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Prediction of Solar Radiation: A Case Study at Hill Station Kushma, Nepal using Artificial Neural Networks (ANNs)

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Abstract

In this study, the neural network toolbox (NN tool) of MATLAB is used for the prediction of solar radiation. The satellite data of solar radiation of Kushma, Hill Station Parbat is taken from internet duration the period of 2004 to 2014. The objective of this research work is to predict the solar radiation for optimum utilizitation of solar energy resources to mitigate the adverse effect of environment, maintain the climate change and to mitigate the energy crisis.. For prediction of solar radiation, maximum temperature, minimum temperature, precipitation, wind speed and relative humidity are utilized as input variables. The different models were utilized by varying the number of inputs. The Feed-Forward Back-Propagation neural network and Levenberg-Marquardt algorithm were used for training and testing purposes. At the end, the best model was obtained when all of the input variables and the number of 20 hidden layer neurons were used. Finally, the best model is Artificial Neural Network (ANN) is found by validation of finding data of solar radiation using the correlation coefficient (R) for training are 0.904 and 0.877 for testing. The error values of Mean Average Error (MAE) and Mean Square Error (MSE) for this ANN model I are 1.177 and 2.451 respectively. It is concluded that the obtained results showed that the ANN model and techniques can be used to accurately predict the monthly average global solar radiation in Kusma Parbat.

Keywords

forecasting, energy crisis, climate change, meteorological parameters, ANN tool, solar radiation

1. Introduction

The solar energy is an important for living creatures and has been used by humans since ancient time using various types of technologies [1]. In nature, it is the greatest renewable clean, green and non polluting energy source which plays a significant role in drawing energy conversation devices [2]. Nepal lies in global solar belt map. So, there are about 300 sunny days in a year. The national average sunshine hours are about more than 6.8 per day [3] and annual average solar insulation is about 4.23 kWh/m2/day is found [1]. It is identified that under the clear and intermediate sky conditions, larger the altitude larger the solar radiation, but the solar radiation is very low under the overcast days in comparison with bright days. Solar energy is the best option among the all renewable energies if it can be used in a cost effective manner, because the technology is also environment friendly. Solar radiation data are essential for solar engineers, agriculturists, architects and hydrologists for various applications such as solar heating, drying, cooking, and interior illumination of buildings. There is high demand of green and clean solar energy in the nation; however, there are not sufficient numbers of solar radiation measuring stations and instruments to get the authentic data because of financial and technical constraints. For the promotion of solar energy technology, more solar radiation data is required to promote alternative energy sources.

The need for renewable energy sources and difficulty in assessing the potential of production of renewable energy come together with great challenges, physically and economically in developing countries like Nepal. The Sun, as the ultimate source of all kinds of energy, could be decisive in producing renewable energy for daily usage not only to solve the clean energy demands but also help to mitigate the pollution and climate change as well. However, there are not sufficient numbers of solar radiation measuring sites and instruments to get the data because of financial and technical constraints. More solar radiation data is required to promote alternative energy sources. In these circumstances there must be need of the appropriate model for the prediction on the basis of meteorological data and interpolated data to determine the worth of various locations in order to choose the greatest potential sites for something like a solar power plant [4]. Artificial Neural Network is an efficient Artificial Intelligence model for making predictions by training the model with suitable data variables.

Nepal is situated in the monsoon climatic region, with an average amount of precipitation ranges from 1,000 to 2,500 millimeters. About 80% to 90% of precipitation falls during the summer monsoon specially from June to September and the rest of it in other seasons. Throughout the summer, typical maximum temperatures range from 40°C in the lowland Terai to around 20°C in the midland highlands, and less than 16°C over 2000 meter above sea level. In the winter, temperatures at higher elevations are substantially colder [2]. The abundance of past records in climatic service archives, and even the notion that ANNs are statistics approaches capable of conducting nonlinear mappings among collections of input and output variables, making this modeling tool particularly appealing. [5]. Kusma hill station is one of the tourist hubs in the world not only for travelers, and adventure tourists but also environmental, scientists, ecologists, geologists and many more. It is because of biodiversity and many bridges high above and long enough that will add a thrilling and totally new experience including the bungee jump. That is why this site has many bridges, so it is also known as the city of the high suspension bridges of Nepal. In spite of this, it is the gateway to Muktinath and Lomanthan upper Mustang and also a way to trek to Annapurna Circuit which is one of the best trekking routes and study of biodiversity at high Trans-Himalaya in the world. In this arena, there is no more sufficient amount of clean energy available for the growing population.At the same time there is no proper utilization of easily and freely available renewable energy including solar energy at that location. So it is essential to study and to find facts and figures of solar radiation in that area. Our main objectives of this study is to find the appropriate techniques and tools to predict the solar radiation so that optimum utilization of locally available solar energy can be harnessed and ultimately this type of techniques will be utilized in other parts of the country.

The use of historical data of any place makes the study reliable by including the possible variations in solar energy striking a certain place over a period of time. By using basic sigmoid function as the activation, the Levenberg– Marquardt (LM) technique produced a rather effective model [6]. Due to the high expense of solar irradiation measuring devices, they cannot be installed everywhere [7]. Numerous scholars outside Nepal [8, 9, 10, 11], and [12] employ ANN approach to predict global solar radiation considering meteorological data, according to available literature. Due to the seasonal climatological and diverse geographical conditions of Nepal, several more simulations cannot be employed effectively [13]. Because of the unpredictability of solar radiation as well as the forecasting capabilities using artificial neural networks (ANNs), ANN approaches have been used to estimate more accurate solar radiation [14].

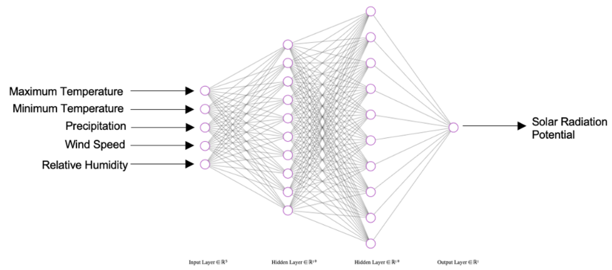

Figure 1: A web of neural networks

2. Literature Review

The annual global solar radiation for Parbat district, Nepal is estimated to be 4.090 kwh/m^2 /day [15]. However, the contemporary techniques are more costlier and require higher technical skills for their operation just to determine the amount of solar power potential. So, researchers developed and tested generalized models and found it valid for geographical and meteorological parameters. It's critical to develop model for predicting solar radiations using easily available meteorological data [16]. Regression equations is being used to estimate global solar radiations during the procedure [2]. Since, the Levenberg– Marquardt (LM) algorithm is also a development of Regression techniques, it is a dependable algorithm. The back-propagation technique is used in the LM algorithm in a feed forward artificial neural network produced best results [17].

Solar radiation obtained would be a quantity associated with various geographical and meteorological characteristics, according to many theories associated with multi perceptron neural networks [6]. When compared to other existing empirical models, simulations based on ANN offered very good predictions of global solar radiation [13]. In Spain, a multi layer perceptron (MLP) approach for solar potential evaluation in the form of a map was tested, and it was found to be superior to the empirical method [18]. Combination of different meteorological parameters provided a strong basis for determination of Global Solar Radiation(GSR), relative humidity being one of the most important as the combinations that included relative humidity as input parameter has least Root Mean Square Error(RMSE), least RE and high R2 values [19].

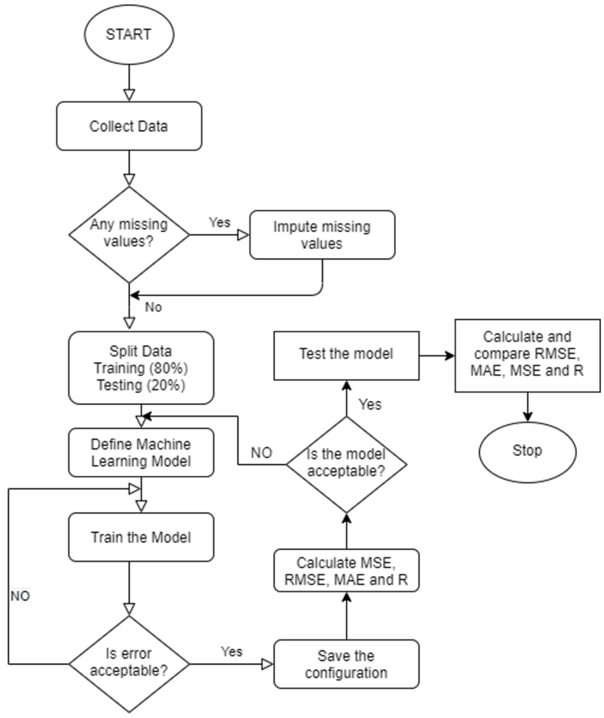

Figure 2: Working of the project

3. Methodology

The Kushma (Lat.28°00'19" N., Alt. 300m to 3000m) Parbat is Hill station is beautiful and diversified geographically. The climate zone includes upper tropical, subtropical, temperature and subalpine in between the elevation ranging from 300m to 3000m where rocky hills surround the place.

This research work was based upon six different meteorological parameters. The parameters used as input are namely: maximum temperature, minimum temperature, precipitation , wind speed and relative humidity. The flow chart of the working mechanism and prediction of solar radiation is given in the figure above. Lacking sufficient data from the ground based sources, the satellite based data were collected from stations (https://globalweather.tamu.edu/). The parameter taken as output is solar radiation. The data we collected is in the time frame between 2004-2014. The 8 years data between 2004 to 2011 period were used for testing or training purposes and the remaining 3 years data between 2011 to 2014 were used for validation of testing and plotting purposes.

An Artificial Neural Network (ANN) is really a system that connects compute nodes that are analogous to biological functional units known as neurons [17]. The interconnection weights, structure, and training procedures determine the computational power of ANN. It is an important tool for researchers because they can assess data classification, estimation of nonlinear functions, grouping, and modeling. They have been employed in a variety of scientific and technological domains [9, 10]. and in the simulation of radiation from the sun [13]. Also they were employed in beam solar irradiance estimation [18], solar potential modeling [20], global irradiation projection [21], and solar radiation estimation [18, 17]. ANN extracts information from data for use in solving nonlinear problems. The network uses an input layer, a hidden layer, and an output layer. The input is multiplied by the composite weight, then their product and the deviation are added together, and then the output is generated through the activation function.

We have used MATLAB as the technical computing language. The MATLAB toolbox named Neural Network Toolbox (nntool) was used for the implementation. The nntool includes techniques, pre-trained systems, and tools for constructing, learning, displaying, and modeling neural networks with hidden neurons (also known as planar neural nets). We may conduct categorization, extrapolation, segmentation, function approximation, time series prediction, and dynamic system modeling and manipulation with the tools supplied.

The Neural Network was trained with a varied number of input variables. The LM methods were used to

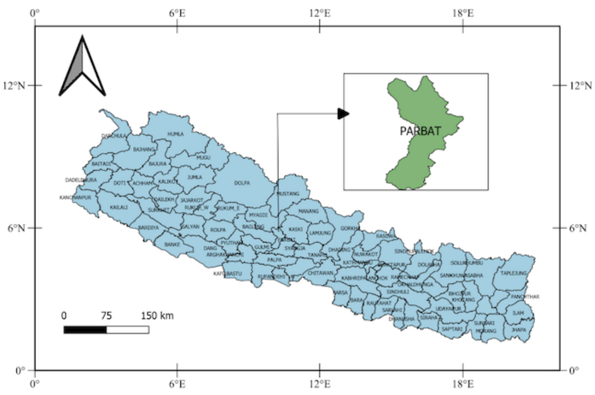

Figure 3: Map of Nepal

train the network. The activation functions used were Tangent and Sigmoid. There were three different scenarios selected to proceed along with the study as shown in table 1.

Table 1: Different input variables or each ANN model

Model	Input variables	Hidden Layers	Total years of data
ANN I	Max temp, min temp, wind speed, precipitation, RH	2	11
ANN II	Max temp, min temp, precipitation, RH	2	11
ANN III	Max temp, min temp, precipitation	2	11

4. Results and Discussion

The five important input variables have been used to create and develop three distinct ANN models in MATLAB release 2012: minimum temperature, maximum temperature, precipitation mean wind speed and mean relative humidity, using the Levenberg-Marquardt (LM) algorithm, just one output variable, monthly global mean solar irradiation, was forecasted.

The MAE, RMSE, and R were used to monitor the efficiency of several of the Models. The mean absolute error (MAE) as well as the root mean square error (RMSE), according to (Solmaz and Ozgoren, 2012), are represented using the mathematical equation:

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

Table 2: Performance of ANN model

ANN Model	Error		Training	Testing	Validation
	MAE	RMSE	R	R	R
ANN I	1.177	2.451	0.904	0.873	0.877
ANN II	1.745	2.521	0.870	0.856	0.887
ANN III	1.826	2.612	0.856	0.860	0.842

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N} | X_i - Y_i |^2} \tag{2}$$

where

- N: total number of data;
- X_i: measured monthly average global solar radiation; and
- Y_i: ANN predicted monthly average global solar radiation.

MAE is a metric for determining how near the projected value is to the measured value. The RMSE represents the degree of dispersion generated by the ANN model. Because the RMSE is low, the constructed ANN model has a high predictive performance. To discover the link between observed and calculated values, the linear correlation coefficient (R) statistic are employed. If R = 1, it signifies that the value obtained and indeed the expected value have a precise linear correlation. The ANN model with the lowest MAE and RMSE readings and the highest R value, on the other hand, is chosen as the best forecasting model. The effectiveness of the ANN model between observed target and anticipated artificial neural network output is shown in table 2 in measures of MAE, RMSE, and R.

From the discussion of the above analysis results, it can be seen that it is very simple to use the The global mean monthly solar irradiation was projected using an ANN model, but there could be some variations between observed value and the predicted value. The underlying statistical anomaly assessment factors, coefficient of determination R^2, and average absolute percentage error(MAPE), can be used to correctly quantify such variation for each station. The test data set is used for testing purposes. Below is the equation to determine the values of R^2 and MAPE.

Table 3: Testing data results of MAPE and R^2

ANN Model	R^2	MAPE(%)
ANN I	0.718	10.076
ANN II	0.554	8.798
ANN III	0.604	8.548

where

$$R^2 = \left(\frac{n\sum xy - (\sum x)(\sum y)}{\sqrt{\left[n\sum x^2 - (\sum x)^2\right]\left[n\sum y - (\sum y)^2\right]}} \right)^2 \tag{3}$$

$$MAPE = \frac{\sum_{i=1}^{n} \mid (X_i - Y_i)/X_i \mid}{N} \times 100 \tag{4}$$

- N: total number of data;
- X_i : measured monthly average global solar radiation; and
- Y_i : ANN predicted monthly average global solar radiation.

Table 3 provides the data error results obtained over all ANN models by using LM algorithm on satellite measurements. The R^2 , in principle, means the proportion of observations that is nearest to the whole data set's best suited line for a given location. The obtained results reveal that the value of R^2 for all ANN models varies around 0.554 to 0.718%. For practically all of the ANN models, the R^2 findings clearly reveal that 55.4-71.8 percent of the projected solar irradiation levels are quite comparable to the measured values.

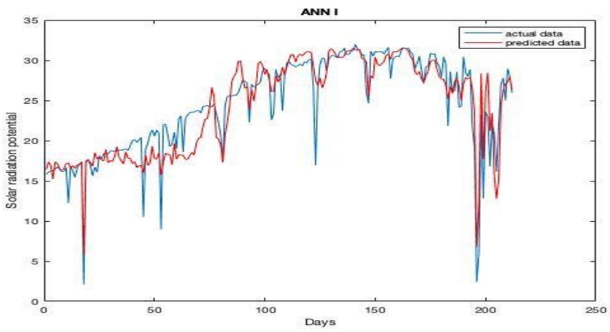

Figure 4: Actual vs Predicted data with ANN model I

The MAPE measures correctness as a proportion of total input information. The MAPE findings demonstrate a higher level of accuracy, with almost all models performing well in the 8.8-10.1 percent range.

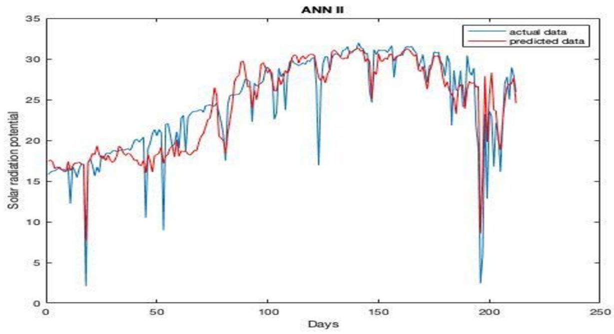

Figure 5: Actual vs Predicted data with ANN model II

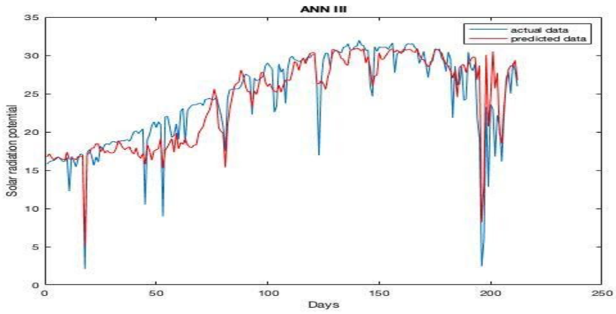

Figure 6: Actual vs Predicted data with ANN model III

TAs a result of the foregoing statistical anomaly evaluation, it can be determined that LM method and all three ANN models operate well with all sensor data used in this study. In addition, the present research backs this up that ANN can accurately predict the solar radiation values of all satellite data with similar meteorological data throughout.

Figure 4, 5 and 6 shows a graphical representation of actual solar radiation vs predicted solar radiation potential for the model ANN I, ANN II and ANN III respectively. The line in blue represents the actual solar radiation for 212 days whereas the line in red represents the predicted solar radiation potential.

5. Conclusion

The coefficient of determination calculation error assessment demonstrates that estimated global solar radiation estimate is close to the measured value of satellite data and all measured data of the ANN model. For 3, 4, and 5 inputs, the MAPE results in the current study showed increased precision. The ANN model constructed using the LM technique throughout this data analysis stands out since it iterates quickly to deliver an optimal calculation with the least error.

Lastly, the findings reveal that artificial neural network method can effectively estimate mean monthly global solar radiation in Kusma Parbat, where no measuring stations exist. The ANN model can also be used to locate lost data owing towards the malfunction of implanted scientific instruments. The solar energy potential needed for photovoltaic systems engineering can be properly evaluated at this site using this ANN model. In addition, the results show that ANN models and techniques can be used in similar geographic locations in Nepal in the next few years.

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