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Research Article

Application of Artificial Neural Network to Solar Potential Estimation in Hilly Region of India

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ABSTRACT

The use of these conventional resources causes continuous depletion of fossil fuels and increased greenhouse effect. Solar power is the major renewable resource used for power generation across the globe. Solar energy activities depend on the available potential of any geographical location. Therefore, prior to the installation of solar technologies for these activities, estimation of solar potential is very important due to costly technologies. Data of solar potential is not present at every location in Himachal Pradesh (H. P.) due to the high cost of measurement instruments. The objective of this study includes the solar potential estimation for 12 cities of the H. P. The present study could be divided into two parts. Initially, Artificial Neural Networks (ANNs) are utilized to estimate global sun radiation utilizing meteorological and geographical data from 23 places. The ANN model with seven input parameters including latitude, longitude, altitude, air temperature, humidity, pressure, and wind speed were used to estimate the solar irradiation. Statistical indicators including Mean Absolute Percentage Error (MAPE) were used for the performance evaluation of these ANNs. The minimum MAPE value was obtained to be 2.39 % with Multi-Layer Perception (MLP) architecture 7-11-1. For the 12 districts of the H. P., the acquired network 7-11-1 was utilized to estimate Global Solar Radiation (GSR). The output of ANN model was implemented in Geographic Information System (GIS) environment to obtain the solar potential map for each month. The available map of the present study may be helpful for solar application in each district.

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1. INTRODUCTION

In recent years, the application of solar technologies has become more popular for sustainable development as they are environmental-friendly or inexpensive [1]. The usage of these traditional resources will not be able to close the gap between supply and demand. Solar offers a wide range of applications including power plants, water heating, water treatment, irrigation pumps, and more [2, 3]. India's solar energy potential is estimated to be at 750 GW. The Indian government plans to install 100 GW of solar electricity by 2022, out of a total capacity of 750 GW [4]. To attain this target, state-wise solar purchase obligations are given by Ministry of New and Renewable Energy (MNRE) in India. In this context, Himachal Pradesh (H. P.) state has given 776 MW generations through solar power. Therefore, it is mandatory by the government to have energy mix through renewable energy sources. The government of H. P. is looking for solar applications in each state. Solar applications, on the other hand, required data such as the state's daily or monthly average GSR [5]. Due to the high expense of radiation measuring tools, routine measurements of global sun radiation are not practicable for each potential state site. The high cost of these instruments motivated the researchers to find other alternative techniques like empirical relation, Artificial Intelligence (AI), etc. Studies [6-8] used sunshine duration parameter to predict GSR using the following equation.

$$\frac{H}{H_0} = a + b\left(\frac{S}{S_0}\right) \tag{1}$$

where H and H_0 are monthly average daily GSR and extraterrestrial radiation, respectively. S represents monthly average daily hours of bright sunshine; S_0 is the monthly average day length; a and b are the coefficients of correlation of regression. To determine solar radiation in any similar region, the main theoretical relation can be considered [9]. Different researchers have proposed empirical models to estimate the solar radiation [7, 10].

Besharat et al. [11] reviewed 78 empirical models in their study. The authors made a case study for Yazd, Iran to estimate GSR by selecting several models from each group and found that sunshine-based model composed of exponential relation had the best performance among other models. The main disadvantage of these models required the values of empirical coefficients. All these empirical

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coefficients have been location dependent [11]. Therefore, the coefficients of one location are not accurate for another location for GSR estimation until both locations do not have similar meteorological characteristics. Different locations have different geographical and metrological parameters that affect the GSR.

In order to deal with complexity and empirical model disadvantages, researchers used Artificial Intelligence (AI) techniques to estimate GSRs for the desired location. Among empirical and AI methods [12], ANN is the most popular machine learning systems due to its capability to handle complexity and nonlinearity of the system [13]. Many researchers have also reported in the literature that ANN models have better accuracy than empirical models [10, 14].

Various parameters including temperature, relative humidity, precipitation, clearness index, wind speed, latitude, sunshine duration, evaporation, etc. are used as input for estimation of GSR.

Almaraashi [15] estimated daily global sun radiation in 7 Saudi Arabian regions using several feature selection algorithms such as the Monte Carlo Uninformative Variable Elimination algorithm (MCUVE), Relief F algorithm, random-frog algorithm, and Laplacian Score algorithm (LS), and NN predictor. Then, 31 input parameters were used for the study and out of these parameters, the most important parameters were selected using feature selection algorithms. After that, the NN predictor was employed to calculate GSR in various Saudi Arabian locations.

Jovic et al. [16] used four-parameter Dry-Bulb Temperature (DBT), Wet-Bulb Temperature (WBT), Mean Sea Level (MSL), and Relative Humidity (RH) to estimate the GSR. The Adaptive Neuro-Fuzzy Inference System (ANFIS) was applied to find the most influential parameters responsible for GSR prediction. Among these parameters, the DBT and RH were found the most influential to estimate GSR. The minimum Root Mean Square Error (RMSE) for the DBT and RH was found to be 3.25 and 3.92, respectively.

Xue [17] used Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) to increase the performance of Back Propagation Neural Network (BPNN) model for GSR estimation in Beijing. The input parameters used for ANN were sunshine duration, mean temperature, month of the year, rainfall, relative humidity, wind speed, and daily global GSR and daily diffuse radiation as output. The results depicted that the BPNN optimized by PSO had RMSE 0.78 and BPNN optimized by GA model had RMSE value 0.867. Therefore, the BPNN optimized by PSO achieved better performance accuracy to estimate GSR.

Premalatha et al. [18] trained the neural network using parameters like minimum, maximum, and difference of temperatures (T_{min}, T_{max}, ΔT); sunshine and theoretical sunshine hours (S, S_o) and extraterrestrial radiation (H_o). Total 32 numbers of input parameters combinations were employed to estimate the monthly mean daily GSR. Authors also concluded that two or three variables were sufficient to predict GSR. The combination of ΔT, H_o and ΔT, S_o, H_o parameters was found to be most influenced combination for GSR estimation. The minimum MAPE obtained for the ΔT, H_o combination was 2.61 %.

Kumar et al. [8] used rainfall and humidity quantity, temperature, sunshine hours, and barometric pressure as input parameters to estimate GSR. Different combinations of the input parameters and hidden layer neurons effect were analyzed by developing three ANN models. According to the authors, the model using all of the meteorological input factors has the best accuracy. The authors' research has been expanded in order to identify the most important parameter for calculating solar radiation. An ANN's synaptic weights were analyzed at the synapse level using the connection weight approach, which revealed that temperature and humidity, followed by pressure, were the most acceptable parameters. With these three inputs, the ANN found a minimum MAPE of 12.15 percent.

Satellite-based data have been used to assess the Global Horizontal Insolation (GHI) of Himachal Pradesh [19]. Yadav et al. (2014) [20] used ANN-based model for solar radiation estimation. Authors also find the most suitable parameters for solar radiation estimation using Waikato Environment for Knowledge Analysis. Authors further extended the study and found the solar potential for Himachal region [21].

Adaptive Neuro Fuzzy Inference System (ANFIS) was utilized by [22] to estimate the GSR of Tamil Nadu (India). To estimate the monthly worldwide GSR (kWh/m^2) in Tamil Nadu, the model used the following input parameters: ambient temperature (°C), atmospheric pressure (kPa), relative humidity (%), and wind speed (m/s). There were 372 samples in all that were used for both training and testing. A total of 204 data samples were used for training, with the remaining 168 data samples for testing. The coefficients of determination (R^2), RMSE, and Mean Bias Error (MBE) were determined as –1.031, 0.0078, and 0.9898, respectively. The obtained results were compared with those of other model available in the literature for other regions and they exhibited better accuracy. From the literature, it can be inferred that ANN can be used for the solar potential estimation. However, the solar mapping for Indian Context is very limited. In the present study, the solar radiation has been estimated using ANN and solar maps have been generated for Western region of Himalaya. The developed ANN model can also use solar radiation estimation for different regions. The generated potential maps can be used for site selection of solar plants along with other solar applications in the present region. Therefore, the objectives of the present study include: a) investigating the solar potential for Western Himalayan region of India, especially H. P., where state government has mandated 776 MW generations through solar power, b) developing the ANN models using different combinations of geographical and metrological parameters; and c) developing a solar map from the estimated GSR for H. P.

2. METHODOLOGY

The following steps are carried out to investigate the solar potential in H. P.:

2.1. Data collection

The location and atmosphere parameters included longitude (Long), latitude (Lat), altitude (H), humidity (RH), pressure (P), wind speed (WS), and air temperature (T) [8-27] to estimate the GSR in H. P. The meteorological parameters namely pressure (kPa), wind speed (m/sec.), humidity (%), and temperature (°C) were taken from NASA [23]. Solar radiation handbook data was used to compile average daily monthly GSR (kWh/m^2/day) data for 23 cities. The monthly average data were taken for the period of 1986 to 2000 [17]. The data on the city, Hamirpur, was obtained from the Centre for Energy situated at institute, National Institute of

Technology, NIT in Hamirpur, H. P., India. The geographical parameters include the latitude, altitude, and longitude of these 23 cities given in references.

2.2. ANN-based methodology for GSR estimation

A neural network is a network of a large number of neurons called processing unit, which maps the input and output data. Neural networks have an ability to generalize, which eases the complex and nonlinear problems. The most commonly used neural network in engineering areas is feed forward trained by the Back-Propagation (BP) having neurons as the major processor. These are divided into three levels: input, output, and hidden layers, with no feedback connections in any of them [24]. All layers are made up of neurons and all neurons are linked together by synaptic weights [25]. Moreover, the number of neurons in hidden layers may changed through trial and error [26, 27]. Gradient descent and gradient descent with a momentum convergence rate are examples of back-propagation techniques that are overly slow. As a result, the Levenberg–Marquardt (LM) method was utilized to train the neural network in this study, which has a fast convergence rate [28, 29]. The fundamental neural network architecture is shown in Figure 1.

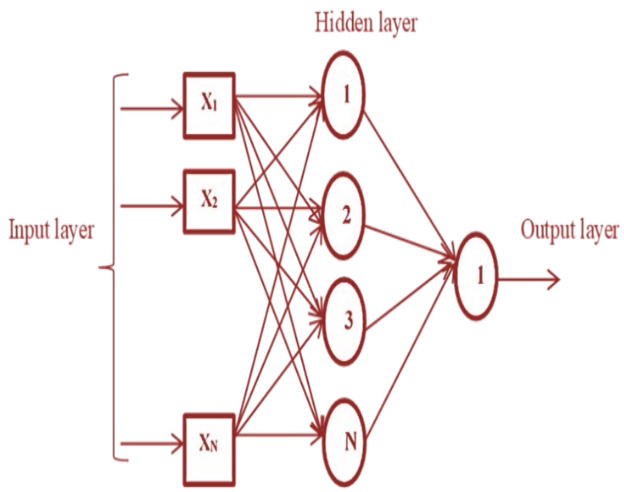

Figure 1. Basic architecture of the ANN

The steps taken in this study are illustrated in Figure 2. The input and output parameters were defined first in order to create the ANN model. For the 23 cities in India, seven characteristics were used as inputs, as explained in data collection. Several MLP designs were trained and evaluated in order to develop an ANN model in this work. The feed forward neural network was trained using the LM algorithm. Data were allocated at random to train the network. 70 % of the data were used for training, 15 % for testing, and the remaining 15 % for validation.

The number of neurons in the hidden layer is updated and the network is trained numerous times to refine the results obtained. The 7 inputs, 1 hidden layer, and 1 output layer lead to statistical error of MAPE using various experiments. MAPE's mathematical equations are as follows:

$$\mathrm{MAPE} = \left(\frac{1}{n}\sum_{j=1}^{n}\left|\frac{SR_{j(estimated)}-SR_{j(actual)}}{SR_{j(actual)}}\right|\right)\times 100 \quad (2)$$

For estimating GSR, the lowest MAPE value and the correlation coefficient value were evaluated. The model with the lowest MAPE value was also used to calculate GSR for 12 districts in H. P., India. The estimated worldwide solar radiation was mapped using the ARCGIS software.

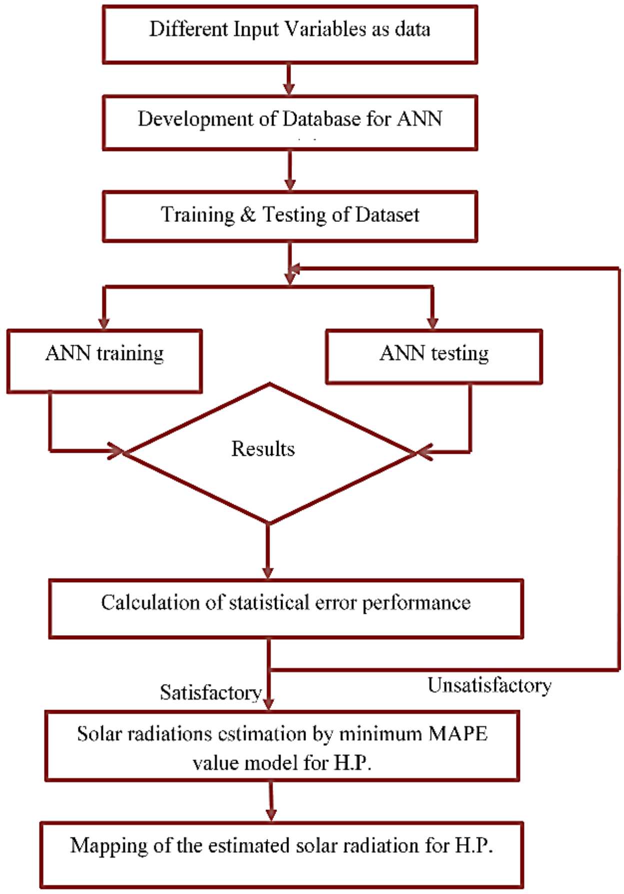

Figure 2. Flow diagram showing different steps to determine the ranking of parameters

Finally, the estimated GSR using the best proposed model by ANN for H. P. was used for mapping solar energy in the GIS environment.

3. RESULTS AND DISCUSSION

3.1. GSR estimation using ANN for 23 cities in India

This study used data from 23 cities in various climate zones to develop an ANN model for global sun radiations. The output of the same is estimated using BPLM technique for ANN. Neurons of the hidden layer of ANN are modified and multiple trainings are executed for achieving an optimum solution. Table 1 shows the training and testing data accuracies of ANN architectures.

Table 1 demonstrates that the estimated and observed values of GSR have the best agreement with an error value of less than 5 %. The network architecture consisting of 7-11-1 neurons in the input, hidden, and output layers, respectively, obtained a minimal MAPE value of 2.39 percent, as shown in Table 1. Figure 3 shows the optimal architectural neural network model given by ANN.

Figure 4 shows the regression plot for ANN architecture 7-11-1 that determines the relationship between output corresponding to the target values for training and that for testing. Scale of 0 to 1 is used to measure the value of R, and the values 0.998 and 0.912 are obtained in the training and testing periods, respectively. The obtained results show the optimal network architecture for calculating GSR with 7-11-1.

Table 1. Training and testing data accuracies of ANN architecture

ANN architecture (No. of neurons)	Correlation coefficient		MAPE	RMSE
	Training	Testing		
7-5-1	0.853	0.770	5.210	1.446
7-6-1	0.958	0.732	2.562	0.731
7-7-1	0.906	0.868	4.792	0.968
7-8-1	0.838	0.808	5.856	1.7834
7-9-1	0.866	0.834	5.291	1.494
7-10-1	0.971	0.921	3.427	0.853
7-11-1	0.998	0.912	2.369	0.719
7-12-1	0.920	0.815	3.768	0.891
7-13-1	0.889	0.835	4.363	0.913
7-14-1	0.880	0.783	5.140	1.038
7-15-1	0.807	0.754	5.879	1.898

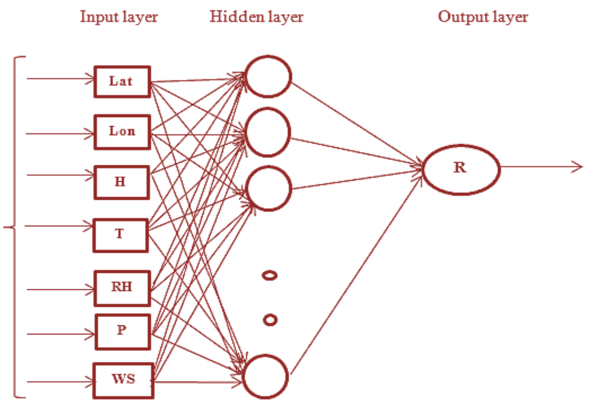

Figure 3. The best proposed ANN model for the GSR estimation in the present study

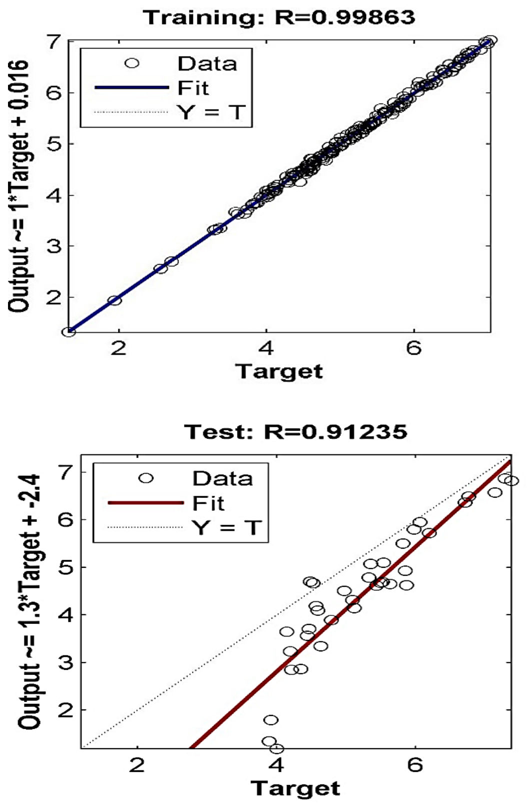

Figure 4. Regression plot for the best ANN architecture 7-11-1

Figure 5 shows the convergence plot for 7-11-1. The convergence plot signifies that as the mean square error increases, epochs continue decreasing. The convergence plot depicts that testing and validation have similar characteristics. The best performance of the convergence plot takes place at Iteration 58 (epoch).

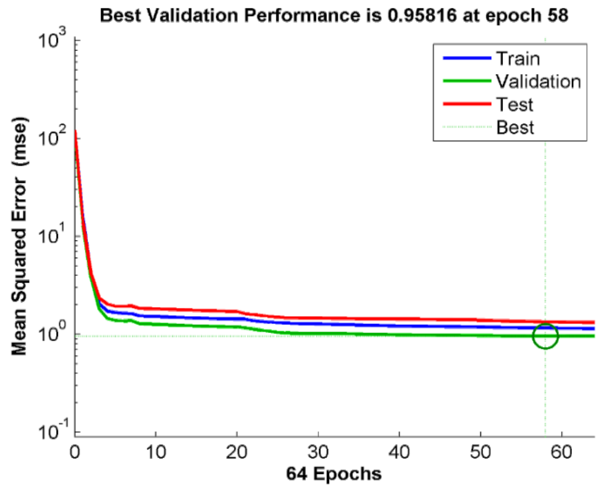

Figure 5. Convergence of neural network 7-11-1

3.2. GSR estimation using ANN for 12 cities in Himachal Pradesh (H. P.)

ANN architecture 7-11-1 with the least MAPE of 2.39 % is utilized in the study to estimate the global sun radiation of H. P. The input parameters taken from NASA include location and atmosphere, i.e., altitude, longitude, and latitude; temperature pressure, humidity, and speed of wind. These parameters are further used to estimate the GSR.

Figures 6 and 7 show the estimated GSRs for H. P. over a twelve-month period. According to the findings, H. P.'s solar potential ranges from 3.7 to 5.8 kWh/m^2. The solar potential of the district Lahaul Spiti was found to be the lowest. Among all the districts in H. P., Kangra has the highest solar potential. The field measurement data for GSR were obtained from the Centre for Energy and Environment, National Institute of Technology, Hamirpur, H. P., India for the validation of the suggested model.

3.3. GSR mapping

The feasibility of solar power plant needs proper site selection. For feasibility analysis, the creation of solar map is an essential part. Therefore, the estimated values of GSRs were depicted in monthly maps. The solar radiation availability for each district was distributed in three classes: (i) Low (below 4.0 kWh/m^2), (ii) medium (4.0 to 6.0 kWh/m^2), and (ii) high (above 5.25 kWh/m^2). The monthly solar energy availability digital maps with provincial boundaries are depicted in Figures 6 and 7. From Figures 6 and 7, it can be concluded that there is seasonal variation of solar potential in each district and the solar potential for the beginning of the months of years has low solar radiation. The Kangra and Una districts have medium solar potential during January. In February, Chamba has medium solar potential. The average value of global solar irradiation in H. P. ranges between 1.9 kWh/m^2 and 6.9 kWh/m^2. In April and May, each district exhibits good solar potential. From Figures 6 and 7, It is clear that the districts Una, Hamirpur, Kanga, and Chamba receive good GSR throughout the year and can be used for solar application.

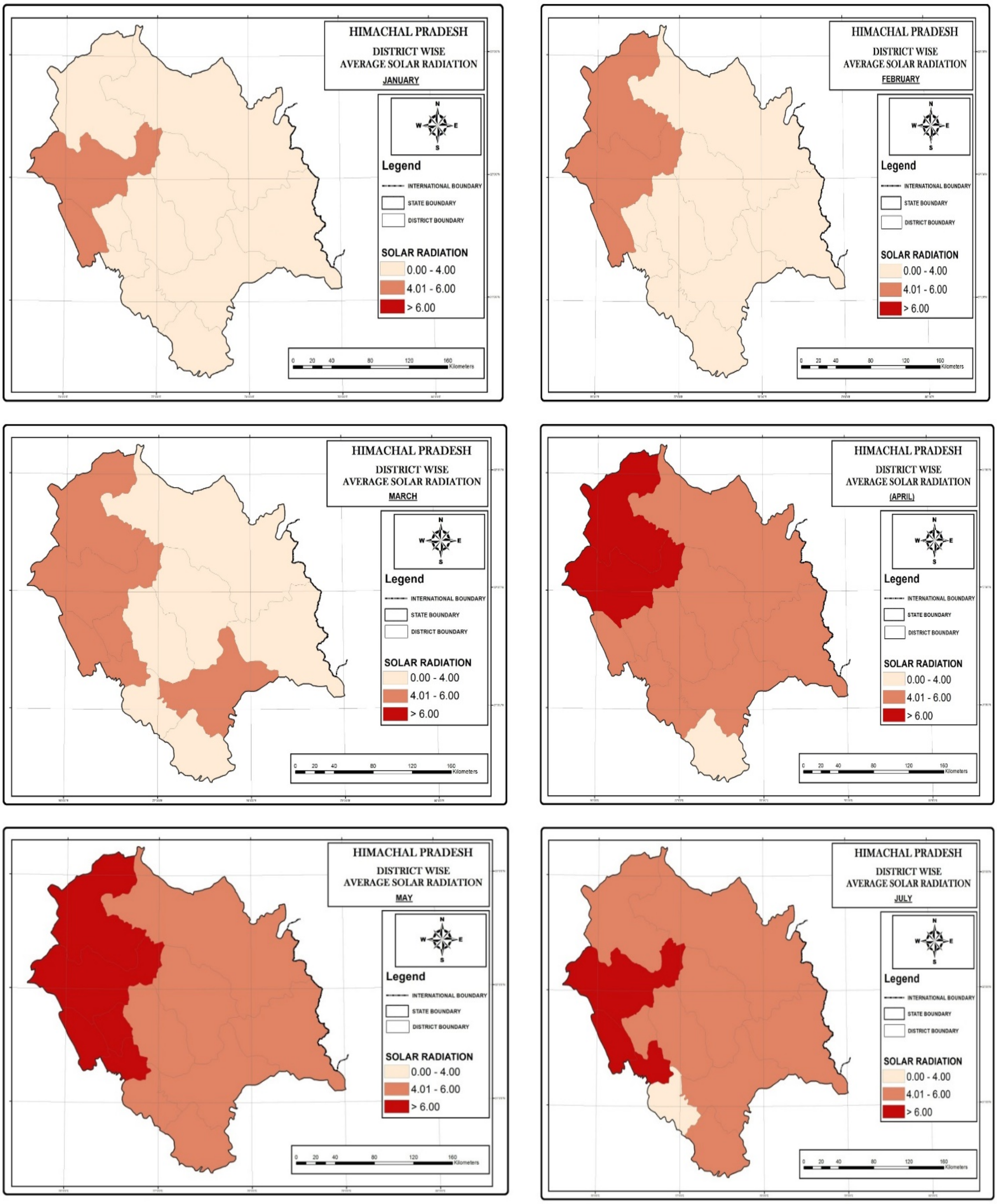

Figure 6. The solar energy maps for months of January to July in H. P.

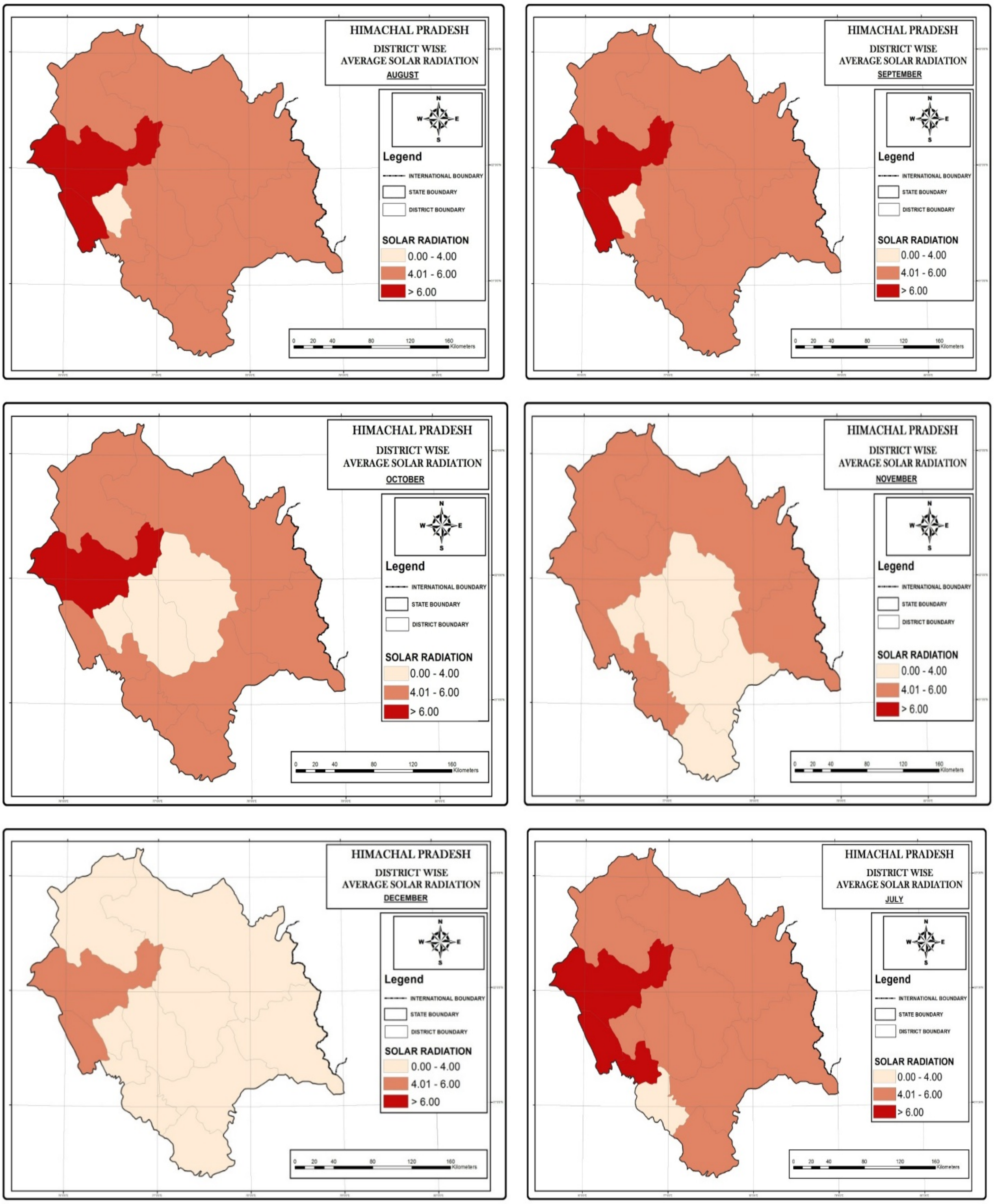

Figure 7. The solar energy maps for months of August to December in H. P.

4. CONCLUSIONS

In the presented work, ANN model was developed to estimate the GSR of different geographical and climatic zones of 23 cities in India. The statistical errors were used for the performance of the model. MAPE and R-values were obtained by different ANN models. The statistical performance error evaluation of accuracy demonstrates that the neural network consisting of 7-11-1 MLP architecture has a minimum MAPE value of 2.369. The neural network model with the architecture 7-11-1 was used to estimate the GSR of Western Himalaya region in Himachal Pradesh. The obtained results show that the ANN model developed in this study are very helpful to find the solar potential where measuring instruments are not installed. The solar potential estimated by ANN model for 12 districts of H. P. state was used to create a solar map of twelve districts of H. P. The obtained solar maps in this study are used for site selection of solar plant in future work.

5. ACKNOWLEDGEMENT

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NOMENCLATURE

MAPE	Mean Absolute Percentage Error
MLP	Multi-Layer Perception
GSR	Global Solar Radiation
GIS	Geographic Information System
ANN	Artificial Neural Networks
H	monthly average daily GSR (W/m^2)
H_0	extraterrestrial radiation (W/m^2)
S	monthly average daily hours of sunshine
S_0	monthly average day length
a, b	coefficients of correlation of regression
Long	Longitude (°)
Lat	Latitude (°)
RH	Humidity (%)
P	Pressure (kPa)
WS	Wind Speed (m/sec.)
T	Air Temperature (°C)
BP	Back-Propagation
LM	Levenberg–Marquardt
RMSE	Root Mean Square Error

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