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Research Article

Machine Learning Based PV Power Prediction Using Different Environmental Parameters of Turkey

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Abstract: The prediction of photovoltaic power generation provides the basis for the generation, transmission, and distribution systems of electrical energy, ensuring the establishment of uninterrupted and reliable energy systems. In the present study, environmental parameters and power values produced from photovoltaic panels were measured and recorded for 1 year with the measurement stations established in three different regions (Adıyaman-Malatya-Şanlıurfa) in terms of environmental parameters. Modeling has been developed for the power estimation to be produced using the MLP, CNN, LSTM, Stacked LSTM, Bidirectional LSTM, and CNN-LSTM methods on the extensive dataset. Predictions were obtained from the developed models with an accuracy rate of 98.9%, 98.6%, 95.1%, 95.0%, 95.0%, and 84.9%, respectively. As a result of the study, it has been seen that all of the proposed methods are successful for the problems of PV power prediction. In addition, it has been determined that the success rate of MLP and CNN methods is superior to other methods. Thus, with the developed forecasting models, PV power prediction for photovoltaic power systems desired to be installed by using environmental parameters belonging to different regions in any part of the world can be estimated with a high degree of accuracy.

Keywords- PV power prediction, Machine learning, Environmental parameters, MLP, CNN.

I. INTRODUCTION

The development of the global economy constantly increases the demand for electricity and exerts a great influence on environmental factors. The intensive use of fossil fuels causes serious problems in terms of greenhouse gas emissions (Luo, Zhang, and Zhu 2021). Renewable energy systems are promoted worldwide in energy production due to reasons such as global warming and climate change. In the modern world, efforts are made to minimize the use of fossil fuels for energy production and to increase the potential of renewable energy sources (Das et al. 2018). Energy is one of the main factors for the development of a country. Over the years, the demand for electrical energy is increasing due to the increasing living standards of people, as well as industrialization, modernization, and population growth (Das et al. 2018; Khandakar et al. 2019). Solar energy systems can be used in all areas of life, as it is an inexhaustible and non-polluting natural energy source. With the ever-decreasing prices of PV modules and the continuous depletion of fossil fuels, the modern electrical power level of PV power is expected to increase further (Khandakar et al. 2019). In recent years, an increasing amount of electricity has been produced from renewable energy sources, among which Photovoltaic power is an important source with a high rate. PV power is particularly promising because of its potential and availability. The total amount of solar energy the world receives at any one time in solar radiation is approximately 1.5 x 1018 kWh/year, which can fully meet the demands of human activities globally (Luo et al. 2021; Mohanty et al. 2017).

In an electric power system, the power value produced by the PV panel depends on the environmental impact parameters. With a short literature review, the prediction problems of PV power systems have been investigated with multiple approaches. Statistical modeling analyzes have developed different prediction models of PV power output for various temporal values ranging from minutes to several days. For the prediction of the power value in solar energy systems, it is frequently applied to analyze the values of environmental impact factors because it is healthy and easily accessible (Kara 2019).

In the study where machine learning-based photovoltaic power prediction using different environmental parameters and computational techniques were used to increase accuracy, and it has been found that the ANN model has outperformed other regression models such as linear regression, M5P decision tree, and Gaussian process regression (GPR) models (Khandakar et al. 2019). Another study using deep learning has presented that the proposed PC-LSTM (physics-constrained LSTM) model has had a stronger predictive ability than the standard LSTM (long short-term memory) model. It has been more robust against the PVPG (photovoltaic power generation) forecasting, and more suitable for PVPG forecasting with sparse data in practice. The PC-LSTM model has also outperformed traditional machine learning and statistical methods with higher PVPG forecasting accuracy (Luo et al. 2021). In a study using LSTM to predict daily solar radiation, it has been presented that the LSTM method has better performance than other machine learning models (Kara 2019). In the study comparing the prediction methods in photovoltaic panels, it has been determined that, overall, for the independent models, LSTM has presented the best performance regarding the root mean square error evaluation metric (RMSE). On the other hand, the hybrid model (CNN–LSTM) has outperformed the three independent models, although it requires longer training data time. The most important finding in this study is that the deep learning models of interest were found to be more suitable than other traditional machine learning models to predict solar radiation and PV power (Rajagukguk, Ramadhan, and Lee 2020). In another study, it was stated that the CNN-LSTM method outperformed the normal CNN method in predicting the PV output depending on the parameters of radiation, panel temperature, ambient temperature, and wind speed (Suresh et al. 2020). In the studies comparing the forecasting methods of different measurement criteria, it has been determined that the LSTM and Deep Long-Short Term Memory (DLSTM) methods have outperformed standard forecasting methods (Ayata, Saraclar, and Ozgur 2017). In another study comparing forecasting methods in photovoltaic power prediction, Wavelet transform and deep convolutional neural network (WT+DCNN) hybrid models have been found to give better results with the methods of mean absolute percentage error (MAPE), root mean square error (RMSE), and mean absolute error (MAE) (Wang et al. 2017).

The motivation of this study is the need to know in advance the solar energy potential of the region where the power plant is going to be established for project design and investments related to photovoltaic power plants. Since predicting the output power of the panels to be used in the projecting and planning studies of photovoltaic applications may provide a more accurate cost configuration, faulty investments are going to be prevented, and added value is going to be provided to the country's budget (Rajagukguk et al. 2020; Suresh et al. 2020).The article should begin with an introduction section, which includes the ideas and the basic objectives and approaches of the article, combining scientific knowledge, evidence-based information and logical discussions in different disciplines. This section should be written considering all readers. Technical terms, symbols and abbreviations should be defined when first used in the article.

II. MATERIAL AND METHOD

Dataset

In order to analyze the effect of PV power performance due to environmental parameters, a PV system recording PV performance and environmental parameters for one year was designed and implemented. The experimental setup was composed of two setups. In order to obtain PV power values with environmental parameters, a roof PV system equipped with sensors and an electronic system that records the parameters in real-time was designed. Data were recorded for one year between August 1st, 2017 and July 31st, 2018, using three different experimental setups in three different provinces of Turkey (Adıyaman, Şanlıurfa, Malatya) (Figure 1).

a b c

Figure 1. (a) Adıyaman, (b) Malatya, (c) Şanlıurfa measurement stations.

Temperature, solar radiation, wind, humidity, module temperature, and generated power parameters (Table 1) came to the microcontroller-controlled application circuit with the help of sensors at each regional test stations. These parameters were saved on the SD card in the application circuit with 5 minutes intervals.

Table 1. Installation parameters of PV systems

	Adıyaman	**Malatya**	**Şanlıurfa**
Module	1 x poly-c Si	1 x poly-c Si	1 x poly-c Si
System Power (Wp)	120	120	120
Longitute	37,747406 N	38,329668 N	37,171730 N
Latitude	38,219258 E	38,447213 E	39,002167 E
Altitude	680 meters	960 meters	510 meters
Global Radiation Value (annual) kWh/m2-day	4,37	4,38	4,34
Sunshine Duration (annual average) hours	8,11	7,87	8,31
Average Temperature (annual) Degree Celsius	17,3	13,7	18,5

III. METHODS

Multilayer Perceptron (MLP)

Multilayer Perceptron (MLP) is a feed-forward artificial neural network model. In the MLP model, communication between neurons is unidirectional and always forward (Gurney 1997). MLP consists of at least three-node layers. These layers are the Input layer, Hidden layer, and Output layer (Figure 2). While creating the input layer, each neuron is given the values of each feature in the dataset. A hidden layer can have one or more than one layers. Having more than one hidden layer will increase the non-linearity. The output layer consists of as many neurons as the number of classes if classification is to be made, and a single layer if regression is to be made. The weights and biases are responsible for completing the final output of the multilayer perceptron from the given inputs. In this case, the calculation of the total function would be according to Equation 1 (Çolak 2020; Gurney 1997; Rumelhart, Hinton, and Williams 1986).

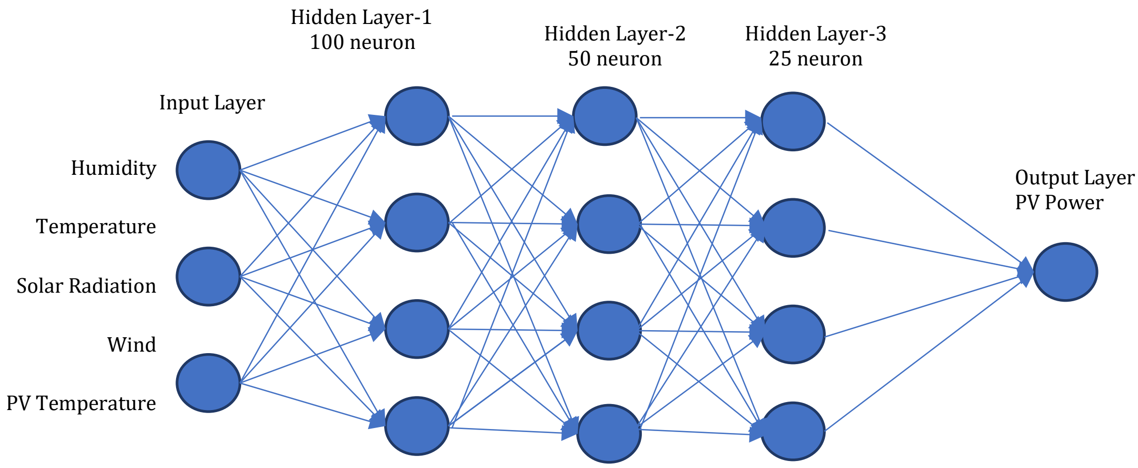

Figure 2. Multilayer Perceptron Mode

$$f_{net} = \sum_{i=1}^{n} W_{ij}.X_i \qquad i = 1,2, \dots n \tag{1}$$

Here n is the number of input neurons, Wi displays the weight values, Xi i. displays the input values.

In the current study, we used Humidity, Temperature, Solar Radiation, Wind, and PV Temperature values as the input parameters. We used 3 hidden layers. The 1st Hidden layer consists of 100, the 2nd Hidden layer consists of 50, and the 3rd Hidden layer consists of 25 neurons. We modeled the output layer as the PV power parameter to be predicted (Figure 2).

Convolution Neural Network (CNN)

CNNs, which are an effective tool for feature extraction and structure discovery in data, are widely used in many areas such as CNN pattern classification, image processing, sound processing, and pattern recognition (Wang et al. 2017). CNNs are similar to traditional ANNs in that they consist of neurons that self-optimize through learning. As in the ANN basis, each neuron performs operations by taking an input value. One of the biggest differences of CNNs is that the layers inside are composed of neurons organized in three dimensions (height, width, and depth) (O'Shea and Nash 2015). A CNN model generally consists of three main layers: the Convolutional layer, the Pooling layer, and the Fully connected layer (Figure 3).

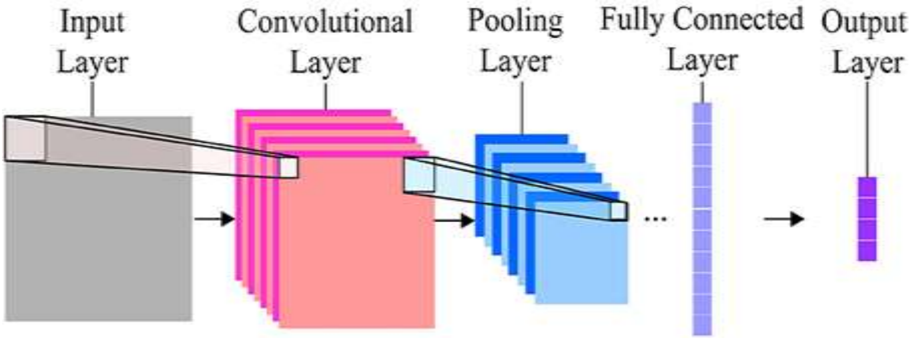

Figure 3. Multilayer CNN model (Peng et al. 2016)

Convolutional Layer: It is the core building block of the CNN model. It constitutes the main part of the computational load of the network. The primary purpose of the Convolutional Layer is to extract features from the input data. There is no connection between neurons in this layer. In addition, neurons in different layers are locally connected to each other with the weight-sharing technique (Wang et al. 2017).

During the convolution operation, the filter matrix slides across the height and width of the input dataset, performing the convolved multiplication, thus obtaining the two-dimensional representation. It is then passed through a user-defined activation function to generate a feature map with Equation 2.

$$y_j = f\left(\sum_{i \in M_j} x_i^{l-1} \otimes w_{i,j}^{l} + b_j^{l}\right) \quad (2)$$

Here $\otimes$ represents the convolution process.

Pooling layer: In order to reduce the number of parameters and computational load used in the CNN architecture, the pooling layer is usually used between the Convolutional Layers. The purpose of the pooling process is to reduce the size of the dataset and to prevent over-learning with network training.

Fully Connected Layer: It states that every neuron in the previous layer is connected to every neuron in the next layer. Similar to ordinary neural networks, in a fully connected layer, all neurons of one layer are connected to all neurons of the previous layer. The output from the Convolutional and Pooling layers represents the high-level attributes of the input dataset. The purpose of the fully connected layer is to use these attributes to classify the input dataset into various classes (Kesici 2019).

Long Short Time Memory (LSTM)

LSTM, developed by Hochreiter & Schmidhubert at the end of the 1990s, is a special type of RNN approach applied for modeling sequential data (Hochreiter and Schmidhuber 1997). The RNN model generally examines each piece of information in the input data iteratively, taking into account the value of the previous output. Although it has been claimed that this architecture performs learning that takes into account the information from previous time periods, it has been stated that this is not possible due to the gradient disappearance/explosion problem (Hochreiter and Schmidhuber 1997; Pascanu, Mikolov, and Bengio 2013). To overcome this problem, the LSTM architecture, which can remember long-term information, has been developed (Kara 2019).

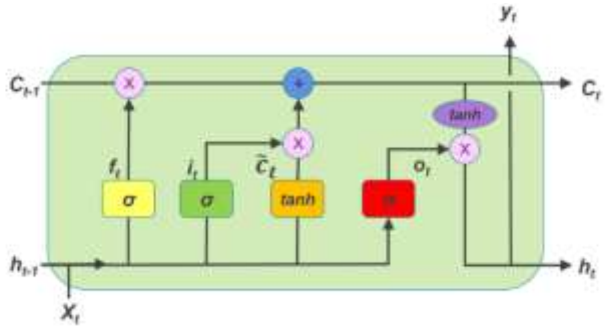

Figure 4. Long Short-Term Memory (LSTM) (Xiao and Yin 2019).

LSTM architecture consists of sequential blocks that repeat each other as shown in Figure 4. In general, the LSTM structure consists of 3 different layers: forget, input, and output layers. In the LSTM architecture, first of all, Xt and $ht{-}1$ information are used as inputs, and it is decided which information to delete. These operations are done in the forget layer (ft) using Equation 3 and sigmoid is used as the activation function.

$$f_t = \sigma(W_{f,x} * X_t + W_{f,h} * h_{t-1} + b_f) \quad (3)$$

In the second step, the input layer, where new information is going to be determined, comes into play, and firstly, (it) the information is updated with the sigmoid function using Equation 4. Then, the candidate information that will form the new information with Equation 5 is determined by the tanh function.

$$i_t = \sigma(W_{i,x} * X_t + W_{i,h} * h_{t-1} + b_i) \quad (4)$$

$$C_t = tanh\ (W_{c,x} * X_t + W_{c,h} * h_{t-1} + b_c) \quad (5)$$

Equation (6) creates new information.

$$C_t = C_{t-1} * f_t + i_t * C_t \quad (6)$$

Finally, the output data is obtained by using Equations (7) and (8) in the output layer.

$$o_t = \sigma(W_{o,x} * X_t + W_{o,h} * h_{t-1} + b_o) \quad (7)$$

$$h_t = o_t * tanh\ (C_t) \quad (8)$$

The process described above continues iteratively. Weight parameters (W) and bias parameters (b) are learned by the model in a way that minimizes the difference between actual training values and LSTM output values (Ayata et al. 2017; Fischer and Krauss 2018; Sagheer and Kotb 2019).

In the current study, we designed an LSTM model consisting of 20 blocks. We used Humidity, Temperature, Solar Radiation, Wind, and PV Temperature variables as input parameters. We predicted the variable PV Power at the output of the LSTM model. In the Stacked LSTM model, which is the new method formed as a result of the serial operation of two LSTM methods, we designed a different LSTM model consisting of 100 blocks in the 1st LSTM layer and 50 blocks in the 2nd LSTM layer.

We developed a model consisting of 200 blocks in the BiLSTM method, which is a bidirectional LSTM method. The BiLSTM method means that the signal propagates forward and backward in time.

Convolution Neural Network (CNN)

Accurate estimation of PV power generation is important to ensure grid stability and encourage PV installation. Therefore, the accuracy measurement of the PV power prediction model is a vital part of this study. Various evaluation metrics have been proposed to measure the accuracy of PV power prediction models. Evaluation metrics selected in this study were decided based on the recommendations of Solar PV power output estimation studies and reports (Madsen et al. 2005; Rajagukguk et al. 2020; Suresh et al. 2020; Yang et al. 2018). Root Mean Square Error (RMSE), Mean Square Error (MSE), Main Bias Error (MBE), Mean Absolute Error (MAE), and Explained Variance (EV) metrics are widely used to evaluate the accuracy of PV power prediction models.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N} e_i^2}$$ (Das et al. 2018)

$$MSE = \frac{1}{N}\sum_{i=1}^{N} e_i^2$$ (Das et al. 2018)

$$MBE = \frac{1}{N}\sum_{i=1}^{N} e_i$$ (Das et al. 2018)

$$MAE = \frac{1}{N}\sum_{i=1}^{N} |e_i|$$ (Das et al. 2018)

$$EV = 1 - (vay\ (y - yi)/var\ (y))$$ (Das et al. 2018)

IV. RESULTS AND DİSCUSSİON

In the current study, all models were implemented in the Spyder editor using the Python programming language. TensorFlow and KERAS libraries were used as deep learning tools. In addition, data analyzes were performed using Sci-kit learn and other basic Python libraries. A computer with Windows 10 operating system, IntelCore i7 2.2 GHz processor and 32 GB RAM was used. At the same time, deep learning algorithms training processes were carried out with an 8 GB GeForce GTX 1070 Nvidia graphics card.

Temperature, Wind, Humidity, PV Temperature, Solar Radiation, and Produced PV Power parameters from Adıyaman, Malatya, and Şanlıurfa regions were measured every 5 minutes and recorded on the SD card. Environmental parameters and generated power data were recorded for 365 days between August 1, 2017 and July 31, 2018. For each region, 288 data per day and 105,120 data per year were used. A total of 315,360 data from Adıyaman, Malatya, and Şanlıurfa regions were used in the model analysis (Table 2). From these data, Humidity, Temperature, Solar Radiation, Wind, and PV Temperature values were used as inputs in the models. Environmental parameters recorded for 7 days are presented in Figure 5.

Table 2. Details of the parameters used for the model

Parameters	Min	Max	Mean	Std	Unit
Humidity	0	99	37,4523	21,7772	%
Temperature	-10	47	17,0627	9,82075	Degree Celsius
Irradiance	23,3465	1460,3	220,535	275,781	Watt/m^2
Wind Speed	0	14,6631	0,92849	1,05857	km/h
PV surface Temperature	-14	66	21,562	13,0396	Degree Celsius
Power	0	136,02	20,3887	29,7764	Watt

The PV Power values produced as a result of the analysis of the models were predicted. The data from Adıyaman, Malatya, and Şanlıurfa were combined. The PV output power (288 x 1) generated from the environmental parameters (288 x 5) measured during 1 day was predicted by randomly separating the data for 20% test and 80% train.

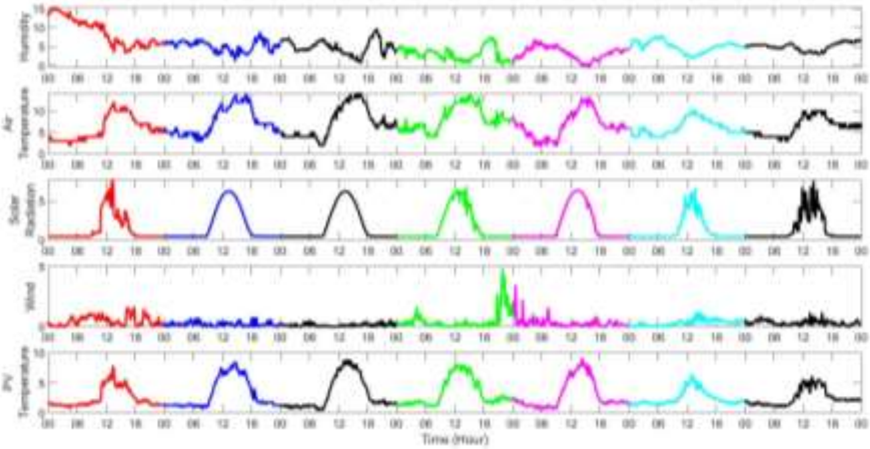

Figure 5. Environmental parameter values for one week.

Separate models were created using MLP, CNN, LSTM, Stacked LSTM, Bidirectional LSTM, and CNN-LSTM methods. The PV power value was predicted for each model using the input parameters humidity, air temperature, solar radiation, wind, and PV temperature (Figure 6 to Figure 11). The maximum power of the PV panel in the middle of the day and the bell shape pattern provided by the values close to zero in cases after sunrise or sunset has been clearly observed.

Figure 6 demonstrates the monitored and estimated PV output power as a result of the model developed with the MLP method. It has been seen that the monitored power and estimated power values for a day from the spring, summer, autumn and winter seasons present a satisfactory performance in the graph. Monitored and estimated PV power values in CNN (Figure 7), LSTM (Figure 8), Stacked LSTM (Figure 9), Bidirectional LSTM (Figure 10) and CNN-LSTM (Figure 11) methods are presented.

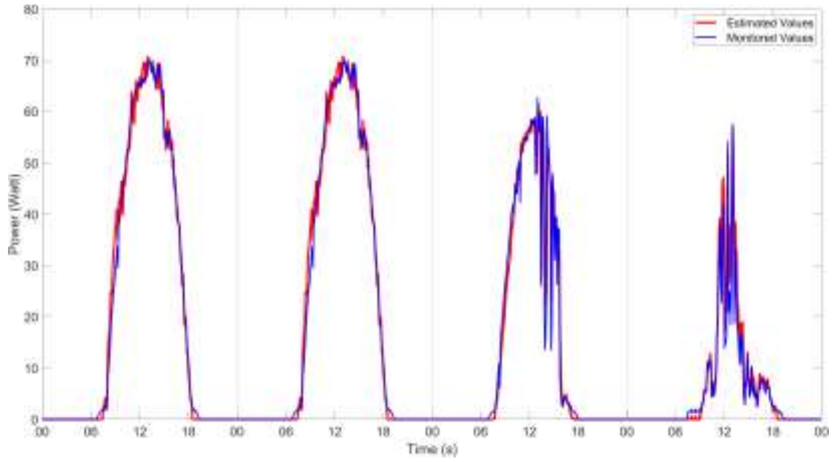

Figure 6. Comparison of the monitored and estimated values of the PV output power with the MLP method.

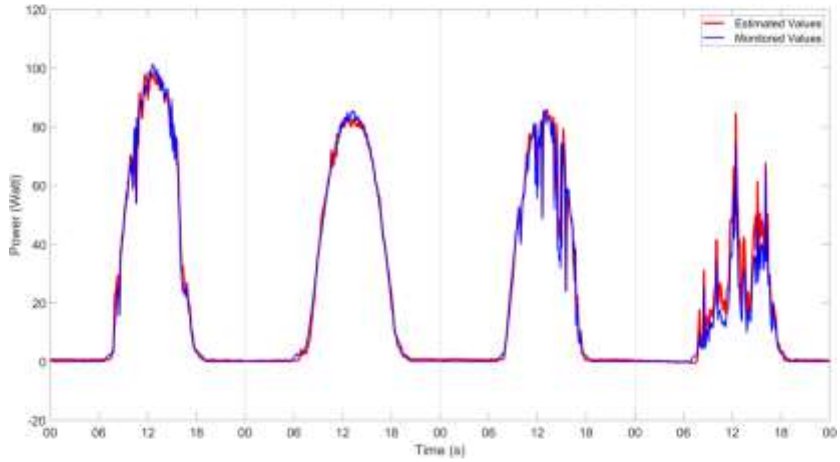

Figure 7. Comparison of the monitored and estimated values of the PV output power with the CNN method.

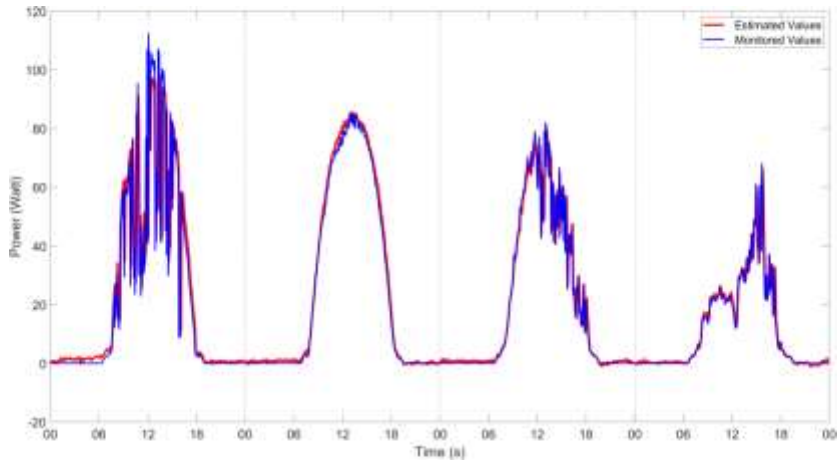

Figure 8. Comparison of the monitored and estimated values of the PV output power with the LSTM method.

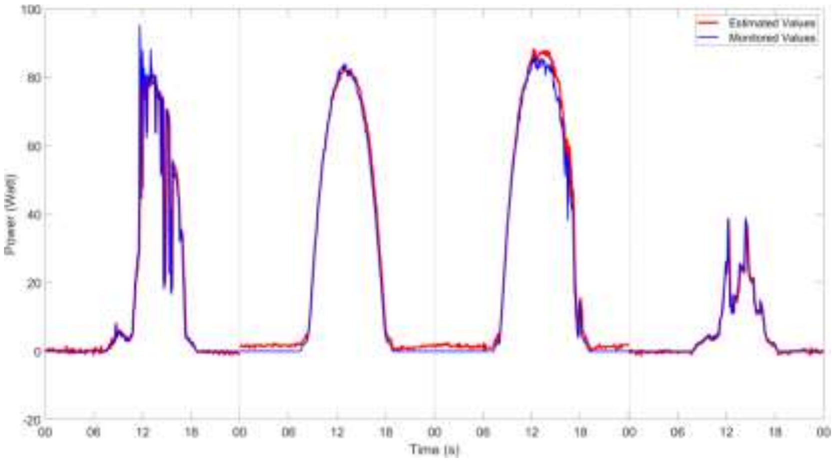

Figure 9. Comparison of the monitored PV output power and the estimated PV output power by the Stacked LSTM method.

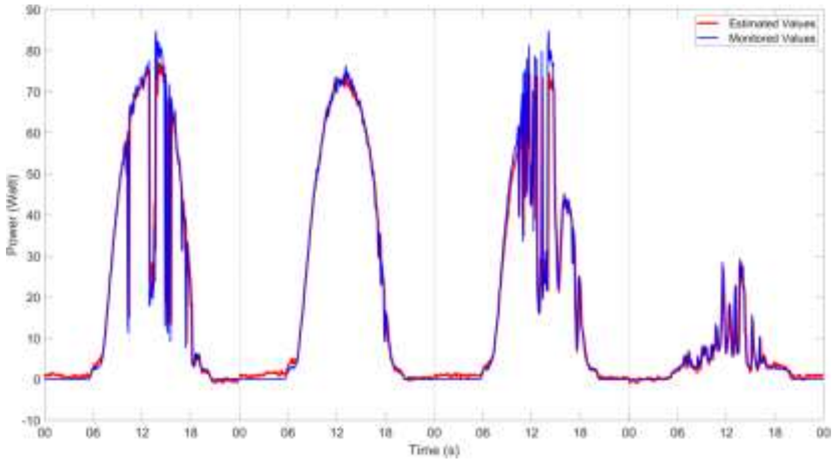

Figure 10. Comparison of the monitored PV output power and the estimated PV output power by the Biderctional LSTM method.

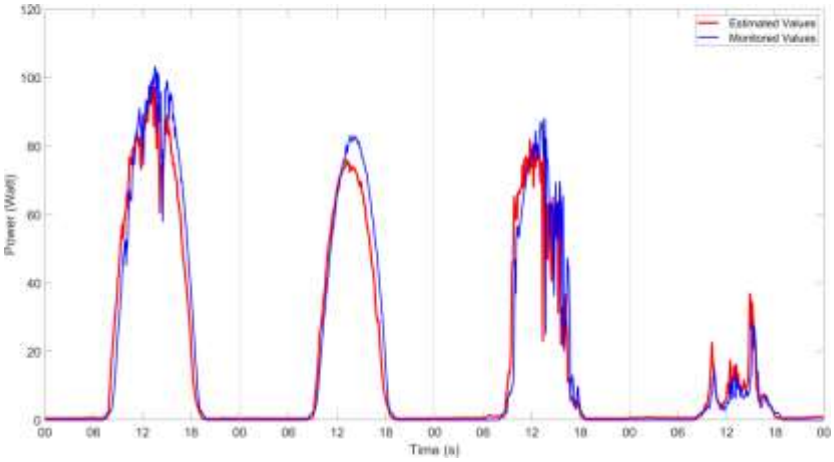

Figure 11. Comparison of the monitored PV output power and the estimated PV output power by the CNN_LSTM method.

From Figures 6-11, it can be seen that all models made using the MLP, CNN, LSTM, Stacked LSTM, Bidirectional LSTM, and CNN-LSTM methods can fulfill the PV power estimation task with acceptable accuracy. The estimated curves are generally compatible with the measured PV power values. However, the result obtained with the MLP and CNN model is smoother and better than the results of other models. It should be noted that the effects of environmental parameters in PV power prediction can cause some difficulties in the estimation, so it should be noted that not all methods can make a very good estimation at the same rate.

To better understand Figures 6-11, the evaluations of performance comparisons of the above PV power prediction methods are presented in Table 3. The results are similar to the graphical analyses. Higher R2 scores seen in MLP and CNN models indicate better prediction performance, confirming the superiority of MLP and CNN models over other compared models.

Table 3. RMSE, MAE, R2, MSE, and EV of each prediction model

Method	RMSE	MAE	R2	MSE	EV
MLP	3,360	1,691	0,98807	11,292	0,989
CNN	3,749	2,046	0,98554	14,059	0,986
LSTM	5,969	2,774	0,95018	35,626	0,951
Stacked LSTM	6,029	2,878	0,94917	36,352	0,950
Bidirectional LSTM	6,039	2,935	0,94900	36,473	0,950
CNN-LSTM	9,640	4,153	0,84876	92,933	0,849

V. CONCLUSION

One of the biggest problems in photovoltaic panel applications is the high costs they have at the initial installation stage. Although there have been serious cost reductions in recent years, the amount of energy these systems produce in response to plant costs is not high. Increasing energy demand requires the integration of solar energy into electrical grids. For projects and investments related to photovoltaic power plants, it is extremely important to predict the power to be produced by using the environmental parameters of the region where the power plant is going to be established. Accurate prediction of Photovoltaic power generation is essential throughout the development of the photovoltaic industry due to the need to meet increasing energy demand, mitigate climate change, and stabilize power grid systems. The amount of electrical energy produced by photovoltaic panels depends primarily on solar radiation, air temperature, humidity, wind speed, and photovoltaic module temperature. In the current study, environmental factors (solar radiation, temperature, wind, humidity, PV module temperature) and power values obtained from photovoltaic panels were measured and recorded for 1 year with the measurement stations established in three regions (Adıyaman-Malatya-Şanlıurfa) that are different from each other in terms of environmental factors. Modeling has been done for the power prediction to be produced using the MLP, CNN, LSTM, Stacked LSTM, Bidirectional LSTM, and CNN-LSTM methods on the extensive dataset. As a result of the research, it has been seen that all of the proposed methods are successful for PV power prediction problems. In addition, the success rate of MLP and CNN methods was found to be superior to other methods.

VI. CONFLİCT OF INTEREST STATEMENT

There is no conflict of interest between the authors.

VII. FUNDİNG

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VIII. AUTHOR CONTRİBUTİONS

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Yasin Icel and Mehmet Ismail Gursoy. The first draft of the manuscript was written by Yasin Icel and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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