Photovoltaic Generation Forecasting – A Case Study

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***Abstract*— The increasing demand for renewable energy sources has empowered their integration into existing power networks. This initiated an interest in investigating the capabilities of these clean sources and how can then be efficiently utilized to support the balance of energy markets. In this regard, forecasting energy generation has become an essential research problem to improve the reliability of energy systems. It is of key importance to meet the energy demand, as well as to bridge the gap between energy consumption and production in energy markets. In this research, we present a case study to investigate the performance of ensemble learning models for forecasting the energy generation of photovoltaic (PV) modules. For this purpose, we utilize a dynamic energy forecasting tool to perform various experiments with different combinations of input data fields. Primarily, the performance of 3 ensemble learning models (Adaboost, Random Forest, and Gradient Boosting Regressor) has been investigated and then compared to the predictions of two previously undertaken neural network-based methods. The results indicated higher accuracy of the ensemble approaches in almost all experiments. Which was also better than the accuracy of the neural networks-based methods.**

Keywords-Energy Prediction; Energy Forecasting Tools; Prediction Models; Machine Learning.

I. INTRODUCTION

The rapid shift from traditional fossil fuel-based energy towards renewable energy sources is one of the core strategies in developing sustainable future energy systems [1]. As a constant source of energy, sunlight is used to meet the ever-increasing energy needs, and solar energy becomes a suitable substitute for fossil fuels [2]. The forecasting of wind and solar energy is getting much attention over the last two decades. Primarily, due to the increasing amount of energy generated from these renewable sources. That said, special emphasis is given to predicting wind and solar energy records because of their variability and limited predictability, as well as instantaneous response to weather phenomena [3].

On the other hand, the prediction of solar power using photovoltaics is crucial to mitigate the random fluctuations in the incoming values. Many approaches have been utilized to predict the generated energy from Photovoltaic Panels (PV). Most of them make use of traditional statistical methods and Machine Learning (ML) approaches. Furthermore, historical data sets used to make predictions usually combine a variety of weather characteristics, cloud motion tracking, solar radiation, and many others. Nevertheless, time-horizon and climate have the most noticeable impact on the performance of solar energy forecasting [4].

In this article, we contribute to the current efforts by assessing the performance of 3 ensemble learning methods in predicting energy generation from PV panels. We also compare the results to the output of two other Artificial Neural Networks (ANN) and Deep Neural Networks (DNN) based models. The goal of this case study is to explore better forecasting circumstances by manipulating various prediction models and different input fields. The rest of this research is organized as follows. Section II summarizes a state of the art of currently used models to forecast solar energy production. Section III describes the conducted case study, including the used energy forecasting tool, data sets, and methods. In this section, we also present, discuss, and compare the results. Finally, Section IV highlights the conclusion and future perspectives of this research.

II. STATE OF THE ART

Energy forecasting is crucial in energy markets, it basically aims to build accurate forecasting models to inspect future generation/consumption scenarios. Forecasting of energy production has been widely covered in the literature to balance the supply and demand in energy systems. Attempts from workers in various fields have been made to obtain as accurate prediction models as possible. The accuracy of the forecasting models has significantly increased in the last decade. Various methods have been utilized to undergo short-term prediction experiments for energy generation obtained from photovoltaic panels. Namely, statistical methods and machine learning based methods.

A state-of-the-art of the accuracy of solar energy forecasting is conducted by Blaga, R., et al. [4]. The compared forecasting models cover various classes: persistence, classical statistics, machine learning, cloud-motion tracking, numerical weather prediction, and hybrid models. As a result, machine learning and hybrid models have the best performance for intra-hour predictions in all climates. However, according to Tato, J.H. and Brito, M.C. [5], using meteorological and historical data is not enough to produce accurate solar energy forecasts. Instead, the authors integrate a Smart Persistence prediction algorithm with Random Forests to analyze the data of six solar PV modules. The results showed a great improvement in the accuracy of short-term forecasts.

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Furthermore, due to the dependency of PV panels on solar radiation, Global Horizontal Solar Irradiance (GHI) has a strong influence on PV production. An ANN based model was proposed to predict the next-day produced power from PV panels [6]. The model makes use of real-time solar irradiance to provide a set of decision rules for a proper prediction system. The research shows that machine learning algorithms hold some promise in this regard. Another research based on a non-linear autoregressive neural network was presented in [7]. It aims at forecasting global horizontal solar irradiance as input to a photovoltaic simulator presented in another study [8]. This system estimates the energy generation profiles of PV systems in real-sky conditions. The goal of this process is to predict energy production in short-term time periods. In a similar manner, authors of Cannizzaro, D., et al. [9] present a methodology to forecast GHI from the next 15 min and up to the next 24 hours. The proposed approach implements ML techniques including Variational Mode Decomposition (VMD), Convolutional Neural Networks (CNN), Random Forest (RF), and Long Short-Term Memory (LSTM).

On the other hand, authors of Gellert, A., et al. [10] propose a technique to predict the electricity production and consumption in a household with photovoltaics and storage systems. They analyze statistical models based on previous values aiming at increasing the self-consumption and reducing the dependency on the power grid. However, the study lacks considering environmental-specific input parameters, such as weather characteristics and contextual details. In a later study [11], the authors evaluate two statistical prediction methods: ARIMA and TBATS, and compare them to other models: Markov model, Multi-Layer Perceptron (MLP), Gated Recurrent Unit (GRU), Bayesian Regression Structural Time Series (BRSTS), and LSTM. The evaluation results showed a better mean absolute error for TBATS over what was obtained by the other models.

Deep learning methods have been also approached to tackle energy forecasting in solar systems. Three deep learning-based forecasting models were introduced for the continuous prediction of energy generated by concentrated solar power plants in Spain [12]. The proposed models are Naïve cloud-cover, ANN, and LSTM based approaches. The authors used as inputs the irradiance values and weather conditions forecasts. Another deep learning approach established on LSTM was introduced in [13]. It aimed at forecasting one hour-ahead energy production from a solar-PV plant. In this study, two other data-driven methods were also applied, and the results revealed that the LSTM model gave the best results.

Moreover, a method for detailed PV energy yield forecasting is presented in [14]. This study utilizes a local sky-imager and neural networks for horizons up to 15 min. The proposed approach eliminates the usual models, from irradiation forecast to energy yield estimation, and reduces the propagated errors. Another approach was presented to predict local PV power output based on short-term solar forecasting using ground-based cameras [15]. The research also analyzes the benefits of the forecasts to the power system. Furthermore, daily energy production forecasting methods for photovoltaic solar panels were presented using mathematical methods and fuzzy logic models [16]. The studies showed that the best model is a two-input Takagi-Sugeno system with nonlinear membership functions. In their study, authors also present a prototype software implementing the best-performing models.

Our approach brings novelty in many aspects: first, instead of considering radiation values and cloud tracking, we employ historical weather information, time contextual fields, and previous energy values as input to train our ML models. In addition, to obtain the most accurate results, we focus our efforts on conducting various experiments considering different combinations of the available input fields. Finally, we successfully utilize the tuned model to predict the energy production for a whole week instead of a couple of upcoming hours.

III. Case Study

A. Overview

The aim of this case study is to investigate the performance of three ensemble learning methods in forecasting energy generation. In this context, we use a dynamic forecasting tool to perform and compare various experiments in different conditions. We also use a historical data set that combines the instant generation of 3 PV panels. Primarily, results of the considered models are presented, discussed, and then compared to previously undertaken predictions using two neural network-based models. The forecasting of PV generation data will be used and integrated by an Energy Resource Management System (ERMS), in a collective residential building, to support the management of all building resources aiming to minimize the electricity consumption costs.

B. Energy Forecasting Tool

In this case study, we used a dynamic energy forecasting tool that was developed by the GECAD research group [17]. The tool is a web-based application that extends a set of machine learning models to provide dynamic energy forecasting services. It provides interactive user interfaces to predict energy generation/consumption, build forecasting models, compare predictions, and fine-tune prediction models. The used tool utilizes five supervised machine learning estimators which include: Adaboost.R2 (Ada.) [18], Random Forest Regressor (RF) [19], Gradient Boosting Regressor (GBR) [20], Support Vector Regression (SVR) [21], and Linear Regression (LR) [22]. Furthermore, the tool maintains two common validation mechanisms: Train Test Split and Cross-validation. Services provided by this tool cover a set of training, predicting, and tuning features with various input and output capabilities. In Figure 1, we show a sample of the tool's training interface, in which the user controls the configurations of 3 prediction models. This tool has been used previously in conjunction with other aspects that might benefit from the energy forecasting services. Mainly, in building trust models for Local Energy Markets [23] [24].

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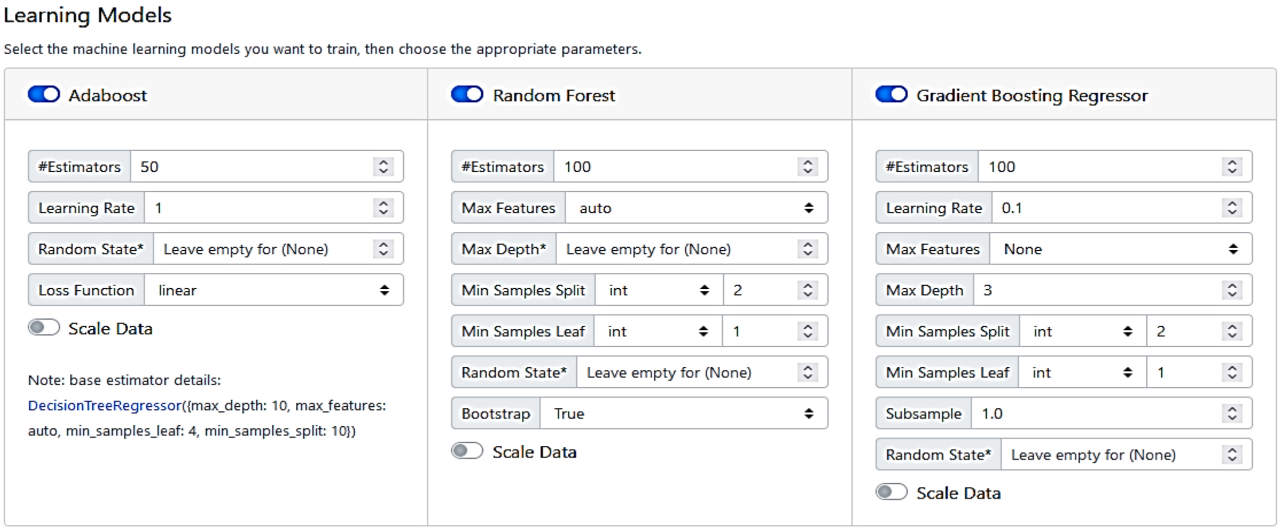

Figure 1. Energy Forecasting Tool: An example of the model training interface, it shows 3 models with their default parameters.

C. Data Sets

The historical data used in this case study combines the energy generation of three different photovoltaic solar modules installed and operated in Porto. The PV generation system under analysis is installed on the roof of a residential building consisting of 15 apartments of different typologies. There are 28 PV panels installed, each with a power of 400 Wp, for a total installed capacity of 11.2 kW. This total PV power is distributed into three sets of producers, each with a 3.68 kW installed PV power [25]. The data set represents the generated energy values in kW for each solar panel as well as the total generated values. It was internally collected and registered in a timestamp interval of 15 min and covers the whole year of 2019.

Furthermore, to enrich the input data fields, we managed to retrieve detailed weather values of the exact location where the panels are installed. For this sake, we used a global weather API provided by World Weather Online [26]. Collected weather values include but are not limited to temperature, wind speed, direction, precipitation, humidity, visibility, pressure, cloud cover, etc.

For the sake of transparently comparing the output predictions, the data set also includes forecasting results of two other prediction models. ANN and DNN were previously trained and used to forecast energy generation for the first week of September of the same year (2019) [27]. In this study, four forecasting performance metrics (Mean Absolute Error, Symmetric Mean Absolute Percentage Error, Weighted Absolute Percentage Error, and Normalized Root Mean Square Error) were used to evaluate the accuracy of both forecasting algorithms. The obtained forecasting results showed that both techniques had similar prediction behavior, however, and based on the obtained forecasting evaluation errors, the ANN presented a slightly better prediction performance in comparison with DNN.

D. Methods

We utilized the energy forecasting tool to perform multiple experiments. Primarily, we made use of 3 main services: a) model training with default parameters, to train models using a historical data set and generate downloadable trained models, b) bulk prediction, to use trained models to predict multiple future records, and c) model tuning, to find the best parameters for each model considering specific input data fields. Moreover, as per a case study undertaken using the same tool [17], ensemble learning methods had proven the most accurate results in energy forecasting in similar conditions. Consequently, we used the three ensemble learning methods: Ada., RF, and GBR. To validate trained models, we preferred to opt for the cross-validation mechanism over the train test split. Although this validation method is more expensive in terms of computational cost, it brings better and more reliable accuracy values.

As input, the tool accepts three categories of data fields: contextual fields, weather attributes, and preceding consumption/generation values. In this case study, we consider all available contextual fields, weather fields that might affect the solar reflection on panels and, thus, affect the generated energy, and up to 10 previous generation values (see Table I).

TABLE I. INPUT DATA FIELDS CONSIDERED IN THE CASE STUDY

Input Categories	Input Fields
Contextual values	Minute (min), Hour (h), Day of the week (dw), Day of the month (dm), Month (m), Year (y).
Weather attributes	Temperature (temp), Wind speed (ws), Cloud cover (cc), Visibility (vis), Precipitation (p).
Previous values	Up to 10 previous generations, where (v_{t-1}) refers to the 1st previously generated value, (v_{t-2}) refers to the 2nd previously generated value, and (v_{t-n}) refers to the nth previously generated value.

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For this case study, we used the tool to perform 14 training experiments for each model (Ada., RF, and GBR). Each experiment examines a different combination of input fields (see Table II). To obtain the most reliable results, we developed our case study as the following: first, we trained the three models using only contextual fields (Exp^1). Then, we combined both contextual and weather fields to check the expected influence of weather conditions (Exp^2). After that, to adjust the best number of previous values to be incorporated, we combined contextual fields with 1, 2, 3, and up to 10 previous values ($Exp^{3\text{-}12}$). Afterward, we combined the contextual fields, weather data, and the best number of previous values for each model (Exp^{13}). Finally, we used the tuning module to fine-tune the resulted models and perform the final experiment (Exp^{14}).

That said, for each experiment, we trained the three ensemble models using the total generated energy records, from January until August 2019. Then, we validated the trained models using the cross-validation technique and registered the averaged prediction accuracy for each model/experiment. Finally, to compare results with the previously conducted ANN and DNN methods, we used the bulk prediction service to predict energy generation during the 1st week of September of the same year. Nevertheless, although all models can be generalized to cover multiple years energy records, we had to consider 8 months to compare results with ANN and DNN predictions.

TABLE II. TRAINING EXPERIMENTS, INCLUDING INPUT DATA FIELDS FOR EACH ONE

Exp.	Input Fields
Exp^1	Contextual (min, h, dw, dm, m, y)
Exp^2	Contextual (min, h, dw, dm, m, y), Weather (temp, ws, cc, vis, p)
Exp^3	Contextual (min, h, dw, dm, m, y), Previous Values (v_{t-1})
Exp^4	Contextual (min, h, dw, dm, m, y), Previous Values (v_{t-1}, v_{t-2})
Exp^5	Contextual (min, h, dw, dm, m, y), Previous Values (v_{t-1}, v_{t-2}, v_{t-3})
Exp^6	Contextual (min, h, dw, dm, m, y), Previous Values (v_{t-1}, v_{t-2}, v_{t-3}, v_{t-4})
Exp^7	Contextual (min, h, dw, dm, m, y), Previous Values (v_{t-1}, v_{t-2}, v_{t-3}, v_{t-4}, v_{t-5})
Exp^8	Contextual (min, h, dw, dm, m, y), Previous Values (v_{t-1}, v_{t-2}, v_{t-3}, v_{t-4}, v_{t-5}, v_{t-6})
Exp^9	Contextual (min, h, dw, dm, m, y), Previous Values (v_{t-1}, v_{t-2}, v_{t-3}, v_{t-4}, v_{t-5}, v_{t-6}, v_{t-7})
Exp^{10}	Contextual (min, h, dw, dm, m, y), Previous Values (v_{t-1}, v_{t-2}, v_{t-3}, v_{t-4}, v_{t-5}, v_{t-6}, v_{t-7}, v_{t-8})
Exp^{11}	Contextual (min, h, dw, dm, m, y), Previous Values (v_{t-1}, v_{t-2}, v_{t-3}, v_{t-4}, v_{t-5}, v_{t-6}, v_{t-7}, v_{t-8}, v_{t-9})
Exp^{12}	Contextual (min, h, dw, dm, m, y), Previous Values (v_{t-1}, v_{t-2}, v_{t-3}, v_{t-4}, v_{t-5}, v_{t-6}, v_{t-7}, v_{t-8}, v_{t-9}, v_{t-10})
Exp^{13}	Contextual (min, h, dw, dm, m, y), Weather (temp, ws, cc, vis, p), Previous Values (Best of $Exp^{3\text{-}12}$ for each model)
Exp^{14}	Same as Exp^{13}

E. Results and Discussion

In Table III, we summarize the prediction accuracy R^2 (1) achieved by each model in all performed experiments.

$$R^2(y,\hat{y}) = 1 - \frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{n}(y_i-\bar{y})^2}, where\ \bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i \qquad (1)$$

TABLE III. PREDICTION ACCURACY FOR EACH MODEL IN ALL EXPERIMENTS

Exp	Description	Ada. R^2	FR R^2	GBR R^2
Exp^1	Only contextual fields	93.6 %	95.2 %	83.7 %
Exp^2	Contextual + Weather	94.5 %	95.8 %	86.5 %
Exp^3	Contextual + 1 previous value	95.9 %	96 %	96.2 %
Exp^4	Contextual + 2 previous values	96 %	96.1 %	96.3 %
Exp^5	Contextual + 3 previous values	96 %	96.2 %	96.3 %
Exp^6	Contextual + 4 previous values	96 %	96.3 %	96.4 %
Exp^7	Contextual + 5 previous values	96.1 %	96.3 %	96.3 %
Exp^8	Contextual + 6 previous values	96.1 %	96.3 %	96.3 %
Exp^9	Contextual + 7 previous values	96.1 %	96.3 %	96.3 %
Exp^{10}	Contextual + 8 previous values	96.2 %	96.3 %	96.3 %
Exp^{11}	Contextual + 9 previous values	96.1 %	96.3 %	96.3 %
Exp^{12}	Contextual + 10 previous values	96.2 %	96.3 %	96.3 %
Exp^{13}	Contextual + Best previous values* + Weather	96.2 %	96.3 %	96.4 %
Exp^{14}	Exp^{13} TUNED	96.3 %	96.4 %	96.4 %

* For Ada.: 8 (or 10) previous values, For RF: 4 (or 5-10) previous values, For GBR: 4 previous values

Looking into the detailed results, all models could obtain high accuracy in almost all experiments. This might be explained in terms of the consistent generation of the considered solar panels. Even when using only contextual fields (Exp^1), we get high accuracy with a minimum of 83.7% for the GBR model. Such results clearly indicate the significant influence of contextual fields on energy predictions. Furthermore, we also notice the enhancement that weather fields achieved when combined with contextual data (Exp^2). Nevertheless, as weather conditions highly affect energy generation using solar panels, we still expect greater impacts of weather fields in different circumstances. For example, with a lower base contextual accuracy when dealing with less or inconsistent generation values.

On the other hand, the results also show an increasing accuracy upon considering preceding values ($Exp^{3\text{-}12}$), especially in the very early stage when we started to combine the latest generation values ($Exp^{3\text{-}6}$). These experiments also indicate that the more previous values to consider do not necessarily mean higher prediction accuracy. As we can notice a phase of fluctuation for each model after reaching a specific number of previous values. Nevertheless, with a 15-min interval data log, 10 previous values cover 2:30 hours. Consequently, we also expect a downgrade in prediction accuracies when combining a longer prior period which might involve much divergence in the actual generated energy. Finally, as expected, combining all input fields (Exp^{13}) as well as utilizing tuned models (Exp^{14}) were eventually able to bring the best accurate results.

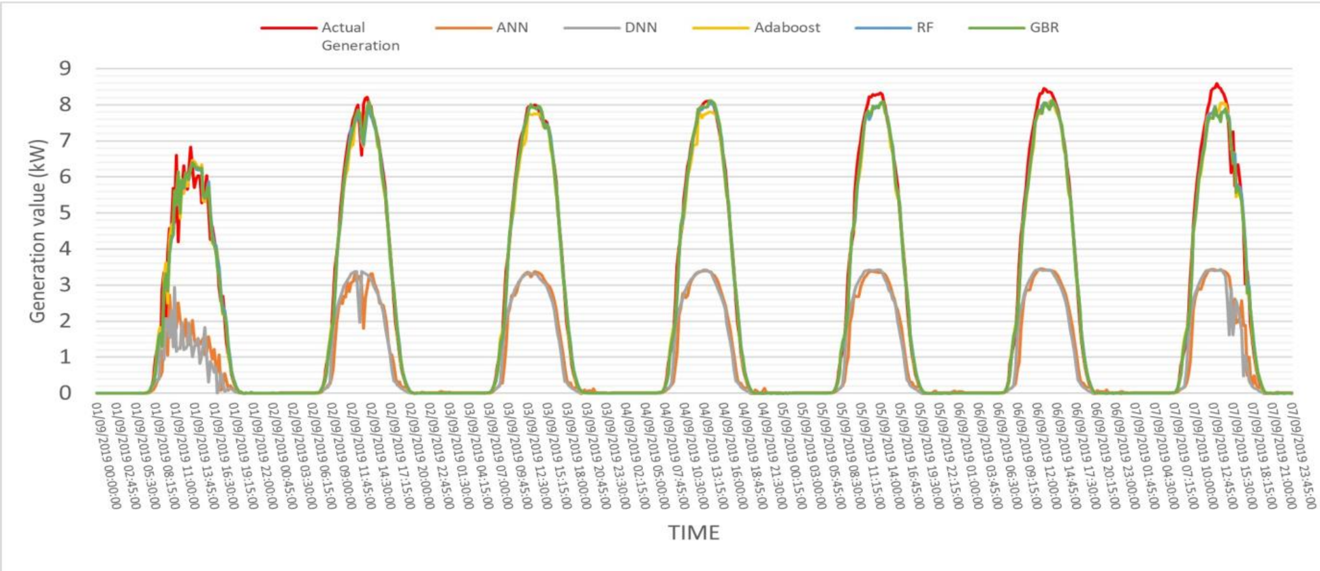

Figure 2. Actual generation and predictions for the 1st week of September, 2019.

Regarding the forecasting models, we could notice, in general, not much difference in the performance of the three considered models. However, we could see relatively better results of Adaboost and Random Forest in the first two experiments (Exp[1,2]). While the performance of all models turned too close during the later observations.

F. Comparison

As mentioned earlier, to better assess our prediction models, we used the three models resulting from Exp[14] to predict the energy generation values during the first week of September 2019. We also compared the results with previously undertaken predictions for the same period using ANN and DNN [27]. All predictions were conducted in a time interval of 15 min. Figure 2 shows the prediction results and the actual generation during the first week of September for all considered models. Furthermore, Table IV presents the accuracy (R^2 score) for the predicted generation values during the considered period.

TABLE IV. PREDICTION ACCURACY FOR EACH MODEL FOR THE 1ST WEEK OF SEPTEMBER. 2019

Prediction Model	Artificial Neural Networks	Deep Neural Networks	Adaboost	Random Forest	Gradient Boosting Regressor
R^2 Score	97.9 %	96.1 %	99.6 %	99.7 %	99.7

It is clearly noticeable that the predictions of the three ensemble learning methods are almost identical to the actual generation along the whole observed period. This is reasonable in terms of the higher accuracy of the trained models obtained during the case study. Likewise, we can observe some deviation in the predictions of the other two ANN and DNN models from the actual generation, especially during the day hours when there is actual energy generation. We could also notice that, although ANN and DNN predictions were consistently low in comparison to the actual generation, they could relatively reflect the overall trend of the generated values.

IV. CONCLUSION

This research is a contribution to the efforts to obtain accurate energy forecasting from photovoltaic panels. In this regard, we conducted a case study to predict the energy production from 3 PV modules installed and running in Porto. The used dataset combines historical records of weather data, time-contextual fields, and previous generation values. We used a dynamic forecasting tool to undergo various prediction experiments using 3 ensemble learning models (Adaboost, Random Forest, and Gradient Boosting Regressor). Obtained results are then compared with the results of two ANN and DNN based models. The results indicate relatively high accuracy of the ensemble approaches in almost all experiments. Which was also much better than the accuracy of the previously conducted neural networks-based methods.

This case study shows interesting new results. However, obtaining high accuracy in forecasting energy generation in specific conditions doesn't eliminate the investigation process. Each forecasting problem has its own circumstances that are not necessarily the same in another environment. Upcoming challenges in the production of renewable energy always require better forecasting models. Future work might imply performing further experiments at multiple scales, utilizing a wider range of combinations between input fields, as well as investigating the effects of solar radiation when combined with other fields already considered in this research. The ultimate goal for such experiments would be to obtain as accurate results as possible within specific prediction conditions.

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