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Single Step Ahead Assessment Of Solar Irradiation Using Ann Model Based On Various Combination Of Meterological Parameter

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Abstract— **Solar energy is a valuable resource on earth but the availability of solar resources relies on meteorological variables. In this paper, forecasting models using the artificial neural network are developed by the changing the input meteorological parameters from five to seven. The two years data are used to train the model whereas the testing is performed using one year data on different seasons following single step ahead. The input parameters are relative humidity, pressure, temperature, solar zenith angle, wind speed, wind direction and precipitable water. Three artificial neural network models (ANN-I_5, ANN-I_6, ANN-I_7) are developed to estimate the global horizontal irradiance and performance of all developed models are measured on the basis of Mean Absolute Percentage Error (MAPE), Relative Root Mean Square Error (RRMSE) and Correlation Coefficient (R^2). Results indicates that ANN-I_7 shown better performance as comparison to other developed models. The average MAPE and RRMSE of ANN models such as ANN-I_7, ANN-I_6, ANN-I_5 are 14.52%, 16.53%, 18.97% and 20.74%, 22.28%, 24.43% respectively. The ANN-I_7 having an input meteorological parameters relative humidity, pressure, temperature, solar zenith angle, wind speed, wind direction and perceptible water showed good accuracy as comparison to other two developed models. This study indicates that accuracy of solar irradiation forecasting depends on meteorological parameters**

Index Terms— **Artificial Neural Network, Global Horizontal Irradiation, Meteorological Parameters, Mean Absolute Percentage Error.**

I. Introduction

With rising energy demand and limited availability of fossil fuel all over the world encouraged us to move towards the use of renewable energy resources: solar, biomass, wind, geothermal, hydro and ocean energy. Among this solar energy is one of the most promising resources of energy that is naturally available on earth [1]. Solar radiation estimation is related to three components such as Direct Normal Irradiance (DNI), Diffuse Horizontal Irradiance (DHI) and Global Horizontal Irradiance (GHI) which is the sum of DNI and DHI. For estimation these components, we need a measuring instrument but the cost of measuring instrument is very high. So, it is not possible to install these instruments everywhere. Hence it is highly appreciable to build an optimum model for predicting solar radiation component [6]. An optimum model will provide a great help to grid operators to balancing the electricity demand between suppliers and customers. Various models developed in the literature to forecast solar irradiation at various origins with different-2 combinations of meteorological parameters to enhance the accuracy of forecasting model.

N.Kumar et al. used wind speed, average temperature, minimum temperature, hours of sunshine, extra-terresterial radiation, relative humidity, precipitation to develop an ANN model for predicting global solar radiation of 10 Indian cities. Statistical measure (RMSE, MBE and MAPE) were evaluate to assess the accuracy of forecasting model and used to compare the effectiveness of the proposed model [2]. M.A.Behrang et al. developed ANN model for estimating daily global solar radiation. The input combinations are temperature, sunshine hours, wind speed and relative humidity. The accuracy of the model was observed using the MAPE along comparison with several conventional models [3]. Premalatha Neelamegam et al. proposed two ANN model for predicting monthly average global solar radiation. ANN-I used four station data for training and one station data for testing while ANN-II used five station data for training and testing. ANN-II performs better as comparison to ANN-I in terms of RMSE, MAE and R2[4].

Rahat Hossain et al. used eleven climatic parameters as an input to the ANN model. The correlation coefficient was used to evaluate the performance of model which was 0.963 for solar and 0.948 for wind energy [7]. Quammi et al modeled monthly solar radiation of 41 Moroccan sites using ANN model. The data period is taken from 1998 to 2010. The data period is taken from 1998 to 2010. The measured solar radiation lies in between 5030 to 6230 Wh/m2/day [8]. Ahmet Koca et al. developed six different ANN models with different-2 combinations of input. The six models having input from latitude, longitude, altitude, month, average humidity, sunshine duration, average wind velocity. The minimum RMSE for the designed model was 0.0358 whereas correlation coefficient was 0.9974 [9]. Moreover, proper selection of input parameters of the models stills a big challenge to design a forecasting model with improved accuracy. Therefore, this paper aims to access the performance of three neural network based models: ANN-I5, ANN-I6 and ANN-I7 on the basis of different-2 combinations of meteorological parameters. Different meteorological variables: precipitation water, wind direction, wind speed, pressure, relative humidity, temperature, solar zenith angle, wind speed is used in this study as input to the models while GHI is used as the ouput of the model. The performance of the model is evaluated using MAPE, RMSE and R2.

The residing paper is structure as follows:

Section 2 describes the artificial neural network model for solar irradiation forecasting.

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Section 3 explains the methodology and data preparation for the forecasted model used in the paper. The outcome and analysis are presented in Section 4. Section 5 present conclusions.

II. Artificial Neural Network

The ANN technique is almost comparable with the human brain that makes the decision based on the biological neuron. The neuron in the human brain performs a different type of parallel processing, pattern recognition analysis. The same can be used in solving non-linear mathematics like as forecasting, image processing etc. [10]. This technique trains the ANN model repeatedly to obtain the best value of weight to map the input and output. Three layers (i) input layer (ii) hidden layer (iii) output layer are include in the ANN model. The ANN definition suggested by the McCulloch and pits in 1934. The ANN uses the different-2 type of algorithm like as Levenberg Marquardt (LM), Scaled Conjugate Gradient (SCG) and Gradient Descent (GD) to predict the output value [11-12]. The basic architecture of ANN is shown in Figure 1.

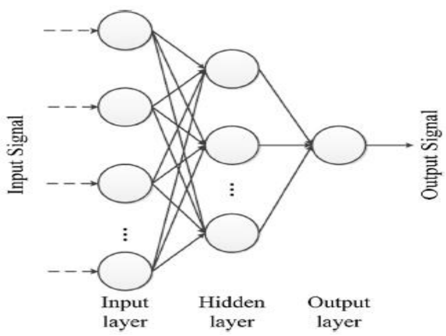

Figure 1 Basic ANN Architecture

In the present work we use LM algorithm because its performance and speed are better as comparison to other algorithms. The weighted sum of input neurons in the ANN is applied to the activation function represented by the equation (1) to produce the output signal [13].

$$Y=\phi\sum_{i=1}^{n}w_i x_i \tag{1}$$

Where Y is output, W represents weight ϕ is called activation function and x represent input value.

III Study area and ANN data preparation for forecasting model

In India, installation of measuring instrument for solar irradiation is not possible everywhere due to its cost, upkeep and calibration. Daily data for wind speed, wind direction, precipitation water, temperature, pressure, relative humidity, solar zenith angle and global horizontal irradiation of Delhi location are collected for a period of three years (2012-14) from National Solar Radiation Database (NSRDB). Two year data (2012-13) used for training while one year data (2014) is used for testing the network in which divide on season wise: winter, spring. Summer, monsoon and autumn as per given in the official Tourism website [12]. The total collected data are normalized using equation (2) and then restored to its original format after simulation [6].The Table 1 shows the parameter select for present study.

$$X_{norm}=\frac{X_R-X_{\min}}{X_{\max}-X_{\min}} \tag{2}$$

X_{norm} represent the normalized value, X_R is the value to be normalized, X_{min} is the minimum value and X_{max} is the maximum value in all the values for related variable

The test conditions followed in the current study shown in Table 1. The latitude, longitude and altitude of the study area (Delhi) are 28.7041°N, 77.1025°E and 225 meters [12]

Table 1 Test Parameters in the current study

Network type used	Feed Forward neural network
Transfer function	Log Sigmoid
Number of hidden neurons	30
Input variables	Varied from 5 to 7
Output variables	1
Hidden layer used	1
Training function	TRAINLM
Performance function	MSE

The combination of input parameters varies from five to seven

First model having all inputs and it is represented by ANN-I_7

ANN-I_7=F [T, P, RH, SZA, PW, WD, WS]

In second model, six parameters are used as inputs and it is represented by

ANN-I_6=F [T, P, SZA, PW, WD, WS]

In the third model, five parameters are used as inputs and it is represented by ANN-I_5

ANN-I_5=F [T, SZA, PW, WD, WS]

For training, testing and validation we use levenberg marquardt algorithm. The value of hidden neurons varies from 10 to 30. Network trained number of times to get the best value. The proposed methodology for the present work is shown in Figure 2.

IV Result and Discussion

The performance of ANN model is evaluated on the basis of MAPE, RRMSE and R^2 express by the equation [13]

$$MAPE=\left(\frac{1}{n}\sum_{i=1}^{n}\frac{\left|GSR_{i(predicted)}-GSR_{i(actual)}\right|}{GSR_{i(actual)}}\right)\times 100 \tag{3}$$

$$R^2=\left(1-\left(\frac{\sum_{i=1}^{n}\left|GSR_{i(predicted)}-GSR_{i(actual)}\right|^2}{\sum_{i=1}^{n}GSR_{i(actual)}}\right)\right)\times 100 \tag{4}$$

$$RRMSE=\frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(GSR_{i(predicted)}-GSR_{i(actual)}\right)^2}}{\frac{1}{n}\sum_{i=1}^{n}GSR_{i(actual)}} \tag{5}$$

The MAPE represent the uniform prediction error in percentage while RRMSE indicates the divergence between predicted and observed value and R correlation coefficient represents the relation between measured and forecast value. if R=1 indicate the exact relation between measured and forecast value. However, an ANN with least value of MAPE, RRMSE and higher value of R represent the best model for forecasting. Table 2 and Table 3 represent the value of MAPE and RRMSE to examine the prediction accuracy of model. The developed models forecasting accuracy in terms of MAPE, RRMSE and R^2 as shown in Table 4.

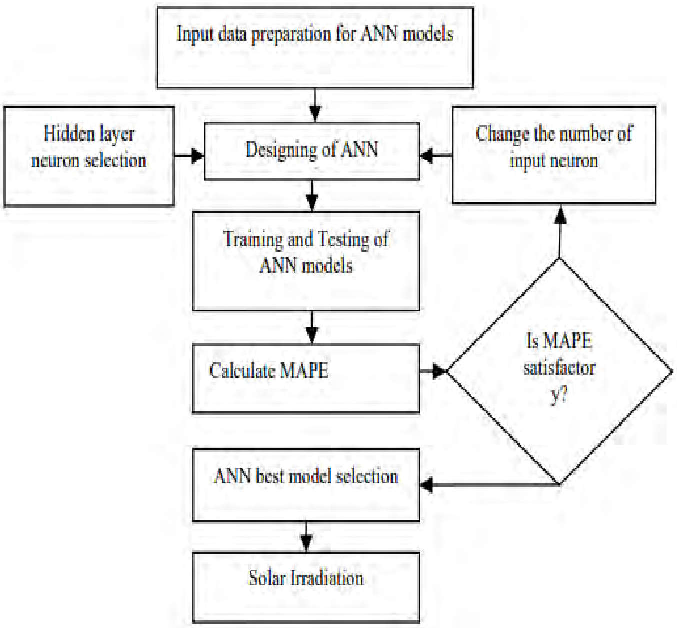

Figure 2: Flow chart of the Proposed Methodology

Table 2 Range of MAPE to analyze forecasting accuracy [17]

Range of MAPE	Performance evaluation of forecasting model
<10%	Excellent accuracy
10%<MAPE<20%	Good accuracy
20%<MAPE<50%	Normal accuracy
>50%	Bad accuracy

Table 3 Ranges of RRMSE to analyze forecasting accuracy [17]

Range of RRMSE	Performance evaluation of forecasting model
<10%	Excellent
10%<RRMSE<20%	Good
20%<RRMSE<50%	Normal
>50%	Bad

The developed model ANN-I_7 having input parameters temperature, pressure, solar zenith angle, relative humidity, wind speed, wind direction and perceptible water perform batter as comparison to ANN-I_6 and ANN-I_5.

Table 4 Error Metrics for ANN Models

Number of input parameters	Seasons	MAPE (%)	RRMSE(W/m^2)	R^2
First Model ANN-I_7=F[T,P,RH,SZA,PW,WD,WS]	Winter	18.03	24.73	85.74
	Spring	16.97	20.25	84.36
	Summer	9.76	16.49	94.12
	Monsoon	20.56	26.89	79.36
	Autumn	7.27	15.34	97.02
	Average	**14.523**	**20.745**	**88.12**
Second Model ANN-I_6=F[T,P,SZA,PW,WD,WS]	Winter	20.87	26.80	81.08
	Spring	17.00	22.69	85.07
	Summer	11.86	17.01	93.57
	Monsoon	23.78	29.25	78.84
	Autumn	9.15	15.66	96.45
	Average	**16.538**	**22.286**	**87.00**
Third Model ANN-I_5=F[T,SZA,PW,WD,WS]	Winter	24.74	30.57	81.97
	Spring	19.01	24.73	84.53
	Summer	13.98	19.91	92.57
	Monsoon	26.85	32.23	77.88
	Autumn	10.26	14.74	96.34
	Average	**18.972**	**24.439**	**86.65**

The developed model ANN-I_7 having input parameters temperature, pressure, solar zenith angle, relative humidity, wind speed, wind direction and perceptible water perform better as comparison to ANN-I_6 and ANN-I_5. The performance evaluation of developed ANN models in terms of average MAPE and average RRMSE indicates that if we decrease the number of input meteorological parameters accuracy of the forecasting model go on decreasing. The regression coefficient shows that if we have the least MAPE than value of correlation coefficient is higher.

V Comparison of present model with existing ANN models

The performance of present model is compared with the existing ANN models shown in Table 5. Comparison of models is done on the basis of MPAE values. B.Sivaneasan reported highest MAPE while present study produced lowest MAPE [5]

Table 5 Comparison of present work with previous published model

Author	Location	MAPE (%)	Proposed Method
B.Sivaneasan et al., [5]	Singapore	29.6	ANN with fuzzy logic
Mohandes et al., [14]	Kwash (Saudi Arabia)	19.1	ANN/MLFF
Sanjay Kumar et al., [15]	Himachal Pradesh	16.45	ANN/LM
N.Kumar et al., [2]	Various location of India	14.68	ANN with forward unity gain
Present work (ANN-I_7)	Delhi	14.52	ANN/LM

VI Comparison of present models with benchmark model in terms of MAPE, RRMSE and R^2

For the selected Delhi location, the performances of the developed neural network models were compared with the performance of the Naïve Predictor. The comparative study represents that developed models perform better than Naïve Predictor in all aspects. The performance plot of ANN-I_7 model is shown in Figure 3-7.

Table 6 Comparison of ANN-I_7 model and benchmark model on MAPE, RRMSE and R^2

Seasons	ANN-I_7 Model			Naïve Predictor		
	MAPE	RRMSE	R^2	MAPE	RRMSE	R^2
Winter	18.03	24.73	85.74	21.04	29.09	80.04
Spring	16.97	20.25	84.36	19.64	24.49	78.25
Summer	9.76	16.49	94.12	12.93	19.42	81.79
Monsoon	20.56	26.89	79.36	24.10	33.66	72.34
Autumn	7.27	15.34	97.02	10.62	12.10	90.21
Average	**14.523**	**20.745**	**88.12**	**17.666**	**23.752**	**80.52**

Table 7 Comparison of ANN-I_6 model and benchmark model on MAPE, RRMSE and R^2

Seasons	ANN-I_7 Model			Naïve Predictor		
	MAPE	RRMSE	R^2	MAPE	RRMSE	R^2
Winter	20.87	26.80	81.08	27.35	32.93	77.04
Spring	17.00	22.69	85.07	21.54	26.44	79.48
Summer	11.86	17.01	93.57	14.39	22.61	85.21
Monsoon	23.78	29.25	78.84	29.67	34.12	69.14
Autumn	9.15	15.66	96.45	12.64	19.56	87.15
Average	**16.538**	**22.286**	**87.00**	**21.118**	**27.132**	**79.60**

Table 8 Comparison of ANN-I_5 model and benchmark model on MAPE, RRMSE and R^2

Seasons	ANN-I_5 Model			Naïve Predictor		
	MAPE	RRMSE	R^2	MAPE	RRMSE	R^2
Winter	24.74	30.57	81.97	31.26	36.79	74.37
Spring	19.01	24.73	84.53	24.22	29.44	80.86
Summer	13.98	19.91	92.57	18.11	23.93	85.54
Monsoon	26.85	32.23	77.88	31.13	39.91	67.79
Autumn	10.26	14.74	96.34	15.12	20.11	85.39
Average	**18.972**	**24.439**	**86.65**	**23.968**	**30.036**	**78.99**

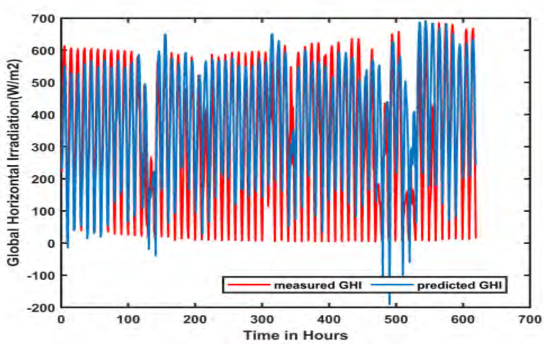

Figure 3 ANN-I_7 winter season

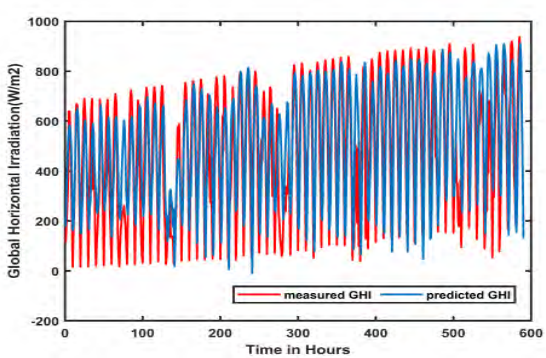

Figure 4 ANN-I_7 spring season

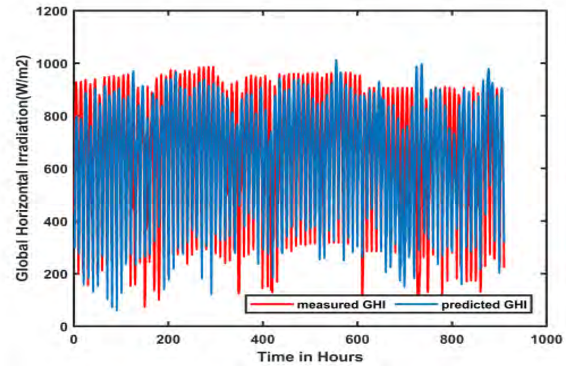

Figure 5 ANN-I_7 summer season

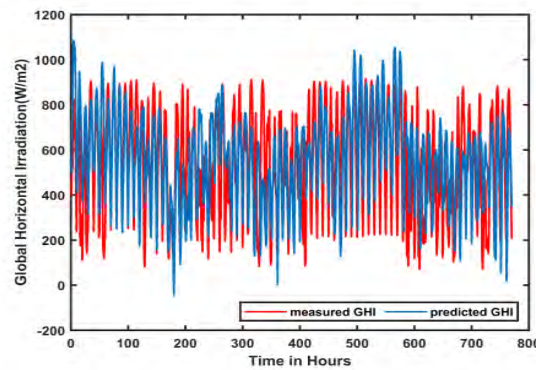

Figure 6 ANN-I_7 monsoon season

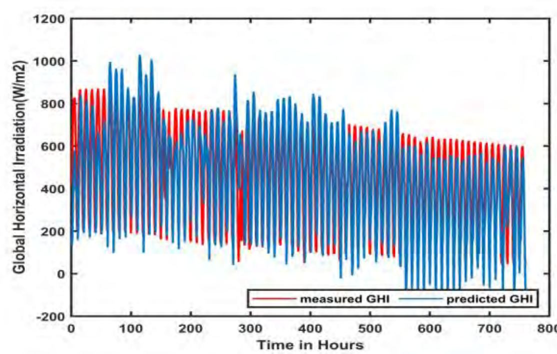

Figure 7 ANN-I_7 autumn season

VII Conclusion

This study developed three nerual network based models (ANN-I_5, ANN-I_6, ANN-I_7) with different cobminations of meterological parameters. Different meteorological variables: precipitation water, pressure, temperature, relative humidity, solar zenith angle, wind speed and wind direction were used in this study as an input to the models while solar GHI is used as the output of the model. Two year data(2012-2013) of Delhi location were used for training and one year data(2014) used for testing the models on different seasons following one hour ahead. Performance of the models is evaluated on the basis of MAPE, RRMSE and R^2.The result obtained from these developed models indicate that ANN-I_7 perform better as comparison to other neural network based models. The number of hidden neuron varies from 1 to 30 in the case of each model to achieve the best forecasting accuracy. The developed neural network based models also outperform the naïve predictor performance in the estimation of global horizontal irradiation. The result shows that if we reduce the meteorological parameters, performance of the forecasting model also decrease. In future, we can use more significant meteorological parameters which affect the solar irradiation assessment.

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