Daily Prediction of PV Power Output Using Particulate Matter Parameter with Artificial Neural Networks

Erdal Irmak, Mehmet Yesilbudak, Oguz Tasdemir
Gazi University, Faculty of Technology, Department of Electrical and Electronics Engineering, Ankara, Turkey.
Nevsehir Haci Bektas Veli University, Faculty of Engineering and Architecture, Department of Electrical and Electronics Engineering, Nevsehir, Turkey.
Kırşehir Ahi Evran University, Vocational College of Kaman, Department of Electricity and Electronics, Kırsehir, Turkey.
erdal@gazi.edu.tr, myesilbudak@nevsehir.edu.tr, oguz.tasdemir@ahievran.edu.tr

***Abstract*—Renewable energy sources play a critical role in meeting the increasing energy demand. Among them, solar energy stands out with the advantages of being environmentally friendly and protecting the ecosystem. However, its variable structure requires predicting the energy to be produced, properly. In this study, the impact of PM10 parameter on the power output prediction of photovoltaic (PV) energy plants was analyzed in a detailed manner. By the developed prediction model based on artificial neural networks (ANNs), lower root mean squared error and mean absolute percentage error were achieved. As a result, PM10 parameter has seemed to be an efficient input for the daily PV power prediction.**

Keywords—PV power, daily prediction, artificial neural networks, PM10 parameter

I. INTRODUCTION

In recent years, the interest in renewable energy sources has increased due to the rise in traditional fuel costs and the increasing awareness of global warming problems. Especially, photovoltaic power plants have increased their share in the energy market due to their rapidly falling costs and increased efficiency [1]. According to the International Energy Agency (IEA) [2], global PV power generation increased by 22% in 2021 to exceed 1000 TWh. In addition, in order to realize the zero-emission scenario until 2050, an annual average production increase of 25% is planned for the years from 2022 to 2030. In parallel, there has been a great increase in the PV energy production in Turkey. As of the end of June 2022, the installed power based on PV energy reached 8479 MW with the ratio of 8.35% in the total installed power [3]. Figure 1 shows the change in the installed PV power in Turkey.

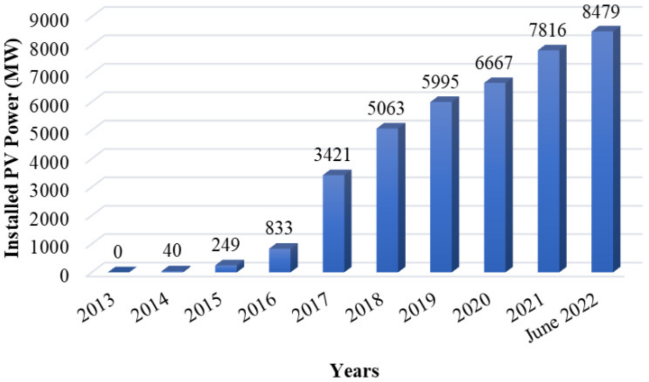

Fig. 1. Installed PV power change in Turkey

The instability and randomness of PV power generation are its major disadvantages. In order to eliminate these problems and to increase PV power reliability, it is important to correctly predict the PV power output [4, 5]. Since, PV power prediction is the most economical and feasible solution to control photovoltaic power [6, 7]. In case of examining the current literature in this issue, PV power output, meteorological data and numerical weather prediction data were used in [8]. Normalized root mean squared error (nRMSE) and mean absolute percentage error (MAPE) were realized as 6.11% and 4.7% for ANN, respectively. Solar radiation, air temperature, wind speed, air pressure, relative humidity and precipitation were employed in [9]. Long short term memory neural network model provided the MAPE of 22.31% and the RMSE of 0.71 MW. Variational mode decomposition and ant colony optimization-based 2NN model outperformed ANN, genetic ANN and ant colony optimization-based ANN models in hourly forecasts in [10]. Long short term memory model provided lower errors than ANN, autoregressive integrated moving average and deep neural network models in [11]. It performed better, especially in the time periods when meteorological data were very variable.

Numerical weather prediction data and SCADA data were used in [12]. Whale optimization algorithm-based least squares support vector machine model was found effective for the daily forecasts. Solar radiation, average temperature, panel temperature and relative humidity were utilized in [13]. In the daily prediction, RMSE and MAPE were realized as 0.11 and 3.31% by k-means-genetic algorithm-based back propagation ANN model, respectively. Air temperature, relative humidity, total horizontal and diffuse horizontal solar irradiation were employed in [14] and grey wolf optimization-based multilayer perceptron model provided the most successful daily prediction with the MAPE of 2.598%. PV power output, solar radiation, air temperature, relative humidity, wind speed, cloudiness and air pressure were utilized in [15]. Long short term memory model was found more successful, especially in the spring season. Relative humidity, precipitation, air temperature, sunshine duration and cloudiness were used in [16]. ANN was found good in the mid-term PV power prediction. In addition to these studies, ANN was found as one of the most-used methods for the PV power prediction in the literature [17].

In this study, in addition to the widely-used meteorological parameters in the literature, PM10 parameter has been utilized for the daily PV power prediction. The artificial neural network model based on PV power output, solar radiation, air temperature and PM10 inputs provided efficient prediction results.

II. ARTIFICIAL NEURAL NETWORKS

Artificial neural networks (ANNs) are inspired by the structure and function of the human brain, especially the neural networks inside the brain [18]. In general, the neuron model used in the design of many ANN models consists of a group of connections called synapses, each of which has its own weight [19]. Each input x_j is multiplied by the synaptic weight w_{kj}. The linear combiner output v_k is the sum of the inputs weighted by the respective synaptic strengths of the neuron. The bias b_k is responsible for reducing or increasing the net input of the activation function $\varphi(.)$. The neuron k illustrated in Figure 2 is described by (1) and (2). Hyperbolic tangent sigmoid activation function was utilized in this study.

$$v_k = \sum_{j=1}^{m} w_{kj} x_j \tag{1}$$

$$y_k = \varphi(v_k + b_k) \tag{2}$$

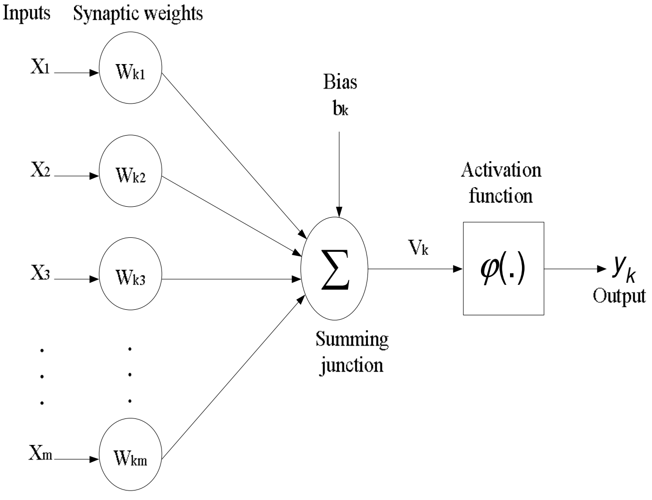

Fig. 2. Nonlinear model of a neuron, labeled k [20]

III. POWER OUTPUT PREDICTION RESULTS

In this paper, the total dataset employed for power output prediction contains PV power output, solar radiation, air temperature, relative humidity and PM10 parameters. This dataset covers daily measurements during the summer season of 2021 for a PV power plant located in Bursa, Turkey. PM10 denotes the particulate matter whose aerodynamic diameter is equal to or less than 10 µm [21]. In the power output prediction phase, two different datasets, named Dataset-1 and Dataset-2, were created from the total dataset. PV power output, solar radiation, air temperature and relative humidity inputs were included in the Dataset-1, while PV power output, solar radiation, air temperature and PM10 inputs were used in the Dataset-2.

Root mean squared error and mean absolute percentage error, expressed in (3) and (4) [22, 23], were utilized in order to compare the prediction results. In these equations, j is the number of data, PV_{act_i} is the actual power output of i^{th} observation and PV_{pre_i} is the predicted power output of i^{th} observation. Each dataset was divided into three subsets, named training, validation and test. 80% of each dataset was used for training the prediction model, while the remaining subsets with the ratios of 10% were used to validate and test the prediction model, respectively.

$$\mathrm{RMSE} = \sqrt{\frac{1}{j}\sum_{i=1}^{j}\left(\mathrm{PV}_{\mathrm{act}_i} - \mathrm{PV}_{\mathrm{pre}_i}\right)^2} \tag{3}$$

$$\mathrm{MAPE} = \frac{1}{j}\sum_{i=1}^{j}\left(\frac{\mathrm{PV}_{\mathrm{act}_i} - \mathrm{PV}_{\mathrm{pre}_i}}{\mathrm{PV}_{\mathrm{act}_i}}\right) \times 100 \tag{4}$$

For the training, validation and test subsets of Dataset-1, respectively, RMSE results were found as 1266.97 kW, 825.82 kW and 2178.12 kW, while MAPE results were computed as 2.22%, 1.55% and 3.83%. The power output prediction results for the test subset of Dataset-1 are illustrated in Figure 3. For the training, validation and test subsets of Dataset-2, respectively, RMSE results were obtained as 1055.25 kW, 907.28 kW and 984.7 kW, while MAPE results were calculated as 1.99%, 1.63% and 1.86%.

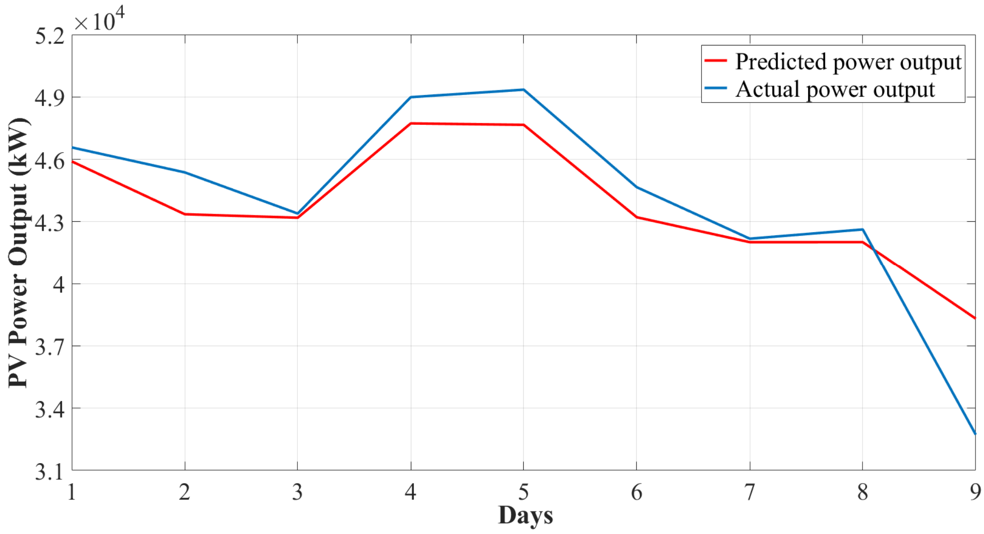

Fig. 3. Power output prediction results for the test subset of Dataset-1

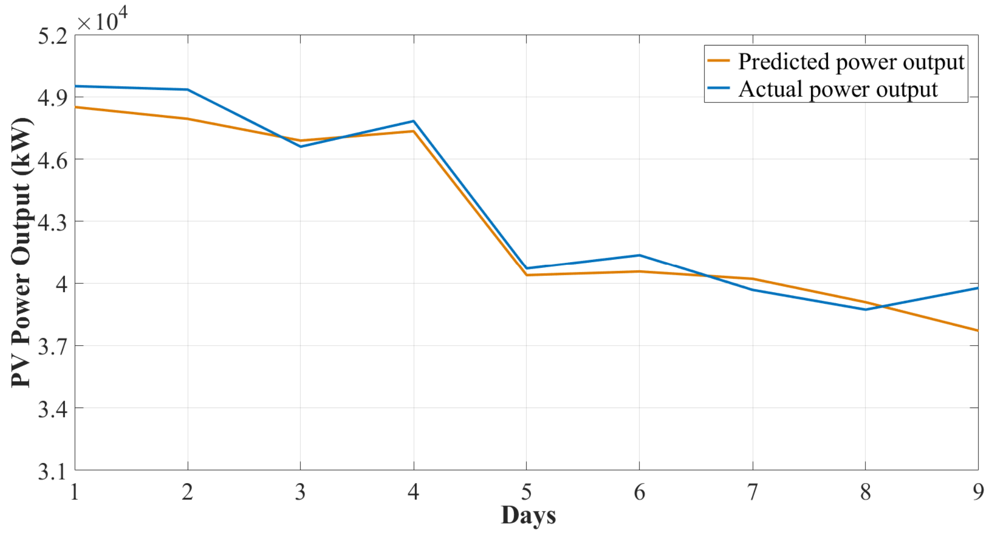

Fig. 4. Power output prediction results for the test subset of Dataset-2

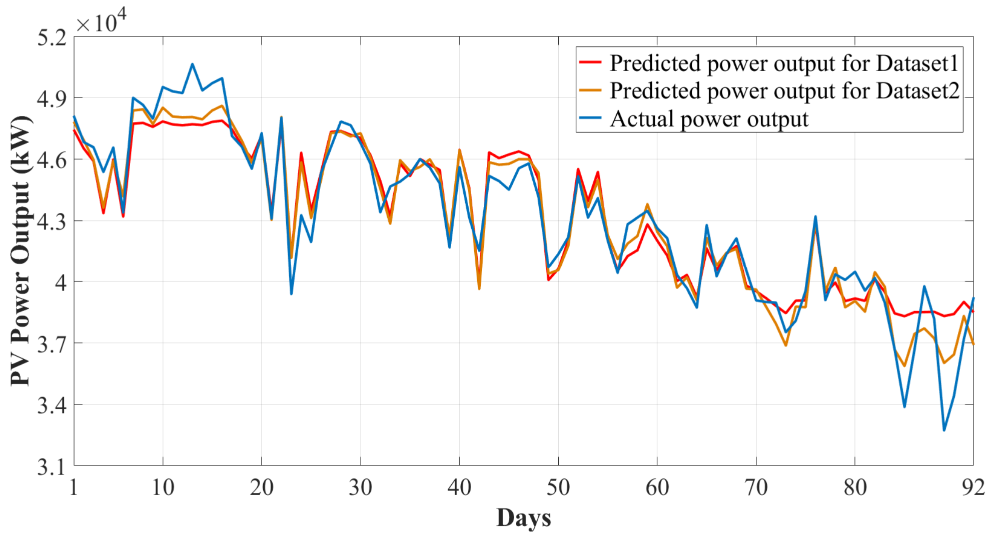

Fig. 5. Actual and predicted PV power outputs for all data

The power output prediction results for the test subset of Dataset-2 are depicted in Figure 4. In addition, RMSE and MAPE were found as 1349.81 kW and 2.32% for the entire Dataset-1, while the ones were obtained as 1034.92 kW and 1.94% for the entire Dataset-2. Furthermore, actual and predicted PV power outputs for all data are presented in Figure 5.

In line with these results, it was observed that the ANN-based prediction model developed using Dataset-2 provided more accurate results than the one developed utilizing Dataset-1. It can be concluded that the PM10 parameter contributes to improve the prediction accuracy of PV power output.

IV. Conclusions

PV power generation is affected by meteorological factors. For this reason, accurate prediction of PV power output is a crucial requirement. In this study, in order to evaluate the effectiveness of PM10 parameter on the prediction of PV power output, two different datasets based on PV power generation and meteorological data were created, and used by an artificial neural network model. According to the achieved results, the ANN-based prediction model employed for PV power output, solar radiation, air temperature and PM10 inputs performed well. Its improvement percentages were obtained as 23.33% and 16.38% for RMSE and MAPE measures, respectively. As a result, it has been observed that PM10 parameter has contributed to increase the prediction accuracy of PV power output. In future studies, the impact of PM10 parameter during other seasons can be analyzed together with other air pollution parameters.

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