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Photovoltaic Power Forecasting based on Artificial Neural Network and Ultraviolet Index

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ABSTRACT The accuracy of photovoltaic (PV) power generation forecast can seriously affect the penetration ability of PV power into the existing power grid, which is one of the key approaches to achieve emission peak, as well as realize carbon neutrality. In the conventional forecasting methods, Global Horizontal Irradiation (GHI), Diffuse Horizontal Irradiance (DHI), temperature, wind speed, rainfall, etc. are considered as the mainly factors to forecast the PV output power, but ignore the impact of PV power generation caused by the whole PV system's decay over the 25–30 years lifecycle. The ultraviolet (UV) index, which reflects the quantity of 10–400 nm irradiation, has a strong correlation with such decay and power generation. This paper proposes a novel PV power forecasting model that involving UV index in an artificial neural network, using Adam method to optimize the training process with the Keras-tuner employed for optimization of the hyperparameters. Experiments demonstrate that the proposed model achieves more precise performance than conventional methods.

KEYWORDS PV power forecasting; artificial neural network; backpropagation neural network; UV index; Adam optimizer; Keras-tuner hyperparameter optimization.

I. INTRODUCTION

A. Background Information

In recent years, the usage of renewable energy has attained increased importance around the world. The environmental and ecological problems caused by greenhouse emissions have led governments and environmental organizations to work on shutting down old thermal power plants and encouraging the development of energy from renewable power instead. Currently, one of the most reliable and applicable renewable energy solutions is photovoltaic (PV) power.

However, the current power grid principle is that electricity production (power) and electricity consumption (load) should be equal. The disadvantage of PV is that the electricity generated by this means is not persistently stable, and it is difficult to use PV power independently. PV generation relies on solar radiation, so it is significantly affected by the weather and cannot be produced at night.

To overcome these disadvantages of PV power and enable its optimal use in the current power grid, accurate forecasting of PV power is vital. With more accurate predictions of PV power, the power grid could be controlled and dispatched efficiently and stably [1], thereby significantly increasing the penetration rate of renewable power.

B. Literature Review

Various methods of predicting the PV power output have been proposed. One type of forecasting approach involves applying historical data from the PV system to a time series model [2]. Regression model forecasts can be obtained by detecting the weights of individual data points to avoid outlier data having an adverse effect on the model [3]. Complex detailed models, which mainly use data from satellite measurements, can also predict the PV power [4], although the accuracy of the solar irradiation forecast plays a key role [5].

Artificial neural networks (ANNs) have become very popular in recent years for forecasting PV power, because they can easily handle nonlinear data sources, such as solar irradiation, ambient temperature, and humidity [6, 7]. Backpropagation neural networks (BPNNs) have also achieved good forecasting results. However, very few studies have taken ultraviolet (UV) data into consideration for enhancing the PV prediction accuracy.

UV irradiation performs almost highest irradiation of energy density, shows at Fig. 1 below, which seriously degrades silicon PV cells, ethylene-vinyl acetate encapsulated film, glass, cables, and other electronic parts. Thus, it can be expected that the characteristics of the whole PV system will be degraded by long-term exposure to UV irradiation [8]. Furthermore, as shows in Figs. 1, 2 below, that 200-400nm UV irradiation would contribute the power produce directly. Thus, using UV data in the forecasting model is likely to result in more accurate predictions, especially for long-term PV power generation [9].

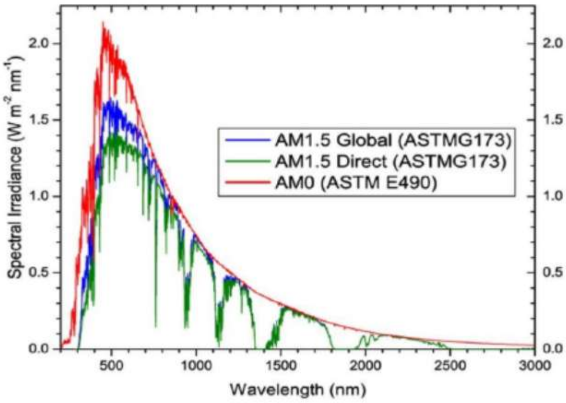

Figure 1. the distribution of spectrum irradiation under Air Mass1.5, show the distribution of spectrum irradiation under Air Mass1.5 (marked blue), the spectrum irradiation of UV(10-400nm) exceed about 1.35 W/m^2*nm^{-1}, which is almost the highest power of full range of irradiation [10].

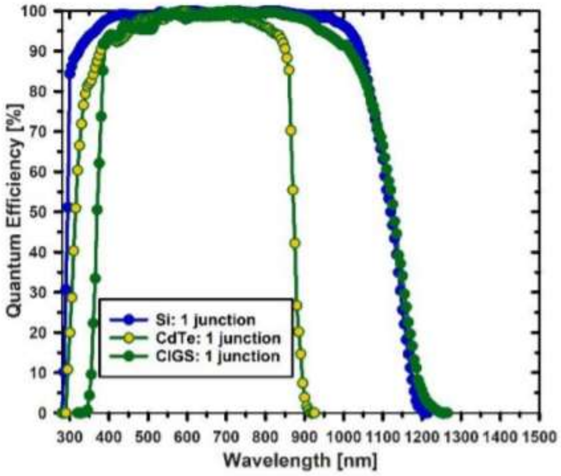

Figure 2. Quantum Efficiency of Silicon cell, shows the quantum efficiency of typical silicon cell at 200-400nm irradiation is 90%-95% [11].

The remainder of this paper is organized as follows. Section II introduces the research methodology, including the forecasting approach, dataset, and performance metrics. Section III presents the forecasting results given by the proposed model and analyzes the improvement over conventional models. Finally, the conclusions to this study are given in Section IV.

II. RESEARCH METHODOLOGY

A. FORECASTING MODEL

The proposed model is essentially an ANN [12], as this structure provides the ability to conveniently fit nonlinear factors in realizing PV power forecasting. Based on the principles of PV, the power is mainly generated according to the irradiation and surrounding circumstances [13].

The forecasting proceeds via a BPNN. The structure of the BPNN model is shown in Fig. 3.

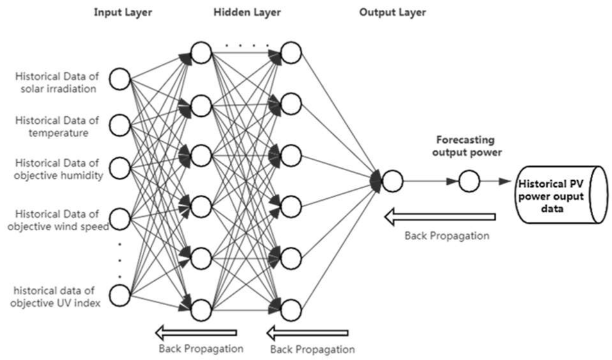

Figure 3. BPNN structure diagram for PV forecasting, shows the structure, forward propagation and back propagation of the neuron network.

Key factors collected from meteorological stations based at the PV plant are fed into the network, victor $\boldsymbol{x^1}$ in the input layer, is consist of input variables $x_1^1, x_2^1, \cdots x_7^1$, which are Global Horizontal Irradiation (GHI), Diffuse Horizontal Irradiation (DHI), Wind Speed (WS), Wind Direction (WD), Ambient Temperature (AT), Rain Fall(RF) and UV index (UV) [14].

After initialize the weights $\boldsymbol{w^i} = \left[w_1^i, w_2^i, \cdots w_7^i\right]^{\boldsymbol{T}}$ and bias $\boldsymbol{b^i} = [b^i]$ vector the forward propagation is through the way as indicated in equation (1), (2) [15]

$$\boldsymbol{a^i} = \boldsymbol{Relu}(\boldsymbol{x^i})\ (\boldsymbol{i} > \boldsymbol{1}) \tag{1}$$

$$\boldsymbol{x^{i+1}} = \boldsymbol{w^i a^i} + \boldsymbol{b^i} = \tag{2}$$

i indicate the no. of layer, if *i*=1, $\boldsymbol{a^i} = \boldsymbol{x^i}$**,** Relu function is the activation function proposed in the model.

By using the gradient descent method and back propagation algorithm, the proper weights and biases for the minimum point of loss can be found through repeated iterations, as shows in Fig. 4.

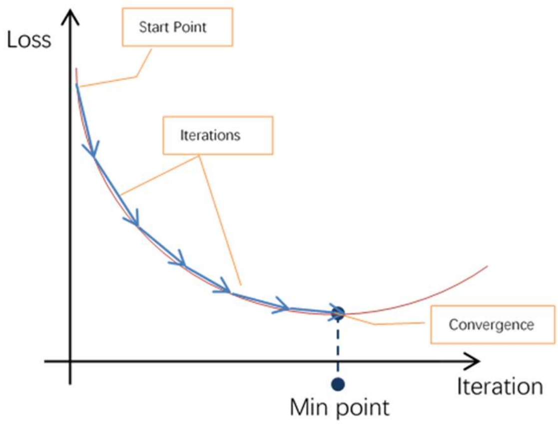

Figure 4. Illustration of the gradient descent method, where the loss decreases on each iteration

To avoid the impact of noisy gradient caused by individual and diversity input variables, meanwhile shorten the training duration, the Adam optimizer is applied to the neuron network and training process [16].

To optimize the hyperparameters within a limited range, the Keras tuner is used [17]. The Keras tuner is a library that helps to identify the optimal set of hyperparameters for the model [18, 19]. With the help of the Keras tuner, the most suitable hyperparameter values, such as the number of layers, number of neurons in each layer, and learning rate, are efficiently selected. The BPNN is then used to train the model using the available dataset.

By using the Keras tuner, suitable ranges of the learning rate, number of layers, and number of neurons in each layer can be determined [20]. The optimization objectives of the random search are to minimize the loss on the training set and validation set, and to maximize the Accuracy on the training set and validation set. The hyperparameter ranges are summarized in Table 1.

Table 1. Range of hyperparameters

Hyper Parameter	Value
Learning Rate	1e-2, 1e-3, 1e-4,1e-5
Number of Layers	2~50
Neurons of each Layer	3~100, step=5
Objective of Search	Loss, Accuracy, Validation_Loss, Validation_Accuracy

B. DATASET PROCESS

The dataset was collected from the Alice Springs DKA PV plant in Australia [21], and includes key factors such as active power, performance ratio, wind speed, temperature, global horizontal irradiation (GHI), diffuse horizontal irradiation (DHI), wind direction, and rainfall. These data are provided at 5-min intervals from March 2013 to September 2020. For the UV index, the available dataset was obtained from the Australian authorities [22], and has a resolution of 1 min.

Almost 1% of the values in the dataset were found to be erroneous, such as negative values of the active power and GHI/DHI values far beyond the 50% range [23]. These data were defined as noise and removed. By analyzing the correlation between active power and other factors, and based on the principles of PV, less-correlated factors, such as wind speed, wind direction, and rainfall, were also removed. As each factor in the dataset had different dimensions, with some values being tremendously higher than others, the remaining data were normalized to ensure that the gradient descent method would be effective [24].

The final dataset consisted of almost 590,000 individual data points. These were classified into a training set, validation set, and test set according to a ratio of 7:2:1. For the test set, the data were fixed, whereas cross-validation was applied to the data in the training and validation sets [25].

C. PEFORMANCE METRICS

To evaluate the performance of the model, we use the accuracy, mean squared error (MSE), and mean absolute error (MAE) metrics. These are defined as follows, where $\hat{y}_i$ and y_i denote the ith forecasted and actual values, respectively, and m is the size of the dataset [26, 27]

$$Accuracy = \left(1 - \left|\frac{\sum_{i=1}^{m}(\hat{y}_i - y_i)}{\sum_{i=1}^{m} y_i}\right|\right) \times 100\% , \quad (3)$$

$$MSE = \frac{1}{m}\sum_{i=1}^{m}(\hat{y}_i - y_i)^2 , \quad (4)$$

$$MAE = \frac{1}{m}\sum_{i=1}^{m}|\hat{y}_i - y_i| . \quad (5)$$

III. RESULTS AND ANALYSIS

To verify the performance of the forecasting model, four optimization objectives were considered in the training stage: loss, Validation_set_loss, Accuracy, and Validation_set _Accuracy. To visualize the performance, the first 24 h of predicted PV power and real PV power are compared in Figs. 5–8 for models with and without the UV index.

Fig. 5–8 show the first 24 h of the test set using loss, Accuracy, Validation_set_loss, and Validation_set_Accuracy, respectively, as the optimization objective. The deviation between the forecast and real PV power with the UV index is consistently smaller than that without the UV index. This is easily observed in the figures, especially for the peak range of power during the daytime.

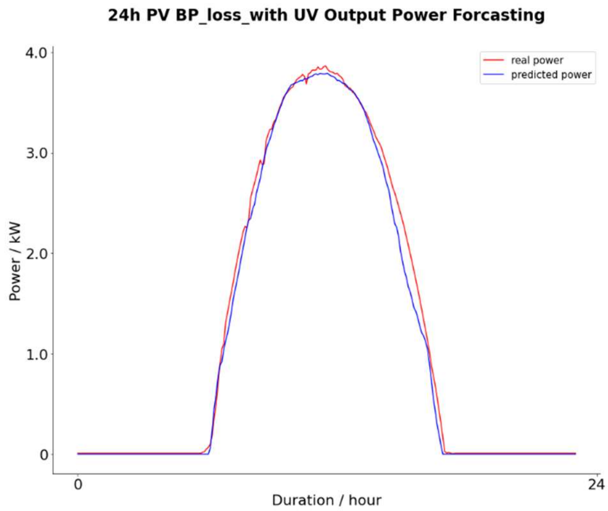

Figure 5. (a) Curve with UV index using loss as the optimization objective

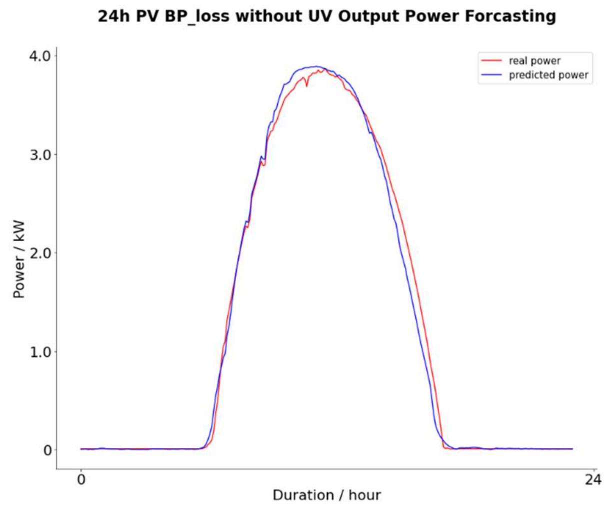

Figure 5. (b) Curve without UV index using loss as the optimization objective

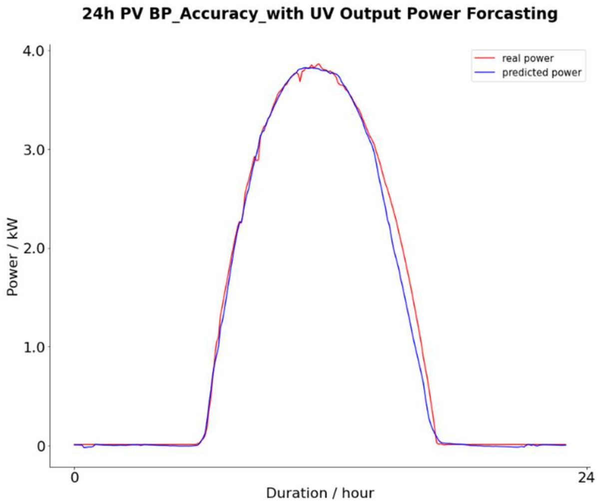

Figure 6. (a) Curve with UV index using Accurancy as the optimization objective

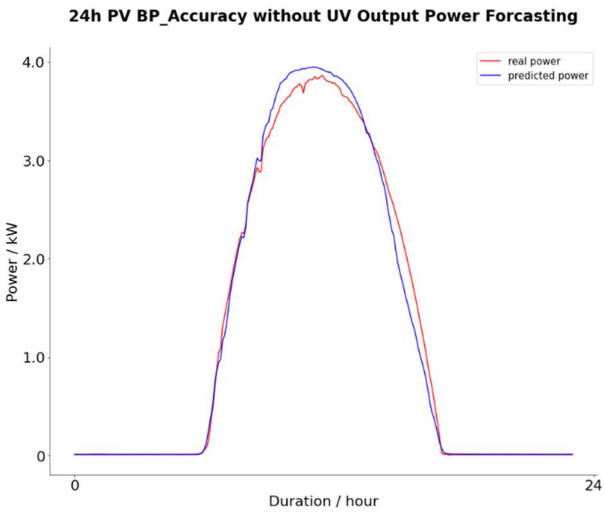

Figure 6. (b) Curve without UV index using Accuracy as the optimization objective

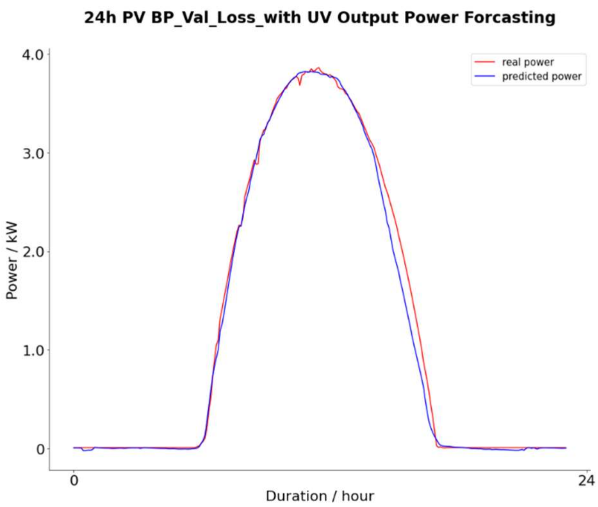

Figure 7. (a) Curve with UV index using Val_Loss as the optimization objective

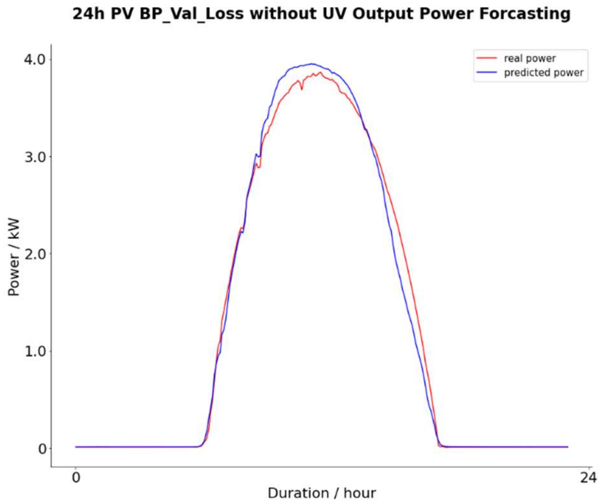

Figure 7. (b) Curve without UV index using Val_Loss as the optimization objective

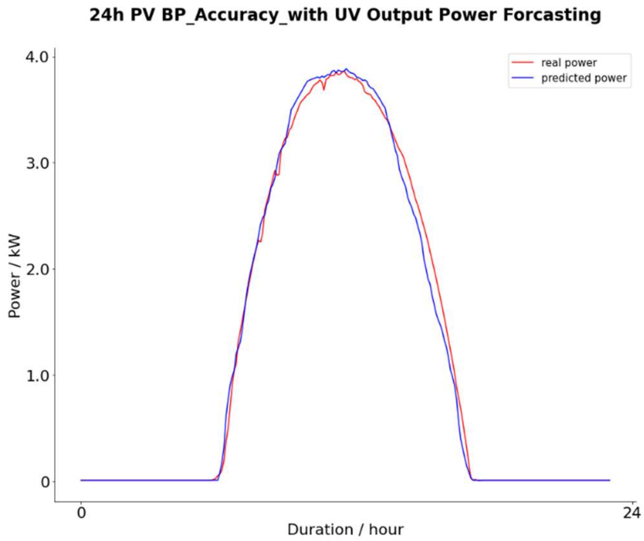

Figure 8. (a) Curve with UV index using Val_Accuracy as the optimization objective

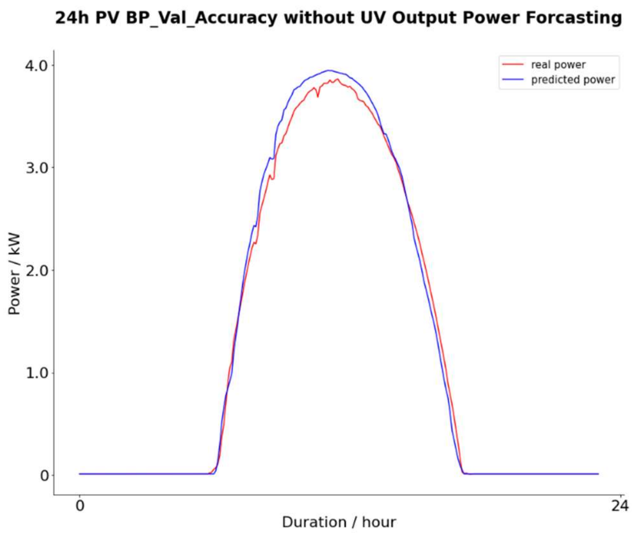

Figure 8. (b) Curve without UV index using Val_Accuracy as the optimization objective

Examining the model performance quantitatively, the forecasting results significantly improve when the model uses the UV index, regardless of whether the accuracy, MSE, or MAE metric is considered. As shown in Fig. 9, the improvement rates are 4.28–6.78% in terms of accuracy, 25.82–43.35% in terms of MSE, and 13.46–28.69% in terms of MAE (these values were calculated using the whole of the test set; details are presented in Table 3).

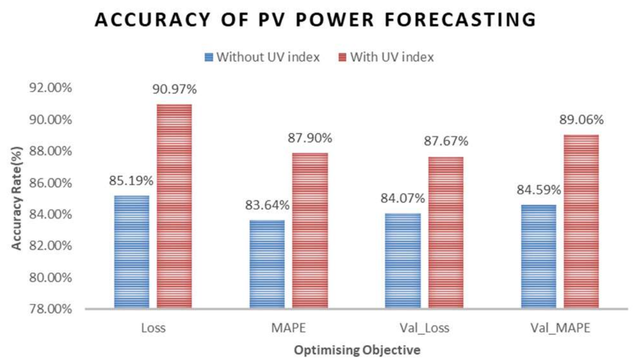

Figure 9. (a) Accuracy of PV power forecasting between models with and without UV index

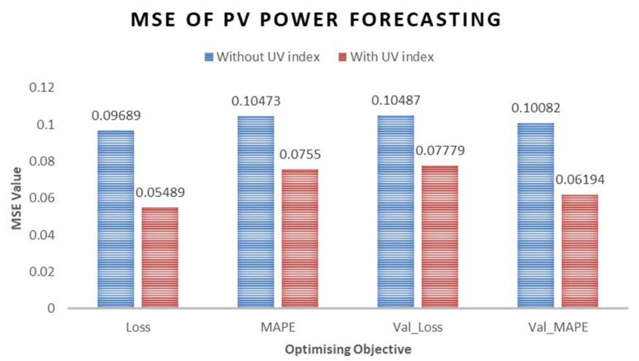

Figure 9. (b) MSE of PV power forecasting between models with and without UV index

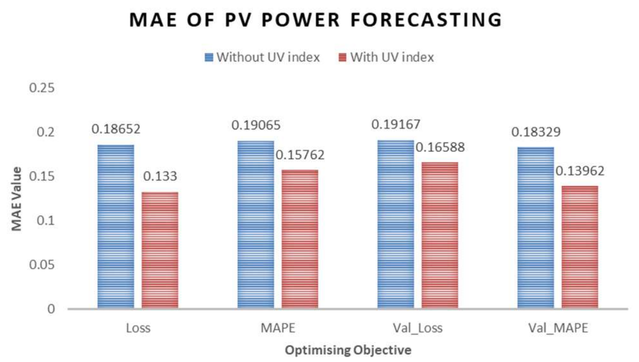

Figure 9. (c) MAE of PV power forecasting between models with and without UV index

Table 2. Comparison of accuracy, MSE, MAE using loss, Accuracy, Val_loss, Val_Accuracy as optimization objective

Optimizing Objective		Loss	ACC	Val_Loss	Val_ACC
ACC	w/o UV	85.19%	83.64%	84.07%	84.59%
	w/ UV	90.97%	87.90%	87.67%	89.06%
	Imp Rate	6.78%	5.09%	4.28%	5.28%
MSE	w/o UV	0.09689	0.10473	0.10487	0.10082
	w/ UV	0.05489	0.07550	0.07779	0.06194
	Imp Rate	43.35%	27.91%	25.82%	38.56%
MAE	w/o UV	0.18652	0.19065	0.19166	0.18328
	w/ UV	0.133	0.15762	0.16588	0.13962
	Imp Rate	28.69%	17.32%	13.46%	23.82%

where Acc– Accuracy, Imp – Improvement, w/ – with, w/o – without.

Table 3. Comparison of computation time using loss, Accuracy, Val_loss, Val_Accuracy as optimization objective

Optimizing Objective		Loss	ACC	Val_Loss	Val_ACC
Average Computation Time /second	w/o UV	2159.3	2475.5	2232.2	2597.1
	w/ UV	2596.2	2977.6	2459.8	2844.3

where w/ – with, w/o – without.

From Figs. 5–8, it is clear that the forecast output power matches the real output power very well. Moreover, by integrating the UV index into the model, the forecasting performance is obviously improved. The forecasting results for the whole test set are verified in terms of accuracy, MSE, and MAE in Fig. 9 and Table 2. The forecasting performance is significantly enhanced when the UV index is included in the model. Meanwhile, the computation cost have been evaluated by the average computation time as indicated in Table 3, due to involve much more data, the computation time of with UV index is a littlbe bit higher than without UV index.

IV. CONCLUSIONS

In this paper, we have presented a new method for forecasting the PV output power by introducing the UV index into the model. This allows the decay of parts during long-term operation to be considered, while enhancing the weight of 10–400 nm solar irradiation.

After filtering meaningless values from the dataset and removing factors with weak correlation, we applied the Keras tuner to identify the optimal parameters, which is more reliable than the conventional method of manual parameter tuning. Analysis and evaluation of the forecasting results in terms of accuracy, MSE, and MAE clearly indicate that our proposed method significantly improves the accuracy of PV power forecasting.

Compare to the existing model, such as times series model, regression model and etc., which the accuracy range is about 74%-87.8%, our proposed method have much promotion on forecast accuracy which is 83.64%-90.97%.

The limitation of this study is that our proposed method does not distinguish forecast in different weather. The future work will focus on promote the forecast accuracy by distinguishing different weather, furthermore, will investigate on that integrating time series as the auxiliary method in terms of weather gradient changes to promote forecast accuracy.

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