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Forecast of Solar Photovoltaic Power Output Based on Polycrystalline Panel-based Employing Various Ensemble Machine Learning Methods

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***Abstract*—This paper presents solar photovoltaic (PV) energy prediction based on Polycrystalline technology utilizing various ensemble machine learning (ML) models. Several ML models like Extra Tree Regressor (ETR), Decision Tree Regression (DTR), Random Forest Regressor (RFR), Adaptive Boosting (AdaBoost), and Gradient Boosting Regressor (GBR) were utilized to forecast PV power output and the performance of all models is evaluated according to performance metrics. The selected ensemble models are based on bagging and boosting approaches. The primary input parameters such as solar radiation, wind speed, time, and the actual power generated by the Polycrystalline PV panel based on the 2019 data set were considered for forecasting solar PV output power. The results showed that AdaBoost outperformed the other ensemble ML algorithms, whereas DTR performed the poorest. The AdaBoost model had the best performance, with Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) values of 15.36and 25.05, respectively. On the other hand, the DTR model performed poorly, with an RMSE of 35.72 and an MAE of 23.47, respectively.**

Keywords— Machine Learning, Photovoltaic Systems, An Hour Ahead Power Output Forecast, AdaBoost, ensemble.

I. Introduction

Solar photovoltaic (PV) power is the most common and promising renewable energy source. As a result, numerous nations have designated solar power as a priority for growth and advancement [1, 2]. The smart grid makes extensive use of solar power plants. The deployment of large-scale grid-connected solar PV power plants has imposed stringent constraints on the power grid's balance, stability, reactive power compensation, reliability, and frequency responsiveness. However, the instability and intermittent nature of solar energy hinder PV power generation development [3]. The key to resolving this issue is to precisely forecast PV power and arrange a scheduled plan [4, 5]. In the last several years, many experts worldwide have focused their attention on forecasting the PV power output accurately [6, 7]. Unfortunately, predictions based on traditional physical models are challenging and have low accuracy [8, 9].

Therefore, artificial intelligence-based statistical prediction methods are a prominent topic in the study. Support Vector Machine (SVM) [10, 11], Artificial Neural Network (ANN) [12], Extreme Learning Machine (ELM) [2], Markov Chain, Adaptive neuro-fuzzy inference system (ANFIS) [13], and Regression models are popular approaches. However, the literature mentioned above only utilizes one approach for forecast, and the unpredictability of PVs frequently leads to poor model generalization and lower prediction accuracy. For instance, persistence [14] and statistical [15] techniques are inapplicable to nonlinear data. Simultaneously, techniques such as ANN and ANFIS demonstrate difficulties with complicated structure, local optima, and overfitting [16, 17].

Furthermore, SVM has difficulty with parameter sensitivity, including penalty factor and kernel function. On the other hand, the ELM method has problems with randomizing input weights and hidden node bias. Ensemble learning is a term that refers to a set of statistical or physical approaches that combine several models with distinct properties to overcome the constraints of a single model and improve predicted performance [18, 19]. In the realm of PV power forecasting, ensemble learning is being used to help enhance the model's prediction accuracy.

Furthermore, Deep Learning (DL) approaches [20, 21] were applied to address the limitations of prior models. PV power output provides deep advantages that beat earlier methodologies and models. Several DL models predicted the production of PV power, including RNN [22], RNN-LSTM [1, 23], and SSA-RNN-LSTM in [24] and CNN [7]. However, those DL models take ample time for convergence and are much more complicated than the Machine Learning (ML) models. To compensate for the shortcomings of the DL models, ML models were also employed [25]. In [26] presents, as an example, a one-day-ahead forecast of PV power output using data-driven ML and statistical post-processing. In [27, 28], the PV solar irradiance is predicted using random forests. To estimate short-term PV power production, Usman and Zhanle [6] developed a method to compare several machine learning models and feature selection algorithms. It was claimed that the XGBoost algorithm outperformed other ML approaches.

As there is a lack of research addressing the influence of many input factors on the performance of PV panels [29-32], it is vital to understand the intricate relationship between these parameters and the output power of PV systems [33, 34]. Therefore, the goal of this study is to use ensemble models based on bagging and boosting techniques such as Extra Tree Regression (ETR), Random Forest Regressor (RFR), Gradient Boosting Regressor (GBR), Adaptive Boosting (AdaBoost), and Decision Tree Regression (DTR) to forecast the power output of Polycrystalline (PC) PV based panels for data from the year 2019.

II. Methodology

This section describes data collection and preprocessing at the Power Electronics and Renewable Energy Research Laboratory (PEARL) at the University of Malaya Engineering Tower rooftop and demonstrates the performance metrics used to evaluate the models. Finally, a brief explanation of the models used for forecasting PV power output.

A. Data preparation and partitioning

Their confirmation has validated the impact of data preparation and partitioning on the convergence of the models. It involves several procedures, including data collection, division, and standardization using several formulas. In this study, the dataset is gathered with a 5-minute interval from 1 January 2019 to 31 December 2019 [35]. Then, this year's forecast is made, and the data is separated into two pieces. The first portion is 80% for training, while the second part is 20% for testing so that the suggested ML models may be compared more effectively (ETR, DTR, RFR, GBR, and AdaBoost); the data separation is shown in Fig. 1. Finally, the application of the standard deviation achieved the normalization of the data. The following equations [36] outline the steps of this technique.

$$\mu = \frac{1}{N}\sum_{n=1}^{N} Data_{set} \tag{1}$$

$$\sigma = std(Data_{set}) = \sqrt{\frac{\sum(d_i-\mu)^2}{N}} \tag{2}$$

$$Data_{set}{}^{standardized} = \frac{(Data_{set}-\mu)}{\sigma} \tag{3}$$

$$Y_{Pred.-Actual} = \sigma \cdot Y_{pred.-standardized} + \mu \tag{4}$$

The μ indicates the mean, while σ denotes the standard deviation of the employed data set. In addition, N represents the amount of the dataset, and d_i represents the value of each data in the dataset. Eq.(3) represents the standardization of the data before training, and Eq.(4) specifies the actual data projected ($P_{Pred.-Actual}$) to evaluate the performance of the testing model relative to the trained model [37]. All experiments used in this study are performed using Python 3.8 on a local machine with six Core i7-9750H microprocessors, 16 GB memory, and NVIDIA GeForce GTX 1660 Ti with Max-Q design.

B. Indicators of measurement used to assess the models' effectiveness

Equations (5-8) define the performance metrics for all models. The first evaluation matrix is the Mean Absolute Error (MAE), which is illustrated by the equation (5). The second is the Mean Square Error (MSE), which is described

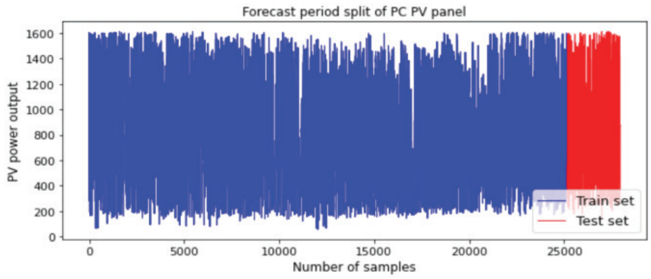

Fig. 1. Forecast period split for Polycrystalline PV panel for the year 2019.

in Eq.(6), followed by the Root Mean Square Error (RMSE) and the Coefficient of determination (R2), which are described in Eqs. (7) and (8), respectively. The values of y_i and $\hat{y}_i$ corresponded to the expected and actual values, respectively. While y_{avg} represents the median of the actual values.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|(\hat{y}-y)| \qquad (Wh/m^2) \tag{5}$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(\hat{y}-y)^2 \qquad (Wh/m^2) \tag{6}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{y}-y)^2} \qquad (Wh/m^2) \tag{7}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(\hat{y}-y_{avg})^2}{\sum_{i=1}^{N}(y-y_{avg})^2} \tag{8}$$

C. Machine Learning Model

In this work, different ensemble ML models, including ETR, DTR, RFR, AdaBoost and GBR, were utilized to forecast the power output of PC PV based panels for the 2019-year data and determine the appropriate predictive method which achieves the minimum error according to performance matrices

1) Decision Tree Regressor (DTR)

DTR is an efficient regression problem-solving technique. The primary premise of the DTR method is to decompose a difficult task into multiple simpler ones, which may result in an easier-to-understand solution [38]. A DTR represents a set of criteria that are hierarchically arranged and applied gradually from the tree's roots to its leaves [39]. The structure and interpretability of DTs are transparent. Decision Trees generate a trained model that can express logical rules, afterwards utilized to forecast new datasets by repeatedly dividing [40]. According to Breiman et al. [39], in a DTR technique, data characteristics are described as predictor variables. The target variables in regression issues are continuous.

2) Random Forest Regressor (RFR)

RFR is a tree-based ensemble approach created to overcome the weaknesses of the Classification and Regression Tree (CART) method. RFR comprises many weak DTs learners generated parallel to minimize the model's variance and bias [41]. First, random forest is trained using N bootstrapped sample sets from the source dataset. Then, every bootstrap is utilized to construct a regression tree. In this stage, just a limited number of randomly picked K predictors are chosen as split candidates rather than employing all available predictors. These two stages are continued until M such trees are created. Then, new data is predicted by integrating the M trees' predictions. RFR utilizes bagging to improve the diversity of the trees by growing them from several training datasets, hence decreasing the model's total variance [28]. The expression of an RFR is expressed as in Eq. (9):

$$\hat{f}_{RFR}^{M}(\mathrm{x}) = \frac{1}{M}\sum_{i=1}^{M} T_i(x) \tag{9}$$

Where M is the number of trees, $T_i(x)$ represents each DT built based on the bootstrapped samples, and x is the input variable.

3) Extra Trees Regressor (ETR)

ETR [42] strategy is a relatively new ML approach created to expand the RFR method and is less probable to overfit a dataset. ETR adopts a similar approach as RF and trains each base estimator using a random subset of characteristics [40]. Nonetheless, it randomly picks the best feature and corresponding value for dividing the node [40]. In addition, ETR trains each regression tree using the complete training dataset. However, RF employs a bootstrap replica to train the model.

4) Gradient Boosting Regressor (GBR)

Based on the Decision Tree and Boosting methods, GBRT is another sort of ensemble method. Using a gradient descent algorithm, this approach calculates the model loss after every base learner is added to the GBRT ensemble. Then, the procedure augments the model with a tree that reduces the loss. To increase the ensemble's performance, the output of every base learner is added to the outcome of the sequences created by the tree. This method is described in full in [43].

5) Adaptive Boosting (AdaBoost)

AdaBoost is an ensemble technique that merges several base learners into one powerful learner. DT method with a single level is the most common method used with AdaBoost. In this strategy, DTs are added successively and taught as base learners. The procedure is repeated till a certain number of learners have been produced or until the training error can no longer be reduced. AdaBoost is utilized for regression tasks by computing the weighted median prediction of the ensemble's learners. This procedure is outlined in [44].

To conclude, Figure.2 describes forecasting solar PV power output based on Polycrystalline technology employing several ensemble models mentioned above. The following steps will be performed during the entire procedure:

***Step 1**:* The first step contains inputs such as wind speed, solar radiation, time, and the actual power produced by the Polycrystalline PV panel. All prior inputs with the seven previous readings of solar radiation and actual energy produced will be integrated to provide a dataset for resolving the forecast PV power output problem [45]. The consideration of time as an input feature is inspired by the idea of domain encoding [46], which was used in deep transformers (position encoding), and in ConvOrient (rotation encoding) [47]. Domain encoding is an inductive bias that reduces the deficiencies of bottom-up approaches [48, 49].

***Step 2**:* A preprocessing step separates the collected data into training and testing, with 80% of the data going into training and 20% testing.

***Step 3**:* The selected ensemble models are trained to forecast PV power output.

Step 4: The regression ensemble models are evaluated utilizing the performance metrics detailed in the methodology section.

***Step 5**:* The best regression model is selected, and the final PV power generated forecast is stated

III. Results and Discussion

Several ensemble ML methods were used to forecast the solar PV's output power. The effectiveness of ML approaches to accurately forecasting the output power of a PV system was proved by comparing forecasted data to actual data.

Table 1 shows the PC PV panel power ML prediction data. The AdaBoost model had the best performance among the ensemble models, with MAE and RSME values of 15.36 and 25.05, respectively, while the other ensemble models achieved good results; for instance, ETR attained a value of 25.96 and 16.13 for RSME and MAE, respectively. On the other hand, the single model DTR performed poorly, with an MAE of 23.47 and RMSE of 35.72. The differences between the ensemble and single model were shown through the results presented in Table 1. The ensemble models (bagging and boosting approaches) were created to address CART's weaknesses. DTR suffers from bias and variance where simple trees have a significant bias, but complicated ones have a huge variance. Many DTs are combined to generate higher prediction performance than using a single decision tree alone in ensemble approaches. The ensemble model is based on the idea that a collection of weak learners might produce a strong learner when they work together, making the model more stable and achieving better results. For forecasting the hourly PV power output, base regression trees are insufficient. In contrast, ensembles of these trees substantially improved model performance. It may be inferred that AdaBoost has a strong capacity for nonlinear mapping generalization and can accurately forecast hourly PV power output.

From Fig. 3, it was evident that methods, including the AdaBoost and ETR, predicted well the actual data achieving lower RSME and MAE than the other ensemble models (RFR and GBR). Nevertheless, the single model, DTR, disclosed large deviations, with a gap from the centerline, resulting in significant deviations from the actual data. Moreover, AdaBoost and ETR models showed the highest

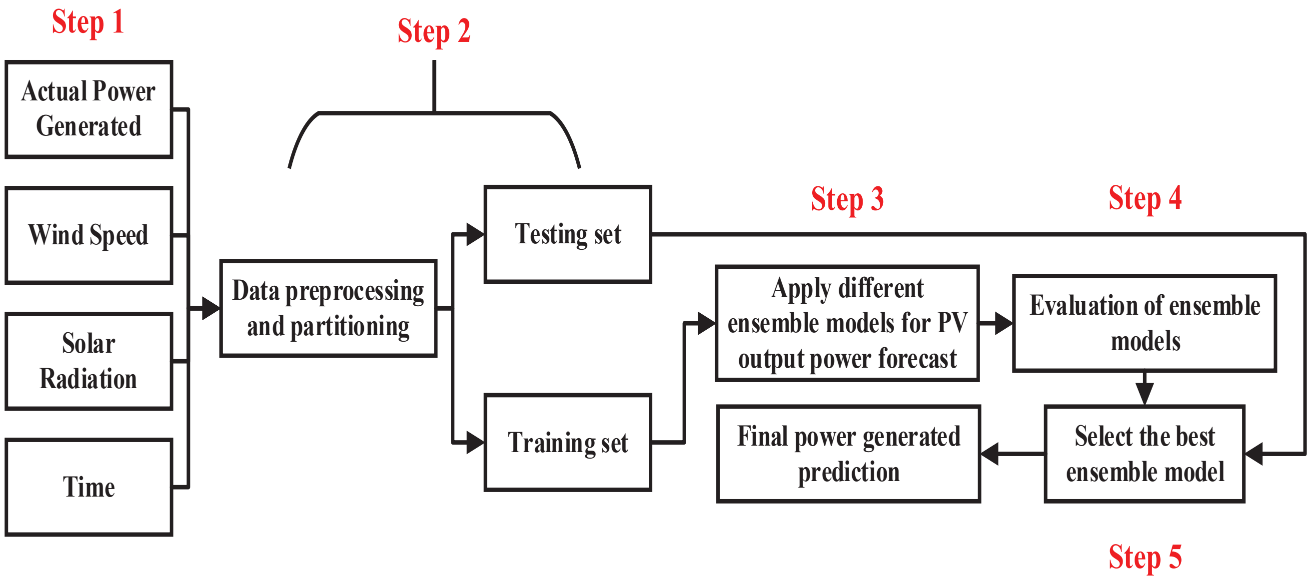

Fig. 2. Flowchart of the suggested approach for forecasting PV output power using Polycrystalline technology.

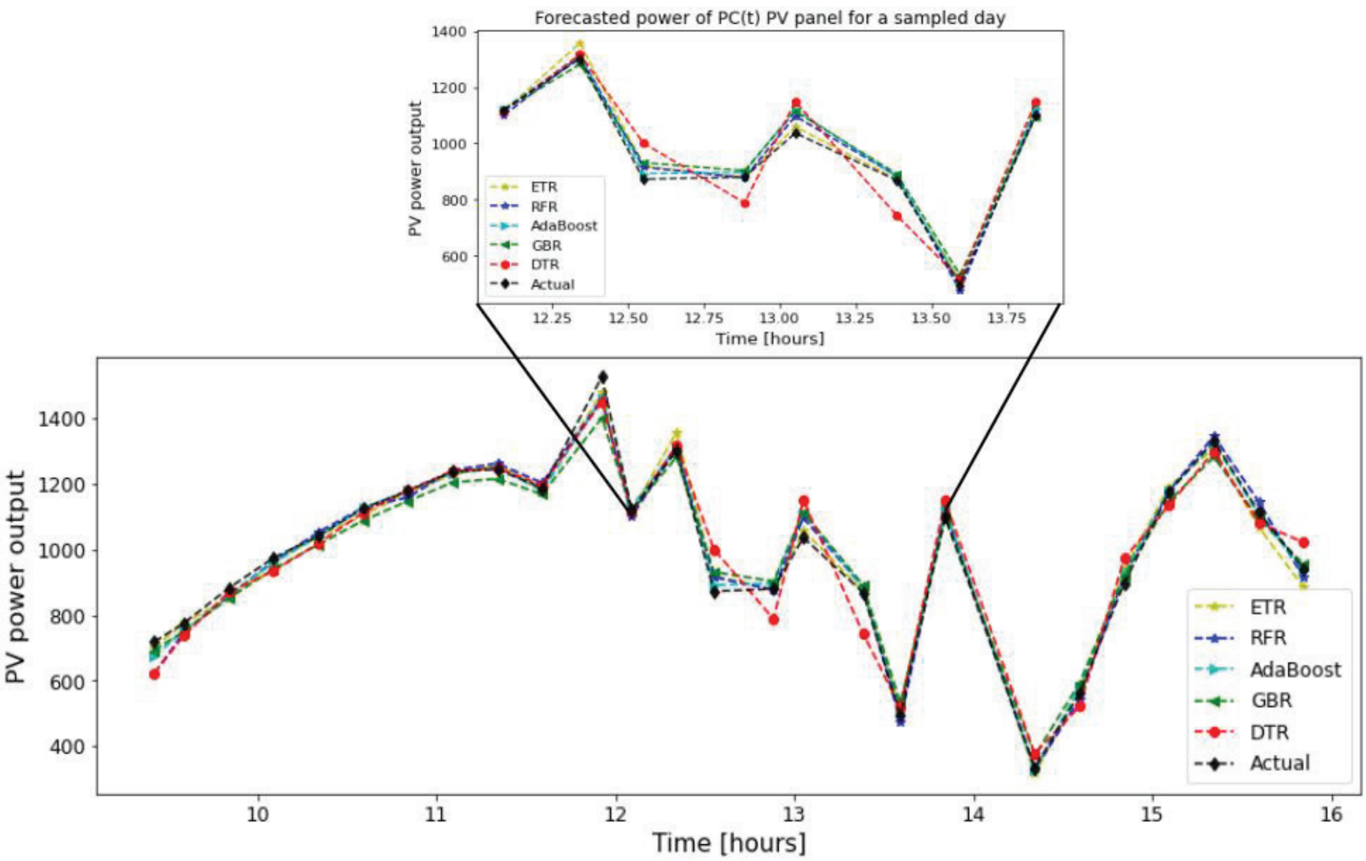

Fig. 3. The forecast results utilize several ensemble machine learning models with 2019 data for the Polycrystalline PV system.

Coefficient of determination R^2 of 0.9956 and 0.9953, respectively, indicating these two models' good performance and accuracy. The AdaBoost ensemble model achieved the best performance where it works better with interactions, revealed strong nonlinear mapping generalization capability, and can effectively predict hourly PV power output. The two ensemble models based on the bagging approach (ETR and RFR) achieved comparable results. However, the DTR method failed to catch the peaks of PV power generation, resulting in poor outcomes than other algorithms.

TABLE I. THE OBTAINED FORECASTING RESULTS USING DIFFERENT ML MODELS FOR THE PC PANEL-BASED USING THE 2019 DATA SET.

Results for the 2019-year data of PC based panel					
Performance Index	**Models**				
	AdaBoost	ETR	RFR	GBR	DTR
RMSE	**25.05**	25.96	26.16	27.27	35.72
MAE	**15.36**	16.13	16.34	17.94	23.47
MSE	**627.34**	674.04	684.56	743.51	1276.26
R^2	**0.9956**	0.9953	0.9952	0.9948	0.9911

Figure.4 illustrates how AdaBoost achieved the lowest RMSE and MAE based on the evaluation criteria compared to the other ML models. In addition, Figure.5 demonstrates that the AdaBoost model had the highest R^2 among the ML models utilized in this study.

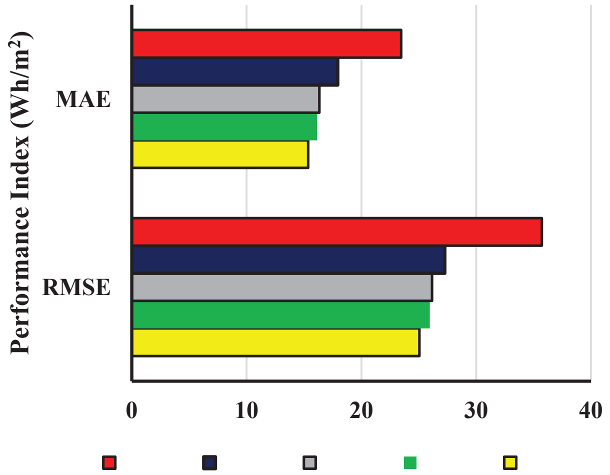

Fig. 4. Comparison between different ML models in terms of RMSE and MAE.

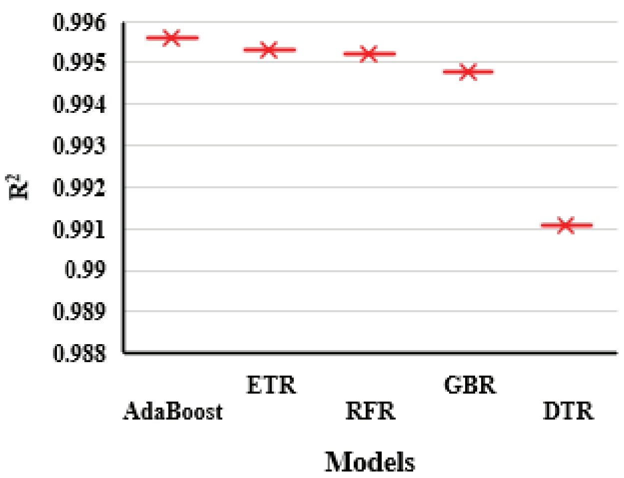

Fig. 5. Comparison between different ML models in terms of R^2.

IV. CONCLUSION

This paper examines the prediction of solar photovoltaic (PV) output energy using several ensemble machine learning (ML) models based on Polycrystalline technology. The PV power production is predicted by several ensemble machine learning models, including AdaBoost, ETR, RFR, GBR, and the single base model DTR. Solar radiation, wind speed, time, and the actual power delivered by Polycrystalline PV panels in 2019 were the primary input elements evaluated for forecasting solar PV output power. This study proposes and compares the AdaBoost model for forecasting PV power output to other ensemble machine learning techniques. AdaBoost outperformed the other selected machine learning techniques. However, DTR performed poorly. Root Mean Square Error (RMSE) values for the AdaBoost model were 25.05 and Mean Absolute Error (MAE) values were 15.36. In contrast, the DTR model fared badly, with MAE and RMSE values of 23.47 and 35.72, respectively. The tree-based ensemble algorithms developed are capable of producing reliable and accurate hourly forecasts. The extension of this work will investigate hybrid ML models with hyperparameters tuning method to improve the PV power output forecast.

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