Accurate estimate of wind and solar energy is essential to reduce the cost of renewable energy and to effectively and efficiently integrate variable energy sources into power grid operations [6]. Since solar energy varies depending on time, ambient temperature, solar irradiation, wind speed, humidity, pressure, etc., the estimate of Photovoltaic (PV) power output has become mandatory [7]. Solar energy has its own challenges. One is the variability of PV output power, which leads to electrical fluctuations due to changes in meteorological conditions [8]. The power generated by solar power plants depends on the intermittent energy provided by the sun. The variability caused by the daily solar cycle and other meteorological factors causes uncertainties in determining this energy production [9]. The latest techniques and approaches are emerging worldwide every year to reduce the uncertainty in estimates and improve the accuracy of models [10]. Solar irradiation forecasting in particular is an important component in solar energy production. Giving forecasts to PV plant managers and power grid operators helps them better plan their use of solar storage and other energies. The integration of PV into the network is therefore facilitated and optimized [10-13].

Solar irradiation prediction contributes to the literature using Physical, Time Series Statistical and Community (Hybrid) Methods and many methods included in them [9,14]. However, in recent years, artificial intelligence techniques, which are statistical methods, have been used as one of the most reliable and effective techniques for predicting solar irradiation [15-17]. Brenna et al. [17] have proposed an ANN-based forecasting model for estimating solar irradiation and load power consumption using external factors such as ambient temperature or wind speed, as well as time values (date, time) of these vectors. Sudirman et al. [18] have used Artificial Neural Networks (ANN) to predict short- and medium-term solar irradiation with air temperature, precipitation and day length data. Rami Al-Hajj et al. [19] estimated the value of solar irradiation in the United States with the help of daily meteorological data with the help of widely used Machine Learning models. Bâra et al. [20], in their study in Romania, estimated solar irradiation with a total of 50,000 data, adding wind direction data in addition to the data set specified in [18] and [19]. Deng et al. [21] have estimated solar irradiation from 10 different weather stations in China between 1993 and 2000, including geographic parameters (latitude, longitude, height) and days of the year. The study has shown that the performance of ANN models, geographical parameters, days of the year and sunlight are the most important factors for predicting daily global solar irradiation. Assas et al. [22] have estimated the irradiation in Djelfa, Algeria, with data on irradiation, relative humidity, temperature, atmospheric pressure and wind speed provided by the Algerian meteorological station, with the ANN network model. Alluhaidah et al. [23] using weather temperature, relative humidity, pressure, cloud cover, wind speed and direction and day information obtained between 2007 and 2010 in Riyadh, Saudi Arabia, they determined that cloud cover was the most effective parameter for predicting solar irradiation with the ANN model. Mbaye et al. [24] have used temperature and relative humidity data from 2016 to 2017 to assess the short-term (20-minute) impact of solar potential forecasting. Shaw et al. [25] have performed solar irradiation predictions using moisture, temperature and pressure data from meteorological parameters using artificial intelligence. Kumar et al. [26] have used ANN to estimate solar irradiation with four input meteorological variables of New Delhi's day, air temperature, relative humidity and atmospheric pressure between 2002 and 2003. Narvaez et al. [27] using machine learning method, they have estimated solar irradiation using the global horizontal irradiation (GHI), direct normal irradiation (DNI), solar zenit angle, temperature, wind speed and clock data as input data.

In this study, the estimation of solar irradiation, which is the most important parameter for the production of electrical energy in PV systems, was tried to be estimated using the MLP algorithm. In this study, solar irradiation prediction was carried out using real meteorological data (ambient temperature, relative humidity, atmospheric pressure, wind speed) recorded at 1 minute intervals from the meteorological station located at Hakkari University, on the campus of Çölemerik Vocational School.

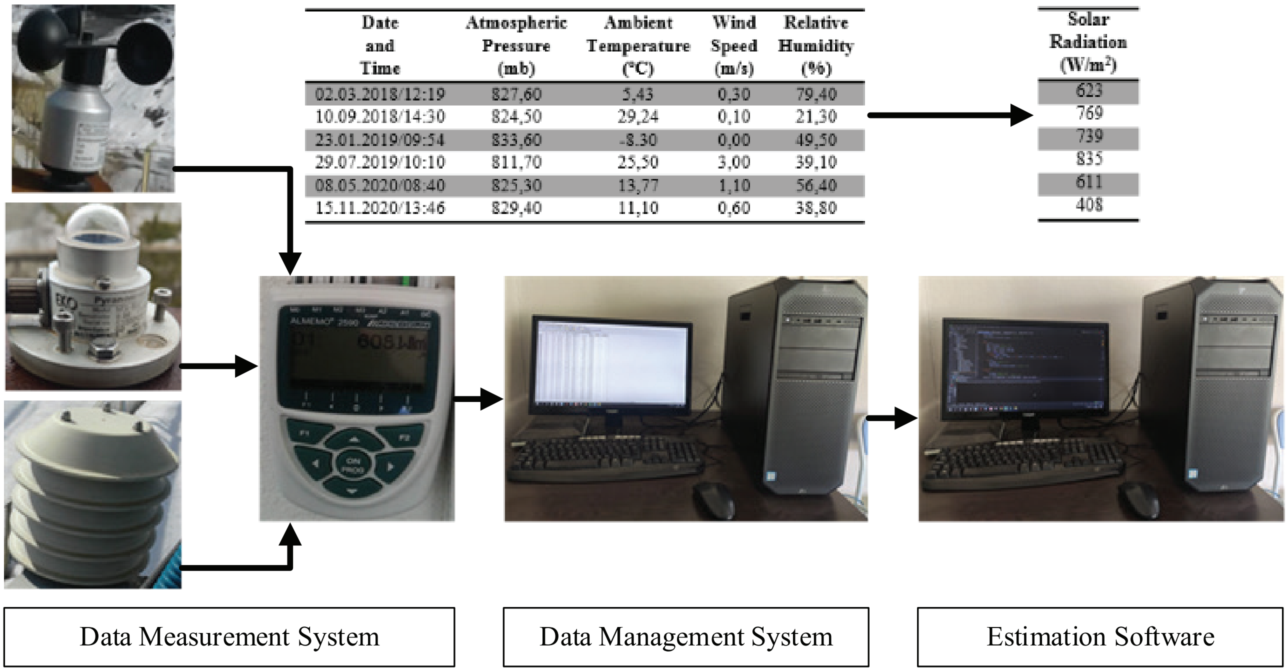
In the second part of the study, modeling of the proposed structure and network structure are included. In order to prove the performance of the model proposed in Chapter 3, various case studies were carried out and interpretations of the results obtained were included. In the last chapter, the results of the study are examined.

## MATERIALS AND METHODS

In the study, the solar irradiation values measured using energy house measurement station data at Hakkari University, on the campus of Çölemerik Vocational School were estimated through MLP. In order to prevent problems that may be caused by power outages and fluctuations, a backup power unit supported by PV panels has been installed in the energy house. The Ahlborn Almemo 2590 Datalogger and its corresponding measurement sensors were used as a measuring device for reading and recording data.

The purpose of this study is to try to determine the proximity of the relationship between meteorological measurement data for later use. For this purpose, the pressure, temperature, humidity and wind speed measured in the station are used in the input layer of MLP, while solar irradiation values are used for training and estimation in the output layer. The data used for training and estimation consists of values measured at intervals of 1 minute between 2018 and 2020. The sample data set used in the training and estimation study is given in Figure 1.

The data obtained was made through the Matlab program, based on a workstation in the energy house with a 20-core Intel Xeon Silver processor and a Quadro P2000



| Date and Time | Atmospheric Pressure (mb) | Ambient Temperature (°C) | Wind Speed (m/s) | Relative Humidity (%) |
|---|---|---|---|---|
| 02.03.2018/12:19 | 827,60 | 5,43 | 0,30 | 79,40 |
| 10.09.2018/14:30 | 824,50 | 29,24 | 0,10 | 21,30 |
| 23.01.2019/09:54 | 833,60 | -8.30 | 0,00 | 49,50 |
| 29.07.2019/10:10 | 811,70 | 25,50 | 3,00 | 39,10 |
| 08.05.2020/08:40 | 825,30 | 13,77 | 1,10 | 56,40 |
| 15.11.2020/13:46 | 829,40 | 11,10 | 0,60 | 38,80 |

| Solar Radiation ($W/m^2$) |
|---|
| 623 |
| 769 |
| 739 |
| 835 |
| 611 |
| 408 |



**Figure 1.** The sample data set and model used in the study.

graphics card with 1024 Cuda content. The MLP model used in the study was created using NNToolbox in the Simulink library in the Matlab interface. The library, which freely allows the formation of a wide range of networks, allows the use of parallel processes during calculation. Thanks to its comprehensive, easy and fast-to-apply parametric structure, it allows for a rapid evaluation of many different network structures and the optimal combination to best suit the data set. The data, which was quickly evaluated through smaller network structures, was tested on larger networks after selecting the best combinations and the final test results were obtained.

After the data was uploaded to the Matlab library, normalization was performed using the 'mapminmax' command as the first operation. Normalization is the process of compressing the data set set received at any value into a desired value area. The mathematical equation for the normalization process is given in Eq.1.

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

Each data obtained as a measurement result was narrowed to a range of 0 and 1, depending on the largest ($X_{max}$) and smallest ($X_{min}$) values in its set. The purpose of this is to ensure processing speed and to eliminate the memorization problems in the network that may arise due to the use of high levels of data. In addition, the data processed in each parameter within the network is subjected to a similar process with the help of ignition functions before being taken to the next processing section. Therefore, in order for the data to be recalled at a meaningful value on the network output, the normalization process parameters must be obtained at the output of the process. The 'mapminmax' function used allows each input and output data set to be normalized ($X'$) and its parameters to be maintained without requiring complex equations. On the other hand, for the denormalization process of the forecast results, it provides a great convenience in obtaining the output normal values easily through the parameters previously held. The mathematical expression of the denormalization process is included in Eq. 2.

$$X = X'(X_{max} - X_{min}) + X_{min} \tag{2}$$

After normalization of the data, a network was created through the newff command with various parameters. In the first parameter of this network, there is input and output data, and in the second, there is a 3-layer network model with 2 custom 200 and 1 custom 2 neurons. In the third and fourth parameters, the ignition function (poslin) and the calculation algorithm (trainlm) used for the model were used respectively. Previously, the input and output values of each data set in the rows were transposed so that the sets were located in the columns and modeled 200*200*2 in matrix format. The representational picture of the MLP model with 3 layers and 200, 200 and 2 neurons in each layer, respectively, is shown in Figure 2.

Each neuron here holds data on and in interconnection depending on the previous and next neurons and updates these values based on the algorithm used to store the information of each data set on it. According to the diversity of the data set and the low impact value of each data line, the

Clean Energy Technol J,, Vol. 1, No. 2, pp. 71–77, December, 2023

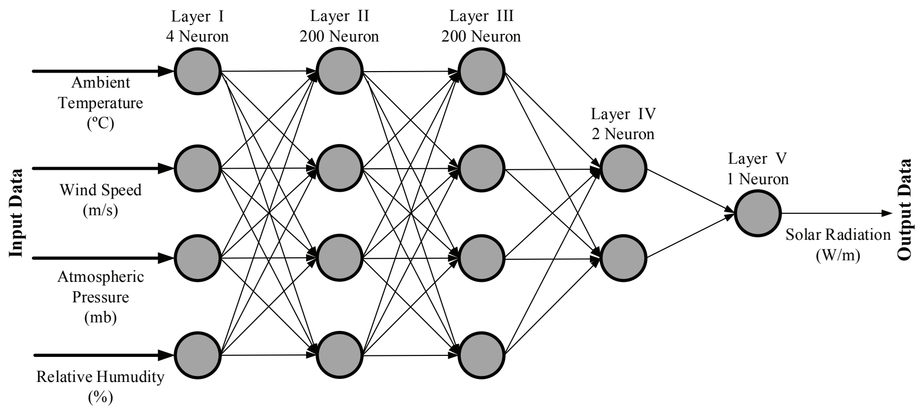



**Figure 2.** MLP model used in the study.

training is of higher quality. The data set used in the study includes independent measurement of 1051200 in this context and is sufficient as a result of the findings made to reveal the relationship between the variables.

Activation function, another parameter used in the model, was added to the study as a result of testing various functions in the Matlab library and selecting the most appropriate function. In this context, 'poslin' function was identified as the most successful function on the data set studied and this function was used in the training process of the network. On the other hand, in the algorithm section, it was determined that the 'trainlm' algorithm produced the most successful results on the data set studied after various experiments by using the algorithms in the Matlab library, as in the activation function, and it was decided to train with this function in the network.

## CASE STUDY

60% were used for training, 20% for verification and the remaining 20% for testing purposes of the 1051200 data sets used in this study. As a result of the Mean Square Error (MSE) method used for MLP performance measurement, the performance graph obtained through Matlab is shown separately in Figure 3 for training, verification and testing stages. The epoch value seen in Figure 3 refers to the number of cycles in which the deviation rate of approximately 2 percent occurs. In addition, after 6090 cycles on the training data set and verification, the best performance value is obtained and the training of the network is stopped in order to prevent memorization in epoch 6096 due to the occurrence of repetitions. As can be understood from the graph, it is understood that there are close relationships between the input data used and the solar irradiation values and that these relationships can be modeled using MLP.

One of the generally accepted methods for better understanding the interdependence of input and output data sets is the regression analysis method. Here, the data of dependent and independent are shown on the graph and expressed

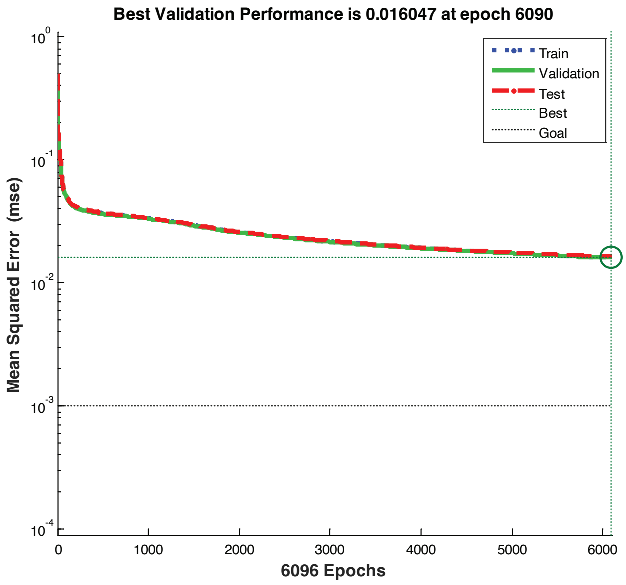



**Figure 3.** MSE graph of training, validation and testing phases.

mathematically using the correlation coefficient. Correlation allows the connection between the two variables to be measured. As the correlation coefficient approaches 1, the bond between the two variables becomes stronger. The correlation coefficient reaching values close to zero indicates the weak link between the two variables. Figure 4 shows a graph of the relationship between forecast results and actual measurement values based on regression analysis.

In Figure 1, the change in predicted solar irradiation values through the MLP neural network model, based on the data measurement and management system detailed in the figure, can be interpreted through a qq plot graph in comparison to actual solar irradiation values obtained regionally. In this study, the comparison of measured solar irradiation values with the solar irradiation values obtained through the prediction model is illustrated in the qq plot

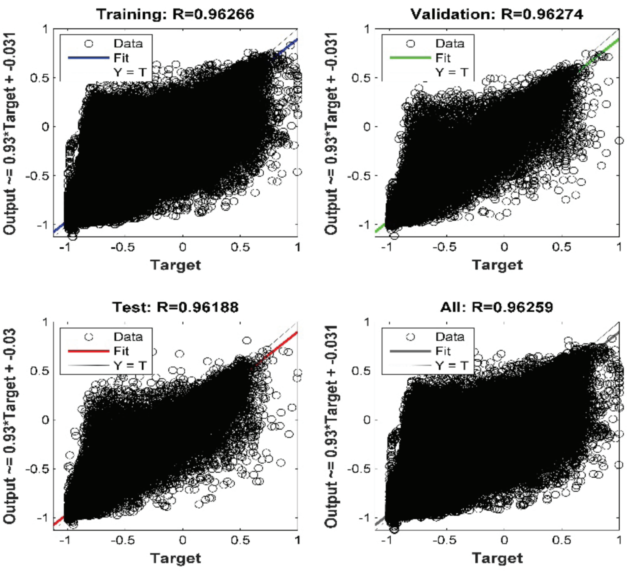



**Figure 4.** Regression graph of training, validation and testing phases.

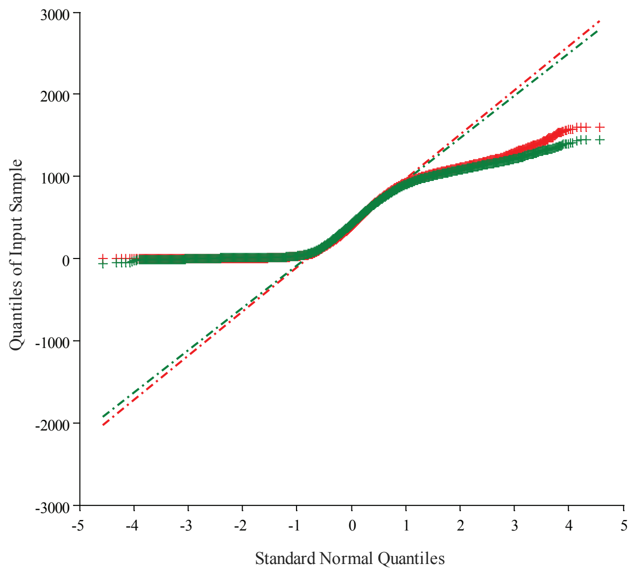



**Figure 5.** qq plot chart created to compare the prediction results of the study with real data.

graph shown in Figure 5. In this graph, it is observed that the actual solar irradiation values (green line/point) and the predicted solar irradiation values (red line/point) change in a highly consistent manner. The crucial aspect to pay attention to in the graph is the angle between the deviation lines. According to the obtained results, a low deviation angle in the graph indicates a successful prediction process. Additionally, the relationship between the actual and predicted solar irradiation data progresses similarly due to the smooth variation in the deviation ratio occurring in the MLP neural network model.

## CONCLUSIONS

The interactions of natural phenomena with each other can be modeled with MLP and the size of these relationships can be observed with great success rates. This indicates that another of the natural phenomena that can be predicted by various methods can be predicted under certain parameters. In this study, instant solar irradiation values were estimated through MLP using meteorological data such as wind speed, atmospheric pressure, ambient temperature and relative humidity obtained from the energy house measuring station located at Hakkari University, on the campus of Çölemerik Vocational School. In order to test the solar radiation prediction success of the created MLP model, instantaneous changes of the data were observed and various model studies were carried out using real data measured at 1 minute intervals. As a result of the study with the data set containing different measurement results 1051200, the solar irradiation values measured by the station were compared with the forecasting results and it was determined that the estimation of the model created with a deviation rate of approximately 2 percent.

In prediction studies conducted using ANN, the inclusion of all the data in the input layer of the constructed network model serves to increase the amount of information related to the condition being predicted. This enhances the comprehensibility of the interdependencies among the data, contributing to a more thorough understanding of the relationships between them. Therefore, forecast performance can be improved by using larger training data sets in future studies.

## AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

## DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

## CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

## ETHICS

There are no ethical issues with the publication of this manuscript.

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