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Artificial neural networks based prediction of insolation on horizontal surfaces for Bangladesh

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Abstract

In this work, Artificial Neural Network (ANN) based model for predicting the solar radiation in Bangladesh has been developed. Standard multilayer, feed-forward, back-propagation neural networks with different architecture have been designed using MATLAB's Neural Network tool. The training and testing data of 64 different locations spread all over Bangladesh were obtained from the NASA surface meteorology and solar energy database. The input parameters for the network are: latitude, longitude, elevation, month, average daylight hours, mean earth temperature and relative humidity while the solar insolation on horizontal surfaces are the target parameters. The overall Mean Square Errors (MSE) during training 0.0029, regression value of 0.99707, small percentage of error (0.16% to 1.71%) in response to unknown input vectors indicate that the developed model can be used reliably for predicting insolation of locations where there is no direct irradiance measuring instruments.

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Artificial neural network; insolation; mean squared error; Levenberg-Marquardt backpropagation algorithm; reneuable energy; Bangladesh

1. Introduction

Like many other countries, Bangladesh is facing immense energy challenges, characterized by low rate of access to the electricity, frequent load-shedding and unsatisfactory power quality. Solar energy provides Bangladesh government with the opportunity to address these challenges. This country is endowed with sufficient solar radiation

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potential that can be effectively harnessed as renewable energy resource [1,2]. To do that, detailed information about the availability of solar radiation on horizontal surfaces in different geographical locations is essential. This is considered as one of the most important parameters for the optimum design and study of solar energy conversion systems.

Solar radiation data of individual location of Bangladesh are not available due to high cost of measuring instrument and complicated techniques involved. Solar resources are known to exhibit a high variability in space and time due to the influence of various geographical, meteorological and climatic variables, such as, sunshine duration, cloud cover, humidity, temperature, pressure, altitude, etc [3]. Therefore, precise solar radiation estimation tools are critical in the design of solar systems for accurate, short-term and long-term knowledge of the solar radiation characteristics of various locations. Several empirical formulas have been developed to calculate the solar radiation using various parameters [4,5]. These developed empirical models are location specific and hence are limited in scope and application. For addressing and overcoming these limitations, nowadays artificial intelligent techniques are being used successfully for solar radiation mapping or modeling in several countries [6].

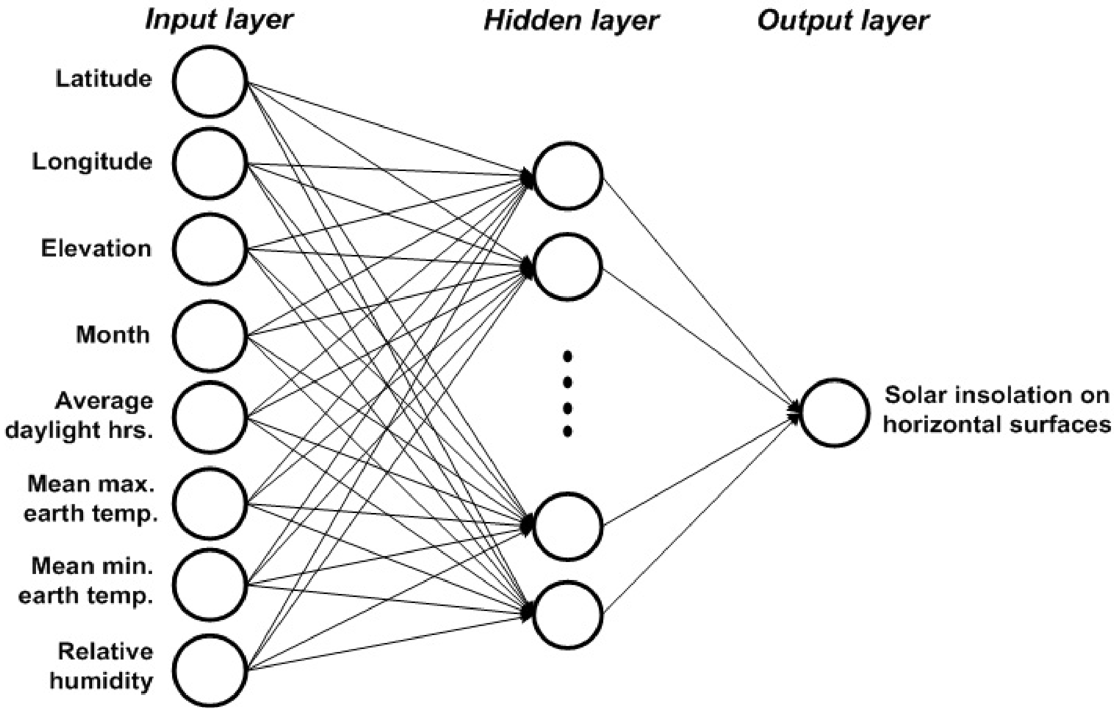

Fig. 1. ANN architecture for the insolation prediction model

ANN is a modeling and prediction tool, widely accepted as an alternative way to tackle complex and ill-defined problems. ANN models are efficient and less time consuming in modeling of complex systems compared to other mathematical models, such as, regression. Artificial neural network (ANN) modeling technique offers a better solution for developing a more generalized model for prediction of solar radiation data using climatic and meteorological parameters [9].

There have been several articles that have used artificial neural networks for predicting solar radiation [7-13]. Some initial works in this field were presented by Al-Alawi & Al-Hinai, 1998, Mohandes et al., 1998 and Lopez et al., 2001. In the article of Al-Alawi & Al-Hinai, 8 different parameters as the inputs of ANN model is used for predicting solar energy in Oman. Their model has shown good accuracy about 93% [7]. A. Sozen et al. applied ANN model for forecasting solar radiation in Turkey. In this article 6 different input parameters were used and finally an accuracy about 93% was acquired [8]. In the work of F.S. Tymvios et al. 4 parameters as the inputs of the model were totally used. The ANN model with different forms of these input parameters was run and finally the acquired results of ANN model were compared with the results of conventional angstrom model [9]. Senkal and Kuleli (2009) also used artificial neural networks for the estimation of solar radiation in Turkey. Meteorological and geographical data (latitude, longitude, altitude, month, mean diffuse radiation and mean beam radiation) are used in the input layer of the network. Solar radiation is the output. By using the ANN and a physical method, solar radiation was predicted for 12 cities in Turkey. The monthly mean daily total values were found to be 54 W/m^2 training cities, and 91 W/m^2 and 125 W/m^2 and 64 W/m^2 for the testing cities, respectively. According to the results of these 12 locations, correlation values indicate a relatively good agreement between the observed ANN values and the predicted satellite values [10]. Rehman and Mohandes (2008) used the air temperature, day of the year and relative humidity values as input in a neural network for the prediction of global solar radiation (GSR) on horizontal surfaces. For one case, only the day of the year and daily maximum temperature were used as inputs and GSR as output. In a second case, the day of the year and daily mean temperature were used as inputs and GSR as output. In the last case, the day of the year, and daily average values of temperature and relative humidity were used to predict the GSR. Results show that using the relative humidity along with daily mean temperature outperforms the other cases with absolute mean percentage error of 4.49%. The absolute mean percentage error for the case when only day of the year and mean temperature were used as inputs was 11.8% while when maximum temperature is used instead of mean temperature is 10.3% [11]. Tymvios et al. (2005) used artificial neural networks for the estimation of solar radiation on a horizontal surface. In addition, they used the traditional and long-utilized Angström's linear approach which is based on measurements of sunshine duration. The comparison of the performance of both models has revealed the accuracy of the ANN [9].

Limited number of solar radiation measuring equipment for various geographical locations of Bangladesh has limited the development of solar energy applications. Therefore, it is rather important to develop a methodology to estimate the solar radiation based on other climatic parameters that are easily measured with more available equipment [7]. Therefore, applying ANN can be valuable in determining the effects of meteorological parameters and finally prediction of solar radiation.

In this work, we have developed a simple multilayer feed-forward neural network as shown in figure 1. Easily available and conventional geographical and meteorological parameters have been used as the input parameters to predict the insolation on the horizontal surfaces. Training and test performance of the proposed network is satisfactory enough to predict insolation with negligible errors.

2. Artificial neural networks

ANNs are simply mathematical techniques designed to accomplish a variety of tasks. They can be configured in various arrangements to perform a range of tasks including pattern recognition, data mining, classification, forecasting and process modelling [14]. ANNs are composed of attributes that lead to perfect solutions in applications where we need to learn a linear or nonlinear mapping. Some of these attributes are: learning ability, generalization, parallel processing and error endurance. These attributes would cause the ANNs solve complex problem methods precisely and flexibly.

ANNs consists of an inter-connection of a number of neurons. There are many varieties of connections under study, however here we will discuss only one type of network which is called the Multi Layer Perceptron (MLP). In this network the data flows forward to the output continuously without any feedback. Figure 2 shows a typical three-layer feed forward model used for forecasting purposes. The input nodes are the previous lagged observations while the output provides the forecast for the future value. Hidden nodes with appropriate nonlinear transfer functions are used to process the information received by the input nodes. The model can be written as:

$$y_t = \alpha_0 + \sum_{j=1}^{n} \alpha_j f\left(\sum_{j=1}^{m} \beta_{ij} y_{t-i} + \beta_{0j}\right) + \varepsilon_t \quad \text{.......} (1)$$

Where m is the number of input nodes, n is the number of hidden nodes, f is a sigmoid transfer function such as the logistic: $f(x) = \dfrac{1}{1+\exp(-x)}$. $\{\alpha_j, j = 0,1,....,n\}$ is a vector of weights from the hidden to output nodes and, $\{\beta_{ij}, i = 1,2,....,m; j = 0,1,2,.....,n\}$ are weights from the input to hidden nodes. α_0 and β_{0j} are weights of arcs leading from the bias terms which have values always equal to 1. Note that Equation (1) indicates a linear transfer function is employed in the output node as desired for forecasting problems. The MLP's most popular learning rule is the error back propagation algorithm. Back Propagation learning is a kind of supervised learning introduced by Werbos (1974) [15] and later developed by Rumelhart & McClelland (1986) [16]. At the beginning of the learning stage all weights in the network are initialized to small random values. The algorithm uses a learning set, which consists of input–desired output pattern pairs. Each input–output pair is obtained by the offline processing of historical data.

These pairs are used to adjust the weights in the network to minimize the Sum Squared Error (SSE) which measures the difference between the real and the desired values overall output neurons and all learning patterns.

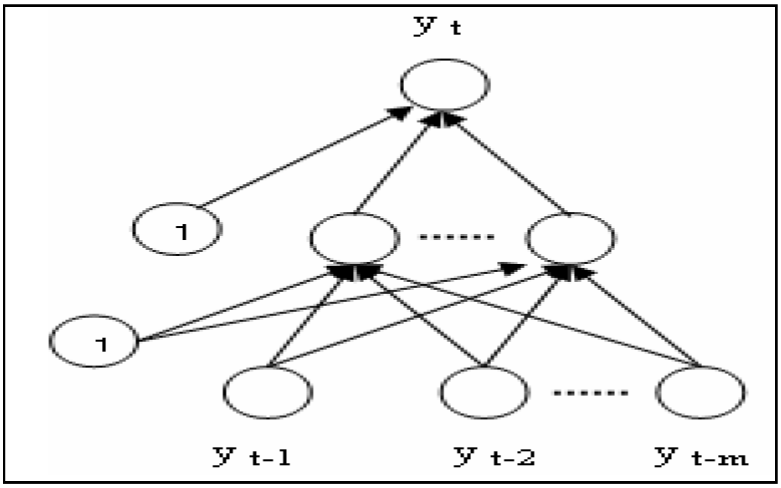

Fig. 2. A three layer MLP network

After computing SSE, the back propagation step computes the corrections to be applied to the weights. The ANN models are researched in connection with many power system applications, short-term forecasting being one of the most typical areas. Most of the suggested models use MLP. The attraction of MLP has been explained by the ability of the network to learn complex relationships between input and output patterns, which would be difficult to model with conventional algorithmic methods.

There are three steps in solving an ANN problem which are: training, generalization and implementation. Training is a process that network learns to recognize present pattern from input data set. We present the network with training examples, which consist of a pattern of activities for the input units together with the desired pattern of activities for the output units. For this reason each ANN uses a set of training rules that define training method. Generalization or testing evaluates network ability in order to extract a feasible solution when the inputs are unknown to network and are not trained to network. We determine how closely the actual output of the network matches the desired output in new situations. In the learning process the values of interconnection weights are adjusted so that the network produces a better approximation of the desired output. ANNs learn by example. They cannot be programmed to perform a specific task. The examples must be selected carefully otherwise useful time is wasted or even worse the network might be functioning incorrectly. The disadvantage is that because the network finds out how to solve the problem by itself and its operation can be unpredictable. In this paper the effort is made to identify the best fitted network for the desired model according to the characteristics of the problem and ANN features [17].

3. Data Collection

Geographical and meteorological data of 64 locations spread all over Bangladesh for the period of 22 years (1983-2005) were obtained from NASA surface meteorology and solar energy data set [18]. This data set contains solar parameters principally derived from satellite observations and meteorology parameters from an atmospheric model constrained to satellite and sounding observations. There are parameters for sizing and pointing solar panels, solar thermal applications, and energy-storage systems. Information is also provided for clouds, temperature, humidity, and wind parameters. The data includes geographical parameters: latitude, longitude, elevation, month of the year, and average monthly meteorological parameters: daylight hours, temperature, and relative humidity, and insolation on horizontal surface. Table 1 shows the latitude and longitude of the selected locations. For predicting insolation on horizontal surfaces in the selected locations, we have considered 8 different parameters (latitude, longitude, elevation, month, average daylight hours, minimum and maximum mean earth temperature and relative humidity) as the inputs of ANN model. As these data were gathered for a period of 22 years, the monthly average of different input data such as maximum and minimum temperature, relative humidity, duration of sunshine were considered. The single output parameter of the model is insolation on horizontal surface. For this parameter monthly average of daily insolation has been taken into account, too.

Table 1. Latitude and longitude of selected locations.

Sl.	Latitude	Longitude	Sl.	Latitude	Longitude	Sl.	Latitude	Longitude	Sl.	Latitude	Longitude
1	22.095	90.112	17	22.657	92.173	33	25.016	90.010	49	24.590	88.271
2	22.800	90.370	18	23.767	90.383	34	24.247	89.921	50	24.010	89.180
3	22.689	90.641	19	23.500	89.830	35	22.334	89.776	51	24.358	88.639
4	22.641	90.199	20	24.000	90.430	36	23.600	88.700	52	24.450	89.717
5	22.354	90.318	21	23.013	89.822	37	23.183	89.167	53	25.621	88.634
6	22.580	89.970	22	24.920	89.960	38	23.553	89.175	54	25.250	89.500
7	21.744	92.381	23	24.433	90.783	39	22.817	89.550	55	25.750	89.660
8	24.045	91.135	24	23.170	90.100	40	23.900	89.000	56	26.000	89.250
9	23.214	90.636	25	23.850	90.010	41	23.400	89.400	57	25.950	88.950
10	22.267	91.817	26	23.525	90.337	42	23.782	88.616	58	26.271	88.595
11	23.456	91.182	27	24.749	90.403	43	23.130	89.500	59	25.733	89.233
12	21.439	92.008	28	23.617	90.500	44	22.718	89.070	60	26.028	88.459
13	23.016	91.398	29	23.920	90.730	45	24.844	89.376	61	24.422	91.443
14	23.132	91.949	30	24.807	90.829	46	25.100	89.100	62	24.481	91.764
15	22.904	90.829	31	23.715	89.587	47	24.900	88.750	63	25.031	91.404
16	22.830	91.100	32	23.000	90.000	48	24.426	89.018	64	24.892	91.883

4. Design of the artificial neural network model

Multi-layer feed-forward back-propagation networks have been designed using the neural network fitting tool (nftool). **nftool** provides a graphical user interface for designing and training a feedforward neural network for solving approximation (fitting) problems. The networks (figure 3) created by nftool are characterized by:

- One hidden layer (the number of hidden units can be changed by the user)
- The hidden units have a sigmoidal activation function (tansig or logsig) while the output units have a linear activation function

- The training algorithm is Backpropagation based on a Levenberg-Marquardt minimization method (the corresponding Matlab function is trainlm).

The learning process is controlled by a cross-validation technique based on a random division of the initial set of data in 3 subsets: for training (weights adjustment), for learning process control (validation) and for evaluation of the quality of approximation (testing). The quality of the approximation can be evaluated by:

- Mean Squared Error (MSE): it expresses the difference between the correct outputs and those provided by the network; the approximation is better if MSE is smaller (closer to 0).
- Pearson's Correlation Coefficient (R): it measures the correlation between the correct outputs and those provided by the network; as R is closer to 1 as the approximation is better [19].

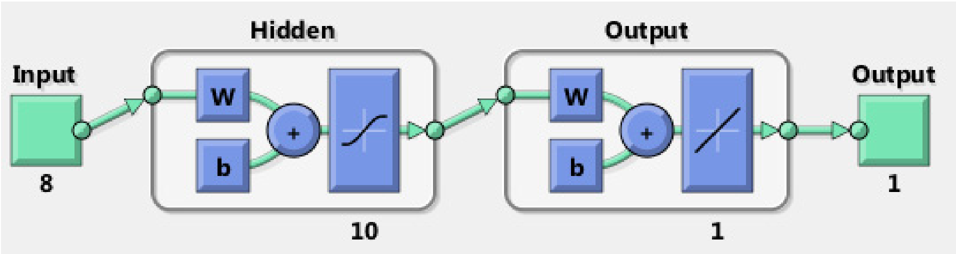

Fig. 3. nftool created feed-forward neural network

There are eight input parameters into the network and only one output parameter. Different networks with different number of hidden neurons were used; the number of neurons was varied from 5 to 30. For training the networks, the input vectors and target vectors have been randomly divided into three sets as follows: 70% used for training, 15% used to validate that the network is generalizing and to stop training before overfitting and remaining 15% used as a completely independent test of network generalization.

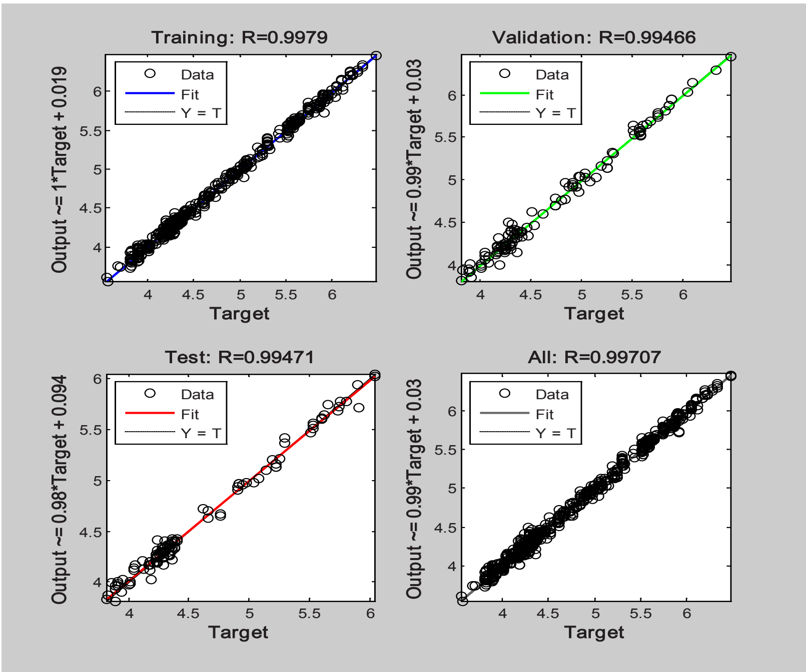

Fig. 4. The regression plot for the proposed network

5. Simulation Results and discussion

The performance function for this network is Mean Squared Error (MSE) which is the average squared difference between outputs and targets. Lower values are better. Zero means no error. During training period of network the numbers of neurons in the hidden layer have been varied to find the smallest MSE values for training, validation and testing. With the help of trial and error method the smallest MSE for training, validation and testing of 0.0018, 0.0052 and 0.0055 respectively have been found for 12 neurons in the hidden layer. It has also been observed that the training performance of the network deteriorates when the numbers of hidden layer neurons are more than 30 or less than 7 and there is no considerable difference when they are varied around 10.

These small MSE values are indicating that the network performance is good to predict the insolation accurately. The regression plots are also used to validate the network performance. The regression plots shown in figure 4 depict that the fit is reasonably good for all data sets, with regression (R) values in each case of 0.99466 or above. A comparison between network predicted and actual values of insolation has been demonstrated by the figure 5. This figure is also showing the error values for each input vector. It is apparent from this figure that the predicted values are very much close to the actual values and most of the errors are close to zero.

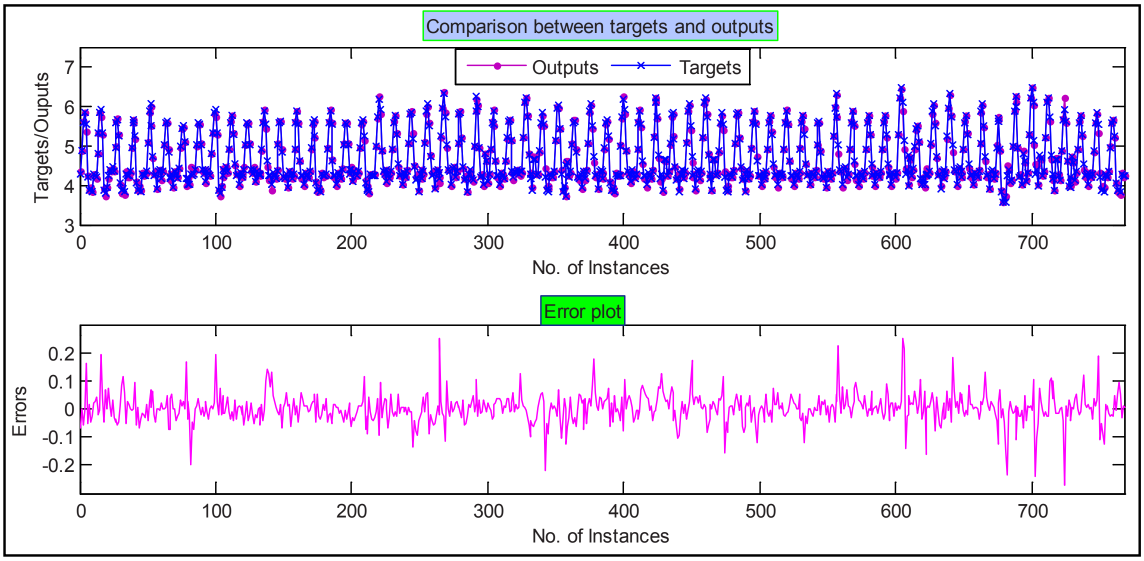

Fig. 5. Comparison of network outputs and targets

After the network has been trained satisfactorily, a simulink model (fig. 6) of that network has been created which simulates the output for any given input vector. Here we have tested the network with ten totally unknown input vectors which have not been used during training to get the response of our proposed network for any possible input patterns. Table 2 is showing the inputs vectors, network outputs, actual or measured value and percentage of error in prediction of insolation. We have found that the highest and the lowest error is 1.71% and 0.16% respectively. Therefore, it is evident that our proposed network is capable to predict insolation for any given location in Bangladesh with negligible difference.

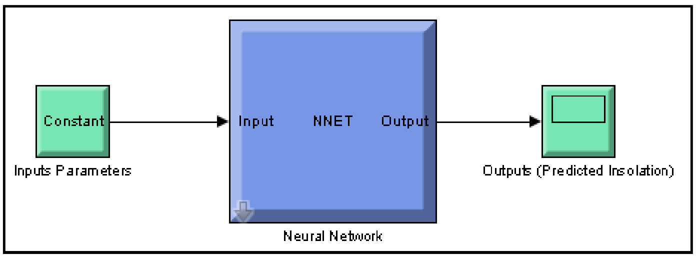

Fig. 6. The simulink model of the proposed network

Although our developed network using MATLAB's nftool showing good accuracy in predicton, it may sometimes experience problems like: become trapped in a wrong local minima, under or over fitting during training. The error surface of a nonlinear network is more complex than the error surface of a linear network. The problem is that nonlinear transfer functions in multilayer networks introduce many local minima in the error surface. As gradient descent is performed on the error surface, depending on the initial starting conditions, it is possible for the network solution to become trapped in one of these local minima. Settling in a local minimum can be good or bad depending on how close the local minimum is to the global minimum and how low an error is required. Therefore, it is to be remembered with caution that although a multilayer backpropagation network with enough neurons can implement just about any function, backpropagation does not always find the correct weights for the optimum solution. It may be needed to reinitialize the network and retrain several times to guarantee that the best solution has been found.

Network is also sensitive to the number of neurons in their hidden layers which has been observed during training. Too few neurons can lead to underfitting while too many neurons can contribute to overfitting [19]. Manual or trial error basis selection of correct numbers of neurons is not always a easy task. So, automatic optimization of hidden layer neurons might be useful solution for these type of fitting problems [20].

6. Conclusion

The use of artificial neural networks in predicting insolation on horizontal surfaces in Bangladesh has been investigated in this work. It has been found that the ANN based prediction models can predict solar radiation data accurately using conventional and easily available meteorological and geographical parameters. The use of this technique in the remote locations where solar measurement devices are not available can be beneficial as an effective tool to select the most efficient locations for exploiting solar energy.

Further work is needed to find out the weaknesses of this prediction model and ways to overcome these to make the model better, compact and more generalized. This type of prediction problem having only one output parameter can be implemented by Support Vector Machine (SVM) and other state of the art classifier. Hence, it is still to reveal which technique will serve the best until a comparative study of the fully developed and mature models is done.

Table 2. Summary of the responses of the simulink model to unknown samples

Serial no.	Latitude	Longitude	Elevation (m)	Month	Day light hour (hr)	Min. Temp. (^{0}C)	Max. Temp. (^{0}C)	Relative humidity (%)	Predicted insolaton (kWh/m^2/day)	Measured insolaton (kWh/m^2/day)	Error (%)
1	21.493	92.318	240	1	10.9	10.7	30.9	52.7	4.866	4.80	1.38
2	22.248	89.247	11	2	11.4	17.9	39.1	50.8	4.802	4.88	1.60
3	22.908	92.126	345	3	12.0	16.6	36	57.2	5.666	5.64	0.46
4	22.693	90.386	50	4	12.7	23.0	37.6	69.5	5.698	5.76	1.08
5	23.785	89.066	22	5	13.2	24.6	36.3	78.0	5.553	5.53	0.42
6	24.227	89.267	59	6	13.6	25.2	33.5	84.4	4.758	4.74	0.38
7	24.267	91.307	225	7	13.4	23.9	31.3	85.8	4.121	4.18	1.41
8	25.799	88.934	194	9	12.3	23.4	31.7	84.8	4.041	3.99	1.28
9	22.198	90.629	30	10	11.6	23.5	32.0	79.4	4.283	4.29	0.16
10	25.016	90.124	307	12	10.6	12.1	28.1	60.8	4.282	4.21	1.71

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