model aligns with the standard single-pricing mechanism applied to non-enabled programmable units.

The total imbalance settlement is the algebraic sum of three components:

- For the portion of the actual imbalance outside the tolerance band, the imbalance is valued at the same price as defined in Option I (standard non-enabled unit pricing).

- For the portion of the actual imbalance within the tolerance band, the imbalance is valued at the zonal hourly price established on the DAM.
- For the absolute value of the imbalance within the tolerance band, a settlement price is applied based on a zonal balancing component (Compensazione Perequativa Zonale).

The choice to apply or not to apply a tolerance band lies entirely with the dispatching user. In essence, Option I treats NP-RES units in the same way as programmable non-enabled units in terms of imbalance valuation.

- Option II – Tolerance Band Model for NP-RES: The second option introduces tolerance bands, which are applied to the PVMC and differentiated by energy source. This model ensures that all imbalance settlement costs are allocated exclusively among non-dispatchable renewable producers, thereby avoiding socialization across other market participants. The tolerance band widths (α) for NP-RES units are defined as follows:

- Wind > 10 MW: 49% of PVMC;
- Solar > 10 MW: 31% of PVMC;
- Wind ≤ 10 MW: 8% of PVMC;
- Solar ≤ 10 MW: 8% of PVMC;
- Run-of-river hydro: 8% of PVMC;
- Other NP-RES: 1.5% of PVMC.

Within the tolerance band, any negative imbalance is settled (i.e., paid) and any positive imbalance is rewarded (i.e., received) at the DAM price plus the zonal balancing component.

The zonal balancing component is a fixed settlement term, calculated by the system operator (Terna) based on the residual imbalances within the tolerance bands of all NP-RES units in the same zone.

For each dispatching point associated with a non-enabled NP-RES unit that has not opted for Option I, and for each market zone and hourly interval, the imbalance price is calculated as:

$$\pi_{sbil,i} = \pi_{MGP,i} \cdot \frac{sbil_i}{|sbil_i|} + \pi_{\mathrm{CompPer,z}} \tag{1}$$

where:

- $\pi_{DAM,i}$ is the zonal DAM price for hour i;
- $\pi_{CompPer,z}$ is the zonal balancing component for zone z;
- $sbil_i$ is the actual imbalance for unit i.

The zonal balancing component is computed as follows:

$$\pi_{\mathrm{CompPer,z}} = \frac{\sum_i\left[\left(\pi_{UPNA,i,z}-\pi_{MGP}\right)\cdot\left(min\{|sbil|;|\alpha\cdot E_{prog}|\}\right)_i\cdot\left(\frac{sbil_i}{|sbil_i|}\right)\right]}{\sum_i\left[\left(min\{|sbil|;|\alpha\cdot E_{prog}|\}\right)_i\right]} \tag{2}$$

where:

- α is the tolerance band width for the relevant NP-RES unit;
- i indexes each non-enabled NP-RES unit that has not opted for Option I;
- $\pi_{UPNA,i,z}$ is the imbalance price applied to unit i in zone z, as defined under Option I;
- $E_{prog,i}$ is the scheduled energy (PVMC) for unit i.

This zonal component acts as a redistribution mechanism to balance residual imbalances within tolerance bands among the relevant NP-RES units of the same zone.

Imbalance penalties are structured to reflect the impact of the discrepancy on the reliability of the grid and on the procurement costs. A producer who generates less than forecasted faces more significant imbalance penalties, due to the urgency and higher costs of sourcing additional energy. Upward balancing tends to be more costly than downward balancing, especially in stressed grid conditions or in markets with high prices. Surplus production, while still penalized, typically carries a lower financial penalty. However, the specific cost of imbalance varies hour by hour and depends on the sign and amount of the overall system imbalance.

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5. Evaluation and Improvement the Imbalance Impact in the Electricity Market

Firstly, the experimental results obtained with the HPANN method, on the available data set, are reported.

Some statistical indicators have been considered in order to appreciate the effectiveness of the HPANN estimation:

- normalized Relative Root Mean Square Error (*nRMSE*, [%]) [13]: $\mathrm{nRMSE} = \frac{\sqrt{\sum_{i=1}^{N}(y_i-p_i)^2}}{\bar{y}}$;
- normalized Mean Bias Error (*nMBE*) [23]: $nMBE = \frac{\sum_{i=1}^{N}(y_i-p_i)}{N\cdot\bar{y}}$;
- Coefficient of determination (R^2) [23]: $R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i-p_i)^2}{\sum_{i=1}^{N}(y_i-\bar{y})^2}$

where y_i are the measured values of P_{AC}, p_i are the forecasted values of P_{AC}, $\bar{y}$ is the mean of the measured values of P_{AC} and N is the amount of data.

In Table 4 values of statistical coefficients obtained using the HPANN to forecast the AC power are reported.

Table 4. Statistical coefficients obtained using the HPANN to forecast the P_{AC}.

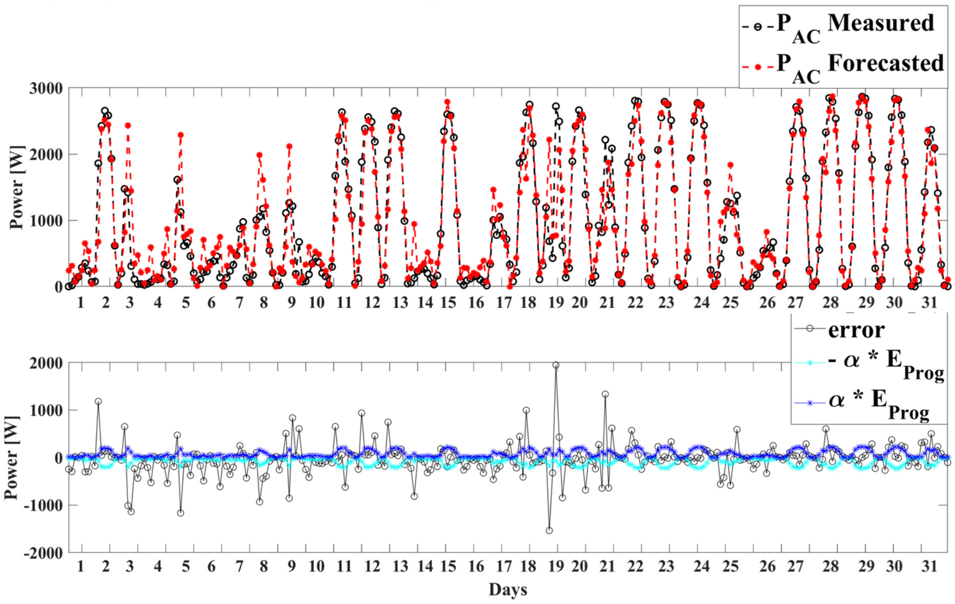
nRMSE	nMBE	R^2
25.95 %	0.73 %	0.90

The imbalance between the measured and the forecasted P_{AC} has been calculated as:

$$error_i = y_i - p_i \tag{3}$$

The tolerance band widths (α) for NP-RES unit analyzed in this paper is equal to 8%. This means that to avoid charge imbalances the value of the error should be $-\alpha\cdot E_{prog} \le error \le \alpha\cdot E_{prog}$. The comparison between the measured and the forecasted P_{AC} is shown in Figure 1, along with the *error* and the thresholds $\pm\alpha\cdot E_{prog}$. For the sake of clarity, only a winter month (Figure 1(a)) and a summer month (Figure 1(b)) are reported.

As can be seen from Figure 1, the allowable error range is very narrow, making it likely for the error to fall outside of it, especially when solar irradiance is low (at sunrise and sunset hours and on cloudy days), where the economic impact remains limited.



(a)

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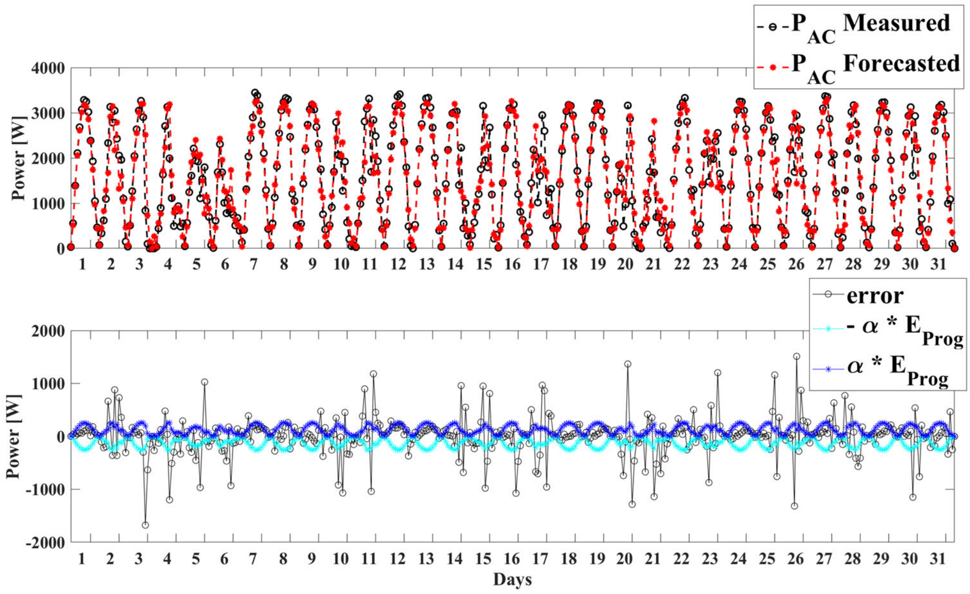


(b)

Figure 1. Measured and Forecasted PAC: **(a)** a winter month (January); **(b)** a summer month (July).

To better understand the results, the measured vs forecasted data is reported in Figure 2. It can be observed that the PV power forecasting in the desired time horizon is quite satisfactory.

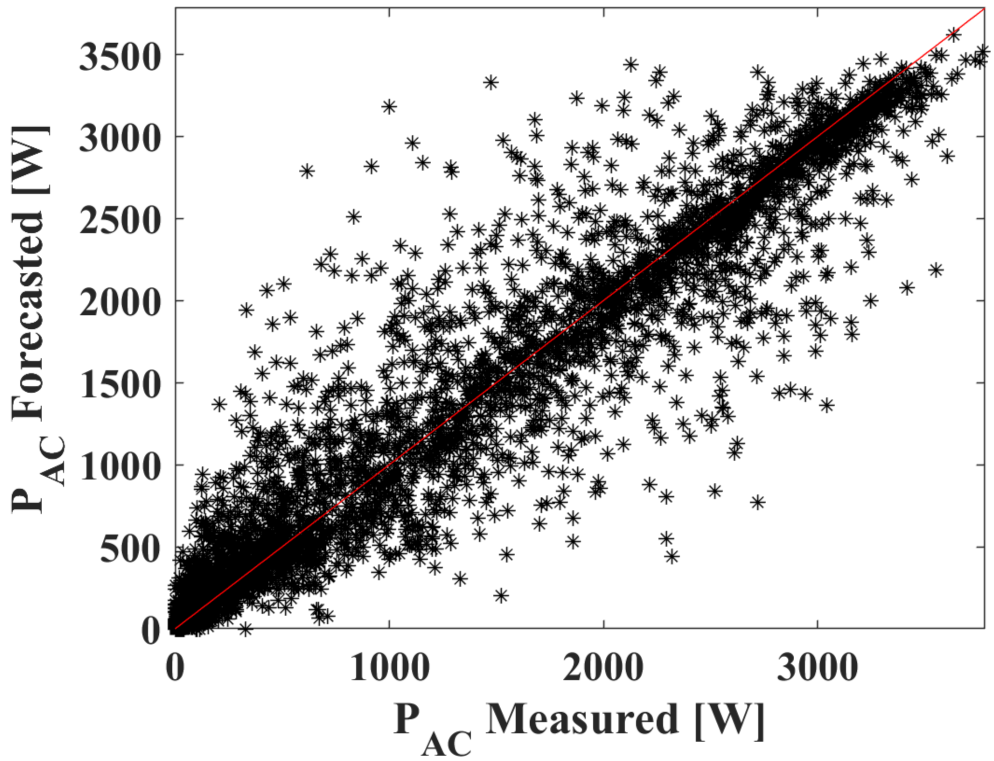
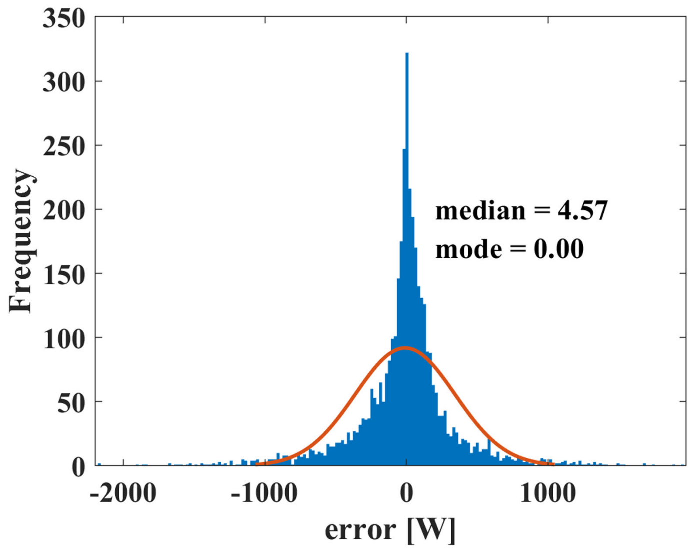
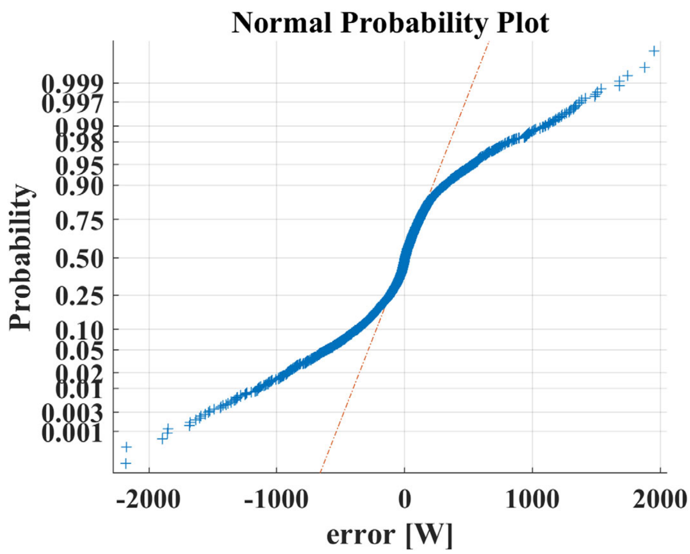


Figure 2. Measured vs forecasted PAC power.

In order to analyze the distribution of data, Figure 3 shows the histogram and the Normal Probability plot of the error, respectively.



(a)



(b)

Figure 3: Histogram and Normal Probability plot of the error between measured and forecasted P_{AC}.

The histogram in Figure 3(a) shows a positive skewed distribution, with a mode at 0 indicating a peak at zero, while the median at 4.57 suggests that most values lie above zero. This implies a tendency toward underestimation in predictions, as positive median values suggest that actual values are often higher than predicted.

The economic results of the application of the proposed forecast method for PV power, in the Italian markets context, are highly dependent on the following prices: day-ahead market (π_{DAM}), balancing markets (π_{MB}) and equalizing (π_{equal}) that depend on the behavior of the other NP-RES power systems that are in the same zone. Therefore, the economic evaluation is highly affected by the volatility of such prices. On the other hand, the precise description of the imbalance charges rules in Italy is important to understand how the different prices can affect the economic results. Under this consideration, in this paper only their energetic evaluation is performed. This has a more general interest for the readers as it can applied also in other countries, where the acceptance bands for the imbalances is applied. Specifically, due to the different technical and economic impacts of positive and negative forecast power errors on balancing markets and imbalance charges, two crucial parameters are evaluated to analyze imbalances: the percentage of occurrences of the exceeding the

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lower and upper thresholds and the total imbalance energy with respect to the total measured PV energy (positive and negative separately).

$$freq_P = \frac{n_{hour}}{N} \cdot 100 \qquad if\ error > \alpha \cdot E_{Prog} \tag{4}$$

$$freq_N = \frac{n_{hour}}{N} \cdot 100 \qquad if\ error < -\alpha \cdot E_{Prog} \tag{5}$$

$$EIP = \frac{\sum_{i=1}^{M} error_i - \alpha \cdot E_{Prog_i}}{\sum_{i=1}^{N} y_i} \qquad if\ error > \alpha \cdot E_{Prog} \tag{6}$$

$$EIN = \frac{\sum_{i=1}^{M} error_i - (-\alpha \cdot E_{Prog_i})}{\sum_{i=1}^{N} y_i} \qquad if\ error < -\alpha \cdot E_{Prog} \tag{7}$$

where M is the number of hours in which the condition is met.

Results are shown in the first row of Table 5, where it is possible to note that the percentage of occurrences of the exceeding the upper threshold is lower than the negative case.

To reduce imbalances and thus avoid penalties, a battery, appropriately sized, can be employed that charges or discharges when the imbalance exceeds the thresholds.

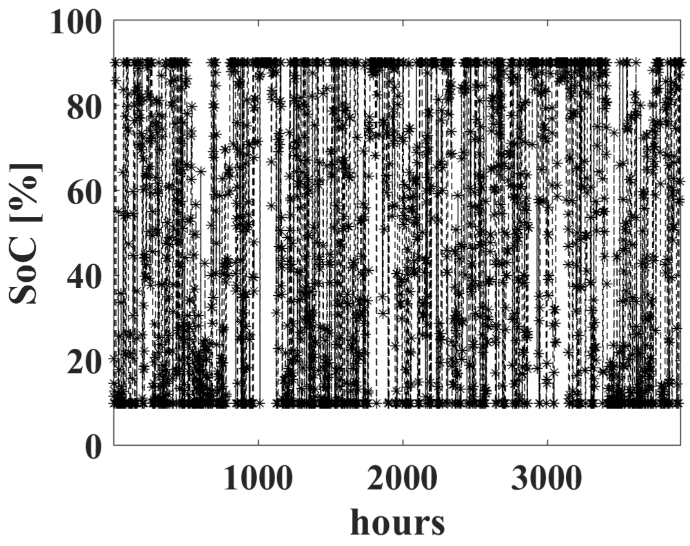
In this paper, a simple battery model was used to calculate the battery's state of charge, *SoC*, (Coulomb Counting Method [24]), expressing the *SoC* as a function of energy (rather than just current) which allows for a more direct representation of the remaining energy capacity and accounts for variations in the battery's voltage. The following parameter values have been used in the model: efficiency of the battery in charge and discharge modes, $\eta = 0.94$; a Depth Of Discharge, $DoD = 0.8$; minimum *SoC*, $SoC_{min} = 10\%$; maximum *SoC*, $SoC_{max} = 90\%$ and initial *SoC*, $SoC_{Init} = 50\%$ and Δt is one hour.

Increasing the capacity of the battery, makes it possible to decrease imbalances. In particular, in Table 5 the values of $freq_P$, $freq_N$, *EIP* and *EIN* are shown as the battery capacity changes.

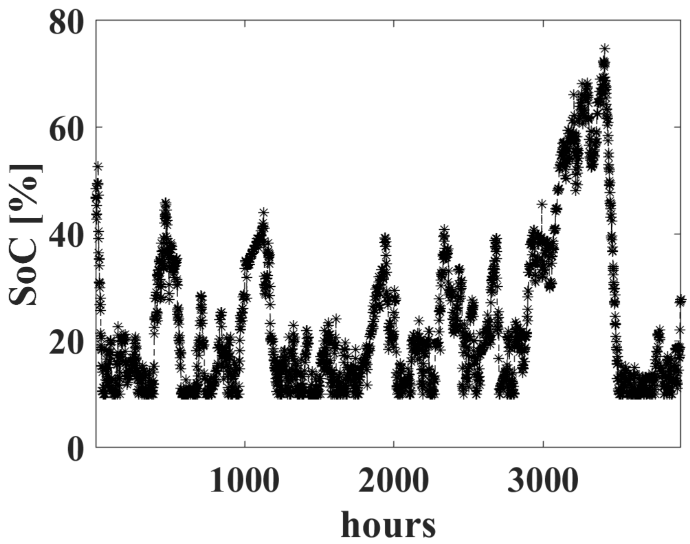
Table 5. Positive and negative errors on P_{AC} when a battery is used.

Battery's maximum energy capacity	$freq_P$ [%]	$freq_N$ [%]	*EIP* [%]	*EIN* [%]
0 Wh	28.64	35.93	4.80	-6.00
1000 Wh	11.68	19.97	1.87	-3.29
3000 Wh	4.23	14.10	0.62	-2.19
5000 Wh	2.45	12.47	0.33	-1.94
7000 Wh	1.43	11.43	0.18	-1.79
9000 Wh	0.59	10.71	0.09	-1.71
11000 Wh	0.46	10.43	0.07	-1.67
13000 Wh	0.23	10.20	0.04	-1.64
15000 Wh	0.08	9.97	0.01	-1.61
17000 Wh	0.00	9.77	0.00	-1.58

As it is possible to note, beyond a certain battery capacity, further increases do not provide additional benefits. This is because, in the scenario analyzed here, negative imbalances exceed positive ones, causing the battery's *SoC* to remain frequently near its lower limit, as can be seen from Figure 4, which shows the *SoC* in the case a battery with a capacity equal to 1 kWh (Figure 4 (a)) is used and using a battery with a capacity equal to 17 kWh, that is, approximately 4 equivalent hours (Figure 4 (b)).



(a)



(b)

Figure 4. SoC of the battery; (a) the Battery's maximum energy capacity is 1 kWh; (a) the Battery's maximum energy capacity is 15 kWh.

To prevent such behavior and completely eliminate imbalances, and thus the associated penalties, a battery charge/discharge control logic was implemented based on the error between the measured and estimated power. The control aims to keep the battery's *SoC* around 50% at all times by slightly modifying the value of the estimated power. This strategy allowed for the elimination of power imbalances using a battery with a Battery's maximum energy capacity of 8 kWh, that is, approximately 2 equivalent hours, as shown in Table 6 and Figure 5.

Table 6. Positive and negative errors on P_{AC} when a battery charge/discharge control logic is used.

Battery's maximum energy capacity	$freq_P$ [%]	$freq_N$ [%]	*EIP* [%]	*EIN* [%]
1000 Wh	6.63	8.82	1.62	-2.04
3000 Wh	1.07	1.20	0.20	-0.28
5000 Wh	0.08	0.15	0.00	-0.03

6000 Wh	0.00	0.05	0.00	-0.01
7000 Wh	0.00	0.03	0.00	-0.00
8000 Wh	0.00	0.00	0.00	0.00

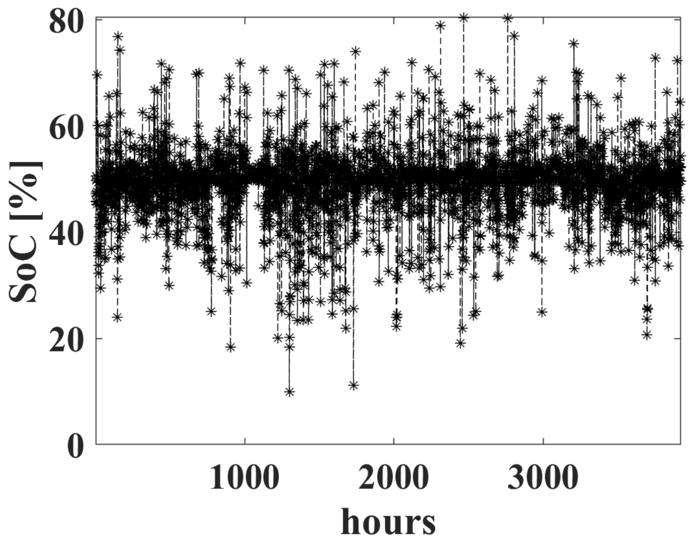


Figure 5. *SoC* of the battery with a capacity of 8 kWh.

6. Conclusion

The increasing share of RESs on the energy market has had a great impact on the electricity market evolution. In particular, the high penetration of PV plants poses a significant challenge for both regulatory authorities and system operators. In this context, accurate forecasting of PV generation is essential for planning the operation of power plants that convert RES into electricity, as it helps PV plant owners improve the accuracy of their final schedules and, consequently, reduce imbalance costs.

The accuracy of PV power forecasts is traditionally assessed using standard metrics such as RMSE, under the assumption that lower errors always lead to better outcomes. However, this assumption does not always hold when actual market conditions are considered. Deviations between scheduled and actual generation result in imbalance penalties for market participants, based on a pricing mechanism that applies different rates depending on whether the imbalance is positive or negative. Therefore, to properly evaluate forecast model performance, the regulatory and market context must also be taken into account.

The present work proposes a methodology to evaluate and eventually reduce the imbalance effects in the electricity market associated with a short-term PV power forecasting model. The analysis focuses on the Italian electricity market, specifically the MI-XBID continuous trading session, where participants can adjust their energy positions up to shortly before delivery. In particular, using a hybrid method based on physical and ANN based techniques, the PV power has been forecast 1-hour ahead and compared with the measured one, obtaining a *nRMSE* equal to 25.95 % and a *nMBE* equal to -0.72 %. It is worth emphasizing that the analysis only included data gathered between sunrise and sunset. Consequently, power outputs equal to zero were excluded. This procedure is pivotal, as incorporating zero values would artificially lower the discrepancy between the measured and predicted results.

The imbalance between real and forecast power has been calculated and compared with the threshold value calculated as a percentage of the final modified scheduled energy. Since positive and negative forecast errors have distinct technical and economic impacts on balancing markets and imbalance charges, the analysis begins with a graphical review of the imbalances for an initial assessment. In addition, two key parameters are introduced to examine these imbalances in greater depth. Then, to reduce imbalances and avoid penalties, the use of a battery is proposed and the methodology presented in this paper makes it possible to determine the optimal battery capacity value to neutralize imbalances, assuming a system with 2 equivalent hours of storage in the case here analyzed. The results indicate that the methodology here presented for evaluating and mitigating imbalance impacts in the electricity market provides users with an effective algorithm for bidding in the IDM.

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References

1. Vinayak Bali: Renewable Energy Market Report 2025 (Global Edition). (2024).
2. Terna: Press release TERNA. (2025).
3. RSE: The Italian Intraday market. (2024).
4. Said, D.: Intelligent Photovoltaic Power Forecasting Methods for a Sustainable Electricity Market of Smart Micro-Grid. IEEE Communications Magazine. 59, 122–128 (2021). https://doi.org/10.1109/MCOM.001.2001140.
5. Abdolrasol, M.G.M., Suhail Hussain, S.M., Selim Ustun, T., Sarker, M.R., Hannan, M.A., Mohamed, R., Ali, J.A., Mekhilef, S., Milad, A., Azar, T., Mosavi, A.: Artificial Neural Networks Based Optimization Techniques: A Review. (2021). https://doi.org/10.3390/electronics10212689.
6. Tina, G.M., Ventura, C., Ferlito, S., De Vito, S.: A state-of-art-review on machine-learning based methods for PV, (2021). https://doi.org/10.3390/app11167550.
7. Gupta, A., Gupta, K., Saroha, S.: A review and evaluation of solar forecasting technologies. In: Materials Today: Proceedings. pp. 2420–2425. Elsevier Ltd (2021). https://doi.org/10.1016/j.matpr.2021.04.491.
8. Iheanetu, K.J.: Solar Photovoltaic Power Forecasting: A Review, (2022). https://doi.org/10.3390/su142417005.
9. Mohamad Radzi, P.N.L., Akhter, M.N., Mekhilef, S., Mohamed Shah, N.: Review on the Application of Photovoltaic Forecasting Using Machine Learning for Very Short- to Long-Term Forecasting, (2023). https://doi.org/10.3390/su15042942.
10. Wentz, V.H., Maciel, J.N., Ledesma, J.J.G., Junior, O.H.A.: Solar Irradiance Forecasting to Short-Term PV Power: Accuracy Comparison of ANN and LSTM Models. Energies (Basel). 15, (2022). https://doi.org/10.3390/en15072457.
11. Tsai, W.C., Tu, C.S., Hong, C.M., Lin, W.M.: A Review of State-of-the-Art and Short-Term Forecasting Models for Solar PV Power Generation, (2023). https://doi.org/10.3390/en16145436.
12. Asghar, R., Fulginei, F.R., Quercio, M., Mahrouch, A.: Artificial Neural Networks for Photovoltaic Power Forecasting: A Review of Five Promising Models. IEEE Access. 12, 90461–90485 (2024). https://doi.org/10.1109/ACCESS.2024.3420693.
13. Gupta, A.K., Singh, R.K.: A review of the state of the art in solar photovoltaic output power forecasting using data-driven models. Electrical Engineering. (2024). https://doi.org/10.1007/s00202-024-02759-0.

14. Bishnu, S.K., Alnouri, S.Y., Al-Mohannadi, D.M.: Computational applications using data driven modeling in process Systems: A review. Digital Chemical Engineering. 8, 100111 (2023). https://doi.org/10.1016/J.DCHE.2023.100111.
15. Antonanzas, J., Pozo-Vázquez, D., Fernandez-Jimenez, L.A., Martinez-de-Pison, F.J.: The value of day-ahead forecasting for photovoltaics in the Spanish electricity market. Solar Energy. 158, 140–146 (2017). https://doi.org/10.1016/j.solener.2017.09.043.
16. De Giorgi, M.G., Congedo, P.M., Malvoni, M., Laforgia, D.: Error analysis of hybrid photovoltaic power forecasting models: A case study of mediterranean climate. Energy Convers Manag. 100, 117–130 (2015). https://doi.org/10.1016/j.enconman.2015.04.078.
17. Klyve, Ø.S., Nygård, M.M., Riise, H.N., Fagerström, J., Marstein, E.S.: The value of forecasts for PV power plants operating in the past, present and future Scandinavian energy markets. Solar Energy. 255, 208–221 (2023). https://doi.org/10.1016/j.solener.2023.03.044.
18. Lindig, S., Moser, D., Curran, A.J., Rath, K., Khalilnejad, A., French, R.H., Herz, M., Müller, B., Makrides, G., Georghiou, G., Livera, A., Richter, M., Ascencio-Vásquez, J., van Iseghem, M., Meftah, M., Jordan, D., Deline, C., van Sark, W., Stein, J.S., Theristis, M., Meyers, B., Baumgartner, F., Luo, W.: International collaboration framework for the calculation of performance loss rates: Data quality, benchmarks, and trends (towards a uniform methodology). Progress in Photovoltaics: Research and Applications. 29, 573–602 (2021). https://doi.org/10.1002/pip.3397.
19. Graditi, G., Ferlito, S., Adinolfi, G., Tina, G.M., Ventura, C.: Energy yield estimation of thin-film photovoltaic plants by using physical approach and artificial neural networks. Solar Energy. 130, (2016). https://doi.org/10.1016/j.solener.2016.02.022.
20. Gairaa, K., Benkaciali, S., Guermoui, M.: Clear-sky models evaluation of two sites over Algeria for PV forecasting purpose. Eur Phys J Plus. 134, (2019). https://doi.org/10.1140/epjp/i2019-12917-2.
21. MERCATO DELL'ENERGIA ELETTRICA REVISIONE DELLA DISCIPLINA DEGLI SBILANCIAMENTI EFFETTIVI-INTERVENTI PRIORITARI.
22. TESTO INTEGRATO DELLA DISCIPLINA DEL MERCATO ELETTRICO.
23. Villegas-Mier, C.G., Rodriguez-Resendiz, J., Álvarez-Alvarado, J.M., Rodriguez-Resendiz, H., Herrera-Navarro, A.M., Rodríguez-Abreo, O.: Artificial neural networks in mppt algorithms for optimization of photovoltaic power systems: A review, (2021). https://doi.org/10.3390/mi12101260.
24. Shrivastava, P., Soon, T.K., Idris, M.Y.I. Bin, Mekhilef, S.: Overview of model-based online state-of-charge estimation using Kalman filter family for lithium-ion batteries, (2019). https://doi.org/10.1016/j.rser.2019.06.040.