Design of an Artificial Neural Network-Based Model for Prediction Solar Radiation Utilizing Measured Weather Datasets

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Abstract: **-** Forecasting solar radiation plays an important role in the field of energy meteorology, as it provides the energy value expected to be produced by the solar plants on a specific day and time of the year. In this paper, a new and reliable artificial intelligence-based model for solar radiation prediction is presented using Artificial Neural Network (ANN). The proposed model is built utilizing real atmospheric affecting measured values according to their locational weather station. In the training process, the Levenberg–Marquardt (LM), Bayesian Regularization (BR), and Scaled Conjugate Gradient (SCG) are used. The mean absolute error (MAE) and the root mean square error (RMSE) are used to evaluate the model accuracy. Results of the investigation show that the proposed model provides the lowest error rate when using the (BR) training algorithm for predicting the average daily solar radiation.

Key-Words: -Hourly solar radiation, Artificial neural network, Backpropagation algorithms.
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1 Introduction

Nowadays, solar energy is globally considered as one of the most expanding resources of energy, due to its economic and environmental advantages as an alternative resource of energy [1]. It has shown to be one of the leading fields through its wide increase of financial spending for investment in this field, which directly impacts the growth of gross domestic product [2]. Solar energy increases the diversity of energy sources, helps in enhancing the reliability of electrical systems, and reduces the voltage difference between busbars [3]. Prediction of solar irradiance and energy has become one of the most recent important topics, as to increase the solar energy reliability [4].

Forecasting has attracted many researchers and became their main interest of search. Recent researches suggested different models for predicting solar production utilizing atmospheric parameters using ANN. Gihan Amarasinghe, s. K. Abeygunawardane proposed an ANN model to predict solar power and compared their results with the smart persistence model at Sri Lanka investigating the (temperature and humidity) weather parameters. It was found that their ANN model was more accurate for solar power prediction at clear and overcast conditions. In addition to that, they found that their prediction errors can be improved when increasing the number of inputs for their suggested model [5]. Gilles Notton, et, proposed two ANN models to estimate the global horizontal irradiation (GHI) and the direct normal irradiance (DNI) as a function of time for one and six hours ahead using temperature, wind speed, and humidity. It was found that their models have errors (RMSE) from 22.57% (for one hour) to 34.85% (for six hours) for the GHI and from 38.23% (for one hour) to 61.88% (for six hours) for the DNI [6]. Donghun Lee and Kwanho Kim Suggested three models for studying the relation between PV output power prediction and meteorological information. Their proposed methods were ANN, deep neural network (DNN), and long and short-term memory (LSTM). Using temperature, humidity, cloudiness, and solar irradiance, they concluded that the LSTM was more accurate in solar prediction than the ANN and DNN, where the LSTM successfully performs better by more than 50% [7]. K.Ranjith Kumara and M.Surya Kalavathib investigated two models (ANN and Adaptive Neuro-Fuzzy inference System) for the solar prediction problem. Using their solar irradiance and production data, they concluded that the ANN model provided better results than the ANFIS in forecasting based on the RMSE errors [8]. Jiaojiao Feng, WeizhenWang, and Jing Li developed back-propagation neural network method with Levenberg-Marquardt algorithm to simulate monthly radiation using clouds, aerosols, and perceptible water vapor. Their proposed method was able to predicate monthly solar radiation efficiently[9]. Tanawat Laopaiboon, Weerakorn Ongsakul, Pragya Panyainkaew, Nikhil Sasidharan proposed back propagation ANN model to predict hour PV irradiation using solar irradiation, average temperature, humidity The model is better to predict solar irradiance by lower error[10]. Graeme Vanderstar, Petr Musilek, Alexandre Nassif forecasting solar energy via sunlight intensity and solar position by ANN model using at none zero solar global horizontal irradiation for temperature, wind speed, and relative humidity. Their model was able to achieve satisfying result with a low error percentage [11]. Premalatha Neelamegama and Valan Arasu Amirtham explain that the quantity of the dataset is affected by the output of ANN. They suggested an ANN model that forecasts monthly solar energy using temperature, humidity, and wind speed [12].

Even though, numerous research models have been proposed on solar radiation prediction, there is a space for result enhancement and improvement. Therefore, in this paper we propose a new ANN model that takes into account all affecting system parameters for prediction daily solar irradiance utilizing real atmospheric datasets. The model will be evaluated using the training algorithms; Levenberg–Marquardt (LM), Bayesian Regularization (BR), Scaled Conjugate Gradient (SCG). The maximum and minimum temperature, relative humidity, maximum, minimum, and average wind speed were used in predicting the solar radiation for a specific location. All of the data were considered for the day light period, while excluding all night periods. The ANN model with the best training algorithm were selected based on the minimum mean absolute error (MAE) and minimum root mean square error (RMSE).

2 Artificial Neural Network

Artificial Intelligent techniques (AI) have the potential for making quicker, better, and more accurate predictions for numerous problems. Artificial neural network is superior to traditional methods for prediction, curve fitting and regression [13]. Neural networks operate as a black box, consists of three layers: an input layer that collects data, an output layer that computes data, and one or more hidden layers that link the input and the output layer. A neuron is a fundamental processing unit in a Neural Network (NN) that consists of two parts: receiving inputs and creating output. As illustrated in Figure 1 (as well known), each input is multiplied with a weight then is passed through an activation function to create an output. The strength of the connection between neurons is represented by weights, which determine how much influence a specific input will have on the neuron's output. The input vector is represented by[14]:

$$\mathrm{X} = [x_1, x_2, \dots, x_i] \tag{1}$$

The weight row vector is represented by:

$$\mathrm{W} = [w_1, w_2, \dots, w_i] \tag{2}$$

The summation of dot product for input vector and weight vector is described in Equation (3), where (i) is the number of inputs, (j) is the number of hidden layers, and (b_1) represents the bias value used to change the output, as well as the weighted sum of the neuron's inputs. Therefore, bias is a constant that assists the model in fitting the data as best it can.

$$h_1 = \sum_{i=1}^{n} x_i w_{ij} + b_1 \tag{3}$$

At the hidden layer, the activation function f_1 is a sigmoid function which can be expressed as follows in Equation (4) to produce the output layer.

$$f_1 = \mathrm{Tan}sig(h_1) = \frac{1}{1 + e^{-2h_1}} - 1 \tag{4}$$

The dot product of the hidden layer function (f_1) and output weight (W_2) is summed to the output layer bias (b_2) as expressed in equation (5).

$$h_2 = \sum_{i=1}^{n} x_i w_{ij} + b_2 \tag{5}$$

The activation function of the output layer is purelin of (h2) described in Equation (6).

$$f_2 = \mathrm{Purlin}(h_2) = h_2 \tag{6}$$

The ANN is trained to find the best fitting value of weights according to optimization algorithms. In this paper, Levenberg–Marquardt (LM), Bayesian Regularization (BR), and Scaled Conjugate Gradient (SCG) are used to train the proposed model for daily solar irradiance prediction.

3 Proposed Methodology

As shown in Figure 2 the prediction methodology is divided into several steps, in order to produce the optimal model with the lowest possible error.

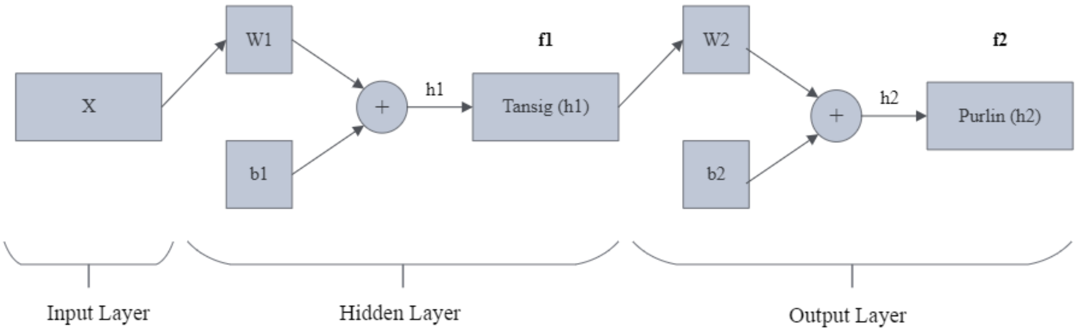

Figure 1: ANN General Architecture Diagram

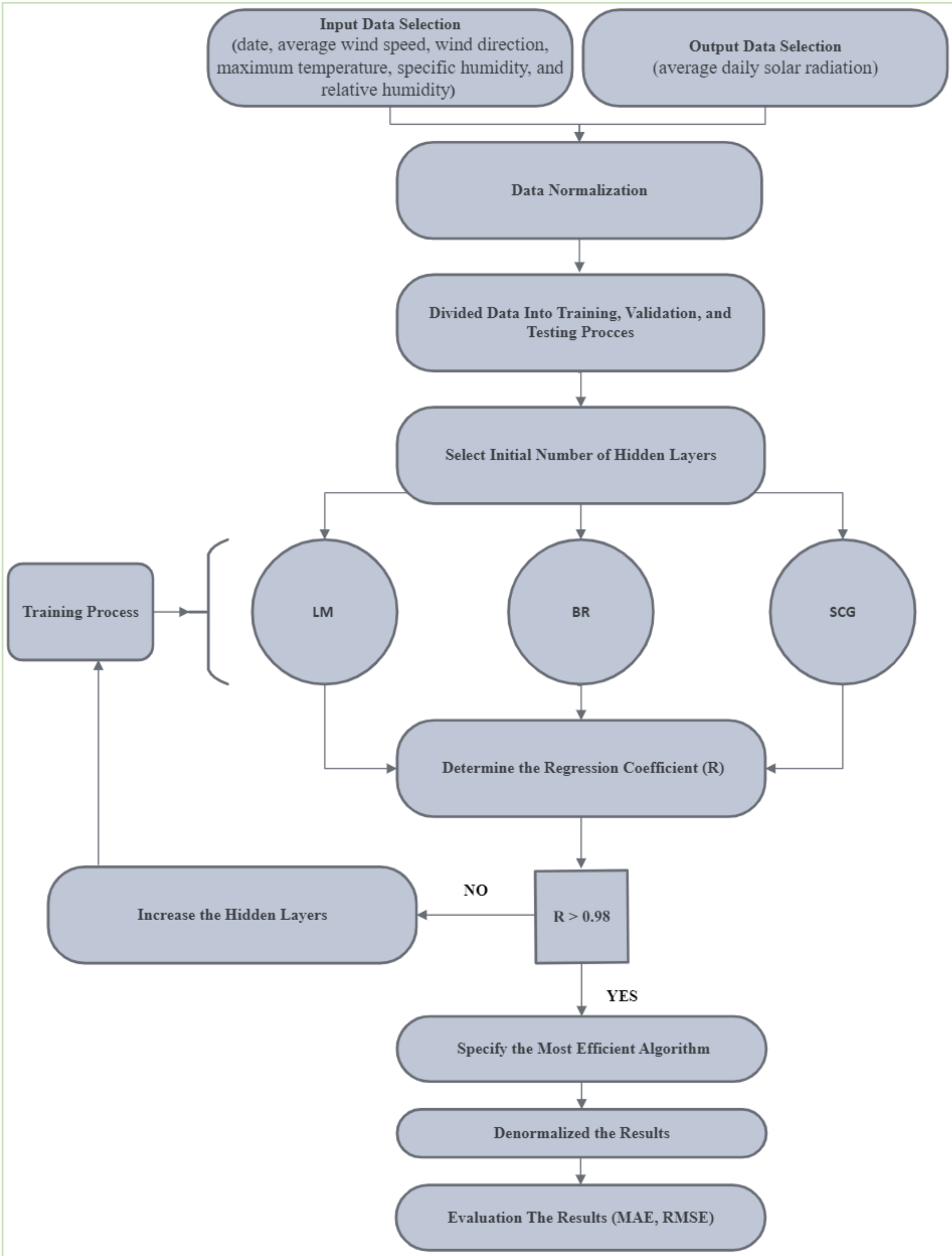

Figure 2: Overall methodology flowchart

3.1 Datasets Collection

The data from the weather station located at the Hashemite University, in Jordan, was used to develop the present based model. The data was about 2196 readings from 1/1/2021 to 31/12/2021, which includes date, average wind speed of a day, wind direction, maximum temperature, specific humidity, and relative humidity. The location of the university has a latitude of 32.102865 and a longitude of 36.181057 with 566-meter altitude.

3.2 Normalization

The dataset for the proposed ANN model was pre-identified as discussed in the previous section. The selection data describe various values with different ranges. Hence, it was required that the data be normalized, as in Equation (7) (common scale), to fit the presented ANN model. As a result the input and output data sets were normalized to the range between 1 and -1, as normally used for the tan sigmoid activation function [15].

$$X_{N}=0.8\left(\frac{X_{R}-X_{MAX}}{X_{MAX}-X_{MIN}}\right)+0.1 \quad (7)$$

Where:
X_N: normalized value.
X_R: value to be normalized.
X_{MAX}: maximum value among all values for related variable.
X_{MIN}: minimum value among all values for a related variable.

3.3 ANN model Implementation

The proposed ANN model consists of three layers, as shown below in Figure 3. The input layer consists of the data previously featured, multi hidden layers which connect the inputs, and the output layer by specific weights were determined to reach the result with minimal errors.

As mentioned in the previous section three training algorithms were used to estimate the output values utilizing the atmospheric data obtained by the weather station. The present ANN model was developed using MATLAB, version R2020a and ANN fitting toolbox.

3.4 Training, Validation and testing processes

The training process was iteratively performed, in which the network was supplied with the training datasets one by one, and the weight values were modified each time. During this phase, the ANN should have learnt to predict the proper output, with the aim of generalizing the prediction to new data sets. The process of evaluating the trained model, using a testing dataset, was referred to as model validation. In conjunction with model training, the model was validated trying to discover an ideal model with the best performance. The data was divided into three categories; training, validation, and testing specified as 70%, 15%, and 15% respectively. The testing dataset was a subset of the dataset that the training dataset was produced from. The objective of that was to see how well the trained model can be generalized.

3.5 number of hidden layers

The Regression Factor (R), which describes the relationship between the inputs and the outputs for evaluating the model and calculating the optimal number of neurons in the hidden layer. To evaluate the model for predicting acceptable outputs and to obtain minimum RMSE errors, the number of hidden layers must be fit to the data used to prevent overfitting and underfitting issues. The optimal number of hidden layers is an important issue that has to be considered. Two approaches exist to find the optimal number of the hidden layers, which can be classified as constructive and pruning approaches. The constructive method starts with under sizing the number of layers and increasing that number each time to get the fit number of hidden layers. On the other hand, the pruning approach starts with oversizing the number of layers and then decreasing that to obtain the optimal number of hidden layers[16].In this paper, the constructive method was used to determine the number of hidden layers for each training algorithms. Based on the analysis shown in Figure 4, it was found that the BR training algorithm provides the best suboptimal value of the regression performance at 16 hidden layers.

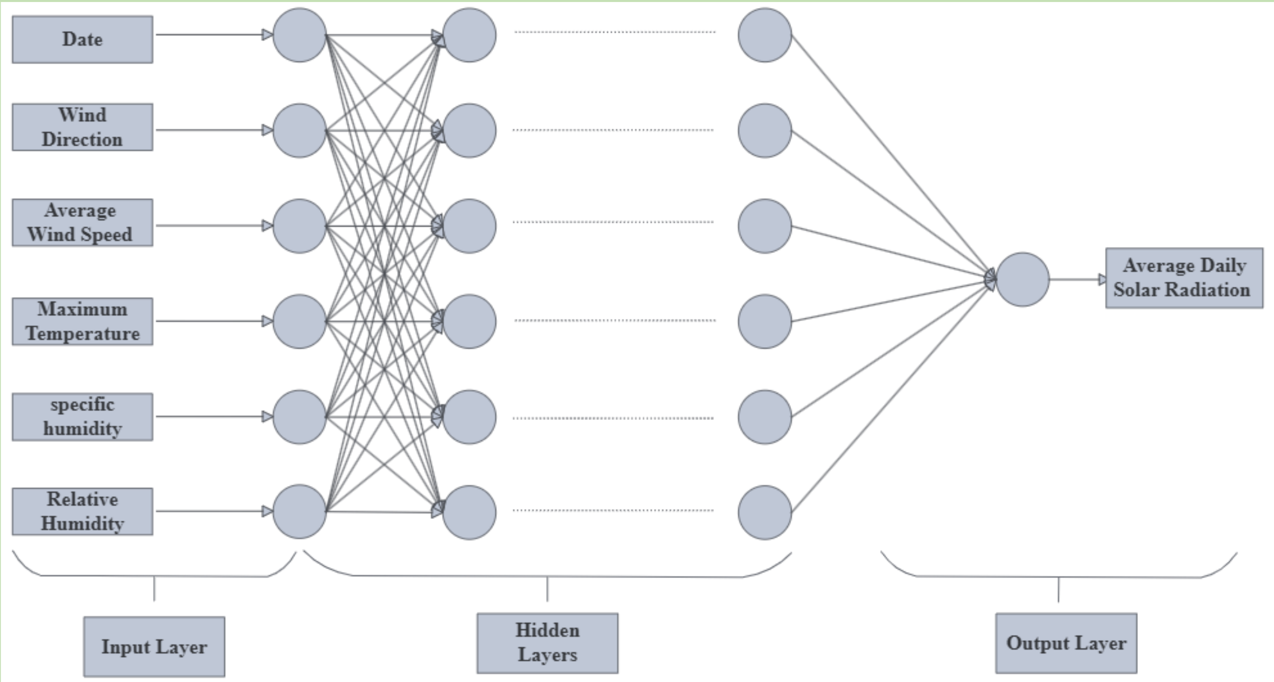

Figure 3: Schematic diagram of the proposed model

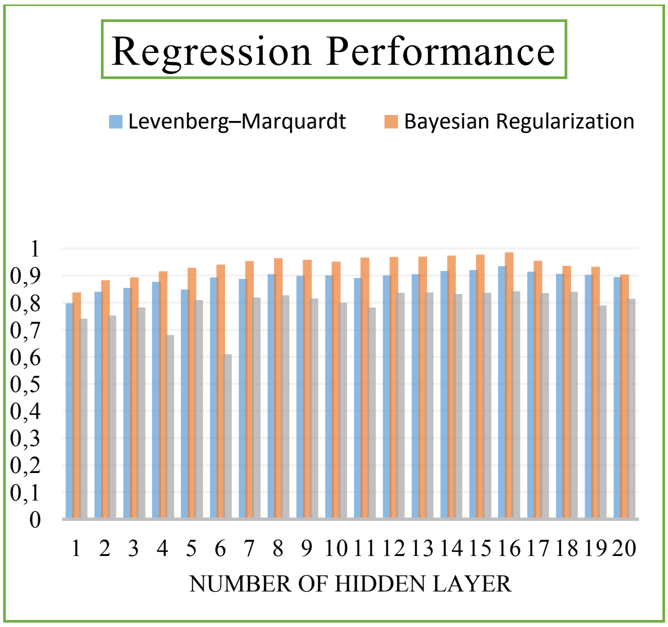

Figure 4: The linear correlation coefficient value for each training algorithm

4 Results

4.1 Data set selection

As known by now that the main objective of the proposed ANN model was to predict the average daily radiation values utilizing different measured weather datasets, the input and output datasets were collected from the Hashemite University, for the period 01/01/2021 to 31/12/2021. The selected datasets were trained and tested for the day, excluding all night periods to avoid the zero-radiation data in order to improve the result and reach lower error rates. The proposed model was designed using six input layers, as mentioned earlier, and one output layer, which includes the solar radiation according to the historical datasets. The model was trained utilizing three backpropagation algorithms Levenberg–Marquardt (LM), Bayesian Regularization (BR), and Scaled Conjugate Gradient (SCG) to determine the most efficient model.

4.2 Model evalouation

Using the BR training algorithm, sixteen hidden layers were found to represent the most efficient model. The performance of this model was evaluated using the mean absolute error (MAE) and the root mean square error (RMSE) [17]. The MAE and RMSE were expressed as follows in equations.

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^{N} |X_i - Y_i| \tag{8}$$

And

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (X_i - Y_i)^2} \tag{9}$$

where:
N: total amount of data.

X_i: average daily solar radiation from historical data.
Y_i: average daily solar radiation from the ANN model.
To evaluate the proposed model, results of the different training algorithms will be compared based on the (MAE) and the (RMSE) at the optimal hidden layers, which ensures obtaining the highest linear regression factor (R). The proposed ANN is presented as shown in Figure 5.

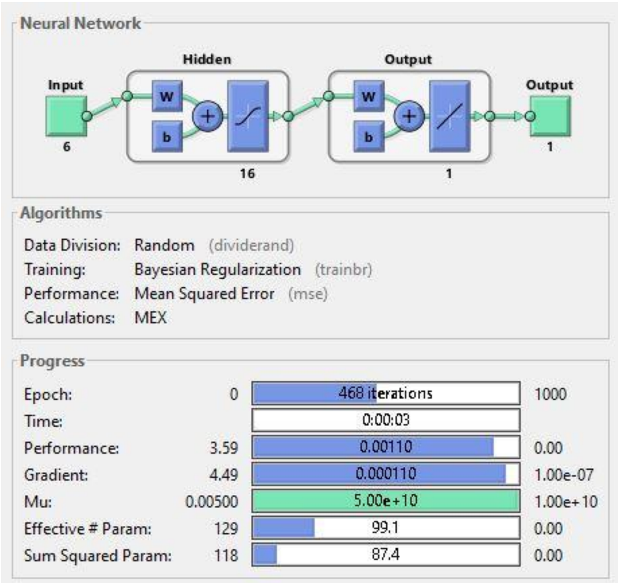

Figure 5: An overview of the proposed ANN model.

Table 1 shows the correlation coefficient (R), (MAE) and (RMSE) for the Levenberg–Marquardt (LM), Bayesian Regularization (BR), Scaled Conjugate Gradient (SCG) training algorithms. In this table, it is shown that depending on the magnitude of the mean absolute error and root mean square error, the BR training approach presents the most efficient model. Therefore, the BR algorithm is considered as to provide the lowest linear regression coefficient factor compared with the LM and SCG algorithms at 16 hidden layers. The best network performance is obtained after 468 iterations.

Table 1 Performance of proposed ANN model for each training algorithms at 16 hidden layers

Training method	Correlation Coefficient (R)	MAE	RMSE
LM	0.9347	1.864	2.65
BR	**0.9855**	**0.692**	**1.376**
SCG	0.8422	2.94	3.89

The performance of the BR model expresses the relationship between the observation values and predicted values; as shown in Figures 6-8, by comparing the results with all datasets. Thus, an observed, the values produced by the proposed model are almost identical to the previously measured values. Therefore, the BR is more efficient than the other algorithms.
The linear regression coefficient factor for the BR model is (0.9855), whereas it is (0.93475) and (0.84222) for the LM and SCG algorithms, respectively. As shown in Figure 9, the correlation coefficients for training and testing were found to be (0.98922) and (0.96213), respectively, where the R value above each plot represents the coefficient of correlation.

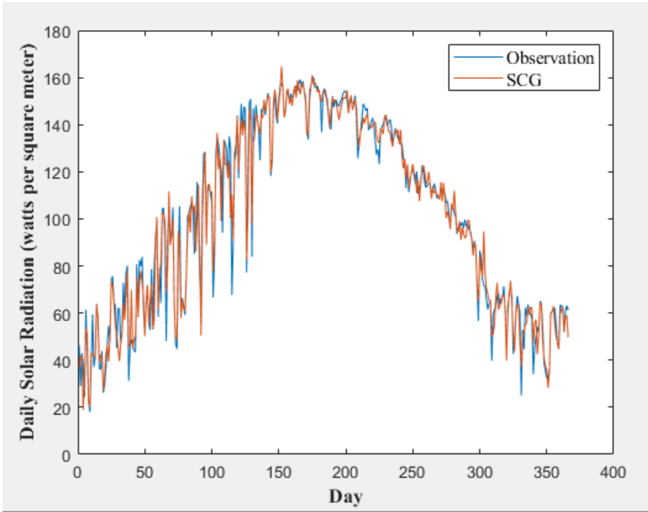

Figure 6: Performance of the ANN SCG model

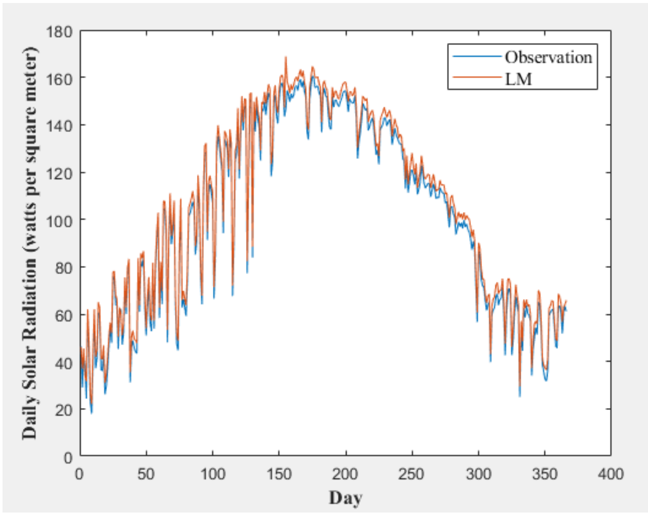

Figure 7: Performance of the ANN LM model

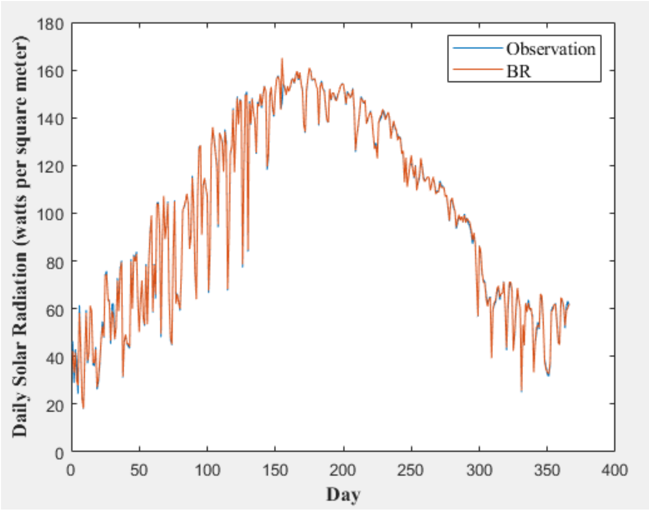

Figure 8: Performance of the ANN BR model

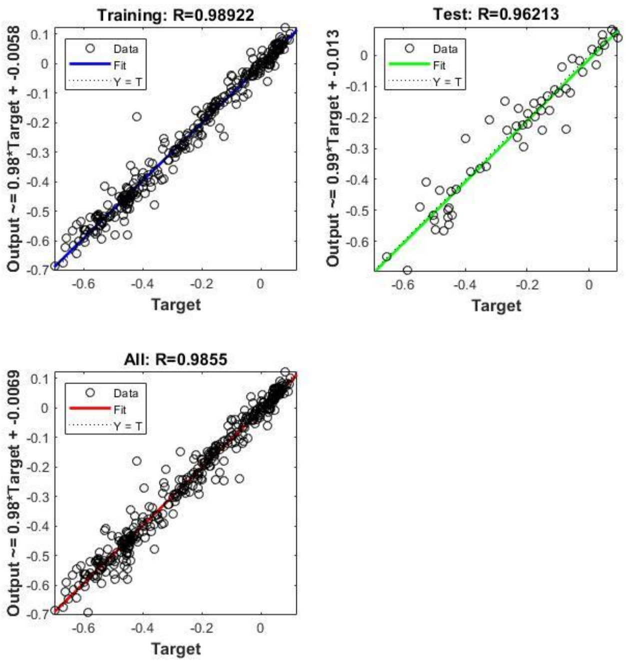

Figure 9: Regression plot for the BR model

The best training performance validation for the BR model, as shown in Figure 10, occurs at epoch 163, as indicated by the vertical dash line. which represents the process of training the neural network with all training data for one cycle. As shown both the training and testing curves have comparable properties. The network is producing best results according to the minimum MSE. Hence, by increasing the number of epochs, the MSE was reduced to a minimum by reaching epoch 163.

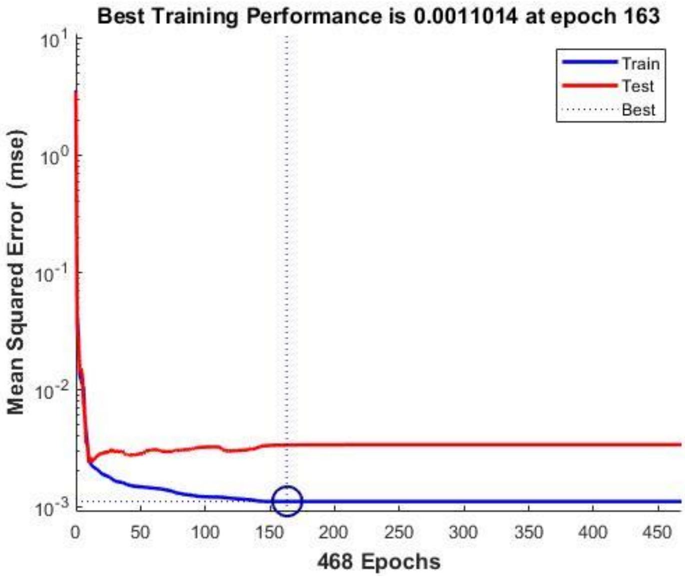

Figure 10: Performance plot for the Bayesian Regularization model

The histogram plot, as shown in Figure 11, emphasizes the accuracy of the network performance to evaluate the variance performance (whether it is appropriately distributed equally around zero), and explain the discrepancies between the target and the predicted values after training the neural network. As shown, most of the data falls around the zero-error line, while the maximum bars fall significantly lower to this.

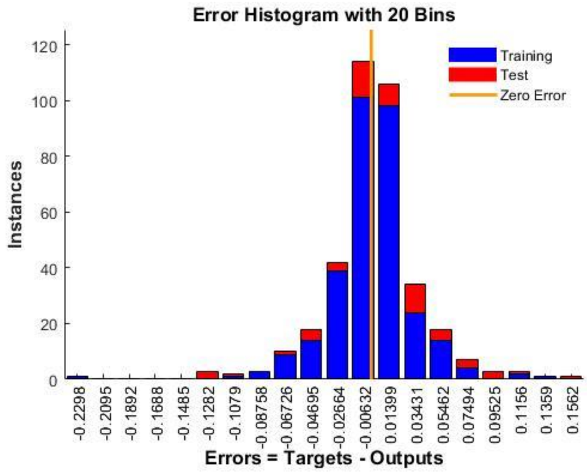

Figure 11: Error histogram plot showing the target and predicted error values

Table 2 represents a comparison of the published studies on similar research using ANN and other approaches. It is clearly seen that the proposed model has the minimum MAE, RMSE, and Mean Absolute Percentage Error (MAPE) in comparison with other similar studies, and thus, the developed model indeed provides superior predictions.

Table 2 Error comparison of similar studies

Model	MAE	RMSE	MAPE %
Sözen et al. [18]	-	-	6.78
Koca et al. [19]	-	5.26	-
Neelamegam and Amirtham [12]	-	-	4.24
Mohamed [20]	-	2.051	4.982
Notton et al. [6]	2.41	3.21	
Present model	**0.692**	**1.376**	**1.01**

5 Conclusion

This paper presents an ANN-based model prediction for the daily solar radiation according to historical data collected by a weather station located at the Hashemite University (in Jordan) for the period 01/01/2021 to 31/12/2021. The proposed model was trained using three different algorithms, Levenberg–Marquardt (LM), Bayesian Regularization (BR), and Scaled Conjugate Gradient (SCG). The selected data were categorized into three classes: training, validation, and testing for 70%, 15%, and 15%, respectively. The number of hidden layers were optimized according to the maximum linear correlation coefficient (R) value. Accordingly, it was concluded that the ANN trained by the BR approach achieved the lowest MSE and RMSE values. Meanwhile, the ANN trained by LM attained low MSE and RMSE values, however relatively larger compared to the BR. Whereas the SCG-trained ANN had the highest error rates, which was regarded as the weakest in terms of forecasting when compared to the previous two models.

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