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Photovoltaic power prediction using deep learning models: recent advances and new insights

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ABSTRACT

Artificial intelligence (AI) and its application across various domains have sparked significant interest, with each domain presenting distinct characteristics and challenges. In the renewable energies sector, accurate prediction of power output from photovoltaic (PV) panels using AI is crucial for meeting energy demand and facilitating energy management and storage. The field of data analysis has grown rapidly in recent years, with predictive models becoming increasingly popular for forecasting and prediction tasks. However, the accuracy and reliability of these models depend heavily on the quality of data, data preprocessing, model learning and evaluation. In this context, this paper aims to provide an in-depth review of previous research and recent progress in PV solar power forecasting and prediction by identifying and analyzing the most impacting factors. The findings of the literature review are then used to implement a benchmark for PV power prediction using deep learning models in different climates and PV panels. The aim of implementing this benchmark is to gain insights into the challenges and opportunities of PV power prediction and to improve the accuracy, reliability and explainability of predictive models in the future.

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1. INTRODUCTION

Renewable energy is experiencing increasing demand globally, driven by environmental concerns and the desire for energy security and economic development. Solar energy derived from photovoltaic (PV) panels is a prominent green and sustainable energy source, requiring minimal maintenance and offering a longer lifespan compared to thermal energy. There are two types of PV solar power: Input power (solar irradiance) and output power (solar power). Solar irradiance corresponds to the light received from the sun and is measured in space or on the PV panel using watts or joules per square meter. Three variants of this energy exist. Extraterrestrial irradiance (EI), global horizontal irradiance (GHI), direct normal irradiance (DNI) and diffuse horizontal irradiance (DHI) [1]. Solar PV power refers to the power generated by the panel. It is measured using watts, joules, watts per square meter or joules per square meter. Precise prediction of power generated by PV panels is pivotal for efficient PV power management, transmission and storage. Accurate predictions enable grid operators and energy providers to proactively balance supply and demand, optimize energy storage systems and enhance overall grid stability. However, traditional prediction methods often struggle to capture the nuances of solar energy dynamics. Herein lies the motivation for harnessing artificial intelligence (AI) in solar power prediction. AI's capacity to analyze vast and complex datasets, adapt to changing conditions and uncover intricate patterns is the driving force behind this motivation. It is worth noting that solar energy forecasting and prediction are two different terms. Forecasting is used when predicting the output at time $t + a$ based on the input at time t. In prediction, input and output data are both at time t. These terms are used interchangeably in this study and in the literature. In this research, we will focus on solar PV power generation (output power) prediction and conduct a comprehensive review of the literature. We will delve into various aspects, including data sources, input patterns, data preprocessing techniques and modeling methods employed by researchers to achieve effective and accurate predictions. We will also provide a critical analysis of previous studies, highlighting their strengths and limitations.

In the extensive body of literature on PV power prediction, diverse datasets have been used, leading to a multitude of conclusions. Each author draws their own insights, often influenced by specific datasets, models, data preprocessing methods and input patterns. This diversity of findings underscores the need for a unified benchmark that comprehensively accounts for all factors affecting PV power prediction. Additionally, proposed systems for predicting PV power are often not thoroughly interpreted or analyzed to identify where the models perform well and where they do not. The generalizability of these models across different climate conditions has also not been adequately explored.

Thus, the primary objective of this paper is to establish an experimental framework that rigorously considers these influential factors in PV power forecasting. By doing so, we aim to validate and substantiate the hypotheses and conclusions put forth in the existing literature, providing a more comprehensive and unified perspective on the field. We also conducted a post-prediction analysis to identify PV panels where the model performs well and where it does not. Additionally, we examined the model's ability to generalize its results across different climate conditions.

This study offers an important opportunity to advance the understanding and identify knowledge gaps in the domain of solar PV power prediction. Several key points distinguish our work from previously published review studies in the field: i) This work comprehensively considers all factors that can impact solar PV energy prediction, including data sources, input variables, forecasting horizons, data resolution, data preprocessing techniques and predictive models; ii) We exclusively review articles published in the last decade and cite only those that are directly relevant to our study; and iii) An experimental setup is developed to compare the performance of the most accurate learning models in the literature within the most commonly used forecasting horizons in two different climates. The impact of data resolution and input variables is also investigated. The experimental setup also includes a post-prediction analysis of model performance across 11 different types of PV panels and a cross-climate comparison. To the best of our knowledge, this is the first study that comprehensively examines all impacting factors from data sources to model learning and includes a detailed experimental analysis.

This paper is organized as follows: section 2 shows a detailed literature review of PV power prediction/forecasting, covering aspects such as data sources, input patterns, data preprocessing techniques and prediction models. In section 3, we present the experimental setup that delves into the aspects discussed in the preceding section. Subsequently, section 4 delves into the discussion of the results. Ultimately, the concluding section encapsulates the findings and provides insights into the future directions of this study.

2. LITERATURE REVIEW

The literature review will concentrate on the prediction of solar PV power generation (output power), with a specific emphasis on effective and accurate predictions. This comprehensive review will examine various aspects, including data sources, input patterns, data preprocessing techniques and modeling methods employed by researchers to achieve these predictions. Through this detailed literature review, we will provide a comprehensive and up-to-date overview of the state-of-the-art in solar PV power generation prediction. This endeavor aims to offer valuable insights for future research and the advancement of robust and accurate predictive models within the domain of solar energy applications.

2.1. Data sources

PV power prediction is very dependent on time and weather conditions. Consequently, researchers try collect data from diverse sources, such as meteorological stations [2], numerical weather prediction (NWP) models [3], websites and services with public, private or limited access [4] or through the deployment of sensors and physical PV plants [2]. This data collection results in a series of unique data records, distinguished by their respective measurement timestamps. There are two types of databases: uni-variate and multivariate. Uni-variate databases consider time as the only factor that can affect the PV power prediction, so only time and PV power are the input variables in this case. In contrast, multivariate databases include additional factors such as weather data (e.g., humidity, air temperature, pressure, precipitation) and PV panel characteristics. Notably, 86% of the databases used in the reviewed articles fall into the multivariate category. These multivariate databases can be further categorized into integrated and separated subsets: i) Integrated databases combine weather data with historical PV power output, while ii) Separated databases are exclusively dedicated to weather data or PV power data. Generally, researchers unify the time steps between records to merge both separated databases into an integrated one. Table 1 represents publicly available integrated datasets used by authors for predicting the solar power generated by photovoltaic panels. Office of scientific and technical information (OSTI) data [5] is one of the smallest datasets in terms of the measurement period, covering approximately one year for each location. However, it excels in terms of locations and input variables with 3 locations and more than 43 input variables. In the existing literature, the publicly available datasets are typically limited in size, rarely extending beyond one year of measurements. Attempting to merge large-scale separated datasets, such as weather and PV power datasets, does not necessarily lead to a substantial database due to variations in data resolution between the two sources. Another significant constraint arises from the high prediction errors associated with NWP models. As a result, measured data has proven to be highly reliable for generating accurate results [6]. Given the critical role of weather forecast data for PV power predictions in real-world applications, further investigations should be conducted to enhance the precision of forecasted weather data, thereby improving the overall efficiency of the system.

Table 1. The used public datasets in the literature

Dataset	Data resolution	Period	Location	Number of input variables
Desert knowledge Australia (DKA) data [7]	5 min	2016-Now	Alice (2016-Now) Yulara (2019-Now)	Weather data: 6 Panel characteristics: 11
OSTI data [5]	5 min	2011-2014	Cocoa (2011-2012) Golden (2012-2013) Eugene (2012-2014)	Weather data: 8 Panel characteristics: 17
SunLab data [8]	1 min	2014-2017	Portugal	Weather data: 8 Panel characteristics: 4
Photovoltaic power output (PVO) data [9]	15 min	2018-2019	China	Weather data: 6 Panel characteristics: 10
Safi data [10]	5 min	2016-2018	Morocco	Weather data: 3 Panel characteristics: 2
Lecce data [11]	5 min	2012-2013	Italy	Weather data: 3 Panel characteristics: 7
SOLETE data [12]	5 min	2018-2019	Denmark	Weather data: 7 Panel characteristics: 5

2.2. Input patterns

Input patterns refer to the input variables, forecasting horizons and data resolution. Within the literature, a plethora of variables are employed, falling into two principal categories: meteorological (weather) and panel characteristics variables. The most used weather variables in the literature include ambient temperature, solar irradiation, wind speed and humidity. Panel characteristics variables have gained recent prominence because they have shown an interesting impact on PV power prediction by improving the accuracy of the models [1], [13]. Among these, panel temperature stands out as the most frequently used variable, showcasing a comparable influence on solar cell performance as ambient temperature [14]. The aforementioned input variables are highly impacting model performance. However, some variables may not be available due to the non-meet of data quality thresholds or the sensor’s high costs. Establishing an efficient feature engineering strategy becomes imperative to extract the causal relationship between input variables and the target variable (i.e., the impact of each variable separately). Consequently, missing variables can be effectively substituted with suitable alternatives, while essential variables can be emphasized. The forecast horizon refers to the future period for which the model generates predictions. There are four types of forecast horizon: i) nowcasting or real-time forecasting, which aims to provide accurate forecasts for a very short period of time spanning minutes, ii) short-term forecasting, which is limited to several hours, a day or at most, a week, iii) medium-term forecasting, applicable for forecasts extending up to several weeks and iv) long-term forecasting, addressing forecasts spanning months or even years. The forecast horizon pattern depends on the producer and consumer needs. For example, nowcasting and short-term forecasting are widely used for electricity marketing, pricing, real-time monitoring and economic load dispatch. In contrast, long-term forecasting is used for managing power transmission, rationing and distribution. Within the literature, the most commonly used terms are “short” and “nowcasting”. Approximately 22% of the reviewed articles opt for 1-day ahead forecasting (1D), while 13% favor 1-hour ahead forecasting (1H). The forecasting horizon is related to data resolution, also known as timestep, data sampling, interval or time horizon. It refers to the time interval between two consecutive data samples. It can be equal to or less than the forecasting horizon. For example, in the context of a 1-day ahead forecasting horizon, 32% of reviewed articles select hourly resolution, 25% opt for 15 minutes resolution (15 min) and 17% adhere to daily resolution. Model accuracy is also related to forecasting horizon and data resolution. In a previous literature review [15], researchers concluded that an increase in the forecasting horizon duration leads to an increase in the error metric. However, it is noteworthy that such a conclusion may not be universally applicable, as demonstrated by Jebli *et al.* [16]. Their study indicated that, while using the random forest model, as the forecasting horizon increases, the error metric tends to decrease. Thus, the relationship between forecasting horizon and model accuracy may vary depending on the specific characteristics of the dataset and the predictive model being employed. Further investigation and analysis are required to fully understand the implications of the forecasting horizon on model accuracy across various scenarios. Data resolution is a crucial factor influencing the accuracy of PV power prediction, as highlighted in the study by Saad *et al.* [17]. To provide the model with more detailed information, it is advisable to utilize small data resolution. By employing finer-grained data, the model can capture and interpret subtle variations in the input variables, ultimately leading to more precise and reliable predictions.

2.3. Data preprocessing

Data preprocessing is a fundamental step in data science projects, where the ultimate goal is to prepare the data for recognition by predictive models and enhance data quality. This process involves various techniques to clean, transform, and organize the data. The most used techniques for PV power data preprocessing in reviewed articles are organized within five sub-steps: data cleaning, data enrichment, features importance, data filtering and data normalization.

2.3.1. Data cleaning

Due to the incorrect formats, erroneous values, or transmission errors, outliers (abnormal data) or Nan values (missing data) could be found and alter inaccurately the model’s learning. Therefore, data imputation strategies become essential. For example, Zhu *et al.* [18] replaced outliers with the previous time point value, demonstrating the impact of data cleaning on model training and the subsequent enhancement in prediction accuracy. Several studies in [19]–[21] respectively excluded Nan values or replaced them using linear interpolation on data from the corresponding time of similar days. However, Wang *et al*. [22] and Nguyen *et al.* [6] removed wholly outliers.

2.3.2. Data enrichment

Data enrichment enhances data quality by adding extra variables, including weather type and season classification [23], [24]. Weather type classification relies on variables like ground radiation intensity and historical radiation ratios. Season classification divides the year into four periods to improve data quality and assess model performance. However, adding weather type based solely on solar irradiance may be unreliable, as other factors like cloud amount and humidity are crucial. Moreover, climate change can cause rapid weather fluctuations within a day. Careful consideration of these factors is essential during data preprocessing.

2.3.3. Features Importance

Features importance serves two primary purposes: data reduction and model output explainability.

- Data reduction: it is a data preprocessing approach aims to reduce data dimensionality and improve model efficiency by limiting the number of used variables. The techniques used in the literature include Pearson correlation [2], [25] where authors remove the variables with low values of the correlation coefficient. Principal component analysis (PCA) which maps the data into a lower-dimensional space [26]. Stepwise and standard regression [19], [27] are used to select the input variables that highly affect the PV power output. Almeida *et al.* [28] and Saad *et al.* [29] figured out that all predictors are important to get more accurate predictions.
- Explainable artificial intelligence (XAI): it is a post-hoc explanation technique, employed to gain insights into the contributions of input variables and provide explanations for black-box predictive models. XAI is particularly prevalent in energy and power systems applications, often used within tree-based models like extreme gradient boosting (XGBoost). Shapely additive explanation (SHAP) and local interpretable model agnostic explanations (LIME) are two widely used XAI techniques in this domain [30]. In the context of PV power prediction, Kuzlu *et al.* [31] compared SHAP, LIME and ELI5 methods for explaining a random forest (RF) regressor. They found that among various methods, SHAP stands out as the only approach capable of providing comprehensive explanations by considering all potential predictions through exhaustive combinations of input variables. Interestingly, the integration of XAI techniques with deep learning (DL) methods in the PV power prediction domain remains unexplored in PV power prediction context.

2.3.4. Data filtering

Data filtering is used for signal processing. The wavelet transformer (decomposition) is the most commonly used technique. With over 14 wavelet transformer families available, selecting the most suitable one depends on the desired variables to be extracted. The Symmlet-5 family is considered convenient by Chiang *et al.* [32], while Zhu *et al.* [33] use the DMeyer wavelet family. Additionally, some authors opt for the maximum overlap discrete wavelet transform (MODWT) and Mallat approaches [34], [35]. Although wavelet decomposition is a potent method for analyzing time series data and capturing frequency-related patterns, its integration with learning models introduces specific challenges. Notably, it can lead to an escalation in data dimensionality and result in information loss during the transformation process.

2.3.5. Data normalization

Normalization is crucial for real-world data with varying ranges to prevent bias in linear predictive models. Rescaling data between 0 and 1 or between -1 and 1 ensures that all variables have equal importance. The min-max scalar method subtracts the minimum value and divides it by the range [36], [37]. Elamim *et al.* [38] used an alternate formula based on actual, minimum and maximum values. Bessa *et al.* [39] employed the clear sky model for PV power normalization. Nevertheless, no previous study has investigated the importance and influence of data normalization in model learning.

It is important to note that the application of certain data preprocessing sub-steps mentioned above may not always be necessary to achieve accurate predictions. For example, data normalization may hold little significance for some learning models (e.g., tree-based models where the splitting decisions are based solely on the ordering of values within each feature and not on the absolute scale of the feature). Data enrichment may cause data redundancy, where the same pattern may exist in multiple features. On the other hand, data cleaning is a critical step, contributing to the creation of a reliable dataset and enhancing its quality. Hence, cleansing techniques and strategies should be carefully selected especially dealing with a substantial number of missing samples or outliers. Further research is needed to provide insights into data enrichment and data filtering strategies and how to avoid data redundancy as well as information loss. Additionally, data reduction methods used in the studied articles, such as PCA and correlation analysis, are still limited in terms of detecting causality relationships between input and output variables and their applicability may vary across different situations, especially in feature engineering scenarios.

2.4. Predictive models

Predictive models learning is an essential step in the artificial intelligence domain. It aims to find hidden data patterns in data and generate predictions by applying complex mathematical functions (i.e., models), each with its unique data input, encoding and normalization requirements. In the studied articles, four types of learning models are used:

2.4.1. Persistence models

These serve as a baseline or reference model, delivering good results for short time horizons and data with low variability [40]. A naive version assumes constant atmospheric conditions between time t and $t+1$, making power at time t equal to power at $t+1$ and relying on real observations at time t as input. While an improved version considers clear sky conditions, especially in non-stationary time series [41]. If the expected output power at the clear sky condition equals zero, the power at time $t+1$ will match the clear sky condition power at time $t+1$. This model quantifies the worst acceptable performance of deep learning, machine learning or statistical models.

2.4.2. Statistical models

Well-suited for small datasets and limited input parameters and have been extensively employed in time series prediction, particularly for PV power output prediction. Notable examples include autoregressive integrated moving average (ARIMA) [42], autoregressive moving average (ARMA) [43] and seasonal autoregressive integrated moving average (SARIMA) [44]. However, these models may face challenges in adequately capturing complex nonlinear relationships inherent in certain time series data. Additionally, their ability to handle intricate seasonal patterns or trends may be limited when compared to the capabilities of some machine learning and deep learning models. As such, the adoption of deep learning models in this domain has garnered attention due to their potential to address these limitations and offer more robust prediction capabilities [36], [41].

2.4.3. Machine learning models

As opposed to statistical models, these models can handle vast data and complex patterns. There is a wide variety of machine learning models, but in this review, we will only discuss the most used and reliable ones, notably support vector machine (SVM), linear regression (LR) and random forest (RF). SVM has gained prominence due to its impressive performance and ability to uncover non-linear dependencies. Recently, several studies have found that deep learning models often outperform SVM [16], [24], [45].

2.4.4. Deep learning models

Situated within the machine learning field, deep learning utilizes artificial neurons to extract data patterns, mirroring the human brain's functioning. Prominent deep learning models include classical artificial neural networks (ANN) or multilayer perceptron (MLP) and long short-term memory (LSTM). 41% of the reviewed articles regard MLP as the most accurate algorithm by comparing it with machine learning models, with LSTM also deemed efficient [17], [46]. Convolutional neural network (CNN), while less common, has demonstrated lower prediction errors in certain cases [34], [47]. Ensemble models, or hybrid models, combine multiple learning models, either of the same or different types, offering enhanced accuracy in predicting solar energy production [48], [49].

2.5. Evaluation techniques

Evaluation techniques play a crucial role in validating forecasting models, especially in the case of PV power forecasting, which falls under supervised learning, a form of regression. To assess the accuracy of regression models, we should quantify and observe how close the estimated (predicted) values are to the observed (real) values by calculating residuals using different mathematical techniques. The literature predominantly relies on root mean squared error (RMSE) and mean absolute error (MAE) metrics (1) and (2), often complemented by graphical representations of predicted versus actual values. RMSE, a commonly used metric, tends to be sensitive to outliers as it penalizes large residuals. On the other hand, MAE offers a more balanced view by considering the average absolute difference between predicted and actual values, giving less importance to extreme errors. The graphical representation of actual versus predicted values remains a valuable method for assessing the closeness between predictions and actual data, but it can become challenging to interpret with extensive test data.

$$RMSE = \sqrt{\frac{1}{n} * \sum_1^n (ObservedValue - EstimatedValue)^2} \tag{1}$$

$$MAE = \frac{1}{n} * \sum_1^n |(ObservedValue - EstimatedValue)| \tag{2}$$

However, while these metrics effectively evaluate model performance, they may not serve as a fair basis for comparing systems across different prediction horizons and datasets. To enable equitable comparisons, normalized metrics such as normalized mean absolute error (NMAE), normalized root mean squared error (NRMSE) and mean absolute percentage error (MAPE) are introduced (3), (4), and (5). Among these, NMAE stands out as the most frequently applied metric in the literature.

$$NMAE = \frac{MAE}{P} \tag{3}$$

$$NRMSE = \frac{RMSE}{P} \tag{4}$$

$$MAPE = \frac{1}{n} * \sum_1^n \frac{|(ObservedValue - EstimatedValue)|}{ObservedValue} \tag{5}$$

Where P is the average, the median or the standard deviation of the power generated in the test set.

2.6. Gap identification

Through the comprehensive analysis of the current state-of-the-art in PV solar energy production prediction, several critical gaps have emerged, highlighting areas where further research and development are essential:

- Temporal data span: a significant portion of publicly available datasets, around 73%, has limited temporal coverage, often not extending beyond one year. This deficiency underscores the urgent need for extensive datasets spanning multiple years, ideally incorporating comprehensive weather and panel characteristic data.
- NWP model reliability: the high prediction errors associated with NWP models raise concerns about their suitability as primary data sources. The reliability of measured data in achieving accurate results has been consistently demonstrated in the literature. To predict PV power generation accurately in real world

conditions, there's a need to enhance the reliability of forecasted weather data, given its inherent inaccuracies compared to measured weather data.

- Input variables and feature engineering: while the literature provides a multitude of input variables, understanding the causal relationships between these variables is not always clear. Also, some variables are often omitted due to data quality limitations or high sensor costs. A more comprehensive exploration of causality relationships can help identify substitute variables for missing data and prioritize essential variables for accurate predictions.
- Data preprocessing impact assessment: data preprocessing for PV power prediction models presents another area of concern. The influence of various data preprocessing techniques within different predictive models requires thorough evaluation.
- Predictive model performance: while deep learning models have gained prominence, there is a need for well-defined criteria to guide model selection based on specific datasets and applications. Furthermore, there is a clear demand for generalized predictive models that can accurately forecast PV power under diverse conditions, including various weather scenarios, climates and panel types. Additionally, the implementation of post-prediction analysis is essential for achieving explainable AI solutions.
- Comprehensive benchmark: given the diverse datasets used in prior research within different experimental setups as mentioned in Table 2, which have yielded a multitude of disparate conclusions, the development of a comprehensive benchmark is imperative. Such a benchmark should systematically consider all factors influencing PV power prediction, providing a unified and holistic perspective on this critical field.

In conclusion, identifying these gaps in the current state of the art underscores the need for further research and development in the field of solar PV power prediction. Addressing these gaps will not only contribute to more accurate and reliable prediction models but also enhance the practical applications of solar energy technology. The subsequent sections provide an experimental analysis addressing some of these challenges and gaps. Especially the need for a comprehensive benchmark and model outcome explanation (post-prediction analysis).

Table 2. The accurate systems in the literature

Article	Period	Forecasting horizon	Input variables	Data preprocessing	Predictive model	Evaluation (NMAE)
Wang *et al.* 2017 [34]	1Y	75 min	PV power	Data normalization Data filtering	CNN	3.82%
Eseye *et al.* 2018 [35]	1Y	1D	Solar radiation/humidity temperature/cloud cover Wind speed/Pressure	Data cleaning Data filtering	SVM	4.22%
Li *et al.* 2019 [37]	1M	15 min	PV power	Data normalization	RNN	1.54%
Wang *et al.* 2020 [46]	5Y	1D	PV power	Data normalization Data enrichment	LSTM	2.78%
Nguyen *et al.* 2021 [6]	1Y	5min	Solar radiation Ambient temperature Wind speed/humidity	Data cleaning	LSTM	3.49%

3. EXPERIMENTAL SETUP

This section meticulously considers all factors influencing accurate solar power prediction. We employ the integrated multivariate dataset, OSTI data [5], as our data source. Following literature recommendations, we consider all available predictors. We choose forecasting horizons of 5 minutes, 15 minutes, 1 hour and 1 day. Data preprocessing prioritizes data cleaning as the most critical step. For modeling, we utilize the three highly accurate learning models: MLP, CNN, and LSTM. To evaluate these models, we use the NMAE as our adopted metric. The experiments were conducted using Python programming language. For data preprocessing, we utilized the libraries NumPy [50], Pandas [51], Matplotlib [52] and Seaborn [53]. TensorFlow [54] and Scikit-learn [55] were employed for model learning and evaluation. The workstation specifications are as follows:

- Processor Intel(R) Xeon(R) Silver 4214R CPU @ 2.40 GHz 2.39 GHz;
- RAM installed 64.0 GB;
- Type of system: 64-bit operating system, x64-based processor.

3.1. Data description

The dataset used in this study, OSTI data [5], encompasses three locations with 5-minute resolution. In our analysis, we select only Eugene (Oregon) and Cocoa (Florida) locations due to more than 30% of missing data in the Golden (Florida) location. Eugene represents a Marine West climate and Cocoa represents a Subtropical climate. As reported in [56], [57], both Eugene and Cocoa follow a categorization approach based on the mean hourly temperature of the day over the years from 1986 to 2016. Days are assigned specific labels according to the range of temperature values. In Eugene, this approach results in the classification of days into five types: cold, cool, comfortable, warm and hot. In Cocoa days are categorized into three types: comfortable, warm and hot. This divergence in classification reflects the distinct climate characteristics of each location. The dataset covers 11 PV panels from 6 different technologies including multi-crystalline silicon, single crystalline silicon, amorphous silicon tandem and triple-junction, cadmium telluride, copper indium gallium selenide and Amorphous silicon/crystalline silicon or heterojunction with intrinsic thin-layer PV modules. This dataset comprises over 43 variables, encompassing weather data, panel characteristics, sensors uncertainties and IV curves data. Rigorous quality assurance techniques are applied to remove data not meeting established quality standards. The data is partitioned into three sets: a training set comprising 70%, a validation set comprising 10%, and a test set comprising 20% of the data. The specific days chosen for each subset are detailed in our previous work [1]. This method allows the model to be trained and tested using data spanning the entire year, from January to December.

3.2. Data preprocessing

In this study, we remove variables that may cause data leakage from the collected dataset. Particularly those associated with PV power generation, such as voltage generated by the PV system or IV curve data. Resulting in the selection of specific variables, including i) weather variables (humidity, temperature, precipitation, precipitation prior maintenance and pressure), ii) panel characteristics (area, voltage, current, maintenance, temperature, number of cells series and parallel cell strings) and iii) time variables. The target is normalized by dividing it by the area of the panel, resulting in the unit W/m², the area of the panel is removed to avoid unnecessary data complexity. We handle missing values by removing days with more than three missing variables (representing only three days). For the precipitation variable containing approximately 3% missing values, we fill in missing values of entire days using the nearest day's precipitation (set to 0). In cases where only half-day precipitation values are missing, we use the last measured value to fill the gaps. Time and maintenance variables are encoded. Time is divided into four sub-variables, representing the month, day, hour and minute, while the maintenance feature is converted into four columns, representing the hour of maintenance start, minute of maintenance start, hour of maintenance end and minute of maintenance end.

3.3. Predictive models selection

The learning models used in this study include MLP, LSTM, and CNN. For model optimization, the Grid search approach [29] is adopted, which exhaustively evaluates various combinations of hyperparameters to select the best-performing regressor. While Grid search increases the computational time and resource requirements due to its exhaustive nature, it remains the optimal strategy for thoroughly exploring all potential parameter configurations. As mentioned in the Figure 1, the input vector $S(t)$ is not the same for all predictive models. For MLP model that is not able to handle multidimensional data, the Aggregation process is adopted and summary statistics are utilized. For humidity and temperature variables, including the temperature of the panel, new variables are generated by extracting minimum, maximum and average values, as these variables exhibit significant fluctuations throughout the day. For pressure, only the average value is considered. Precipitation data is aggregated by considering the accumulated value over the course of the forecasting horizon. The training input data is represented in the shape of $(B \times F)$, where B denotes the number of training samples and F denotes the number of variables. In the case of LSTM and CNN models, the data is structured as $(BL \times F)$, where B represents the number of samples, L represents the sequence length and F represents the number of variables. Data aggregation strategies are not required within LSTM and CNN models, as they inherently handle multidimensional data. For CNN, all distinct 5-minute samples of each horizon are considered $(S(t))$, while LSTM incorporates the previous horizon data $(S(t-1))$ in addition to the current samples. The optimal sequence length for LSTM is determined to be 2, with the number of variables set to $(I * M)$, where I represents the input variables' length and M denotes the number of 5-minute intervals in each horizon.

3.4. Evaluation metrics

In our case, we have chosen to use the MAE (2), RMSE (1) and NMAE (3) as evaluation metrics. Our evaluation criteria were designed with two primary objectives: i) to evaluate prediction accuracy comprehensively and ii) to ensure that higher PV power values, representative of peak conditions, were not unduly penalized in our assessment. MAE and NMAE play pivotal roles as decisive metrics for evaluating the models across different climates and horizons. MAE provides insights into the magnitude of errors produced by the model, offering a clear view of its performance. On the other hand, NMAE enables comprehensive assessments of various learning models, facilitating comparisons of their performance across diverse forecasting horizons, climates and PV panel technologies. This metric is particularly suitable for our specific scenario as it allows us to effectively evaluate data from different prediction horizons and compare it with other models documented in the literature that often employ distinct datasets.

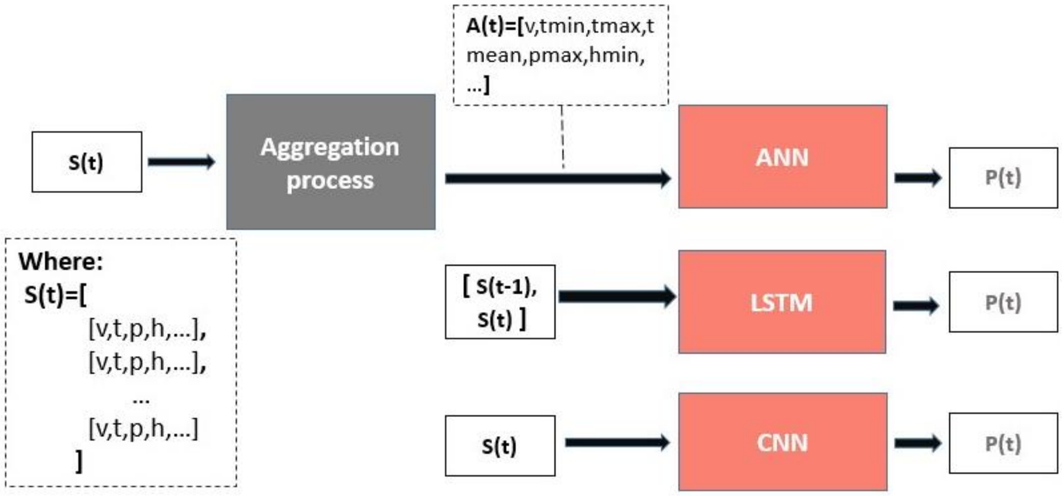


Figure 1. The workflow of prediction process for MLP, LSTM, and CNN

4. RESULTS AND DISCUSSION

4.1. Impact of forecasting horizons and predictive models

In this section, we delve into the impact of forecasting horizons on PV power prediction, utilizing highly accurate learning models and common forecasting horizons from existing literature. Our objective is to predict PV power generation across two geographically distinct locations with varying climates, involving 11 panels. We incorporate data from all panels during the training, validation and testing phases of model development. The metrics summarized in Tables 3, 4, and 5 offer distinct perspectives on model performance, allowing us to assess their effectiveness from various angles. When evaluating the impact of the forecasting horizon, NMAE emerges as the most suitable metric. A significant and positive correlation exists between the forecasting horizon and the NMAE metric across CNN, LSTM, and MLP models for both climates. As the forecasting horizon extends, NMAE increases, primarily due to the growing volume of data available for model training. For a comprehensive assessment of the best model performance, it becomes evident that LSTM outperforms other models in terms of MAE and NMAE, notably in the 15-minute and 5-minute forecasting horizons across both Eugene and Cocoa climates (considering the confidence interval). It achieves impressive NMAE values of 1.69% and 1.39% for 5-minutes predictions and 1.94% and 1.56% for 15-minute predictions in these respective climates. However, the RMSE values do not show significant disparities among the models. The scenario changes when dealing with hourly and daily predictions, as LSTM's performance is closer to or worse than CNN by taking into consideration all metrics. This discrepancy can be attributed to the amount and complexity of training data. LSTM leverages previous observations, proving challenging due to limited data. In contrast, CNN relies solely on weather data for the specific day, simplifying the data's complexity and yielding better results in these scenarios. Our experimental findings provide a valuable comparison to existing literature, as detailed in Table 2. Specifically, our LSTM model achieved NMAE values of 1.39% and 1.69% for the 5-minute horizon in the Cocoa and Eugene locations, respectively, showcasing improvements over the best NMAE of 3.49% reported in previous studies. Additionally, our CNN models for the daily horizon in both Cocoa and Eugene (2.61% and 2.67%) outperformed the existing daily systems documented in the literature (4.22%). Regarding the 15-minute horizon, our results using LSTM in Cocoa and Eugene (1.63% and 1.81%) are comparable to the accurate 15-minute horizon system (1.54%) reported in the literature.

Table 3. The NMAE (%) of learning models in different horizons and climates

Regressor \ Climate	Eugene				Cocoa			
	1D	1H	15 min	5 min	1D	1H	15 min	5 min
MLP	13.48±1.69	8.03±0.31	7.82±0.12	7.15±0.03	16.16±1.51	7.98±0.2	7.15±0.09	6.58±0.05
LSTM	3.86±0.31	2.10±0.07	1.94±0.03	1.69±0.01	4.27±0.54	2.09±0.06	1.56±0.02	1.39±0.01
CNN	2.61±0.16	2.12±0.05	2.00±0.02	1.82±0.01	2.67±0.17	2.12±0.06	1.81±0.02	1.52±0.01

Table 4. The MAE (W/m²) of learning models in different horizons and climates

Regressor \ Climate	Eugene				Cocoa			
	1D	1H	15 min	5 min	1D	1H	15 min	5 min
MLP	548.99±68.7	27.22±1.00	7.29±0.12	2.45±0.02	731.26±68.51	30.24±0.75	7.44±0.09	2.60±0.02
LSTM	157.43±12.75	7.10±0.24	1.81±0.02	0.58±0.005	193.14±24.52	7.93±0.24	1.63±0.02	0.55±0.005
CNN	106.29±6.76	7.20±0.16	1.86±0.02	0.62±0.005	121.01±7.73	8.05±0.22	1.88±0.03	0.60±0.005

Table 5. The RMSE (W/m²) of learning models in different horizons and climates

Regressor \ Climate	Eugene				Cocoa			
	1D	1H	15 min	5 min	1D	1H	15 min	5 min
MLP	1049.76±535.53	53.04±17.55	12.58±2.69	3.61±0.5	1099.41±511.73	43.35±10.7	10.29±1.81	3.69±0.5
LSTM	228.80±122.11	13.15±7.18	2.78±0.54	0.87±0.15	351.62±302.24	12.82±5.17	2.43±0.57	0.91±0.21
CNN	138.00±50.19	10.41±2.3	2.73±0.50	0.92±0.15	152.43±55.83	12.44±4.14	2.79±0.63	0.95±0.21

4.2. Impact of data resolution

To investigate the impact of data resolution on PV power forecasting, LSTM model was employed and evaluated at different temporal resolutions to predict hourly generated PV power. 5 minutes, 15 minutes and 1 hour were the selected resolutions. The results, depicted in the Figure 2, reveal intriguing insights into the relationship between data resolution and forecasting accuracy. As the graph demonstrates, the NMAE values exhibit distinct trends across varying resolutions. A 5-minute resolution results in highly accurate predictions with a low NMAE of approximately 2.10% with a tight uncertainty margin of 0.07. This finer-grained data resolution yielded the most accurate predictions. Transitioning to a 15-minute resolution slightly increases the NMAE to about 2.23%, accompanied by a slight rise in uncertainty. Finally, at a 1-hour resolution, the NMAE further expands to approximately 2.26%, with a greater level of uncertainty of 0.13. These findings highlight the trade-off between resolution and forecasting accuracy. Higher-resolution data, such as 5-minute intervals, leads to more precise predictions, while coarser resolutions sacrifice some accuracy for reduced computational demands.

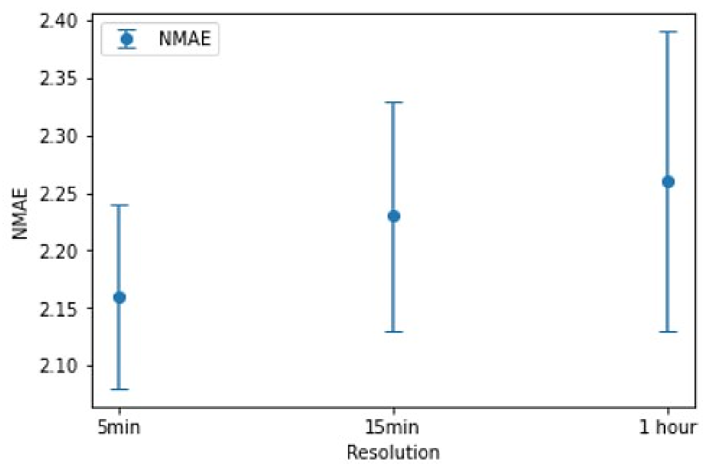


Figure 2. The NMAE of different resolutions for 1-hour forecasting horizon using the LSTM

4.3. Impact of input variables

To delve deeper into the influence of input variables on the prediction of PV power using an LSTM model, we harnessed the SHAP tool to dissect each feature’s contribution to the overarching prediction. As mentioned in Figure 3, the results for both Eugene and Cocoa demonstrate the significance of all predictors with varying coefficients. Notably, the plane of array (POA) irradiance emerges as the pivotal variable, boasting coefficients of 14.03 for Eugene and 13.79 for Cocoa, underlining its paramount informational content. Followed by the fixed panel characteristics, encompassing V_{oc} and V_{mp} voltages, the number of cells in series and the panel technology, which corroborates our prior findings [1]. In sum, the SHAP coefficients, distinct from zero, affirm the essentiality of all the utilized features.

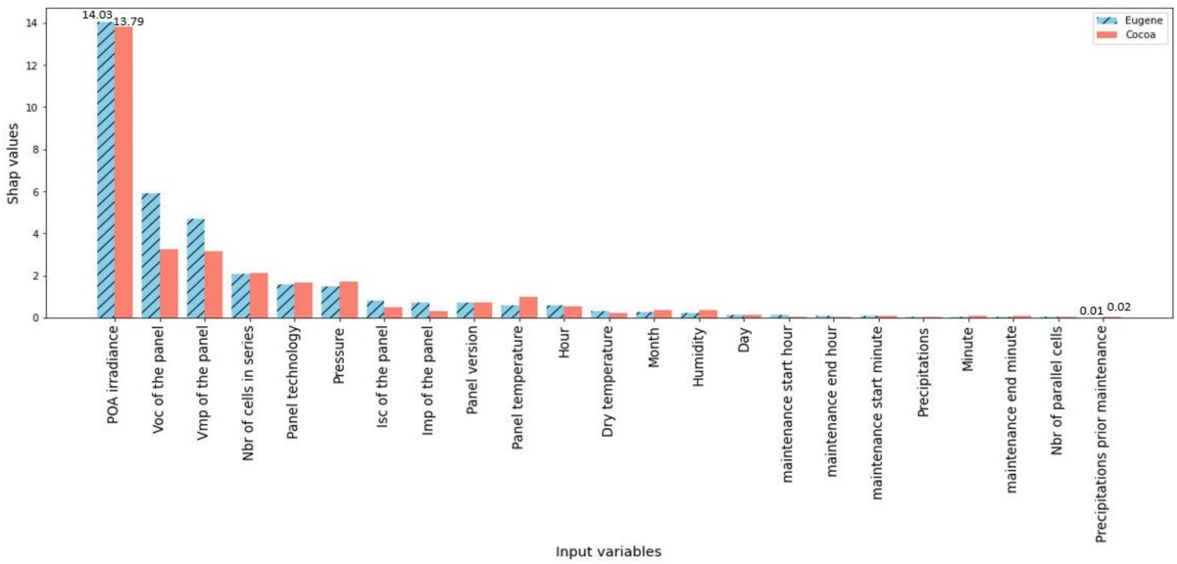


Figure 3. SHAP values for each input variable in Eugene and Cocoa

4.4. Impact of PV panels quality

The LSTM model exhibits compelling performance across various panels, with notable variations in accuracy levels, as depicted in Figure 4. In Eugene, the model's NMAE ranges from 1.18% to 2.33%, while in Cocoa, it ranges from 1.18% to 1.81%. The observed differences in NMAE among panels can be attributed to power fluctuations around the mean. In both types of climates, the first group of panels exhibits a higher standard deviation compared to the second group, as depicted in Figure 5, which illustrates the NMAE and the standard deviation of PV power for Eugene in Figure 5(a) and for Cocoa in Figure 5(b). This implies that the panels with higher standard deviations (GRP1) are more susceptible to fluctuations in solar irradiance, leading to less stable power generation as compared to the second group of panels (GRP2). Remarkably, the LSTM demonstrates a keen attention to highly fluctuating data, particularly from the first group panels, which explains its ability to achieve better accuracy for these panels. The model's ability to capture and leverage the patterns present in the highly sensitive panels contributes to its impressive performance. Further exploration will focus on the model's robustness and generalization capacity, particularly regarding unseen data.

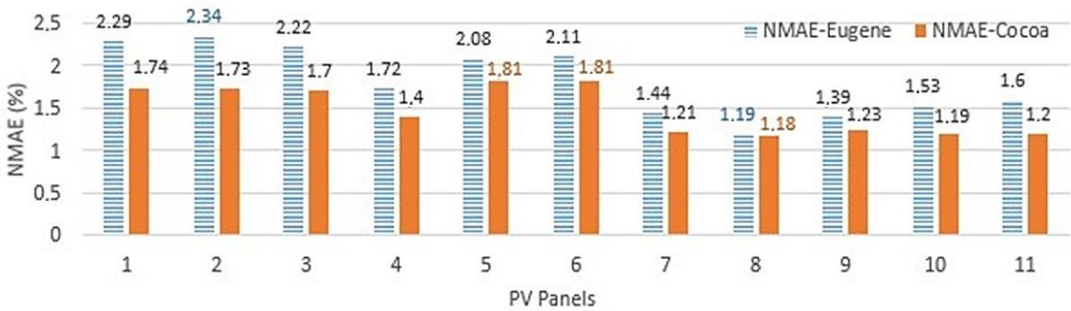
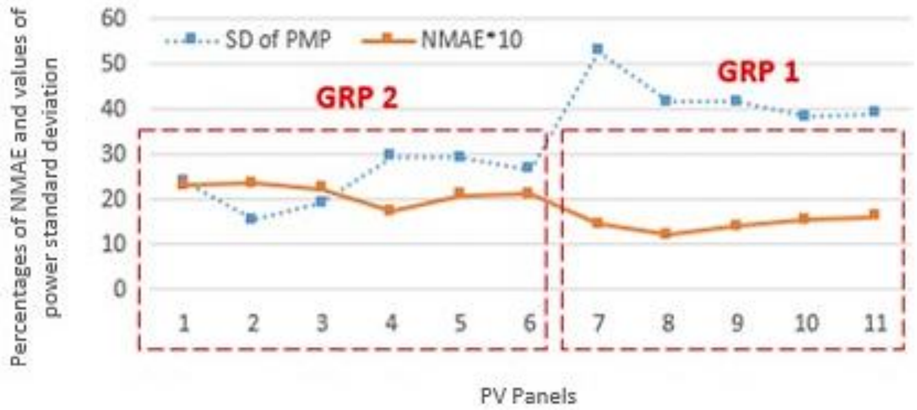
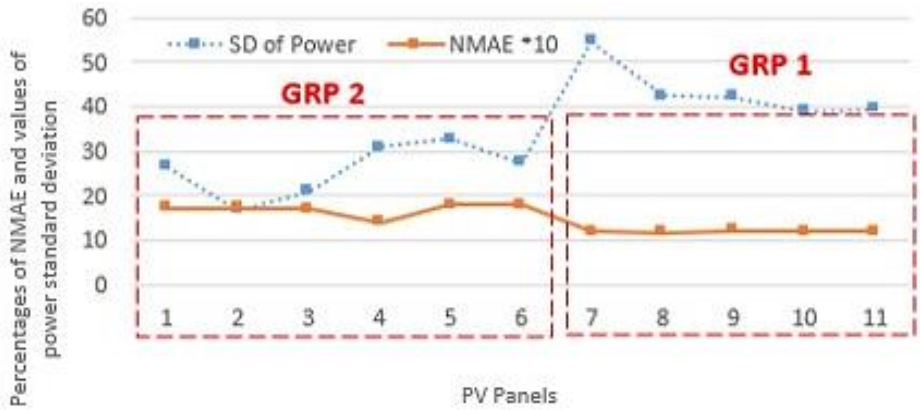


Figure 4. The NMAE of different PV panels in Eugene and Cocoa for 5-minute forecasting horizon using the LSTM



(a)



(b)

Figure 5. The NMAE and standard deviation of PV power of different panels in (a) Eugene and (b) Cocoa for 5-minute forecasting horizon using the LSTM

4.5. Cross-test between Eugene and Cocoa

The results of cross-testing between Eugene and Cocoa climates provide valuable insights into the model's generalization and its ability to handle new, unseen data. As demonstrated in Table 6, both models exhibit excellent accuracy when trained and tested on data from their respective climates. However, their performance significantly deteriorates when applied to predict data in different climates, indicating the presence of climate-specific limitations. For instance, models trained in one climate achieve impressive NMAE values within the same climate but experience a substantial decrease in prediction accuracy in the other climate due to varying weather variables. The observed discrepancies can be attributed to the differences in weather variables prevalent in each climate. While both climates may share similar weather types based on ambient temperature, significant variations arise in factors such as precipitations, humidity and cloud coverage. Indeed, during hot weather in Cocoa, the weather variables indicate high levels of precipitation and humidity, contributing to the challenges faced by the Eugene model when predicting in this climate. Conversely, in Eugene, the absence of precipitation and consistently low humidity levels present unique weather conditions that the Cocoa model struggles to accurately predict. The identified differences in weather variables underscore the need to address climate-specific characteristics when training and deploying predictive models for PV power prediction. Developing models that can accommodate these variations is crucial for accurate predictions across diverse climates.

Table 6. The NMAE (%) of learning models in different climates

Train data \ Test data	Eugene	Cocoa
Eugene	1.69 ± 0.01	4.11 ± 0.04
Cocoa	4.46 0.03	1.39 ± 0.01

5. CONCLUSION

The process of PV power prediction involves several essential steps: data collection, data preprocessing, model learning and model evaluation. These steps collectively contribute to the development of an effective prediction system. This study aimed to review the literature on PV power output prediction and implement experimental setups along various dimensions to provide an up-to-date understanding of the field and its limitations. The key findings are as follows: i) Weather data and panel characteristics are both influencing factors on PV power prediction, ii) LSTM and CNN are the most accurate predictive models, iii) The prediction error is positively correlated with the forecasting horizon due to the increase in data size as the horizon decreases, iv) LSTM exhibits remarkable accuracy across different climates and performs exceptionally well when applied to sensitive and highly efficient panels, and vi) Variances in weather variables across distinct climates present challenges to the model’s generalization ability.

Further research is needed to explore additional constraints, including acquiring more comprehensive datasets with larger sample sizes and input variables. It is crucial to investigate the significance of individual input variables, assess the impact of data preprocessing techniques and propose strategies to enhance the model’s generalization capacity when dealing with real-world data and different climates.

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