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RESEARCH ARTICLE

Extreme Learning Machine-Based Power Forecasting in Photovoltaic Systems

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ABSTRACT With the consuming of fossil fuels, sustainable alternative sources are needed for energy production. Renewable energy is an important source in the fight against climate change and provides economic benefits by increasing energy security. Solar energy is one of the popular renewable energy sources. The photovoltaic system is a technology that produces electrical energy from solar radiation. These systems, which are clean, renewable, and environmentally friendly, are important in terms of meeting our future energy needs. Photovoltaic system power forecasting is an important tool for both energy planning and energy management, as it increases the predictability of bulk power system. In addition, power estimates also allow improving the system efficiency and planning the maintenance date. In this study, due to its high accuracy, fast computation, and easy applicability, Extreme Learning Machine (ELM) method was used to estimate the daily average energy production of a solar power plant located in Elazig/Turkey. To improve the performance of the model, ELM's hyperparameters were optimized using the Modified Golden Sine Algorithm (GoldSA-II). To show the power generation change that occurs in parallel with the seasonal weather change, graphs of the real power of different months from the four seasons and the power estimated by ELM are presented in the study. The radiation, temperature, wind speed, real power, and ELM predicted power values for the ten-month period in which the operating data were obtained are given in the table. By examining this table, the effect of weather conditions on production can be observed more clearly. The R and RMSE values of the ELM model, which are calculated separately for each month, are presented in the form of a radar chart. The average daily R and RMSE values calculated for the ten-month period were calculated as 0.95 and 0.0716, respectively, and the performance of the ELM model used in the study was proven by the calculated R and RMSE values.

INDEX TERMS Extreme learning machine, photovoltaic, power forecasting, renewable energy.

ABBREVIATIONS

AF	Activation Function.
ANN	Artificial Neural Network.
C	Regularization Coefficient.
DT	Decision Trees.
ELM	Extreme Learning Machine.
GoldSA	Golden Sine Algorithm.
GoldSA-II	Modified Golden Sine Algorithm.
GPR	Gaussian Process Regression.
HN	Number of Hidden Neurons.
LR	Linear Regression.
MAE	Mean Absolute Error.
RMSE	Root Mean Square Error.
SVM	Support Vector Machine.

I. INTRODUCTION

Today, the need for energy is constantly increasing. Fossil fuel reserves, which are used extensively in energy production, are limited and are decreasing continuously. In addition, fossil fuels have various negative effects on the environment such as global warming, melting of glaciers, pollution, etc. Therefore, qualities such as environmentally friendly, clean, reliable, and sustainability increase the importance of renewable energy.

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Renewable energy is energy obtained from natural sources that are self-renewing over time. Solar, wind, wave, hydraulic, biomass, hydrogen, etc. are some of the renewable energy sources.

Between the renewable energy sources, solar energy has become one of the most up–and-coming energy sources for generating power for both residential and industrial consumers because of its advantages of being plentiful, inexhaustible, clean, and environmentally friendly.

The establishment of a power plant requires many bureaucratic procedures and is also a costly task in itself. Therefore, before a power plant is built, a feasibility study is carried out for the power plant. How much benefit will be gained from the energy produced in the region where the installation will be made, how much energy is needed, the energy potential of the region, etc. are research topics.

One of these studies is to investigate whether the power plant installation makes sense in terms of economy. In this sense, a financial evaluation is made by taking into account the initial installation, operation and maintenance costs.

If the energy potential of the area to be installed is known in advance, the energy value that can be produced by the plant can be estimated, therefore the installed power of the plant is determined correctly and the equipment in the plant are selected accordingly. In fact, depending on the climatic conditions that change over time, the existing power plant capacity can be expanded by making power estimations again.

In PV power plants, which have faced a great growth in recent years, variable weather conditions cause problems in energy production. Although the highly use of PV in electricity producing systems have economic benefits, it may have negative effects on the stability of the power grid without accurate forecasts. Accurate forecasting of the power from PV energy producing systems is of great importance for efficient management of power grid production, delivery, and storage.

The accurate forecast of the power produced by PV systems is of great importance both in reducing the operation cost by lowering the number of panels and beneficial for system operators, customers, and PV plant managers who prevent possible faults that might occur because of the difference between the real and predicted power.

Moreover, in some electricity markets, solar energy producers can face sanctions if the difference between predicted and generated energy exceeds a predetermined value. Thus, power forecasting from PV energy systems has gained much attention from researchers and practitioners and many studies have been made to reach accurate forecasts.

Therefore, in some previous studies [1], [2], [3], [4], [5], [6], [7], [8], [9], [10], different power estimation studies achieved related to PV systems to contribute to energy planning. In these studies, power estimation was made using various artificial intelligence methods.

In [1], it is planned to compile with a literature review about solar power forecasting. By examining different estimation techniques, the obtained results and their performances are compared. In addition, the importance of estimating power from an economic point of view has been investigated. In [3], a deep Convolutional Neural Network structure and an input signal decomposition algorithm called Empirical Mode Decomposition was proposed for the PV power prediction system. The experiments were realized under different weather conditions on a grid-tied PV Power Plant that has a 1000 kW installed capacity located in Turkey. In [4], design and optimization were performed using an Autoregressive Neural Network model trained using Levenberg-Marquardt optimizer to provide a week ahead forecast of PV Power output. In [10], the prediction of the power production for sunny and cloudy days from a single-axis tracking PV module by using Artificial Neural Network (ANN) architecture was aimed. The performance success of the model has been proven by experimental studies.

In [11], a model that predicts PV energy production one hour in advance is developed using the Support Vector Machine (SVM) for clear and cloudy weather conditions. In [12], which deals with a comparison between machine learning algorithms for day-ahead prediction of solar PV output, ANN, Linear Regression (LR) and SVM are examined.

In [13], in which the results of SVM and Gaussian Process Regression (GPR) models were compared using the root mean square error (RMSE) and mean absolute error (MAE) criteria, it was observed that the GPR algorithm was more successful.

The [14], provides a short-term estimation of solar radiation using the ensemble learning models Boosted Trees, Bagged Trees, Random Forest, and Generalized Random Forest, and then compares the results obtained with GPR, and SVM methods, and compares the success of Ensemble learning models. has shown.

In this study, the power estimation is made using the ELM method the collection of power and the meteorological data from a Solar Power Plant installed in Elazig/Turkiye.

With the energy plans made by public institutions, it is aimed both to ensure network stability and to make an economical design. However, since the power value produced at the PV system output will change with the change of weather conditions, it will be difficult for energy suppliers to fulfill their commitments. With the power estimation, investment and energy costs will also arise depending on the change in power. Therefore, power estimation is an important criterion for designs to be made for both energy suppliers and public institutions.

In this study, temperature, radiation, and wind speed parameters, which directly affect the PV system efficiency, are used for power estimation. In addition to the meteorological data, the real power values produced in the solar power plant, where the estimation will be made, were used.

It is aimed to make a PV power estimation by training the obtained historical meteorological data and power values with artificial intelligence. In this study, the ELM algorithm was preferred because it provides fast and efficient results in PV system power estimation and Modified Golden Sine

Algorithm (GoldSA-II) was used to optimize the hyperparameters of the ELM algorithm. It is aimed that the outputs of this study may help electricity utility authorities to plan their system at the design stage.

This paper is structured as follows. Firstly, how electricity is produced with PV systems is examined and the factors affecting PV system performance are mentioned. The importance of estimating the power that can be produced in the power plant is emphasized by using meteorological factors affecting the PV system efficiency. Then, the ELM algorithm to be used in the study is examined. Finally, the ELM-based power estimation designed in this study is explained and the experimental results are share

II. PHOTOVOLTAIC SYSTEMS

PV systems are systems that directly convert the sun's rays on the panel surface into electrical energy. The smallest unit of these systems is solar cells, and the system consists of semiconductor materials. Semiconductor junctions are formed by adding the needed additive to the "p" or "n" type material. When radiation falls on the semiconductor junctions, electron-hole pairs are formed and are separated from each other by the electric field effect in the joint region. It is called PV conversion.

The performance of PV systems varies depending on environmental conditions (such as temperature, location, cleaning, surface parameters, shading, etc.).

The reflection rate of the radiation reaching the panel surface, that is called the surface parameter is an important factor. In PV systems, the best performance is achieved when the panels are placed in such a way that they receive the radiation vertically and homogeneously. For this reason, the placement of the panels is important. Dust and dirt formed on the PV system surface due to different environmental conditions reduce the radiation area of the PV panel and cause a shading effect in the system. The shading negatively affects system efficiency.

It has been observed in the studies that the PV system performance changes depending on both the amount of radiation falling on the PV panel surface and the angle of incidence of the radiation.

PV systems come to the forefront among renewable energy sources due to their easy installation and operation, flexible structure and modularity, not requiring much maintenance and labor, and also not having any moving parts. At the same time, it is durable, reliable, and long-lasting.

But there are also disadvantages. High investment costs, production can only be done during the day, storage costs, decrease in panel efficiency over the years, and low energy production when the sun's rays do not reach the panel, such as in winter can be listed as the disadvantages of solar energy. It is also a negative feature that it covers a much larger area compared to other power plants.

Unfortunately, the energy to be produced by PV systems has a variable, unstable, and uncertain structure due to the disadvantages mentioned and the efficiency being highly affected by environmental factors. This situation causes difficulties in terms of both energy planning and energy management. At the same time, it causes economic negativities for the suppliers who take responsibility for ensuring the supply-demand balance.

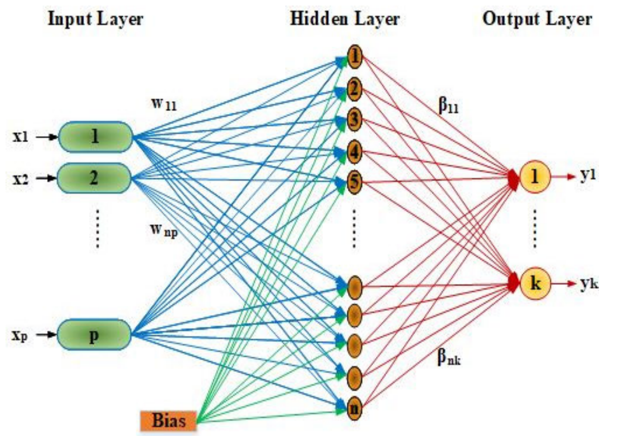

FIGURE 1. The basic structure of an ELM system.

Power estimation has an important place in energy planning and production with PV systems since the generation is not constant and continuous. By making power estimations, uncertainties can be eliminated, and safe energy planning can be made. Therefore, power estimation should not be ignored in energy management.

Since the energy production of PV systems depends on many factors, these factors must also be taken into account to make an accurate estimate. For this purpose, various meteorological data measurements are obtained. For example, factors such as radiation and air temperature directly affect the intensity of radiation and therefore energy production. Therefore, such meteorological data are important for power estimation.

Different methods and models are used to predict the energy production of PV systems [1]. Artificial intelligence-based models are increasingly preferred also to predict the energy production of PV systems, as in every field [1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14]. These systems include machine learning methods such as ANN, fuzzy logic, genetic algorithms, and ELM. These models predict the energy production of PV systems using learning algorithms based on past data.

III. METHODOLOGY

A. EXTREME LEARNING MACHINE

ELM is a machine learning algorithm used in controlled learning operations such as classification and regression. It was first proposed by Huang et al. as an alternative to traditional neural networks as a simple, fast and efficient method [15].

The ELM is a feed-forward neural network with a single hidden layer, as shown in Fig. 1. The neurons in the hidden layer are randomly initialized. The input layer is connected to the hidden layer with random weights and the output layer is calculated using the weights learned in the hidden layer.

Unlike traditional neural networks, ELM does not require iteration or backpropagation. The output is calculated by randomly generating the parameters. This ensures that training is fast and efficient. Also, the absence of iteration or backpropagation makes it usable for large datasets or real-time operations.

The mathematical model for the ELM structure is given in (1) [15]. There are n hidden nodes, and where x is the input value, $\boldsymbol{w}$, and $\boldsymbol{\beta}$ are randomly chosen values and represent the weight vector between the input node and the hidden node and the weight vector between the hidden node and the output node, respectively. b is the bias value.

$$\sum\nolimits_{i=1}^{n} \beta_i f\left(w_i x_j + b_i\right) = o_j, \quad j = 1, \ldots, N \tag{1}$$

The obtained result of the equation represents the output value $\boldsymbol{o}$, and the aim is to keep the difference between the vector $\boldsymbol{o}$ obtained by using randomly selected $\boldsymbol{w}$ and $\boldsymbol{\beta}$ values and the desired output value $\boldsymbol{y}$ close to zero, as given in (2).

$$\sum\nolimits_{j=1}^{N} \left\| o_j - y_j \right\| = 0 \tag{2}$$

The f function used in (1) is the activation function (AF). Various AF are used in the ELM structure. Sigmoid, triangular, basis, sine, hard limit, and radial basis functions are AFs that are used extensively in the literature [16]. The AF in (1) can be represented in matrix form as in (3). Where H is the AF matrix.

$$H = \begin{bmatrix} f\left(w_1 x_1 + b_1\right) & \cdots & f\left(w_M x_1 + b_M\right) \\ \vdots & \cdots & \vdots \\ f\left(w_1 x_N + b_1\right) & \cdots & f\left(w_M x_N + b_M\right) \end{bmatrix}_{nXN} \tag{3}$$

If (1) is rewritten, using the matrix of output weights $\boldsymbol{\beta}$ and H,

$$Y = H\beta \tag{4}$$

obtained. Here $\boldsymbol{Y}$ denotes the output vector. Starting from (4), the output weights can be obtained analytically as in (5).

$$\beta = H^{\dagger} Y \tag{5}$$

where, $H^{\dagger}$ is the Moore-Penrose inverse matrix of H [17].

B. MODIFIED GOLDEN SINE ALGORITHM

In the machine learning models, hyperparameters refer to those parameters introduced externally by the user. Weights, number of neurons, number of layers, AF, etc. are various hyperparameters used in artificial intelligence algorithms. Typically, these parameters are ascertained through a trial-and-error approach. Nevertheless, owing to the direct impact of hyperparameter determination on the model's efficacy, the optimization of these parameters through the application of diverse algorithms serves to enhance the model's performance [18].

For this purpose, optimization algorithms such as particle swarm optimization, genetic algorithm, differential evolutionary, golden sine, etc. are used [19]. These algorithms are used in artificial intelligence techniques to create hybrid models.

The GoldSA-II algorithm is an effective metaheuristic algorithm that optimizes using the decreasing pattern of the sine wave and the golden ratio [20], [21]. GoldSA-II algorithm is a modified version of the Gold-SA algorithm and uses the sine function and golden ratio just like GoldSA [20], [21], [22], [23].

GoldSA-II is proposed to solve both constrained and unconstrained optimization problems. It has been shown to have better performance than other well-known algorithms [20].

Gold search optimization is used to find the maximum or minimum value of single-mode functions. In gold search optimization, equations (6) and (7) are used to determine the appropriate value: a, b are the interval to be searched, and τ is the golden ratio.

$$x_1 = a\left(1 - \tau\right) + b\tau \tag{6}$$

$$x_2 = a\tau + b(1 - \tau) \tag{7}$$

The parameters r_1, r_2, and r_3 are randomly selected values within the $[0, 1]$ range. The parameter r_1 determines the extent of the movement toward or away from the target, allowing for a comprehensive exploration of the entire region. Meanwhile, r_2 is utilized to determine how the target influences the definition of distance and the position of GoldSa-II varies based on the value of r_3. When r_3 is less than 0.5, the new position is determined using (7), when it is greater than or equal to 0.5, the new position is determined using (8). Where, X_i^t represents the i-th current solution value at iteration t, and x_1 and x_2 denote the coefficients derived from the golden section method from (6) and (7).

$$X_i^{t+1} = X_i^t - dr_t sin\left(wtr_1\right) * \left(r_2 x_1 D_p - x_2 X_i^t\right) \tag{8}$$

$$X_i^{t+1} = X_i^t + dr_t sin\left(wtr_1\right) * \left(r_2 x_1 D_p - x_2 X_i^t\right. \tag{9}$$

The parameter dr_t corresponds to the amplitude of the sine function, providing information about the proximity of the new position region to the target area.

Then, the algorithm used in this study can be summarized as in the following algorithm.

The Algorithm Used in the Study

Inputs:

Training data set, $x_j|_{j=1,N}$ (input weights ω and hidden biases b), $\mathrm{X_i^t}$

Activation function, $f(\cdot)$

The number of hidden nodes, n.

Outputs:

The output weights β.

1. Generate the input weights ω and hidden biases b, by using GoldSA-II optimization technique;
2. Compute the hidden layer output matrix H;
3. Calculate the output weights $\beta = H^{\dagger}T$ by using the MP generalized inverse.

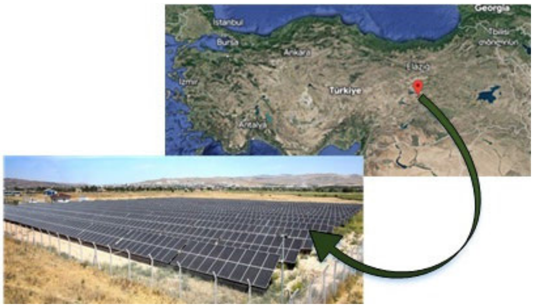

FIGURE 2. The solar power plant in Elazig/Turkiye from which data are taken.

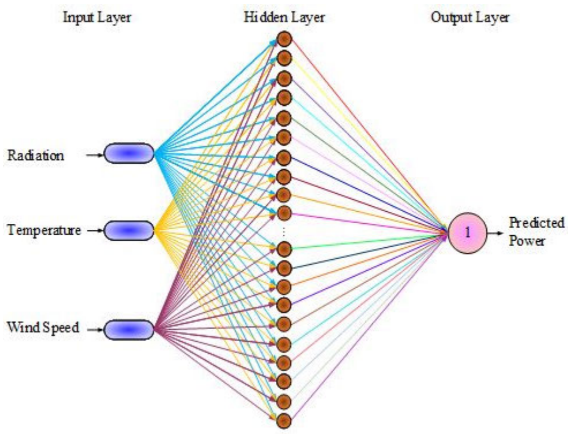

FIGURE 3. ELM model used in the study.

In ELM, the performance of the model is usually measured using metrics such as accuracy, precision, sensitivity and mean square error. Overall, the main advantage of ELM is that it can learn output weights quickly and efficiently without the need for repetitive training or backpropagation [24]. This allows it to be used in a variety of applications such as large datasets or real-time constraints. Then, the obtained statistical results are investigated, the GoldSA-II algorithm provides better solutions for many optimization problems than other methods do [20].

IV. EXTREME LEARNING MACHINE BASED POWER FORECASTING OF A PHOTOVOLTAIC SYSTEM

ELM based power forecast includes training a model with meteorological data such as solar irradiance, wind speed, etc., and historical power generation data.

The ELM algorithm uses a random weight matrix to map input data to corresponding output values. The weights in this matrix are determined using the least squares approach, which optimizes the system for the given input data.

In this study, ELM based daily power estimation was made based on meteorological data with the data taken from a solar power plant established in Elazig-Turkey. The visual of the Solar Power Plant is given in Fig. 2.

In the ELM model used in this study, there are 3 inputs, 1 output, and a hidden layer as shown in Fig. 3.

Daily average solar radiation, temperature, and wind speed parameters were used as inputs. The output is the power estimated by the ELM. A total of 304 data were used in the study. 70% of this data were used for training and 30% for testing.

The system and module information of the solar power plant from which the power data used in this study is taken are given in Table 1.

TABLE 1. Specification of PV system and module.

System	
Latitude	38.59
Longitude	39.33
Area of Solar Power Plant	1000 m^2
Nominal Power	998 kW
No of Panel	3564
No of Modules in parallel	18
No of Modules in series	12
No of Strings	16.5
Module	
PV Module Type	Mono-crystalline
Area	1652 mm x 997 mm
Thickness	42 mm
Max Power Rating	320 W
Rated Voltage	24 V
Rated Current	9.63 A
Short Circuit Current	10.31 A
Open Circuit Voltage	39.20V

TABLE 2. The selected ELM hyperparameters by GoldSA-II optimization method.

The ELM Hyperparameters	Without Optimization	Optimization with GoldSA-II
AF	Hard limit	Hard limit
The number of HN	1000	25
C	100	5

In this study, the GoldSA-II algorithm, which is one of the metaheuristic optimization methods, was used while determining the ELM hyperparameters. Thus, the hyperparameters of the ELM model were optimized and its performance was increased. The hyperparameters optimized with GoldSA-II are the AF, the number of hidden neurons (HN) and the regularization coefficient (C). Sigmoid, triangular, basis, sine, hard limit, and radial basis functions were studied as AF. The working range of the number of HN was chosen between 5 and 1000, and the working range of C was chosen between 0 and 100.

Accordingly, the hyperparameter values optimized with the GoldSA-II algorithm before and after optimization are given in Table 2. While the Hard limit function was chosen as AF in both cases, as a result of the optimization, the number of HN and C were determined as 25 and 5, respectively.

In this study, a total of ten months of data from January 1st, to October 31st, 2022 were used.

From the data collection, the variations of daily average radiation, temperature, wind speed, and real power values for July are given in Fig. 4.

The graph comparing the daily average real power value and the average power values estimated by the ELM in July

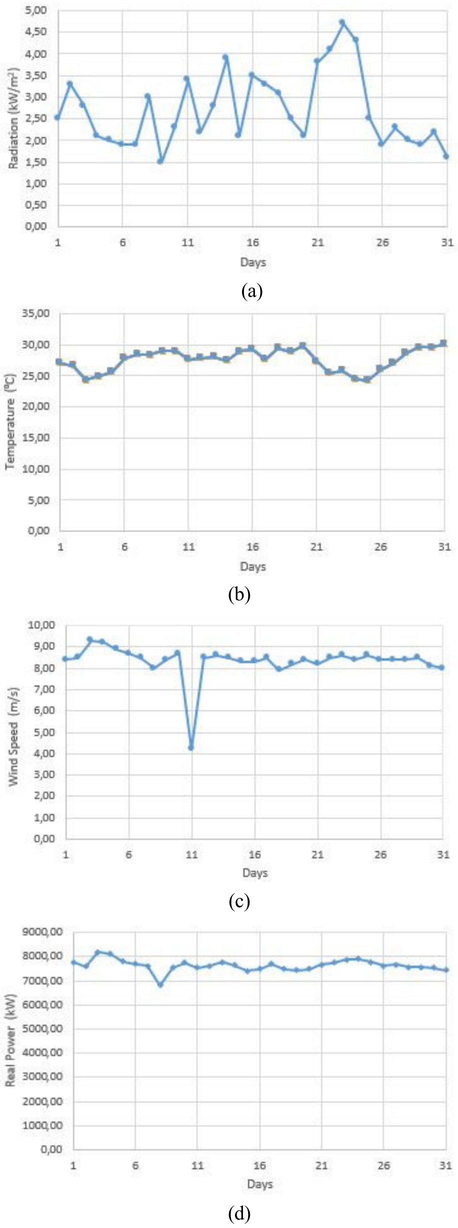

FIGURE 4. For July, the variation of daily average values of (a) radiation, (b) temperature, (c) wind speed (d) real power.

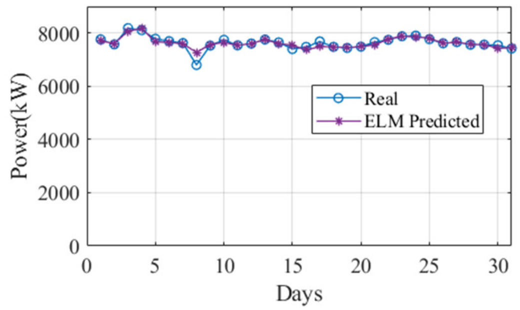

FIGURE 5. Comparison of the daily average real power value of July with the power values estimated by ELM.

TABLE 3. Monthly average irradiance, temperature, wind speed, and real power value for the months selected from the four seasons specification of PV system and module.

	Radiation (W/m^2)	Temperature (°C)	Wind Speed (m/s)	Real Power (kW)	ELM Predicted Power
January	1.9	-0.5	2.78	2319.83	2277.22
February	3.02	4.27	2.39	4384.02	4377.52
March	3.08	3.56	2.49	4457.17	4406.35
April	6.09	14.98	2.68	6213.5	6319.67
May	6.9	15.8	2.56	6156.12	6164.87
June	7.59	23.83	2.32	7175.28	7162.2
July	8.32	27.6	2.69	7440	7627.56
August	7.17	29.47	1.95	7016.27	7020.81
Septembe	5.8	23.49	2.23	6327.89	6335.06
October	4.08	16.64	1.94	4970.28	4971.97

is as seen in Fig. 5. Looking at the graph, it is seen that the power value estimated by the ELM follows the real power value.

RMSE and R value were used to confirm the accuracy of the ELM model. The fact that the R value is close to 1 and the RMSE value is close to zero is directly proportional to the accuracy of the model.

According to the results obtained for July, the RMSE and R values of the ELM model were calculated as 0.0085 and 0.93, respectively.

The monthly average irradiance, temperature, wind speed, real power, and ELM predicted power values of different months selected from the four seasons are shown in Table 3. When Table 3 is examined, it is observed that the power value produced at the power plant also changes depending on the meteorological data that changes with the seasons.

Accordingly, when comparing the months, the radiation value is at the lowest level in January, when the winter season is experienced, and therefore the power produced at the power plant is also at the lowest level. Likewise, the radiation value is at the highest level in July, when the summer season is experienced, and the power produced is at the highest level. A similar situation is observed in the spring-autumn periods. The power value produced in April is higher than in October. Comparing July and August, the power produced in July is higher due to the high radiation and wind speed, as well as the lower temperature. In February and March, the radiation is approximately equal, in February the temperature is higher and the wind is lower. Therefore, the monthly average power generated is higher in March.

The comparison of the daily average real power value for different months selected from the four seasons and the power values estimated by the ELM is shown in Fig. 6.

It should be noted that in January, April, and October, when the weather is variable, the ELM forecast is close to the real power, while in August, when the weather is more stable, the power graph predicted by the ELM is almost the same as the real power.

The comparison of the daily average power value estimated by ELM and the actual power value is as given in Fig. 7 for

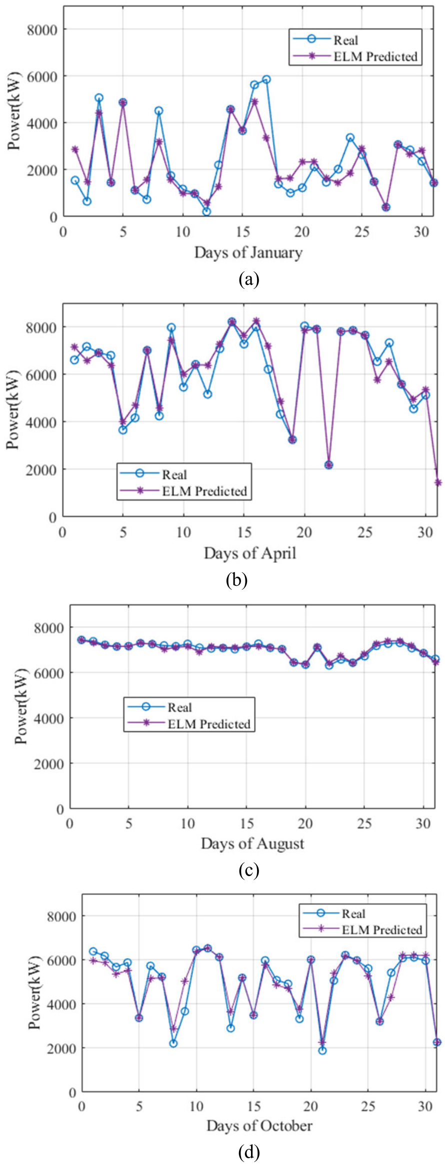

FIGURE 6. Comparison of the daily average real power value and the power values estimated by ELM for (a) January (b) April (c) August (d) October.

the ten-month period from January 1st, 2022 to October 31st, 2022.

According to the results obtained for ten-month period, the RMSE and R values of the ELM model were calculated as 0.0633 and 0.95, respectively.

To show the model accuracy, the monthly average R and RMSE values of the study are given graphically in Fig. 8 (a) and (b), respectively. A success criterion is that the R value is close to 1 and the RMSE value is close to zero. When the graphs are examined, it is seen that the 10-month average R and RMSE values are 0.92 and 0.0495, respectively, proving the performance of the ELM model used in the study.

Additionally, power prediction for 15th day of 4 different months which are January, April, August and September of 2023 which are selected as one for every season is also made

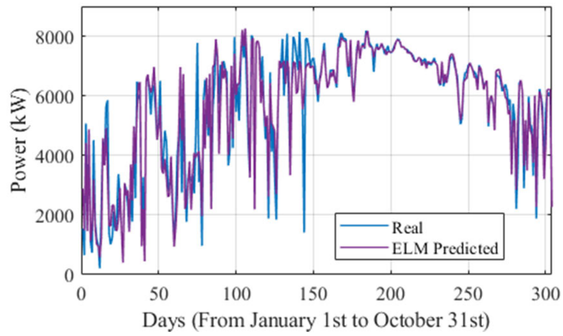

FIGURE 7. Comparison of the daily average real power value and the power values estimated by ELM for the ten-month period.

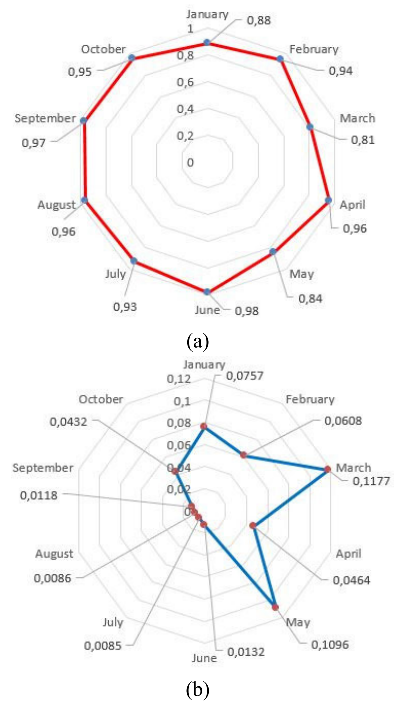

FIGURE 8. The monthly average radar cart of (a) R (b) RMSE values.

with the data measured 15 minute intervals taken from the Solar Power Plant. Fig. 9 shows the real power and the power predicted by the ELM. As seen in Fig. 9 a good relationship is found between the real and predicted power values. It can be clearly seen that the power production gets maximum values at and near the noon hours due to the increase in solar radiation.

To demonstrate the predictive efficacy of ELM, a comparative analysis was conducted involving various machine learning models, including ELM, NN, GPR, Ensemble Methods, SVM, LR, and Decision Trees (DT). In the LR model employed for the comparison, output values are determined by computing regression coefficients that encapsulate the slope and intercept parameters of an optimized linear equation fitted to each feature vector. This equation elucidates the linear association between the dependent and independent variables. In contrast, the SVM model employs a non-linear data separation approach, minimizing errors by guiding data

TABLE 4. Comparison of RMSE value of different machine learning models for July.

	ELM	NN	GPR	Ensemble	SVM	LR	DT
RMSE Value	0.0085	0.051319	0.011706	0.036808	0.021291	0.021653	0.015488

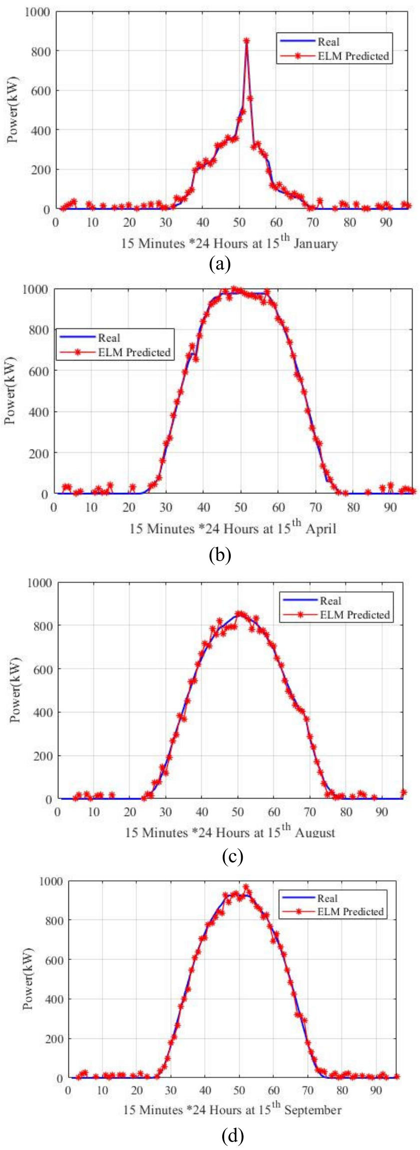

FIGURE 9. Comparison of the real power value and the power values estimated by ELM for 15 minute intervals at 15th day of (a) January (b) April (c) August (d) September.

points to appropriate positions within the feature space. GPR is a versatile model capable of probabilistically characterizing intricate systems while accommodating uncertainty. The NN model emulates the functioning of the human brain, comprising input, hidden, and output layers. Information from the input layer is randomly sampled and learned via weighted connections between layers to produce output information. The ensemble model arrives at decisions by aggregating information from a multitude of models. It partitions input data into subgroups and applies distinct models to each subgroup, subsequently amalgamating the output predictions from these diverse models. The DT model self-organizes into root, node, and leaf entities, where inputs initiate at the roots and result in outcomes at the leaves.

In the analysis conducted for the month of July, various machine learning models were utilized to assess RMSE values. The closer the RMSE value is to zero, the smaller the difference between the real and the predicted values. When Table 4 is examined, it is seen that the RMSE value of the result obtained with the NN model is the highest value with 0.051319. The NN model is followed by the Ensemble model with 0.036808. The RMSE values for the LR and SVM models are 0.021653 and 0.021291, respectively. It is followed by DT with 0.015488 RMSE values and GPR with 0.011706. Upon reviewing the comparative findings presented in Table 4, it is evident that the ELM model exhibits the RMSE value closest to zero.

V. CONCLUSION

Renewable energy sources are of great importance for a sustainable world. Photovoltaic systems, as one of the renewable energy sources, produce energy using solar energy. Renewable energy sources will fly away like time if we don't use them. In other words, it is necessary to transform the existing source into useful energy in line with the possibilities and at the maximum rate. For example, in PV systems, it is not possible to produce energy tomorrow by using today's radiation value. At the end of the day, solar energy sees zero and starts to produce again with the next day. So, it would not make sense to use other energy sources when there is today to produce energy by utilizing the existing solar radiation. By adjusting the output of other energy sources with the power estimation, the system supply-demand situation can be balanced with the estimated power value.

The parameters of the electrical energy generation from PV are the climatic parameters the most effective of which are the total irradiation received by the panels, panel temperature, and wind speed. The radiation is not uniform due to the presence of clouds, which block the Sun's rays. The panel temperature and the wind speed are also dependent on the weather conditions. Variations of these parameters have an impact on the quality of the produced power. All these parameters produce uncertainity in power forecasting and produce problems in the integration of PV systems into the power grid.

Accurate estimation of solar energy for energy production is important for energy planning and management. Moreover, with accurate forecasting, uncertainty in energy production can be reduced and supply-demand balance can be achieved. For this purpose, solar energy production and the amount of energy that can be produced can be predicted more accurately by using new technologies. The ELM method is faster, more accurate, and less costly than other methods.

In this study, ELM based daily average power forecasting was presented based on meteorological data and the power data taken from a solar power plant in Elazig-Turkey.

Once the ELM, whose hyperparameters were optimized with the GoldSA-II algorithm, was trained, it was used to predict future energy production based on weather forecast data. The weather forecast data (Daily average radiation, temperature, and wind speed) are input to the ELM and the system outputs the predicted power generation values in this study.

Since the weather varies seasonally, indirectly the power value to be produced by the PV system also varies. Therefore, a comparison of actual power and ELM predicted power graphs for January, April, August, and October was presented graphically to represent the four seasons. The graphs show that the power graph estimated by the ELM follows the actual power graph.

As can be seen from the average daily radiation, temperature, wind speed, and power comparison graphs of July given to represent the summer period, in this period when the daily air change is low, the daily power change is also low at the same rate. A similar situation can be seen in the power comparison chart for August.

In addition, the monthly average radiation, temperature, wind speed, and power values for the 10-month period are given in a table, and how meteorological data affects the power produced is interpreted.

The daily average real power and the daily average power estimated by the ELM for the 10-month period are presented graphically. The success of the ELM model, which gives realistic results, is presented in this graph.

Finally, for the 10-month period the daily and monthly average R and RMSE values are calculated to verify the performance of the ELM model used in the study.

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