Estimation of Global Solar Radiation using Artificial Neural Network in Kathmandu, Nepal

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Abstract— *There is no doubt that information of the measured data of solar radiation is the best for designing any reliable solar energy systems but in Nepal the measured solar radiation data are not available for most of the sites due to high cost and requirement of daily maintenance of the measuring instruments. The alternative is to use the estimated data of solar radiation using any of available estimation models. In this study an Artificial Neural Network (ANN) was used to estimate the solar radiation in Kathmandu with the help of meteorological data of maximum and daily average temperature, relative humidity, rainfall amount, sunshine hour and solar radiation available for Tribhuvan International Airport. Data from 2002 to 2011 were used to train the Network and it was tested by using the data of 2012 and 2013. A multi-layer feed-forward neural network was devised using MATLAB programming. Five different models with different input combinations were modeled with Feed-Forward Multilayer Preceptors. The results of ANN model were compared with measured data on the basis of root mean square error (RMSE), mean bias error (MBE), mean percentage error (MPE) and Correlation Coefficients (CC) in order to check the performance of developed model. The obtained result indicate that the ANN based model for estimating solar radiation is precise in the selected location thus the model can be used anywhere in the Nepal having similar climate conditions where the meteorological data are available. The best prediction was from Model 1 as it exhibit minimum value of RMSE (0.2781) and maximum value of CC (0.9880).*

Keywords— Artificial Neural Network, Correlation Coefficient, Global Solar Radiation, Mean Bias Error, Mean Percentage Error, Root Mean Square Error

I. INTRODUCTION

Nepal has been facing energy crisis problem since long ago and has to depend on costly fossil fuel to meet the daily demand of energy with very few portion from renewable energy. The annual peak power demand of the Integrated Nepal Power System (INPS) in fiscal year 2013/14 is estimated to be 1,201 MW, with 410 MW power estimated to have been shed. Out of the 791 MW of power actually supplied, 436.4 MW was contributed by Nepal Electricity Authority hydro, 22 MW by Nepal Electricity Authority thermal, 216.4 MW by Independent Power Producer (IPP) hydro and the rest 116.2 MW was import [1]. In the Global context the depleting oil reserves, uncertainty and political issues concerning nuclear generation and the environmental concerns associated with coal and natural gas-fired generation encouraging to look for alternative and sustainable sources of energy. The solar-energy systems in contrast offer ease of installation, declining cost of technology and environmental benefits. On the other hand Nepal is located between 26˚12' and 30˚27'north latitude. Here are over 300 days of sunshine annually and annual average solar radiation is 5kWh/m2 per day [2]. All these data indicate that the country has sufficient solar radiation intensities for solar applications. So the optimum utilization of solar energy could beneficial to reduce the energy crisis problem and to reduce our dependency on costly fossil fuel to some extent.

The utilization of solar energy, like any other natural resource, requires detailed information on availability. Since solar radiation reaching the Earth's surface depends on many factors which are not global character, a study of solar radiation under local weather conditions is also essential [3]. Solar radiation data is always a necessary basis for designing reliable solar energy system such as solar photovoltaic, solar energy supported drying systems and water heaters as well as for a feasibility study of the possible use of solar energy. There is no doubt that the measured data of solar radiation are the best. The traditional way of knowing the amount of global solar radiation (GSR) in a particular region is to install pyranometers at as many locations as possible thus requiring daily maintenance and data recording, consequently increasing cost of GSR data collection which is a difficult task for the country like Nepal. Therefore, it is rather more economical to develop methods to estimate the solar radiation using climatological parameters [4].

Different empirical methods can be used to estimate the global solar radiation of desired locations. Empirical methods to estimate global solar radiation requires the development of a set of equation that relate it to other meteorological parameters

[5]. Artificial neural network (ANN) models are the latest type of solar prediction models. In this study ANN was used to estimate the solar radiation in Kathmandu.

Different literatures reveal that many researchers outside Nepal [6], [7], [8], [9], [10], [11] use ANN model to estimate the global solar radiation using meteorological parameter. These models cannot be used efficiently in Nepal due to seasonal variations, different climatological and geographical conditions. In Nepal researchers [12], [13] carried out the study to estimate the solar radiation for different locations of Nepal using regression models. Another research [14] conducted a comparative study of seven different regression models. However no studies have been carried out on estimation of global solar radiation using Artificial Neural Network Model.

The main objective of this study is to estimate the solar radiation in Kathmandu using ANN. In this present study Meteorological parameters; temperature, relative humidity, rainfall amount, sunshine hours and global solar radiation were used to train the ANN. Among a different variety of ANN topologies, multilayer preceptors (MLPs) are the most common type of feed-forward networks which was used in this study to estimate the GSR in Kathmandu.

II. METHODOLOGY

2.1 Data Collection

This study was based on the six meteorological parameters namely: daily data of maximum temperature (°C), average temperature (°C), sunshine duration (hours), mean relative humidity (%), rain fall amount (mm) and solar radiation ($MJ/m^2/day$). All these data for 12-year period from 2002 to 2013 were collected from Meteorological Department, Kathmandu. After collecting the required data problem of missing data was solved using linear interpolation and data were normalized before presenting the input data to the network.

2.2 Building Network

During this step number of hidden layers, neurons in each layer, transfer function in each layer, training function and weight/bias learning function were specified. In this study five different ANN models were formed using different meteorological input parameters as illustrated in Table 1.

TABLE 1
FIVE DIFFERENT ANN MODELS WITH DIFFERENT INPUT COMBINATIONS

S.N.	Model Name	Input Parameters
1	Model 1	Average Temperature (°C), Mean Relative Humidity (%), Sunshine Duration (Hour) and Rainfall Amount (mm)
2	Model 2	Maximum Temperature (°C), Mean Relative Humidity (%), Sunshine Duration (Hour) and Rainfall Amount (mm)
3	Model 3	Average Temperature (°C), Mean Relative Humidity (%) and Sunshine Duration (Hour)
4	Model 4	Average Temperature (°C), Sunshine Duration (Hour) and Rainfall Amount (mm)
5	Model 5	Average Temperature (°C) and Sunshine Duration (Hour)

Tangent Sigmoid and linear activation functions are used in the hidden layer and in the output layer, respectively. The ANNs models were implemented in MATLAB software package.

2.3 Training Network

After building the network, different input data from 2002 to 2011 were used to train the network. Levenberg-Marquardt back-propagation training function was used to train the network.

2.4 Testing Network

Network was tested using the data of 2012 and 2013. Statistical indicators were used to test the ANNs performance; these are Root Mean Square Error (RMSE), the Mean Bias Error (MBE), the Mean Percentage Error (MPE) and correlation Coefficient (CC). The measured GSR in 2012 and 2013 is used to compare with predicted GSR to compute the RMSE, MPE, MBE and CC. The extent of the error in the predictions was assessed using the RMSE where the MBE was used to describe how much the ANN under-estimate or overestimate the actual data. Lower the value of RMSE, MBE and MPE the better is the ANN model's performance where as higher value of co-relation co-efficient is desirable. Statistical indicators RMSE, MBE, MPE and CC are given below.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(H_i - H_{pi})^2} \tag{1}$$

$$\mathrm{MPE} = \frac{1}{n}\sum_{i=1}^{n}\frac{(H_i - H_{pi})}{H_{pi}} * 100\% \tag{2}$$

$$\mathrm{MBE} = \frac{1}{n}\sum_{i=1}^{n}(H_i - H_{pi}) \tag{3}$$

$$\mathrm{CC} = \frac{(H_i - \overline{H})(H_{pi} - \overline{H_p})}{\sqrt{\left\{\Sigma(H_i - \overline{H})^2\right\}\left\{\Sigma(H_{pi} - \overline{H_p})^2\right\}}} \tag{4}$$

Where H_i are the measured data of Global Solar Radiation and H_{pi} are the predicted value of the Global Solar Radiation

III. PROGRAMMING ANALYSIS

The program started by reading the data from excel file. After reading the data from excel file the training samples were randomized while the order of columns was kept unchanged. After randomizing the training data training and testing set input and target set were specified. The inputs and target data were normalized in order to yield zero mean and unity standard deviation. The output was converted back into the same unit that was used for the original target. Before presenting these data to neural network they were converted into rows.

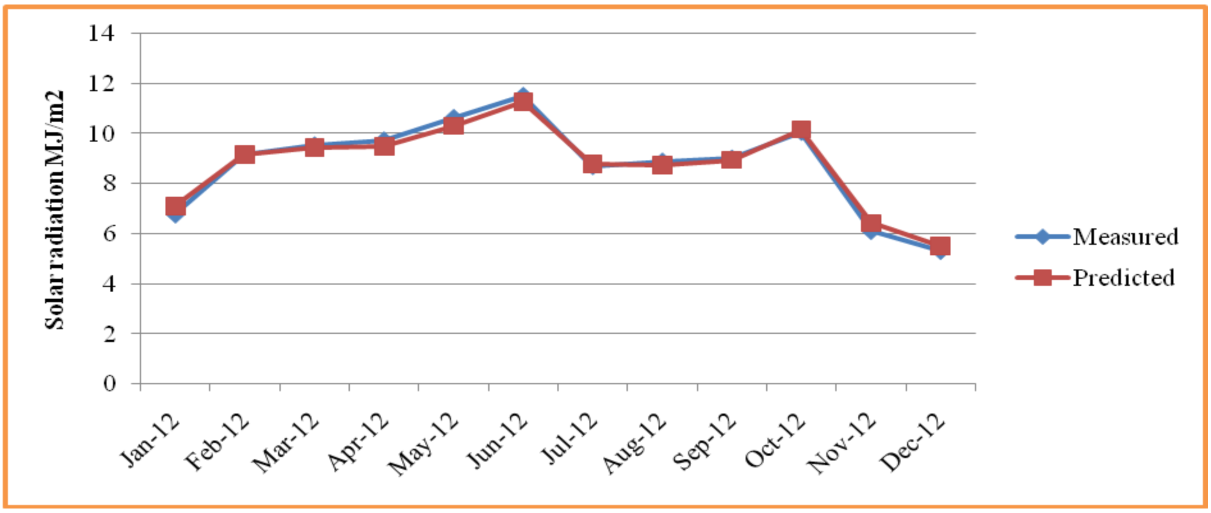
The built-in function ***"newff ( )"*** is used to build the MLP model which creates a feed-forward back-propagation network. With this function the number of hidden layers, the neurons in each layer, the transfer function in each layer can be specified. This command also automatically initializes the weights and biases. After configuring the network the network was trained several times with different number of neuron in hidden layer to get the best result. The trained network with best result was saved for each model.

Since the input data to the network were normalized before presenting them to the network the output obtained from the network (solar radiation for 2012 and 2013) are de-normalized in order to compare it with the measured data. The function ***"mapstd ( )"*** was used to de-normalize the output. Then the daily data (measured and predicted) were processed to produce the monthly mean. The monthly mean values of predicted data were compared with the corresponding monthly mean of measured data to check the validity of developed model and the mean monthly results and corresponding statistical data were written to an Excel file.

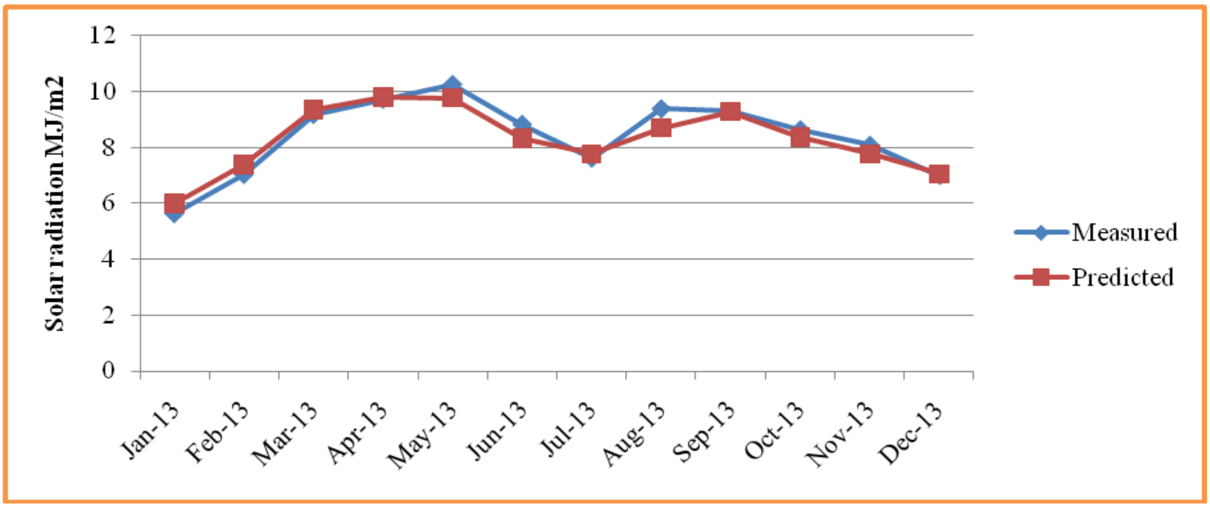
IV. RESULT AND DISCUSSION

4.1 Comparison between Predicted and Measured GSR

Global solar radiation for the year 2012 and 2013 was predicted using five different ANN model. Fig 1, 2, 3, 4 and 5 shows the comparison between measured value of Global Solar Radiation and their predicted values for five different ANN models.

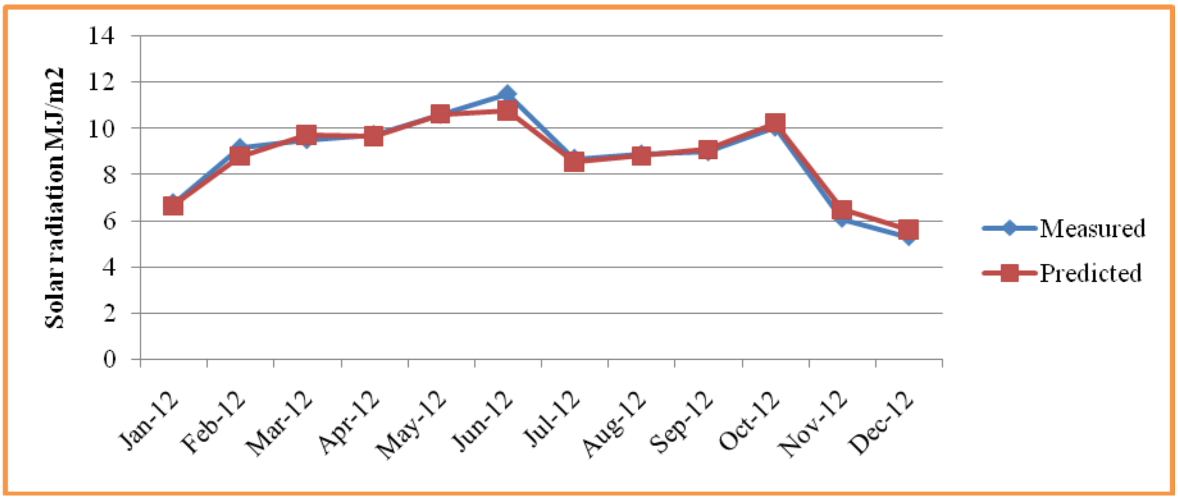


(A) MEASURED VERSUS PREDICTED SOLAR RADIATION-2012
MODEL 1

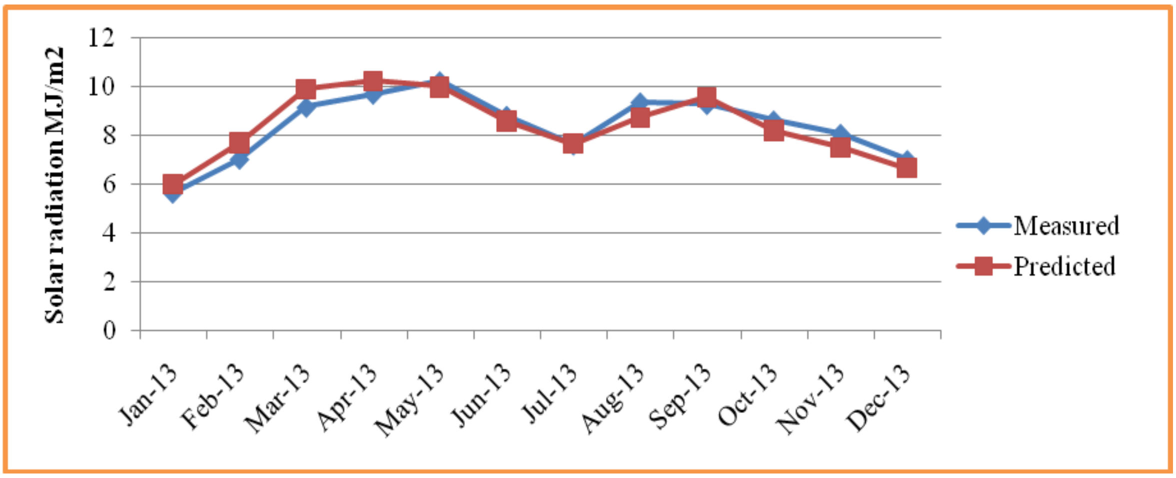


(B) MEASURED VERSUS PREDICTED SOLAR RADIATION-2013
MODEL 1

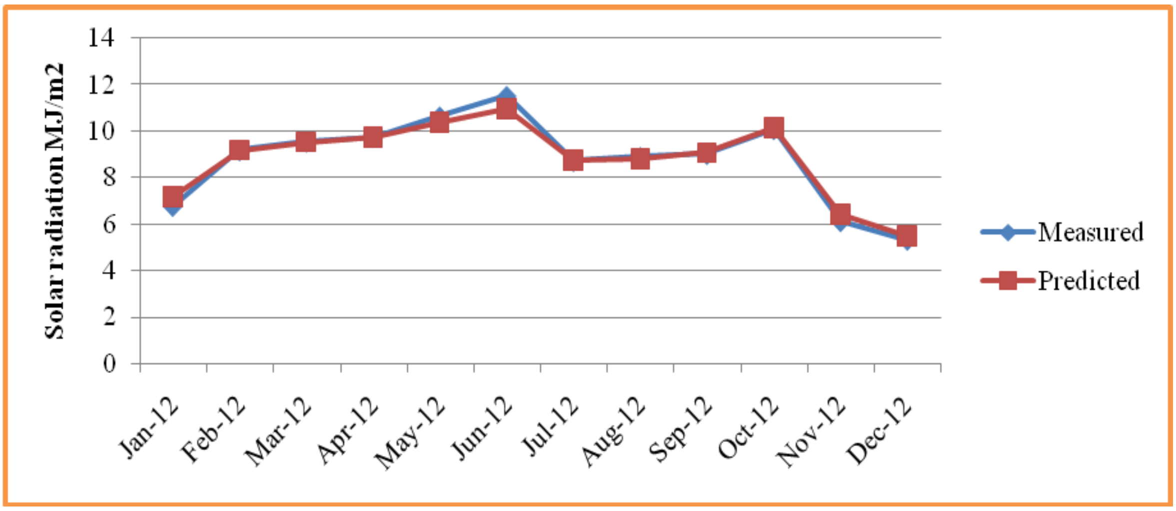
FIGURE 1: COMPARISON BETWEEN MEASURED AND PREDICTED VALUES OF GSR FROM MODEL 1



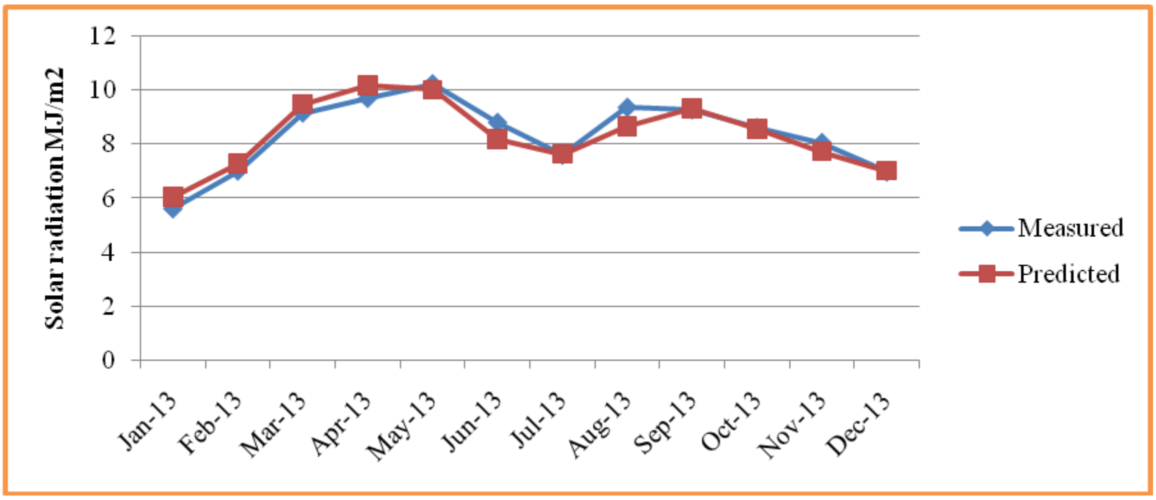
(A) MEASURED VERSUS PREDICTED SOLAR RADIATION-2012
MODEL 2



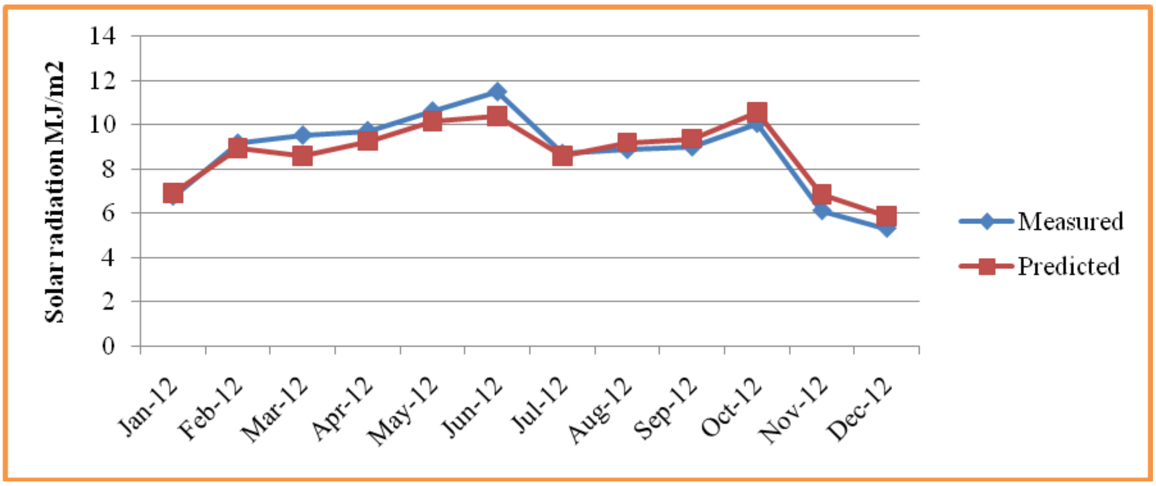
(B) MEASURED VERSUS PREDICTED SOLAR RADIATION-2013
MODEL 2
FIGURE 2: COMPARISON BETWEEN MEASURED AND PREDICTED VALUES OF GSR FROM MODEL 2



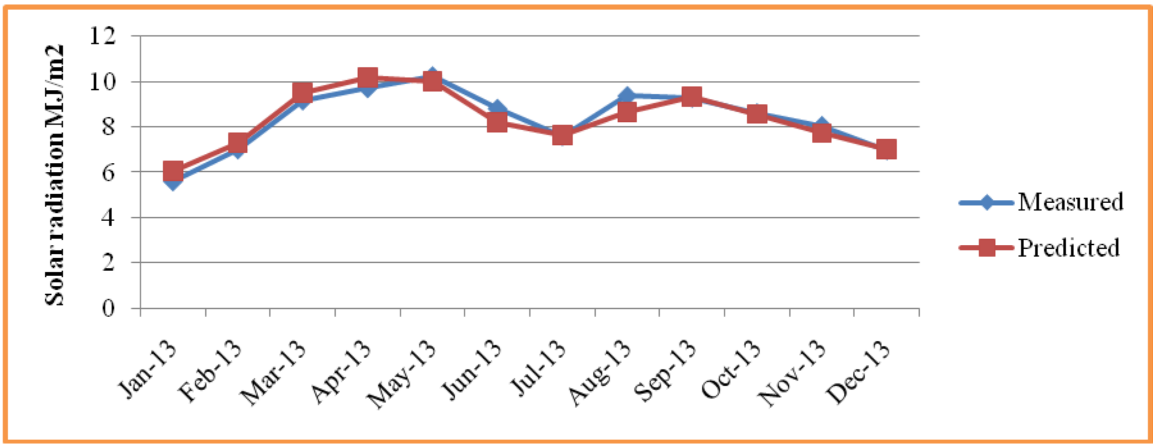
(A) MEASURED VERSUS PREDICTED SOLAR RADIATION-2012
MODEL 3



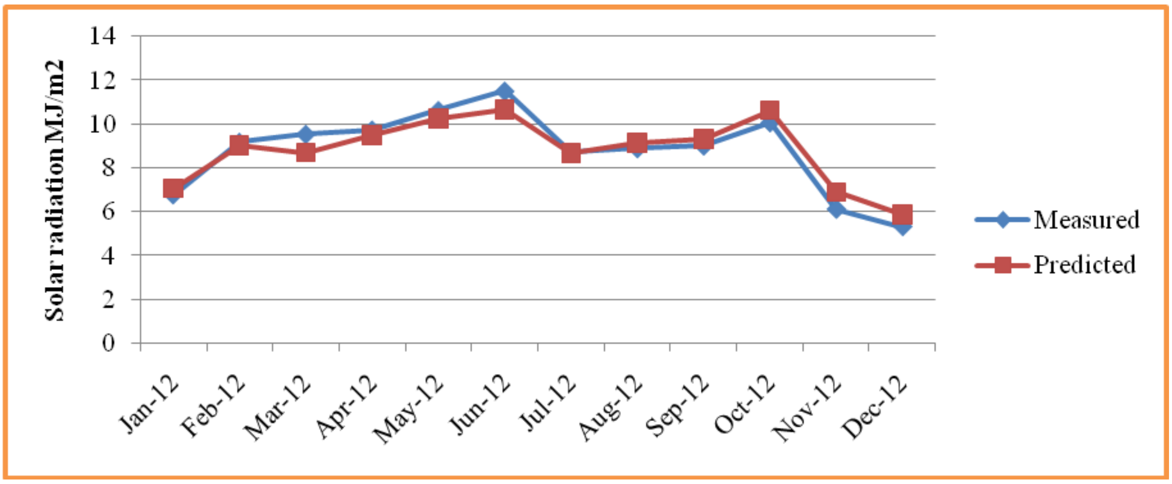
(B) MEASURED VERSUS PREDICTED SOLAR RADIATION-2013
MODEL 3
FIGURE 3: COMPARISON BETWEEN MEASURED AND PREDICTED VALUES OF GSR FROM MODEL 3



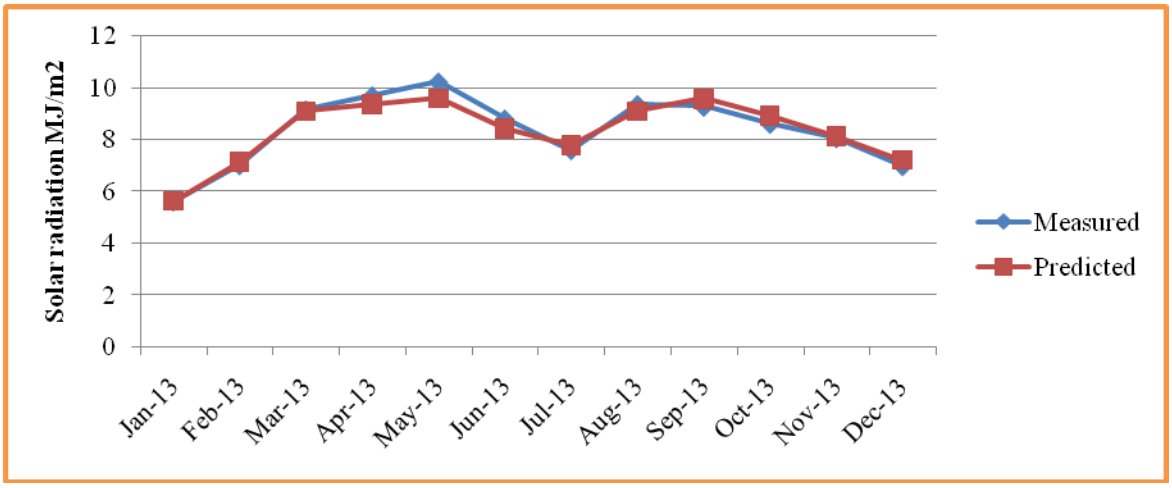
(A) MEASURED VERSUS PREDICTED SOLAR RADIATION-2012
MODEL 4



(B) MEASURED VERSUS PREDICTED SOLAR RADIATION-2013
MODEL 4
FIGURE 4: COMPARISON BETWEEN MEASURED AND PREDICTED VALUES OF GSR FROM MODEL 4



(A) MEASURED VERSUS PREDICTED SOLAR RADIATION-2012
MODEL 5



(B) MEASURED VERSUS PREDICTED SOLAR RADIATION-2013
MODEL 5
FIGURE 5: COMPARISON BETWEEN MEASURED AND PREDICTED VALUES OF GSR FROM MODEL 5

From Fig 1, 2, 3, 4 and 5 we have seen that the ANN models provide a very good prediction of Global Solar Radiation in Kathmandu. As the two lines each one for predicted and measured value of GSR in the Model 1 and Model 3 are more close to each other compared to those for other models, these two models provides better estimation of GSR.

4.2 Statistical Error parameters

Different statistical errors RMSE, MBE, MPE and CC were calculated using the measured value of Global Solar Radiation and that of Predicted values, these error parameters are presented in the Table 2.

TABLE 2
STATISTICAL INDICATORS FOR SEVEN DIFFERENT MODELS

Models	MBE	MPE	RMSE	CC
Model 1	0.0368	0.1243	0.2787	0.9880
Model 2	0.0024	-0.0786	0.3871	0.9690
Model 3	0.0098	-0.1481	0.3138	0.9821
Model 4	0.0807	0.5850	0.4779	0.9604
Model 5	0.0115	-0.2575	0.4206	0.9705

Form Table 2 we observed the Model 1 yields minimum RMSE (0.2787) among the five different ANN models developed here, which is desirable. After the Model 1 the Model 3 exhibit minimum value of RMSE (0.3138) where as Model 4 yield the maximum RMSE (0.4779). Model 2 and Model 5 exhibit RMSE 0.3871 and 0.4206 respectively these values are higher than the RMSE obtained from Model 1 and Model 3 but lower than the RMSE obtained from Model 4.

The MBE for Model 2 is 0.0024 which is lowest among all other models. Model 3 exhibit minimum MBE (0.0098) after Model 2. Model 5 exhibit MBE of 0.0115. Model 1 yields MBE of 0.0368 which is lower than the MBE obtained for Model 4 (0.0807). Model 4 yields maximum MBE of 0.0807 which is undesirable. Although the MPE of Model 1 (0.1243) and Model 3 (-0.1481) are relatively higher than that of Model 2 (-0.0786) this model exhibit lower MPE compared to Model 4 (0.5850), Model 5 (-0.2575).

The Model 1 (0.9880) and Model 3 (0.9821) yield respectively highest value of CC among all other models which means the predicted values of GSR from Model 1 and Model 3 are highly correlated with that of measured values than other four models presented here. However the Model 4 exhibits lowest value of CC (0.904) which is undesirable for good prediction.

From analyzing the result of five different models Model 1 and Model 3 provide the best prediction of GSR compared to other models since these two models have relatively lowest values of RMSE, MBE and MPE and highest values of CC. In Model 1 input parameters are average temperature, relative humidity, sunshine duration and rainfall amount. In Model 3 input parameters are average temperature, relative humidity and sunshine duration. However Model 4 and Model 5 provide relatively bad prediction of GSR among other models.

4.3 Comparison of ANN models with Empirical models

Table 3 shows the statistical error parameters obtained for seven different empirical models based on one year data analysis which has been taken from journal of IOE Graduate Conference 2014 [14]

TABLE 3
STATISTICAL ERROR PARAMETERS OF EMPIRICAL MODELS BASED ON ONE YEAR DATA ANALYSIS [14]

Model	RMSE	MBE	MPE	CC
Model 1	0.5203	0.0290	0.2409	0.9525
Model 2	0.5182	0.0291	0.2455	0.9526
Model 3	0.6303	0.0375	0.2481	0.9385
Model 4	0.5192	0.0312	0.2777	0.9515
Model 5	0.4806	0.0208	0.2403	0.9562
Model 6	1.0060	0.0626	0.8193	0.8233
Model 7	0.3658	-0.0099	0.1413	0.9760

Form Table 3 we have observed that the ANN models presented here provide very good prediction of GSR compared to empirical model presented in that journal. A research [11] conducted in Egypt to estimate the GSR in Qena, Upper Egypt obtained the correlation coefficient of 0.998. In this work the best result achieved is 0.988 which is convincing for the country like Nepal known for complex climate and terrain.

V. CONCLUSION

The ANN models seems promising for estimating the GSR in the locations where there are no solar radiation measurement stations provided that the samples of meteorological parameters such as the samples of temperature, relative humidity and sunshine duration are available. The obtained result in this present work indicate that the ANN based model for estimating solar radiation is precise in the selected location thus the model can be used anywhere in the Nepal having similar climate conditions where the meteorological data are available. The Model 1 and Model 3 provide better prediction of GSR compared to other models presented here as these two models exhibit respectively minimum value of RMSE and maximum value of CC. For Model 1 input parameters were average temperature, relative humidity, sunshine duration and rainfall amount whereas for Model 2 input parameters were average temperature, relative humidity and sunshine duration.

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