Gap Filling in Solar Radiation Data using Artificial Neural Network for Nine Stations in Pakistan

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Abstract

This study presents an approach to fill gaps in ground measured solar radiation data using artificial neural network (ANN). The high quality global horizontal irradiance (*GHI*) measured data without gaps for nine stations in different climatic conditions was used. Six parameters were used as input and GHI as output to ANN. A parametric study was performed to find optimum number of neurons in the hidden layer. Two years GHI data (six days for every week with seventh day as gap) was used to train networks for nine stations. GHI data of seventh day of each week was predicted using trained networks. The predicted data of seventh day of each week was evaluated against actual measured data using statistical parameters (Mean Bias Error (rMBE), relative Mean Absolute Error (rMAE), relative Root Mean Square Error (rRMSE) and correlation coefficient (*R-value*)). The predicted data show good agreement with actual data with R-value ranging from 0.966 to 0.933. The approach proposed in this study can be used to fill gaps in measured data of solar radiation with acceptable accuracy.

Keywords: Solar Radiation, Global Horizontal Irradiance, Data gap filling, Artificial Neural Networks

1. Introduction

Global energy demand is rising steadily, therefore, it is important to use those resources that can produce sufficient energy. Energy extraction from fossil fuels (oil, natural gas, and coal) falls under conventional energy resources. These energy resources have been used for many years due to their ability to produce massive amount of energy. Fossil fuels are depleting and when burnt in large quantities, they emit solid residue and gases that are harmful for the ecosystem. These disadvantages demand an alternative resource that could serve the desired purpose. Now a days, renewable energy resources (wind power, solar power, biogas, biomass, hydropower and tidal energy) are getting popular due to their less adverse effects on the environment and their capability to produce enough energy as per the increasing needs. International Energy Agency has stated that renewable energy resources will make up 66% of the overall global energy supply by the year 2050 (Güney, 2019). Excessive use of fossil fuels for extracting energy leads to gradually increasing CO_2 emissions. Renewable energy resources are more environmentally friendly as compared to non-renewable energy sources because of their less CO_2 emissions which are the biggest pollutant (Gielen et al., 2019).

The initial power generated from wind energy is less expensive, but the maintenance cost of wind turbines is much more than that of solar panels. There are few feasible sites available for setting up wind plants as compared to solar plants. Hydropower plants require massive capital for the construction of dams. Solar energy production has no harmful effect on the environment and solar plants can be installed at any location due to easy availability of solar energy. Selection of site, yearly power output, and temporal performance are crucial factors for any solar project installation. These factors are directly linked with solar resource assessment of site. Solar resource assessment can be done by using ground measured data, satellite data, and reanalysis data (Amjad et al., 2021; Asim et al., 2021). Global solar radiation measurements are less common especially in developing countries because of high cost of installation and maintenance of measuring instruments. The pyranometer and pyrheliometer are the instruments that are commonly used for solar data measurement. (Ağbulut et al., 2021).

Ground measured data can have data gaps due to malfunctioning of instruments and discarded data due to quality issues. Satellite data is not easily available on a global scale and reanalysis data has quality issues due to assimilation methods. Hence, filling data gaps is extremely important for solar resource assessment (Asim et al., 2021; Denhard et al., 2022; Kumar and Ravindra, 2020).

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Several techniques have been developed to estimate global solar irradiance for effective solar resource assessment. Empirical and machine learning models are the most used approaches for estimation of global solar radiation. Empirical models (Sunshine-based, Temperature-based, Cloud-based and Hybrid) estimate global solar radiation by developing a linear or non-linear relationship between the meteorological parameters and global solar radiation. Sunshine-based models are extensively used to predict global solar radiation. Machine learning models are used for complex non-linear cases and hence, these models are more accurate (Fan et al., 2019). In recent decades, artificial intelligence has taken over all conventional methods in almost every engineering domain. Studies have proved that these machine learning methods give more accurate results for the prediction of solar irradiance than the empirical models (Ağbulut et al., 2021).

Several empirical and machine learning models were used in previous literature. The estimation accuracy depends on combination of meteorological parameters and training algorithm. Karakoti et al. (Karakoti et al., 2012) and Fend L et al. (Feng et al., 2018) used clearness index, relative humidity, sunshine duration ratio, and temperature as meteorological parameters to forecast daily and monthly diffused horizontal irradiance (DNI). Zhou et al. (Zhou et al., 2021) developed a novel multi-task learning and Gaussian process regression model to forecast global and diffused solar radiation for several locations in China. The same model was able to predict daily and monthly mean solar radiation simultaneously. Yadav et al. (Yadav and Chandel, 2014) analyzed solar radiation prediction models and concluded that ANN methods can give accurate results as compared to conventional methods. Quej et al. (Quej et al., 2017) used three machine-learning algorithms namely support vector machine, artificial neural network, and adaptive neuro-fuzzy inference system for the daily prediction of solar radiation at six stations in Mexico. Mehdizadeh et al. (Mehdizadeh et al., 2016) used artificial neural networks, adaptive neuro-fuzzy inference systems, and gene expression programming as their training models to predicted daily solar radiation in Kamren, Iran, and concluded that ANN gave the optimum results. In another study, Tyvimos et al. (Tymvios et al., 2005) compared two different models namely Angstrom and Artificial neural network for the prediction of global solar radiation. Authors concluded that ANN turned out to be the best model for it. Marzouq et al. (Marzouq et al., 2019) used ANN, k-NN, and some other empirical models to forecast daily global solar radiation. They concluded that k-NN gave the best results. Quej et al. (Quej et al., 2017) compared three different machine learning techniques (Adaptive Neuro-fuzzy, Support Vector Machine and Artificial Neural Network) to predict daily solar irradiance in a warm semi-humid conditions. Rasheed et al. (Al-Naimi et al., 2014) predicted the average daily global solar radiation of Baghdad using a model based on artificial neural network. Yildirim et al. (Yıldırım et al., 2018) used artificial neural network with regression analysis to estimate monthly global solar irradiance. The analysis was performed for four stations in Turkey and several meteorological parameters were selected for training the algorithm.

This study aims to fill gaps in solar radiation data using artificial neural network technique. The data used was measured by Energy Sector Management Assistance Program (ESMAP) at nine different stations (Lahore, Quetta, Khuzdar, Islamabad, Karachi, Hyderabad, Multan, Peshawar, and Bahawalpur) of Pakistan. Non-linear regressive models were developed with different combinations of input parameters. The evaluation was based on statistical parameters. Statistical insignificant parameters were excluded and a final model was developed for solar data gap filling.

2. Methodology

Gap filling of ground measured solar data was performed using machine learning approach for nine stations in Pakistan (Bahawalpur, Hyderabad, Islamabad, Karachi, Khuzdar, Lahore, Multan, Peshawar, and Quetta). Initially, ANN was used for 9 input parameters including Solar Zenith Angle (SZA), Extraterrestrial Solar Irradiance (G_{toa}), Clear Sky Irradiance (G_{cls}), Clear Sky Irradiance from McClear (G_{mcc}), Relative Humidity (RH), Temperature (T), Periodicity Factor (PF), Wind Speed (WS) and Pressure (P). These parameters were selected from literature based on their performance (Wang et al., 2012). 28 non-linear regression models with different combinations of these parameters were developed. Coefficient of correlation (R), Mean Biased Error (MBE), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Relative Standard Error (RSE), p-value, t-statistical value, normalized Akaike Information Criterion (AIC), Corrected Akaike Information Criterion (AICc) and Bayesian (Schwarz) Information Criterion (BIC) were utilized to assess the accuracy of the models.

Category I was comprised of models M01 to M08 in which SZA and G_{toa} are fixed based on previous studies (Stökler et al., 2016). Category II was comprised of models M09 to M14 in which RH was added at third place in accordance with its observed statistical significance. Category III was comprised of models M15 to M19 in which G_{mcc} was added at fourth place based on its observed statistical significance. Category IV was comprised of models M20 to M23 in which G_{cls} was added at fifth place based on its observed statistical significance. Category V was comprised of models M24 to M26 in which PF was added at sixth place based on its observed statistical significance. Category VI was comprised of models M27 and M28 in which T was added at seventh place based on its observed statistical significance. The models with lower values of errors and higher R-value were selected for further analysis. The details of combinations for these models are as follows;

Category I:

M01: $G_{mq} = b_1 + b_2\,SZA + b_3\,G_{toa}$

M02: $G_{mq} = b_1 + b_2\,SZA + b_3\,G_{toa} + b_4\,PF$

M03: $G_{mq} = b_1 + b_2\,SZA + b_3\,G_{toa} + b_4\,T$

M04: $G_{mq} = b_1 + b_2\,SZA + b_3\,G_{toa} + b_4\,RH$

M05: $G_{mq} = b_1 + b_2\,SZA + b_3\,G_{toa} + b_4\,P$

M06: $G_{mq} = b_1 + b_2\,SZA + b_3\,G_{toa} + b_4\,WS$

M07: $G_{mq} = b_1 + b_2\,SZA + b_3\,G_{toa} + b_4\,G_{cls}$

M08: $G_{mq} = b_1 + b_2\,SZA + b_3\,G_{toa} + b_4\,G_{mcc}$

Category II:

M09: $G_{mq} = b_1 + b_2\,SZA + b_3\,G_{toa} + b_4\,RH + b_5\,PF$

M10: $G_{mq} = b_1 + b_2\,SZA + b_3\,G_{toa} + b_4\,RH + b_5\,T$

M11: $G_{mq} = b_1 + b_2\,SZA + b_3\,G_{toa} + b_4\,RH + b_5\,P$

M12: $G_{mq} = b_1 + b_2\,SZA + b_3\,G_{toa} + b_4\,RH + b_5\,WS$

M13: $G_{mq} = b_1 + b_2\,SZA + b_3\,G_{toa} + b_4\,RH + b_5\,G_{cls}$

M14: $G_{mq} = b_1 + b_2\,SZA + b_3\,G_{toa} + b_4\,RH + b_5\,G_{mcc}$

Category III:

M15: $G_{mq} = b_1 + b_2\,SZA + b_3\,G_{toa} + b_4\,RH + b_5\,G_{mcc} + b_6\,PF$

M16: $G_{mq} = b_1 + b_2\,SZA + b_3\,G_{toa} + b_4\,RH + b_5\,G_{mcc} + b_6\,T$

M17: $G_{mq} = b_1 + b_2\,SZA + b_3\,G_{toa} + b_4\,RH + b_5\,G_{mcc} + b_6\,P$

M18: $G_{mq} = b_1 + b_2\,SZA + b_3\,G_{toa} + b_4\,RH + b_5\,G_{mcc} + b_6\,WS$

M19: $G_{mq} = b_1 + b_2\,SZA + b_3\,G_{toa} + b_4\,RH + b_5\,G_{mcc} + b_6\,G_{cls}$

Category IV:

M20: $G_{mq} = b_1 + b_2\,SZA + b_3\,G_{toa} + b_4\,RH + b_5\,G_{mcc} + b_6\,G_{cls} + b_7\,PF$

M21: $G_{mq} = b_1 + b_2\,SZA + b_3\,G_{toa} + b_4\,RH + b_5\,G_{mcc} + b_6\,G_{cls} + b_7\,T$

M22: $G_{mq} = b_1 + b_2\,SZA + b_3\,G_{toa} + b_4\,RH + b_5\,G_{mcc} + b_6\,G_{cls} + b_7\,P$

M23: $G_{mq} = b_1 + b_2\,SZA + b_3\,G_{toa} + b_4\,RH + b_5\,G_{mcc} + b_6\,G_{cls} + b_7\,WS$

Category V:

M24: $G_{mq} = b_1 + b_2\,SZA + b_3\,G_{toa} + b_4\,RH + b_5\,G_{mcc} + b_6\,G_{cls} + b_7\,PF + b_8\,T$

M25: $G_{mq} = b_1 + b_2\,SZA + b_3\,G_{toa} + b_4\,RH + b_5\,G_{mcc} + b_6\,G_{cls} + b_7\,PF + b_8\,P$

M26: $G_{mq} = b_1 + b_2\,SZA + b_3\,G_{toa} + b_4\,RH + b_5\,G_{mcc} + b_6\,G_{cls} + b_7\,PF + b_8\,WS$

Category VI:

M27: $G_{mq} = b_1 + b_2\,SZA + b_3\,G_{toa} + b_4\,RH + b_5\,G_{mcc} + b_6\,G_{cls} + b_7\,PF + b_8\,T + b_9\,P$

M28: $G_{mq} = b_1 + b_2\,SZA + b_3\,G_{toa} + b_4\,RH + b_5\,G_{mcc} + b_6\,G_{cls} + b_7\,PF + b_8\,T + b_9\,WS$

t-stat and p-value were evaluated to determine the statistical significance of input parameters in each model. t-stat was performed to indicate whether the result is meaningful or not. p-value is a probability that helps to find a correlation between observed values of a sample and population data. t-stat value greater than $|\pm 1.96|$ and p-value less than 0.05 was considered significant for the result.

2.1 Selection of Input Parameters

The input parameters were selected from literature and then shortlisted based on statistical significance. The accuracy of ANN results depends on selection of input parameters, training algorithm and number of neurons. The base model was initially made using two input parameters (SZA and G_{toa}) which were considered to be of primary importance. Different metrological parameters (T, RH, WS, P, PF, G_{cls}, G_{mcc}, Day and Hour) were added to build Subsequent models. Parameters were evaluated and shortlisted based on statistical significance using different statistical parameters such as t-stat, p value, R-value, and AIC, AICc and BIC errors. Only those parameters were selected that have t-stat > $|\pm 1.96|$ and p-value < 0.05 (Mandal, 2017). The selected input parameters based on statistical analysis were day, hour, SZA, G_{toa}, RH, T, G_{mcc}, and G_{cls}. After evaluating the input parameters, optimum number of neurons were estimated. The statistical parameters were used to evaluate the results obtained from ANN.

2.2 Evaluation of Models

The performance of the proposed models was assessed using statistical analysis. The statistical parameters reported in literature are MAPE, MBE, MABE, RMSE, t-stat and R-value. MAPE is commonly used for regression problems and model evaluation. It gives the mean value of relative error between the measured and estimated value as represented by eq. (1). The results will be better when the numerical model gives less errors. The MBE is based on the bias of a model, positive MBE represents overestimation whereas negative MBE represents underestimation by the model. The mathematical expression for MBE is shown by eq. (2). The positive and negative values of observation may cancel each other while calculating MBE, therefore MABE parameter represented by eq. (3). is used. RMSE gives the actual deviation between measured and estimated data. The smaller value of RMSE gives better estimation. The mathematical expression of RMSE is shown by eq. (4). The positive correlation coefficient determines the quality of results and ranges from zero to one, R-value closer to one show good result. t-stat expression is demonstrated by eq. (5). Generally, smaller value of t-stat is considered good for validation of empirical models. The models with high R-value and low errors were considered as best models among all.

$$MBE=\frac{1}{n}\sum_{i=1}^{n}(GHI_{ei} - GHI_{mi}) \qquad \text{(eq.1)}$$

$$MABE=\frac{1}{n}\sum_{i=1}^{n}|GHI_{ei} - GHI_{mi}| \qquad \text{(eq. 2)}$$

$$MSE=\frac{1}{n}\sum_{i=1}^{n}(GHI_{ei} - GHI_{mi})^2 \qquad \text{(eq. 3)}$$

$$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(GHI_{ei} - GHI_{mi})^2} \qquad \text{(eq. 4)}$$

$$t\text{-}stat=\sqrt{\frac{(n-1)(MBE)^2}{(RMSE)^2-(MBE)^2}} \qquad \text{(eq. 5)}$$

The analysis was performed using modern ANN technique of machine learning using MATLAB computation tool. Gaps were created in the high-quality data measured by ESMAP of the World Bank. The estimated solar data was then compared to the available ground measured solar data.

3. Results and Discussion

3.1 Effect of input parameters on ANN

The non-linear regression model with the highest accuracy was identified on basis of statistical parameters. 28 different models were analyzed using different combinations of nine input parameters. The best four models selected after statistical analysis of nine input parameters for forecasting purpose are as follows:

NM01: $G_{mq} = b_1 + b_2\,SZA + b_3\,G_{toa} + b_4\,RH + b_5\,G_{mcc} + b_6\,G_{cls} + b_7\,T$

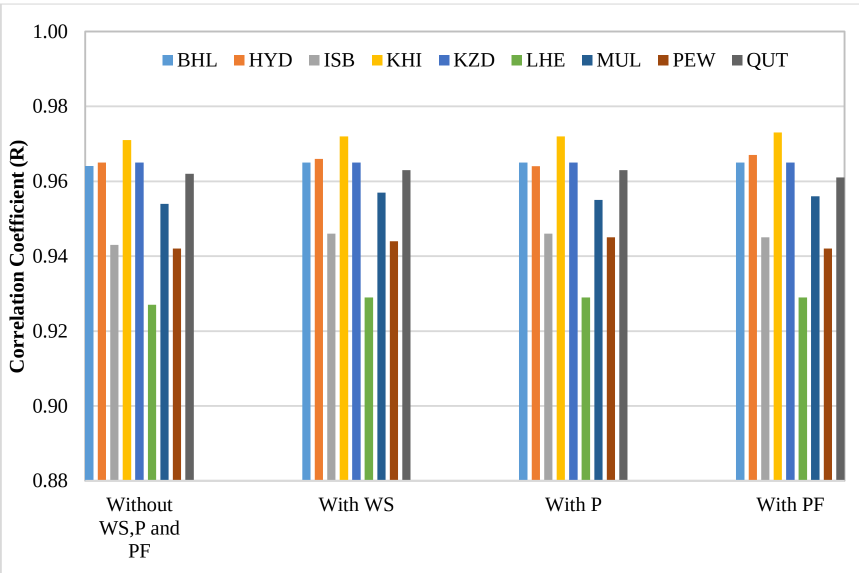
NM02: $G_{mq} = b_1 + b_2\,SZA + b_3\,G_{toa} + b_4\,RH + b_5\,G_{mcc} + b_6\,G_{cls} + b_7\,T + b_8\,P$

NM03: $G_{mq} = b_1 + b_2\,SZA + b_3\,G_{toa} + b_4\,RH + b_5\,G_{mcc} + b_6\,G_{cls} + b_7\,T + b_8\,WS$

NM04: $G_{mq} = b_1 + b_2\,SZA + b_3\,G_{toa} + b_4\,RH + b_5\,G_{mcc} + b_6\,G_{cls} + b_7\,T + b_8\,PF$

The R-value, rRMSE, and rMAE for testing and training four models for nine stations are presented in Fig. 1(a, b, and c) respectively. The findings of this study demonstrate that three parameters (WS, P, and PF) out of the nine were relatively less significant. SZA, G_{toa}, RH, G_{mcc}, G_{cls} and T were included in all four new models based on their statistical significance. Further analysis was made by adding P (NM02), WS (NM03) and PF (NM04).

The addition of these parameters has negligible effect on *R*-value, rRMSE, and rMAE of 0.1, 1.0, and 1.5 respectively, therefore, these parameters were not included in the final model. Hence, NM01 with eight metrological parameters (day, hour, SZA, G_{toa}, RH, G_{mcc}, G_{cls} and T) was used for further analysis of solar data gap filling. The SZA and G_{toa} are considered as the prime parameters for the most accurate non-linear regression model evaluated in this study. The remaining four parameters were added in decreasing order of statistical significance in model NM01. It can be observed that Karachi gives the best result for model NM01 with R-value more than 0.97, rRMSE less than 13.6 and rMAE less than 8.8. The least accurate result was observed for Lahore with R-value more than 0.93%, rRMSE less than 24.5, and rMAE less than 15.9.



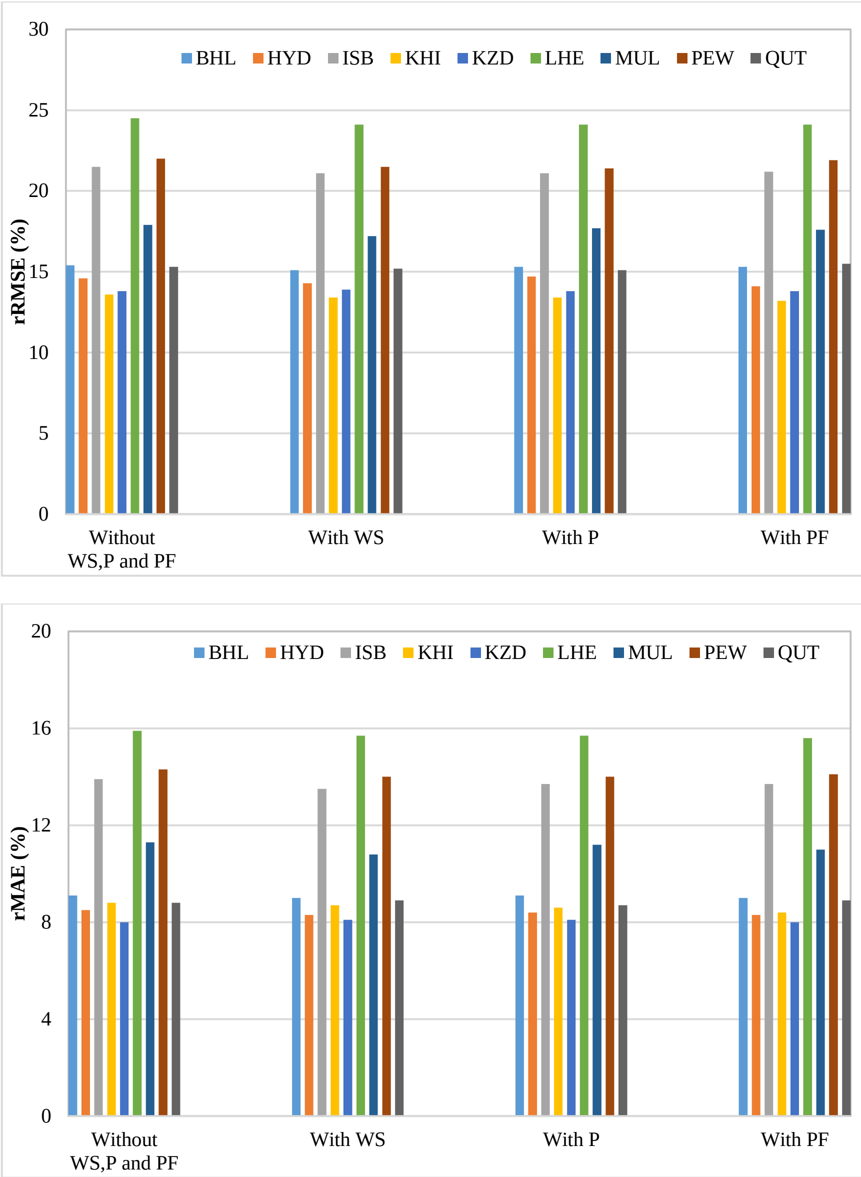


Figure 1: Input parameters (WS, P and PF) versus (a) R (b) rRMSE (c) rMAE for nine stations

3.2 Optimum Number of Neurons

The R-value, rRMSE, and rMAE values for testing and training of the selected model combined are presented in Fig. 2 (a and b) respectively with an increasing number of neurons. rRMSE and rMAE decrease whereas R-values increase with the increasing number of neurons up to five neurons and then became constant. The trend of these curves indicated that the overall performance of the model was converging from five to ten neurons, therefore, ten neurons were selected for further analysis.

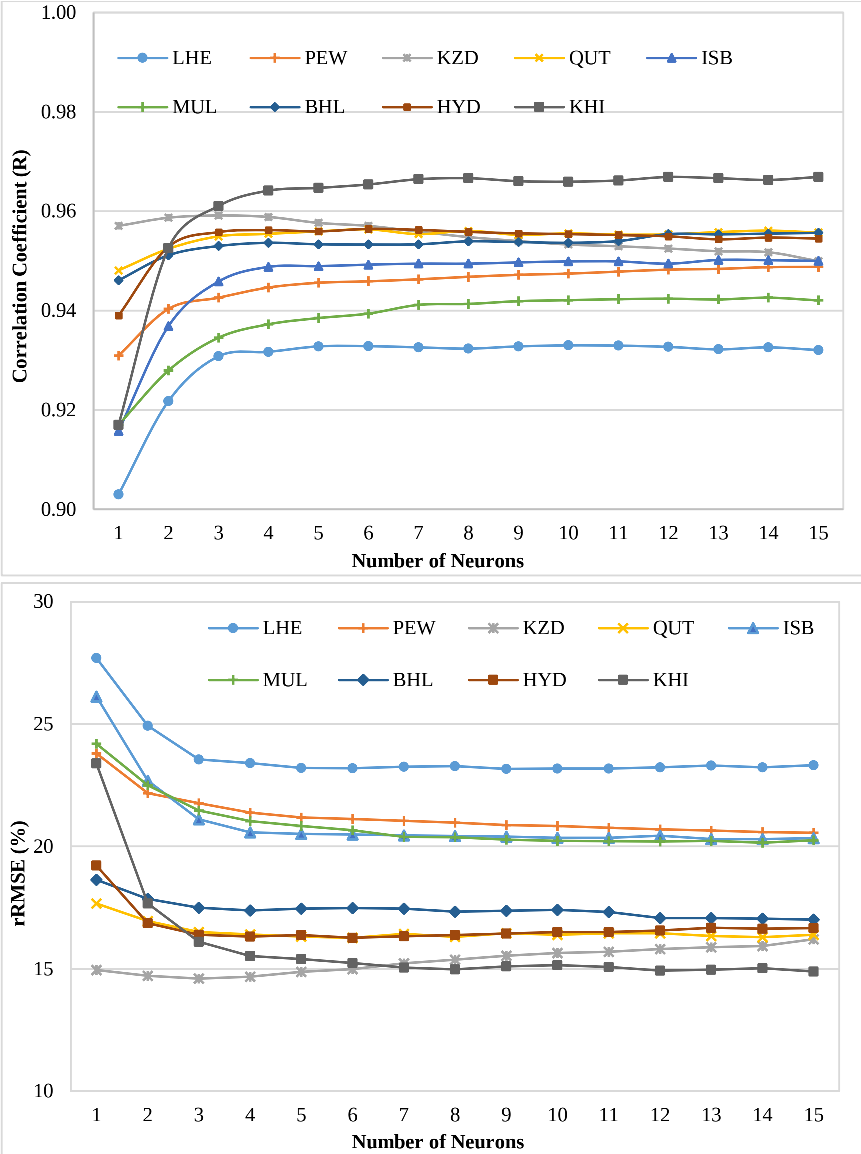


Fig. 2: Effect of neuron numbers on (a) R-value and (b) rRMSE for nine stations

3.3 GHI gap filling with selected model

The proposed model was used with ten neurons to fill the gaps created in measured solar data at nine stations. The predicted GHI values were compared with actual data available for the nine stations. The quality of predicted values in terms of R-value, rMAE, and rRMSE are shown in Fig. 3. Karachi gave the minimum rRMSE of 15.0 and a maximum R-value of 0.967, whereas, Lahore gave a maximum rRMSE of 23.1 and a minimum R-value of 0.933. Lahore also has the highest rMAE (14.8 %) while Khuzdar has the lowest (8.4 %). The low accuracy of *GHI* predictions in Lahore is due to high-grade air pollution and smog in its atmosphere but the correlation is considered significant.

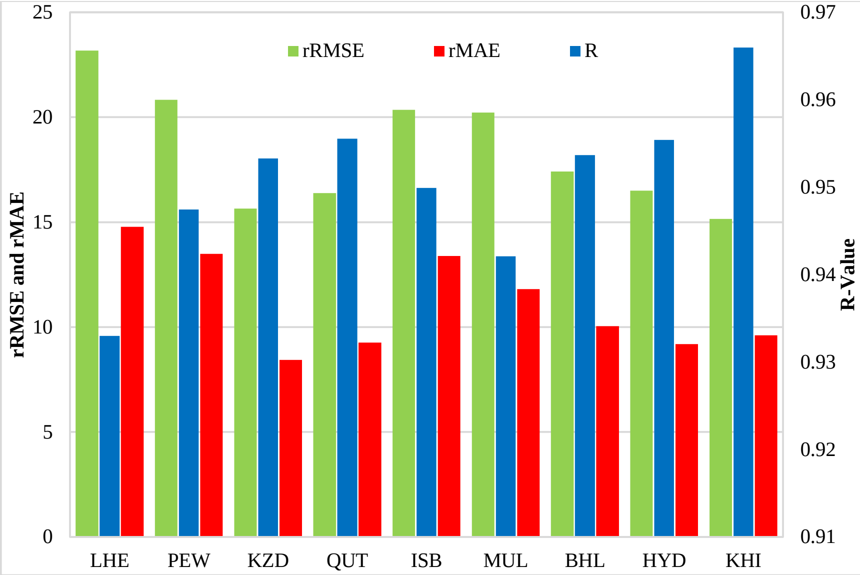


Fig. 3: rRMSE, rMAE and R values for nine stations

4. Conclusion

The self-created gaps in measured solar data were filled using artificial neural networks and predicted results were compared with the available actual data. rRMSE, rMAE, and R-values were evaluated for the prediction of H_g. The SZA, G_{toa}, RH, G_{mcc}, G_{cls} and T are significant training parameters for the nine test stations of Pakistan based on statistical analysis. Training of the ANN model gives best results at a specific number of neurons in the hidden layer. The results for optimum number of neurons in hidden layer converged around ten. Comparative analysis is performed to find the city with best prediction results. The comparison indicated that predicted data were most consistent with measured data for Karachi and least consistent for Lahore. There may be several reasons for the least accurate prediction of results for Lahore. One of them is air pollution. rRMSE for all nine stations was less than 23 % and regression was more than 0.93. The power produced using solar panels may easily be predicted once the data quality is assessed.

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