Comparison of LSTM-Based Models for the 6-Hour-Ahead and Day-Ahead Forecasting of Photovoltaic Power Generation

Comparison of LSTM-based models for the 6-hour-ahead and day-ahead forecasting of photovoltaic power generation

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Abstract. The importance of renewable energy sources has been increasing in recent years due to the advantages they provide, in terms of the preservation of the environment and inexhaustible supply of energy. In particular, photovoltaic (PV) energy will be prioritized in the future and it is expanding worldwide. However, the high variability of solar irradiance and, consequently, of PV power generation causes uncertainty in the planning and operation of power systems. Thus, PV power generation forecasting is crucial to solve this issue. This paper presents the comparison of LSTM-based methods for the 6-hour-ahead and day-ahead forecasting of PV power generated by a PV power station, based on the Global Horizontal Irradiance and the air temperature forecasts of the same period.

Keywords: Photovoltaic power forecasting, LSTM, neural networks, time series forecasting.

1 Introduction

The importance of renewable energy sources has been increasing in recent years, and it is expected that this trend will persist in the future due to the advantages it provides, in terms of the preservation of the environment and inexhaustible supply of energy [1]. Photovoltaic (PV) energy is one of the renewable energies that will be prioritized in the future and it is expanding worldwide. However, the high variability of solar irradiance and, consequently, of PV power production causes uncertainty in power system planning and operation [2]. Indeed, power systems may include multiple sources of energy, such as photovoltaic power stations and cogeneration units: they have the potential to strongly affect the development of strategies for the maximization of savings in economic terms [3] and energy terms. The uncertainty issue of PV power generation can be only partially mitigated via the use of Decision Support Systems [4]. Thus, PV power generation forecasting is crucial to solve this issue.

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Multiple approaches for PV power forecasting have been presented in the literature to perform PV power generation forecasting in recent years. Such methods can be split into three main categories, as described in [5]: statistical methods physical methods, and hybrid methods. In particular, statistical methods leverage historical data of the production process under analysis (or a similar one in case of data scarcity) to train a forecasting model. Physical methods rely on a physical model of the system, as well as on weather forecasts obtained via numerical approaches. It is also possible to classify the statistical PV power forecasting methods into the following groups based on the technique employed: time series-based models like AutoRegressive Integrated Moving Average (ARIMA) model [6]; machine learning methods, including Extreme Learning Machines (ELM) [7] and Artificial Neural Networks (ANN) [8]; deep learning (DL) methods like Convolutional Neural Networks (CNN) [9], Transformers [10], Long Short-Term Memory (LSTM) networks [11] and Gated Recurrent Units (GRU) [12]. Finally, hybrid approaches combine the previous two techniques, such as the one presented in [13]. In particular, LSTM networks are among the most used state-of-the-art DL techniques for time series prediction.

However, PV power generation can considerably vary depending on the topological and environmental characteristics of the PV plant that is considered. Additionally, the life stage of the PV panels and their cleanliness can affect their performance. For such reasons, the use of pre-trained state-of-the-art algorithms does not necessarily guarantee good results, and if they are trained using openly available datasets they may not generalize well to the PV forecasting in different locations. Therefore, PV forecasting algorithms should be trained using locally measured data, but one of the main obstacles that are encountered is the lack of such data: locally collected datasets are often small and are affected by missing data [14].

This paper presents the comparison between an LSTM-based method and an LSTM encoder-decoder method for the 6-hour-ahead and day-ahead forecasting of solar power generated by a photovoltaic power station. For both models, the input exogenous covariates are the Global Horizontal Irradiance (GHI) and the air temperature forecasts of the next 6 hours or the next day: they can be referred to as future covariates. The PV power generated in the previous time interval is an additional input variable in the LSTM encoder-decoder case. A small dataset of a PV power station in the Lazio region in Italy was leveraged to train and test the models. A comparison was made between such methods, as well as a persistence model, and the 6-hour-ahead forecasting LSTM encoder-decoder resulted to be the best-performing one.

The remainder of this paper is organized as follows. Section 2 comprises a description of the case study of this work, the data preprocessing that was carried out, the model selected and the evaluation metrics. The results of the case study experiments are reported and discussed in Section 3. Lastly, the conclusion on this work is drawn and future works are explained in Section 4.

2 Method

2.1 Data

This work focuses on the real case study of a photovoltaic power station in the Lazio region in Italy, with a nominal power equal to 151 kWp. The dataset that was collected for this work includes both PV power data and local weather data of the photovoltaic power station. The dataset contains the PV power production from June 2022 to May 2023, sampled every 5 minutes. Historical weather data collected locally in the same period include the GHI measured by a sensor located inside the PV power station and the air temperature measured by a temperature sensor in the same location. The resolution of weather data is the same as the one of power data, i.e., 5 minutes. Additionally, the 6-hour-ahead and 24 hour-ahead forecasts of GHI and air temperature in the location of the PV power station were downloaded from the Solcast web API [15]. Since such weather forecasts are available only from 1 April 2023 to 31 May 2023, samples collected in this period were used as a test dataset. On the other hand, historical weather data were employed for the training and validation of the model. In particular, the training dataset includes data from 2 June 2022 to 28 February 2023 and the validation dataset those from 1 March 2023 to 31 March 2023. The Python programming language and the Tensorflow library [16] are used for the implementation of the algorithms. As a first step, data were pre-processed to remove duplicate time steps, and gaps in the sequence were filled by duplicating the latest sample available before the gap. Variables were scaled via min-max normalization.

2.2 Models

The models which were selected are a simple LSTM model and an encoder-decoder architecture based on LSTM networks. The LSTM model was presented in [17] by Hochreiter and Schmidhuber in 1997 and it is a recurrent neural network (RNN). The main advantage of the LSTM model is its ability to capture long-term dependencies in time series.

In this work, each model was trained on two separate scenarios: the 6-hour-ahead and the day-ahead photovoltaic power generation forecasting. These two scenarios are part of the requirements of the real use case, where the 24-hour ahead forecast of the production of the PV station is needed for daily energy planning of the power system and the 6-hour ahead forecast is used to update the planning strategy during the day.

Thus, a forecasting horizon F can be defined, which is equal to 6 hours in the 6-hour-ahead forecasting scenario, and 24 hours in the day-ahead scenario.

Regarding the simple LSTM model, it is composed of a single LSTM layer comprising 64 units, followed by a fully connected layer comprising 32 units. The GHI and the air temperature data during the future time horizon (i.e. the F future hours, with F equal to 6 or 24) are the future exogenous covariates fed into the network in the form of a $F \times 2$ matrix. The network then learns to generate the multi-step forecast of the PV power production of the photovoltaic power station in the same future time horizon, with a 5-minute resolution. Fig. 1(a) shows a schematic of the simple LSTM architecture implemented.

On the other hand, the LSTM encoder-decoder model, which will be denoted by LSTM-ED, includes multiple components: the encoder, which is an LSTM layer with 128 units; the decoder, which is an LSTM layer comprising 128 units; and a final fully connected layer with 64 units. Differently from the simple LSTM model, the LSTM-ED model receives two different kinds of inputs: the historical PV power generation data of the past time interval, i.e. the past P hours (with P equal to 6 or 24 hours) are fed into the encoder network in the form of an array of P elements; the GHI and the air temperature data during the future time horizon are the future exogenous covariates fed into the decoder network in the form of a $F \times 2$ matrix. Using as initial states the state vectors of the encoder, the decoder learns to generate the multi-step forecast of the PV power production in the same future time horizon, with a 5-minute resolution. A schematic of the LSTM-ED architecture is represented in Fig. 1(b).

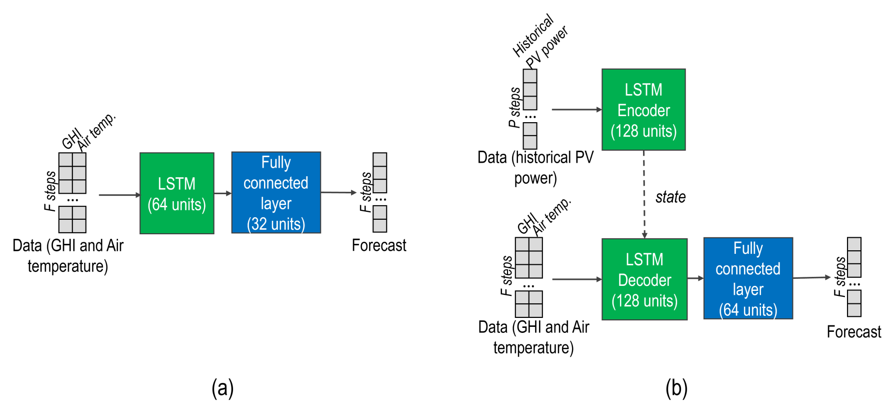

Fig. 1. (a) Schematic of the simple LSTM architecture. (b) Schematic of the LSTM-ED architecture.

In both models, GHI and air temperature data consist of historical local measurements during the training phase, while Solcast API forecasts are used in the test phase, as explained in Section 2.1.

Fig. 2(a)-(b) shows a schematic summary of the different kinds of input data and output sequences of the simple LSTM and the LSTM-ED respectively.

2.3 Evaluation

In order to set a baseline for the evaluation, the persistence model was used. The persistence model is a simple time series forecasting model which assumes

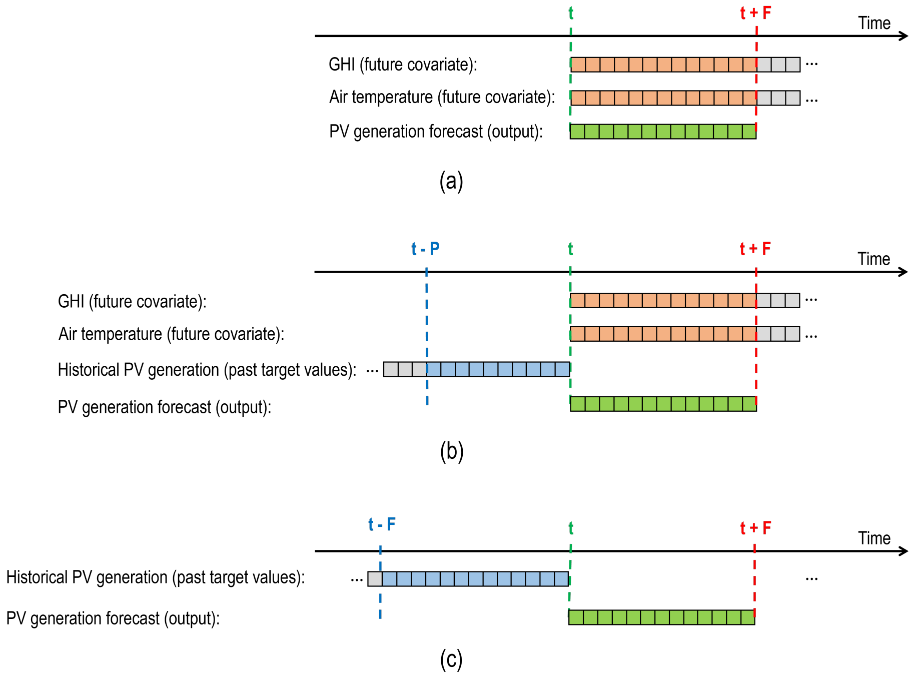

Fig. 2. Schematic summary of input and output sequences of the simple LSTM model (a), the LSTM-ED model (b) and the baseline persistence model (c), based on the current prediction time t. Red cells denote future covariate data, blue cells denote past target data, and green cells denote the outputs.

that the value of the PV power to be predicted at each time will be the same as its value at the same time of the day on the previous day. Fig. 2(c) shows a schematic summary of the input and output sequences of the persistence model.

The metrics used to evaluate the forecasting performance of each approach are the Mean Absolute Error (MAE), the Root Mean Square Error (RMSE), and the Mean Absolute Percentage Error (MAPE), computed only during day-time hours, i.e. from 4 am to 8 pm. These evaluation metrics are defined in the following:

$$\mathrm{MAE}(y, \hat{y}) = \frac{\sum_{i=0}^{N-1} |y_i - \hat{y}_i|}{N} \tag{1}$$

$$\mathrm{RMSE}(y, \hat{y}) = \sqrt{\frac{\sum_{i=0}^{N-1} (y_i - \hat{y}_i)^2}{N}} \tag{2}$$

$$\mathrm{MAPE}(y, \hat{y}) = \frac{100\%}{N} \sum_{i=0}^{N-1} \frac{|y_i - \hat{y}_i|}{|y_i|} \tag{3}$$

where N is the dataset size, y_i is the actual photovoltaic power value, and $\hat{y}_i$ is the forecasted photovoltaic power value.

3 Results and discussion

All methods presented in the preceding section were trained and tested, resulting in the following five experiments:

1. Baseline experiment: forecasting of the photovoltaic power generation by using the persistence model;
2. 6-hour-ahead forecasting of the photovoltaic power generation via the simple LSTM model;
3. day-ahead forecasting of the photovoltaic power generation via the simple LSTM model;
4. 6-hour-ahead forecasting of the photovoltaic power generation by employing the LSTM-ED model;
5. day-ahead PV power forecasting by employing the LSTM-ED model;

The baseline results were computed using a persistence model, which forecasts the PV power in the future horizon as the historical PV power generated by the photovoltaic power station at the same time of the day on the previous day.

A summary of the results of each experiment is reported in Table 1.

The MAE obtained by applying the persistence model was 6.40 kW, the RMSE was 14.19 kW and the MAPE was 89.36%. The second and third experiments consisted of the 6-hour-ahead and day-ahead PV power forecasting using the simple LSTM model respectively. Both models achieved lower error scores than the baseline persistence model, providing an improvement. The best-performing model among these two is the 6-hour-ahead model: it is an expected result since weather forecasts tend to be more accurate the shorter the time horizon is.

Lastly, the fourth and fifth experiments included the 6-hour-ahead and day-ahead photovoltaic power forecasting using the LSTM-ED model respectively. The LSTM-ED models registered an improvement compared to both the baseline persistence model and the simple LSTM models. In particular, the most effective model is the 6-hour-ahead model, as expected.

Table 1. Comparison of the results of each model.

Model	MAE (kW)	RMSE (kW)	MAPE (%)
6-hour-ahead simple LSTM	4.84	9.01	66.00
Day-ahead simple LSTM	4.38	8.49	71.45
6-hour-ahead LSTM-ED	**3.88**	**7.97**	**58.44**
Day-ahead LSTM-ED	4.14	8.29	67.57
Persistence	6.40	14.19	89.36

All the 6-hour-ahead forecasting methods achieved better performances than the persistence model, with a 23.36% and a 30.92% improvement in the MAPE metric by forecasting with the simple LSTM model and the LSTM-ED respectively. The overall best-performing model is the 6-hour-ahead LSTM-ED model.

Figs. 3(a)-(e) show a comparison between the results of the five experiments during an example day, i.e., 25 April 2023. This day was chosen because it is characterized by interesting dynamics: its GHI pattern is mostly bell-shaped but presents strong oscillations due to clouds. Additionally, the previous day was partially cloudy in the first half. Therefore, this visualization allows highlighting a frequent real-life condition which makes the task non-trivial also with regard to the baseline persistence model. In particular, Fig. 3(a) shows the 6-hour-ahead PV power forecasted using the simple LSTM model; Fig. 3(c) shows the day-ahead PV power forecasted using the simple LSTM model; Fig. 3(c) shows the 6-hour-ahead PV power forecasted using the LSTM-ED model; Fig. 3(d) shows the day-ahead PV power forecasted using the LSTM-ED model and Fig. 3(e) shows the PV power forecasted using the persistence model. It is possible to observe that the persistence model failed to precisely forecast the PV power generated on that day because the photovoltaic power production of the previous day presented a different pattern, due to different GHI and air temperature conditions. Conversely, the other methods allowed making predictions with a lower error: in particular, Fig. 3(c) shows that the predictions of the 6-hour-ahead LSTM-ED model are the closest to the actual photovoltaic power produced.

4 Conclusion and future work

The forecasting of photovoltaic power generation is essential for the optimal operation of power systems. However, the use of pre-trained state-of-the-art algorithms does not necessarily guarantee good results due to the specific characteristics of each PV plant. In this paper, a comparison between a simple LSTM model and an LSTM encoder-decoder model is proposed to forecast the PV power generated by a photovoltaic power station located in Italy. The models were trained on two different time horizons: the 6-hour-ahead horizons and the day-ahead horizons. Such two scenarios are motivated by the real requirements of the case study, where both the 24-hour ahead and the 6-hour ahead forecasts are needed for energy planning reasons. The results were then compared to a baseline model. Both LSTM-based models proved successful at predicting the photovoltaic power production compared to the baseline model. In particular, the model which performed best was the 6-hour-ahead LSTM encoder-decoder model, with an MAE equal to 3.88 kW, RMSE equal to 7.97 kW and MAPE equal to 58.44%.

Further improvements will involve the correction of weather predictions based on local historical weather measurements and the comparison of this LSTM encoder-decoder method with other time series forecasting techniques. Furthermore, the proposed model will be utilized in the planning and control of the power system that includes the PV power station considered in this work.

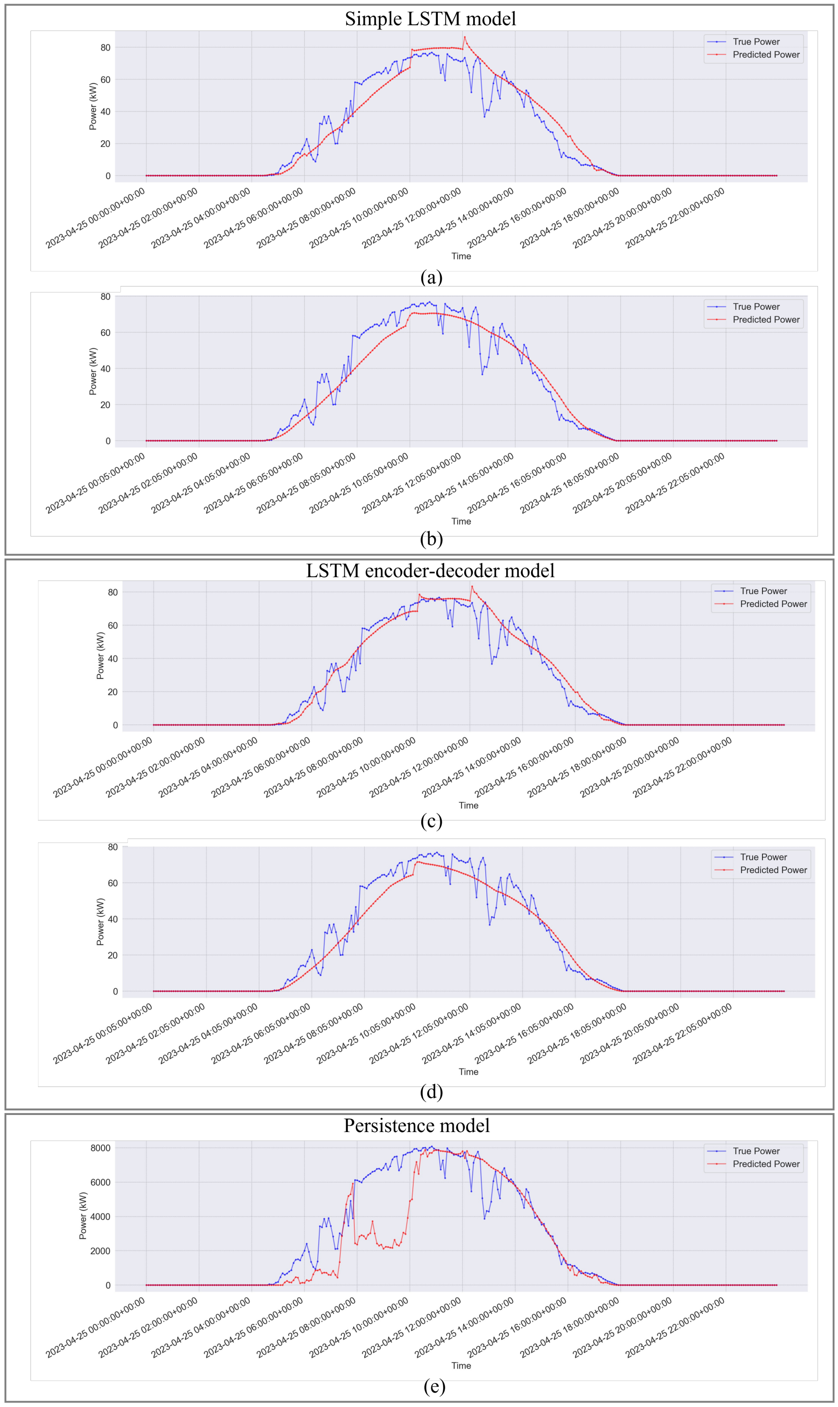

Fig. 3. (a) Actual photovoltaic power production (blue) and its 6-hour-ahead forecast using the simple LSTM model (red) on an example day, i.e. 25 April 2023. (b) Actual photovoltaic power production (blue) and its day-ahead forecast using the simple LSTM model (red) on the same example day. (c) Actual photovoltaic power generation (blue) and its 6-hour-ahead power forecast using the LSTM-ED model (red) on the same example day. (d) Actual photovoltaic power generation (blue) and its day-ahead forecast using the LSTM-ED model (red) on the same example day. (e) Actual photovoltaic power generation (blue) and its day-ahead forecast using the persistence model (red) on the same example day.

5 Acknowledgement

Dr Randazzo acknowledges funding from the research contract no. 32-G-13427-2 (DM 1062/2021) funded within the Programma Operativo Nazionale (PON) Ricerca e Innovazione of the Italian Ministry of University and Research. This publication is part of the project PNRR-NGEU which has received funding from the MUR – DM 352/2022. Lastly, a heartfelt appreciation to Valeria Pellerey and Gioele Porro of Trigenia S.r.l. for their provision of the dataset and assistance.

References

1. Ehsanul Kabir, Pawan Kumar, Sandeep Kumar, Adedeji A. Adelodun, and Ki-Hyun Kim. Solar energy: Potential and future prospects. *Renewable and Sustainable Energy Reviews*, 82:894–900, February 2018.
2. Luyao Liu, Yi Zhao, Dongliang Chang, Jiyang Xie, Zhanyu Ma, Qie Sun, Hongyi Yin, and Ronald Wennersten. Prediction of short-term PV power output and uncertainty analysis. *Applied Energy*, 228:700–711, October 2018.
3. Giorgia Ghione, Vincenzo Randazzo, Alessandra Recchia, Eros Pasero, and Marco Badami. Comparison of genetic and reinforcement learning algorithms for energy cogeneration optimization. In *2023 8th International Conference on Smart and Sustainable Technologies (SpliTech)*, pages 1–7, 2023.
4. M. Badami, G. Fambri, S. Mancò, M. Martino, I.G. Damousis, D. Agtzidis, and D. Tzovaras. A decision support system tool to manage the flexibility in renewable energy-based power systems. *Energies*, 13(1), 2019.
5. Giorgio Graditi, Amedeo Buonanno, Martina Caliano, Marialaura Di Somma, and Maria Valenti. *Machine Learning Applications for Renewable-Based Energy Systems*, pages 177–198. Springer International Publishing, Cham, 2023.
6. Subhra Das. Short term forecasting of solar radiation and power output of 89.6kWp solar PV power plant. *Materials Today: Proceedings*, 39:1959–1969, January 2021.
7. Sameer Al-Dahidi, Osama Ayadi, Jehad Adeeb, Mohammad Alrbai, and Bashar R. Qawasmeh. Extreme Learning Machines for Solar Photovoltaic Power Predictions. *Energies*, 11(10):2725, October 2018. Number: 10 Publisher: Multidisciplinary Digital Publishing Institute.
8. Federico-Vladimir Gutierrez-Corea, Miguel-Angel Manso-Callejo, Maria-Pilar Moreno-Regidor, and Maria-Teresa Manrique-Sancho. Forecasting short-term solar irradiance based on artificial neural networks and data from neighboring meteorological stations. *Solar Energy*, 134:119–131, September 2016.
9. Haixiang Zang, Lilin Cheng, Tao Ding, Kwok W. Cheung, Zhinong Wei, and Guoqiang Sun. Day-ahead photovoltaic power forecasting approach based on deep convolutional neural networks and meta learning. *International Journal of Electrical Power & Energy Systems*, 118:105790, June 2020.
10. F. Tian, X. Fan, R. Wang, H. Qin, and Y. Fan. A Power Forecasting Method for Ultra-Short-Term Photovoltaic Power Generation Using Transformer Model. *Mathematical Problems in Engineering*, 2022, 2022.
11. Chun-Hung Liu, Jyh-Cherng Gu, and Ming-Ta Yang. A Simplified LSTM Neural Networks for One Day-Ahead Solar Power Forecasting. *IEEE Access*, 9:17174–17195, 2021. Conference Name: IEEE Access.

12. N. Zhang, Q. Ren, G. Liu, L. Guo, and J. Li. Short-term PV Output Power Forecasting Based on CEEMDAN-AE-GRU. *Journal of Electrical Engineering and Technology*, 17(2):1183–1194, 2022.
13. Amedeo Buonanno, Giampaolo Caputo, Irena Balog, Giovanna Adinolfi, Francesco Pascarella, Gianni Leanza, Salvatore Fabozzi, Giorgio Graditi, and Maria Valenti. Combined machine learning and weather models for photovoltaic production forecasting in microgrid systems. In *2023 International Conference on Clean Electrical Power (ICCEP)*, pages 216–222, 2023.
14. Dazhi Yang, Jan Kleissl, Christian A. Gueymard, Hugo T. C. Pedro, and Carlos F. M. Coimbra. History and trends in solar irradiance and PV power forecasting: A preliminary assessment and review using text mining. *Solar Energy*, 168:60–101, July 2018.
15. Solcast. Solar Forecasting Data, 2023.
16. TensorFlow Developers. TensorFlow, March 2023.
17. Sepp Hochreiter and Jürgen Schmidhuber. Long Short-Term Memory. *Neural Computation*, 9(8):1735–1780, November 1997. Conference Name: Neural Computation.