■ RESEARCH ARTICLE

Estimating Energy Production of Solar Power Plant at the University of Bakırçay Using Artificial Neural Networks Based on Meteorological Conditions

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Abstract

The rapid depletion of fossil fuels and environmental concerns have led people to work on renewable energy sources. In order to leave a cleaner and more liveable world for future generations and enable developed countries to produce more economical energy using their own resources, major investments have been made in renewable energy resources. Photovoltaic (PV) energy has a large share among renewable energy sources. Turkey has taken its place among the countries that are aware of the PV energy potential and invest in this field. The ratio of installed PV energy power to total installed power is also increased day by day in Turkey. However, meteorological factors affecting PV energy production make it difficult to compute energy production in advance. In this study, the relationship between meteorological data and power generation data was analyzed using the power generation data of the solar power plant (SPP) with an installed power of 400 kW in the student car park of the University of Bakırçay and the meteorological data of the province of İzmir. As a result of the comparison of the tests, energy production with respect to meteorological factors achieve a remarkable success rate with 95.3% when artificial neural networks are employed.

Keywords: renewable energy; photovoltaic energy; energy estimation

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1. Introduction

In recent years, fossil fuels are used to a large extent to meet the increasing energy demand with increasing population and technological developments. However, the utilize of fossil fuels causes rapid depletion of fuels and rapid deterioration of the ecological balance [1]. Renewable energy sources have gained great importance due to the risk of extinction of fossil fuels and their harm to the ecological balance [2].

Renewable energies, which do not have the risk of extinction and treat the environmental balance more positively, have been able to attract the attention of the energy sector. Energy sources such as hydro, geothermal, solar, wind, bio-energy and tides are among

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the renewable energy sources [3]. Renewable energy, which reduce countries' dependence on foreign energy through their own resources, succeeded in creating 19% of total energy needs in 2008 [4]. Among the renewable energy sources, solar energy is the most promising, abundant, and free energy. Photovoltaic (PV) energy that converts sunlight to electricity through the PV effect [5,6].

PV energy is constantly increasing its popularity among renewable energy sources due to its lower maintenance cost and easier application possibilities after installation [7]. Since the 21st century, developed and developing countries have started to shape their investments around PV energy. According to the Global Trends in Renewable Energy Investment 2019 Report by United Nations Environmental Protection Program in 2019, 638 GW solar power plants (SPP) were installed worldwide between 2010-2019 [8]. PV energy potential is a very high energy source. However, PV systems are dependent on certain parameters such as the duration of sunlight, the angle of sunlight, the ambient temperature. For this reason, PV can vary depending on the material used, geographical conditions and weather conditions [10,11].

Forecasting production capacity to make energy investments more efficient will be effective in making the investments more precise. In the investments to be made, energy production can be estimated, on a monthly basis from the historical meteorological data of region be invested. Turkey is among the countries that make investments in the field of solar energy. According to TEİAŞ data, it was announced that in February 2022, Turkey's installed solar power has increased by 518.1 MW in the last 6 months and reached 7953.3 MW [9].

In this study, PV energy production was associated with meteorological data and solar energy production was estimated based on parameters using artificial neural networks. It is aimed to guide the current energy producers to calculate the future energy production based on meteorological forecasts and to make the producible energy capacity estimation for SPPs to be installed in geographical regions with different meteorological conditions.

2. PV Energy from SPP at University of Bakırçay

In this study, the relationship between PV outputs and meteorological data is analyzed. PV energy production of SPP at the University of Bakırçay has been estimated by artificial learning methods with respect to meteorological factors.

2.1. Solar Energy Potential of the University of Bakırçay

Turkey is located in a geographical region with high solar energy potential as shown in Figure 1 which is the Turkey solar energy potential atlas. Due to this potential, in Turkey, which had an installed power of 29.9 *MW* in solar energy in 2014, managed to increase its installed power to 7953.3 *MW* by February 2022 by making investments [9] The average annual total insolation time in Turkey is 2741.07 hours, and the average annual total radiation value is 1527.46 kWh/m^2 [12].

İzmir is a coastal city in the westernmost part of Anatolia and along the Aegean Sea. In İzmir, which is under effect of the Mediterranean climate, summers are hot and dry, and winters are warm and rainy [13]. İzmir province is in an efficient region in terms of solar potential with an annual solar radiation of 1500-1600 kWh/m^2 [12].

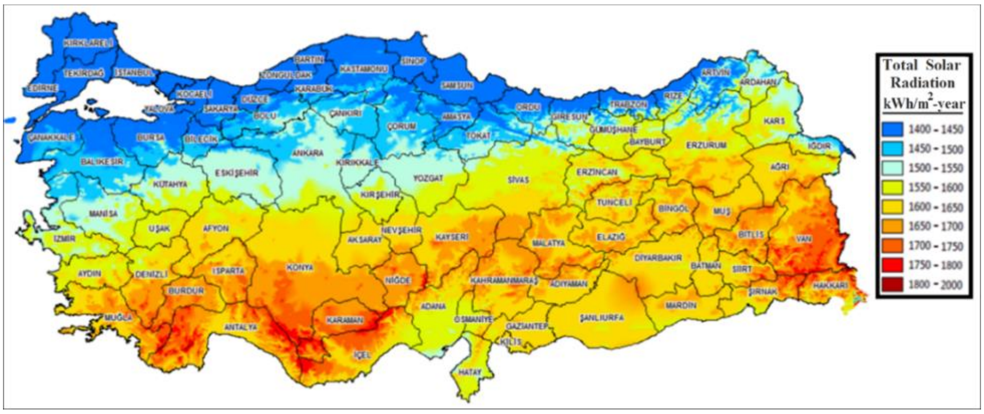

Figure 1. Turkey Solar Energy Potential Atlas (SEPA) [12].

The photovoltaic energy data used in this study belongs to the SPP installed on the roof of car park at the University of Bakırçay where was established in Seyrek village in Menemen district of İzmir. The university, which aims to reduce its dependence on foreign energy by taking action with the slogan of a self-sufficient campus, continues to produce electrical energy by using 1600 PV panels within the body of GES. In the study, meteorological data of İzmir province were used as well as data of SPP at the University of Bakırçay.

2.2. Features of PV Panels and Inverters

A total of 1600 PV panels which are PERLIGHT SOLAR brand PLM250P-60 model 250 W, 30 V polycrystalline silicon PV panels were used in the 400-kW power plant built on 6 rows of steel construction in student car park to the west of the University of Bakırçay Campus. The technical specifications of the used panels are shown in Table 1. SPP at the University of Bakırçay which was completed in 2018, entered into service in May 2019, with the replacement and renewal of all outlets and cables and the washing of its panel.

Table 1. Used specifications panels.

Specification of Panels	
Producer	PERLIGHT SOLAR
Model Number	PLM-250P-60
Cell Type	Polycrystalline Silicone
Maximum Power (W)	250
Maximum Voltage (V)	31.73
Maximum Current (A)	7.88
Open Circuit Voltage (V)	37.58
Short Circuit Current (A)	8.49
Maximum System Voltage (V)	1000
Cell Size (mm)	156×156
Module Size (mm)	1650×992×40

The SPP placed on the steel construction in the parking lot located in the northwest of the campus are shown in Figure 2(a). As seen in Figure 2(b), there are a total of 1600 PV panels, 265 panels in 4 rows and 270 panels in 2 rows.

(a) (b)

Figure 2. (a) Satellite view of the campus and the parking lot in the northwest and (b) placement of PV panels.

In Figure 3, panels that act as canopy for vehicles and also provide energy generation are photographed. The rows of PV panels are constructed at an angle to the ground to better capture sunlight while also allowing it to be cleaned naturally using rainwater.

Figure 3. SPP installed on the steel construction in the parking lot.

A total of 24 inverters which is SMA brand FLX PRO 17 model inverters are used to convert the direct current obtained from 1600 panels to alternating current in line with grid standards. The technical specifications of the used inverters are presented in Table 2.

Table 2. Technical specifications of the inverters used.

Technical Specifications of the inverters	
Producer	SMA SOLAR TECHNOLOGY
Model Number	FLX PRO 17
Rated Power (kVA)	17

Number of Phases	3
Output Voltage (V) (Tolerance)	230-400 (+/- 20%)
Maximum Current (Phase-A)	3-21.7A
Rated DC Input Voltage (V)	715
Maximum DC Input Voltage (V)	1000
Maximum Yield (%)	98
Inverter Size (mm)	500×667×233

2.3. Monthly Energy Obtained from the Power Plant:

The power of from PV panels is obtained as direct current (DC). Therefore, it has no phase angle or frequency, it is measured directly in units of active power, watts. The monthly amount of electricity produced in 2020 is shown graphically in Figure 4.

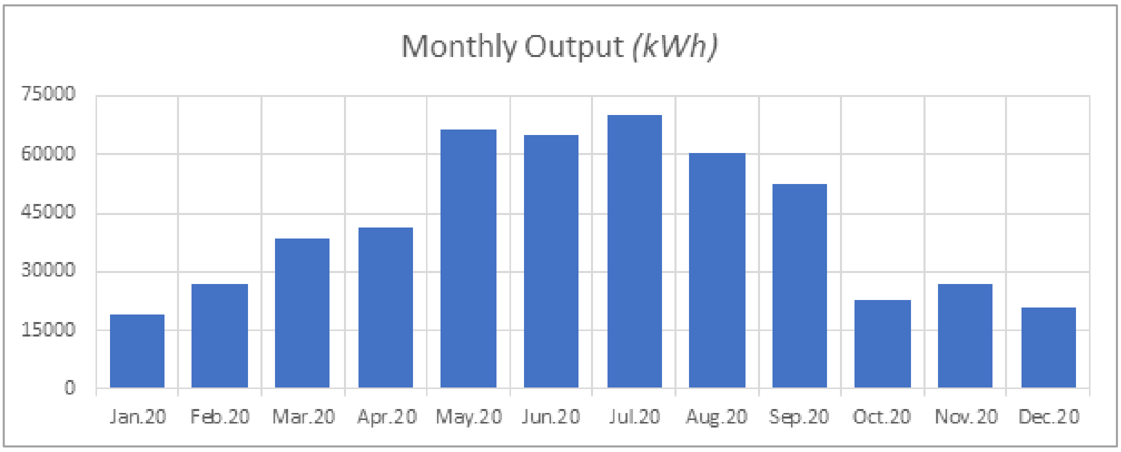

Figure 4. Monthly energy obtained from the power plant.

As can be seen in Figure 4, while higher electrical energy was producing between May and September, lower electricity energy was produced in January and December.

3. Meteorological Measurement Datas From İzmir Region

3.1. Geographical Locations of Meteorological Measurement Stations:

In this study, meteorological data obtained from the İzmir Meteorology Regional Directorate was used. The measurements required for the data analysis were taken at meteorology stations in different regions of İzmir. The locations in İzmir province are indicated on the map in Figure 5.

Figure 5. Geographical locations of the University of Bakırçay Seyrek Campus and some meteorology stations [14].

As shown in Figure 5, the closest meteorological measurement station to the University of Bakırçay SPP *(N38.58208, E26.96403)* is Menemen Station *(N38.62539°, E27.04255°)*. Other meteorological measurement stations located in the south and west of the region, the measurement data obtained from a total of 4 different meteorological stations, namely Çeşme Station *(N38.30408°, E26.37264°)*, İzmir Regional Station *(N38.39438°, E27.08137)*, Adnan Menderes Airport Station *(N38.29378°, E27.15173°)*, were used.

3.2. Comparison of Energy Production with Meteorological Data

3.2.1. Comparison with Insolation Time

Figure 6 compares the average daily sunlight time measured at 3 stations with the energy data generated. As shown in Figure 6, it is seen that the energy produced increases at the same rate in the months when the insolation time is high.

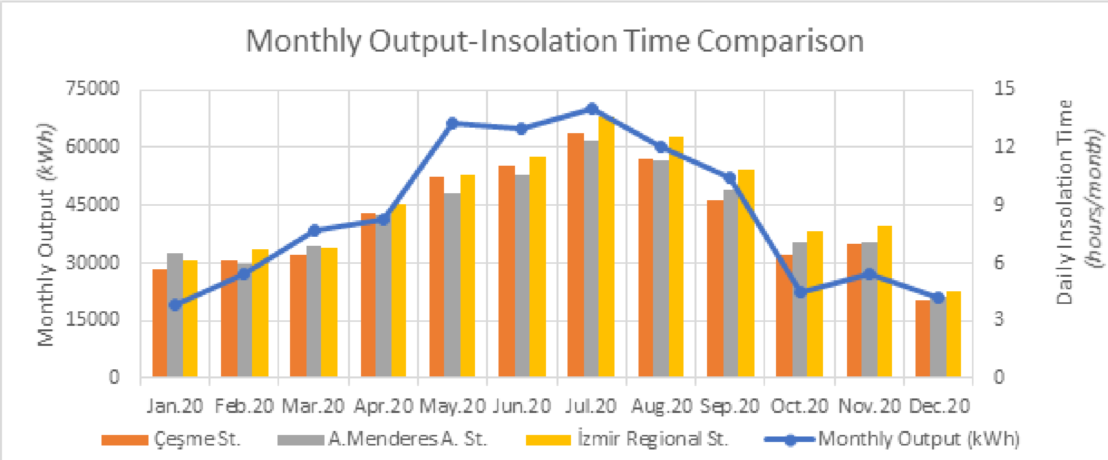

Figure 6. Comparison of energy and insolation time from the SPP.

Exceptionally, it is noteworthy that more energy was produced in May comparison with the insolation time. This may be due to the high average daily insolation intensity in May. At the same time, the precipitation in May can be shown as the reason for the cleaning of the panels and the increase in their efficiency.

3.2.2. Comparison with Average Temperature

The monthly average of the temperatures measured hourly every hour by the meteorological measurement stations was used to achieve monthly average temperature. Comparison with the energy produced is shown in Figure 7.

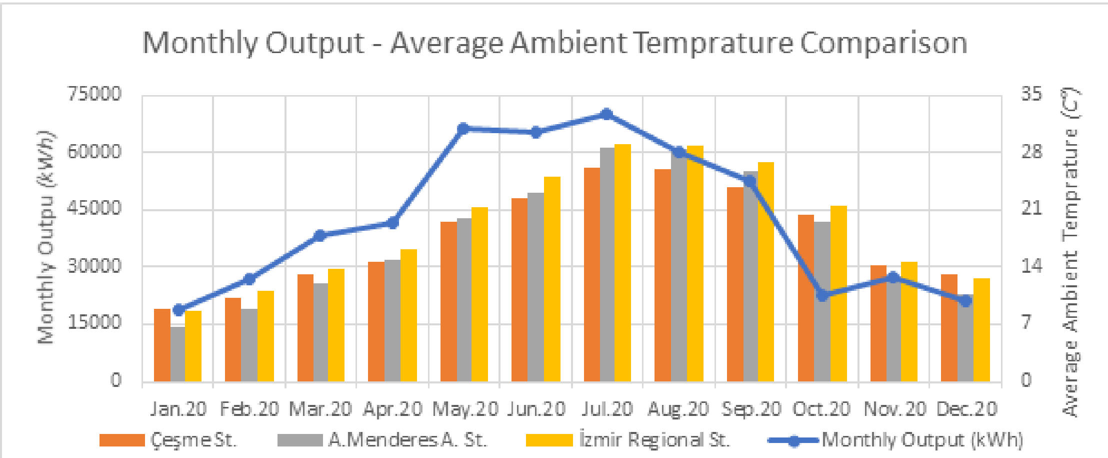

Figure 7. Comparison of the energy obtained from the SPP with the monthly average temperature.

As seen in Figure 7, when the monthly average temperature and the energy produced are compared, it is seen that the energy produced generally increases on the days when the temperature is high. When the solar radiation value is high, the ambient temperature also rises. However, when the temperature value reaches very high degrees, the rate of increase in energy production is less. The reason for this is explained by the increase in the internal resistance of the panels and the decrease in the panel efficiency depending on the temperature. Although the average temperature is high in October, the energy produced is low. This is because the number of cloudy days is greater in October.

3.2.3. Comparison with Monthly Cloudy Days

In Figure 8, when the number of cloudy days per month is compared with the energy produced, it is seen that it is one of the factors affecting the energy produced at the highest rate.

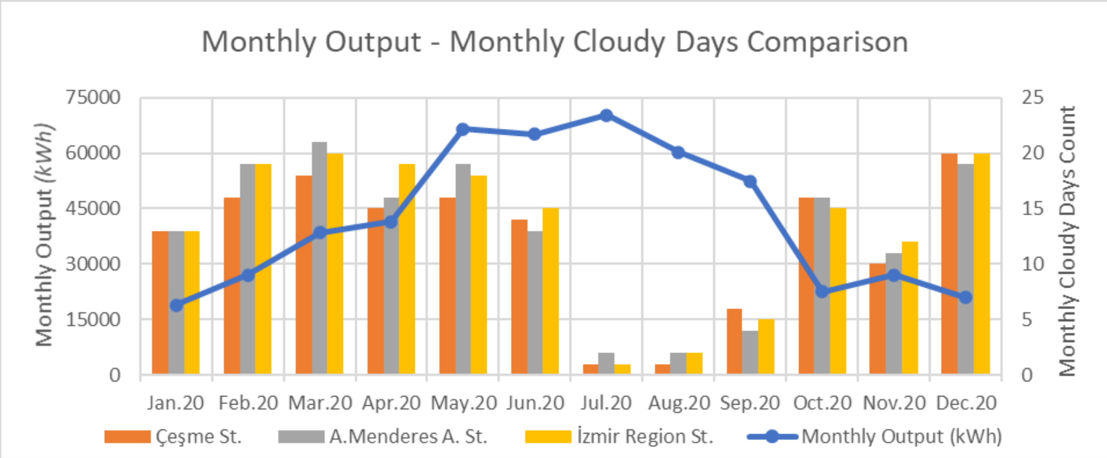

Figure 8. Comparison of monthly cloudy days with the energy obtained from the SPP.

Figure 8 presents that the highest energy production took place in July when cloudy days are few. It is clearly seen that the energy produced is lower in the months when the number of cloudy days is high. The most effective reason for low energy production, especially in October, can be shown as the high number of cloudy days in October. The high energy level in May is due to the fact that the cloudy and rainy days in May are far and short from each other and the panels have been cleaned.

3.2.4. Comparison with Monthly Solar Radiation

When the monthly average solar radiation and the energy produced are compared in Figure 9, it is clearly seen that there is a direct proportionality between the solar radiation and the energy produced.

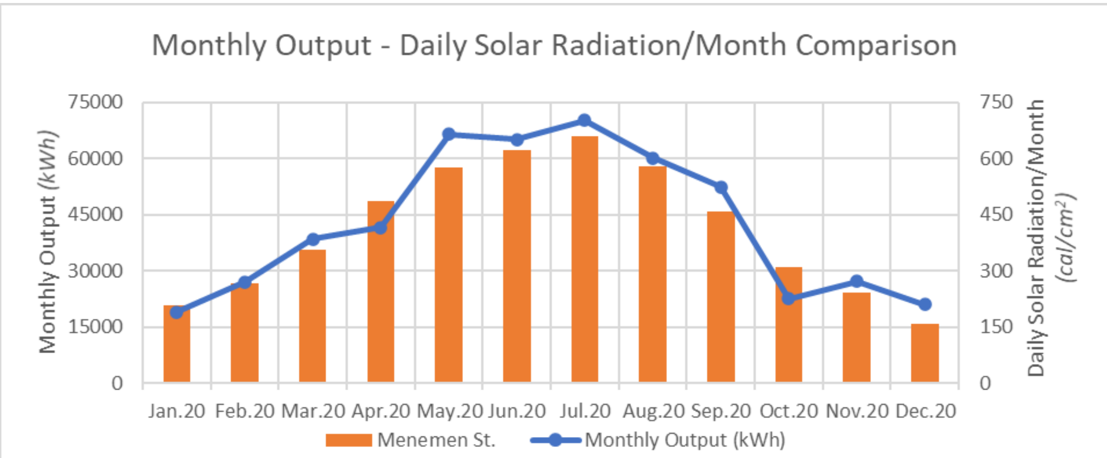

Figure 9. Comparison of the energy obtained from the SPP and the monthly insolation intensity.

In the comparison in Figure 9, the deviations in April, May and October are due to the number of cloudy days and the number of rainy days (cleaning the panels).

4. Properties Of Artificial Neural Networks Used for SPP at the University of Bakırçay

4.1. Structure of Artificial Neural Networks

Artificial neural networks have been developed for utilize in non-linear problem solving [14]. Artificial neural networks are formed by several artificial neurons forming a system. Artificial neurons are created by mathematical modelling of biological neurons. Simply put, artificial neurons consist of inputs, weights, transfer function and activation function and output as shown in Figure 10 [15,16].

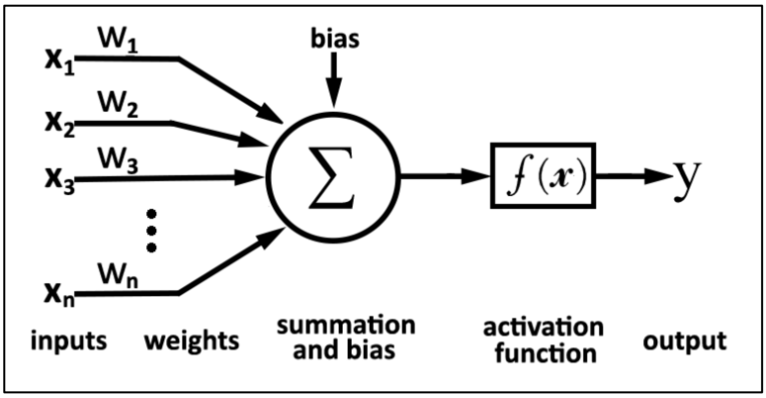

Figure 10. Structure of a simple artificial neuron.

Learning in artificial neurons occurs by changing the weights of the inputs. The weights are initially determined as random values. During the training phase, the weights are updated at each iteration and have a new value. The updating of the weights continues until the success of the network reaches the accepted level or the predetermined number of iterations is reached [17]. Artificial neurons can come together to model many artificial neural networks with different architectures. Artificial neural networks have 3 basic layers consisting of neurons as shown in Figure 11 [17].

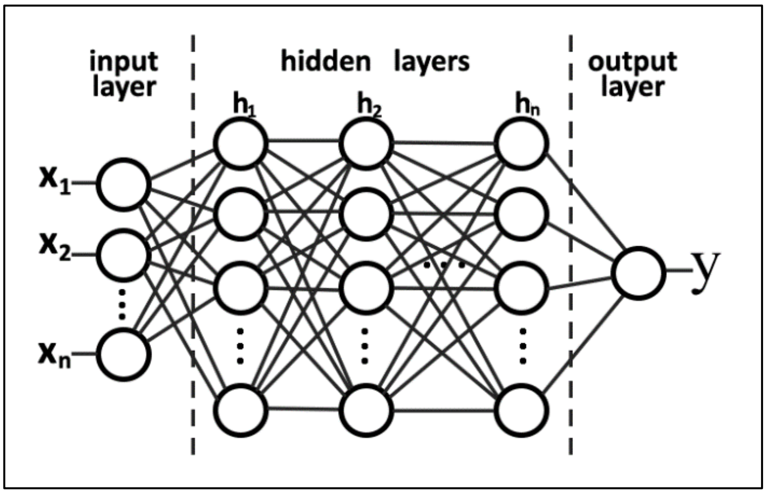

Figure 11. Structure of a simple artificial neural network.

As seen in Figure 11, the number of hidden layers can be increased in artificial neural networks consisting of 3 layers. The first layer input layer, where data is shown to the network, has as many neurons as the number of inputs. The number of neurons and layers in the hidden layer may vary depending on the architecture of the network and its expected performance [19]. The output layer is the layer from which the result is received. In this study, meteorological data was used as input, and the electricity generation of the SPP was used as output.

During the training of the neural network, the predetermined data are used for the training of the network after the normalization processes are made suitable for the network. Data used without normalization can prolong the training time of the network and adversely affect its performance [20]. In this study, some of the data was used to train the network and some of it was used to measure the performance of the network.

4.2. Elimination and Normalization Processing:

Data presented to the network must be compatible with working on the network. In training artificial neurons, the input data should be for the network to learn, not memorization. Therefore, random input data is preferred. Also, data with some exceptional values can be shown in the training of the network [21]. For example, a small amount of data with a much larger numerical value than other data can degrade the training performance of the network. In this case, this data can be deleted from among the entries. These data are selected manually.

Learning in artificial neurons takes place by updating the weights according to the output of the inputs and the weights. If the input data has a very large numerical range, it may take longer to successfully train the network as it will affect the result more. In this study, the "Min-Max normalization" method, which normalizes the data in the 0-1 range, was used to normalize the data. In this algorithm, during normalization operations, the normalization function shown in Equation 1 is applied to each input data series [22].

$$\mathrm{X'_i} = \frac{\mathrm{X_i} - \mathrm{X_{min}}}{\mathrm{X_{max}} - \mathrm{X_{min}}} \tag{1}$$

In Equation 1, X'_i represents the i th normalized input data, X_i represents the i th data to be normalized, X_{min} represents the smallest data in the data array, X_{max} represents the largest data in the data array. As seen in Equation 1, the minimum data value is subtracted from the data values in an array and then divided by the difference between the maximum data value and the minimum data value. Thus, all data is normalized to a range of 0-1 values. The normalized value of the maximum data is equal to 1, while the normalized value of the minimum data is equal to 0.

4.3. Designing Artificial Neural Networks

The data from the sieving and normalization process is ready to work on the neural networks to be trained. Artificial neural networks should be designed according to the amount of data. In artificial neural networks, the number of neurons in the input layer should be equal to the number of inputs [23]. This way each input can be processed with a weight. The data used in this study cover 4 basic inputs between 2019 and 2021. These entries are: Average monthly insolation time, Average ambient temperature, cloudy days, average monthly solar radiation. The neural networks designed with 4 basic input values are trained to try to reach the targeted monthly electricity production value in the output data. The artificial neural networks used in the study were designed with feed forward back propagation (FFB) and Elman back propagation (ELMB) architectures. The networks are trained and simulated based on the inputs.

Feedforward neural networks, one of the simplest forms of artificial neural networks, can be thought of as a transformation that maps an input sequence to an output sequence with the help of randomly assigned very small numbers of weights. This transformation can be expressed simply as in Equation 2 for a single layer network [24].

$$Y_i = f\left(\sum W_{ij} X_j\right) \qquad [2]$$

In Equation 2, X_j represents j th input vector and W_{ij} represents ij th vector's weight. Multiplying the randomly assigned weights by the input vector is summed. By processing this sum with the activation function, the output vector is obtained. It is only possible for the output vector to reach a different value by updating the weights.

Back propagation allows the weights to be updated again based on the error rate in the previous iteration. In short, training the neural network is possible by updating the weights correctly [25].

Elman networks are trained as backpropagation like feed forward networks. However, only feedforward weights are updated in the Elman network [26].

In this study, tangent sigmoid (TANSIG) and logarithmic sigmoid (LOGSIG) functions are used as activation functions. TANSIG, also called "hyperbolic tangent" in the literature, is a function with a dynamic range [-1, 1], showing a nonlinear variation in this range. LOGSIG is an activation function that has a dynamic range of [0, 1] and exhibits a non-linear change in this range. In Figure 12(a) and 12(b), input and output relations of TANSIG and LOGSIG functions are shown, respectively.

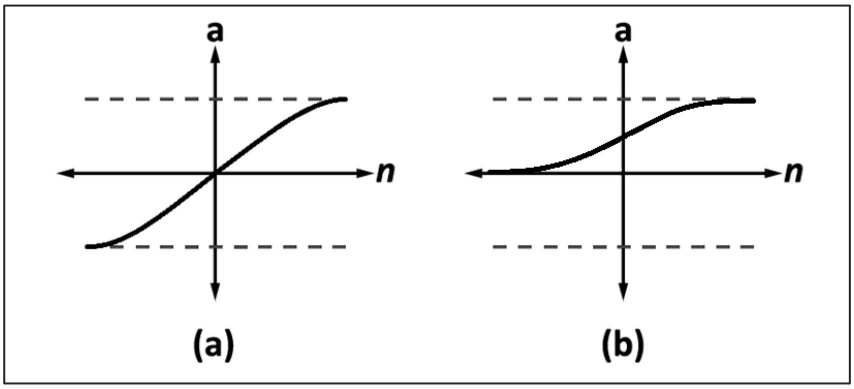

Figure 12 (a). TANSIG function and (b). LOGSIG function.

5. Comparison of Machine Learning Results for SPP at the University of Bakırçay

In this study, 6 different neural networks were tested using the monthly energy production data of the SPP at the University of Bakırçay and the meteorological data obtained from 4 different meteorology stations. Some of the data was used to train the network and some of it was used to simulate the network. While calculating the success and error rates, the average of the ratio of the energy production values estimated by the artificial neural network to the real data used in the testing of the network was used. The properties and test success results of artificial neural networks are shown in Table 3.

Table 3. Training and simulation results on artificial neural networks.

Test Number	1	2	3	4	5	6

Network Type	FFB	FFB	FFB	FFB	ELMB	ELMB
Training Function	TRNGDX	TRNGDX	TRNGDX	TRNGDX	TRNLM	TRNLM
Adaptive Learning	LRNGDM	LRNGDM	LRNGDM	LRNGDM	LRNGDM	LRNGDM
Performance Function	MSE	MSE	MSE	MSE	MSE	MSE
Number of Layers	3	3	3	3	3	3
Neurons at L1	5	10	5	5	5	5
Transfer Function L1	TANSIG	TANSIG	LOGSIG	LOGSIG	TANSIG	LOGSIG
Neurons at L2	5	10	5	5	5	7
Transfer Function L2	TANSIG	TANSIG	LOGSIG	LOGSIG	TANSIG	LOGSIG
Transfer Function L3	TANSIG	TANSIG	LOGSIG	LOGSIG	TANSIG	LOGSIG
Minimum Gradient	1.00E-07	1.00E-07	1.00E-07	1.00E-07	1.00E-07	1.00E-07
Iteration	200	200	200	300	300	300
Best Iteration	114	183	157	117	144	243
Training Regression	85.549%	99.810%	83.455%	74.987%	-	-
Validation Regression	99.810%	90.638%	70.703%	82.619%	-	-
Test Regression	95.278%	99.920%	32.657%	89.304%	-	-
All Regression	91.518%	96.100%	71.278 %	75.849%	-	-
Error Rate	7.774%	4.665%	32.571%	32.922%	10.042%	24.881%
Success Rate	92.226%	95.335%	67.429 %	67.078%	89.959%	75.120%

According to the test results on artificial neural networks given in Table 3, the success rate in trials with Elman Back-propagation networks varies between 75.12% and 89.96%. The artificial neural network trained with 300 iterations using the LOGSIG transfer function does not have an acceptable success as a result of the simulation. It has reached an acceptable level with a success rate of 89.96% in the tests performed using the TANGIS transfer function.

In trials with a feed-forward backpropagation neural network, the success rate ranges from 67.43% to 95.33%. The success rate in the experiment with the LOGSIG transfer function is not at an acceptable level. However, in the trials using the TANSIG function, the success rate was 92.23% when 5 neurons were used in the intermediate layers, while the success rate increased to 95.33% when the number of neurons in the intermediate layers was increased to 10. The artificial neural network was able to predict energy production with a very high success rate as a result of test number 2.

6. Conclusion

By comparing the energy measurement data of SPP at the University of Bakırçay and the measurement data of meteorology stations in the region, the relationship of meteorological factors with energy production has been interpreted. When the relationship between energy production data and meteorological data is compared, artificial learning methods are tried by presenting the same data to artificial neural networks. Artificial neural networks have successfully learned on the relevant meteorological data.

After the training, artificial neural networks were simulated to predict energy production by giving meteorological data that was not presented before. As a result of the simulation, it has been observed that feedforward backpropagation neural networks can predict energy production with a 95.33% success rate using the TANSIG transfer function.

In this study, it was shown that artificial neural networks can predict energy production under different meteorological factors, and it is possible to predict energy production with the help of artificial intelligence in future investments in geographies with different meteorological conditions and to guide future investors aimed.

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