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# Modeling and estimation of solar radiation through artificial neural network using known solar data

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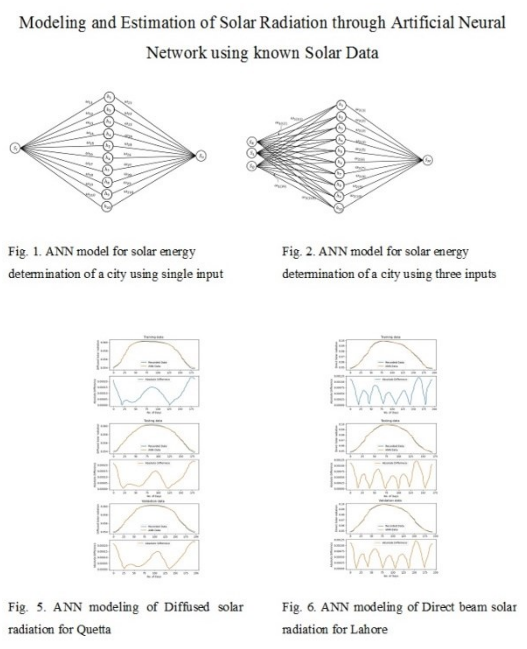
## Graphical abstract




## Abstract

The paper attempts to discover a city's global, direct beam and diffused solar radiation with the help of known solar radiation of its neighbor(s). Two distinctive architectures have been used to find the solar radiation of a city. In the first architecture, we used single input and a single hidden layer of the neuron to find the solar radiation of the city. The solar radiation of Lahore, Multan, and Quetta was found via the solar radiation of Karachi. In the second architecture scheme, we used three inputs and ten neurons' hidden layers to find the solar radiation of a city in the region bounded by three cities lying at the vertices of a triangle. Multan was assumed as such an area; its neighboring cities, Lahore, Quetta, and Karachi, form a triangle, and Multan lies inside the triangle area. In both architectures, three types of solar radiation, DSR, BSR, and GSR, were found with an accuracy of 99.8 %. The coefficient of determination in each case was 0.99. It shows that the results obtained through ANN models agree well with the known values.

**Keywords:** Artificial neural network, global radiation, diffused radiation, direct beam solar radiation

## 1. Introduction

The energy crisis has become the biggest challenge for researchers, and solar energy seems to be a promising and economical solution that is a freely available renewable energy source. The solar industry is developing steadily worldwide because of limited and expansive sources such as fossil fuels. Developing countries like Pakistan may raise their economic status by shifting their power usage to solar energy (Kannan and Vakeesan, 2016). The direct method of collecting solar radiation data is merely adapted due to the high installation cost of observation equipment and their maintenance; other methods of producing these data are needed. Linear, non-linear, and artificial intelligence modeling techniques for solar energy prediction have been studied by Khatib & Mohammad. Sunshine ratio, ambient temperature, and relative humidity were the correlated coefficients for predicting solar energy. ANN models are considered the most accurate for predicting solar energy compared to linear and non-linear models (Khatib *et al*., 2012; El-Sebaii *et al*., 2010; Li *et al*., 2011; Teke *et al*., 2015). Ammar H. Elsheikha suggested that compared to experimental investigations, fewer experimental tests are needed to determine the input/output linkages with the application of ANNs (Elsheikh *et al*., 2019). O¨mer Ali Karaman and D. Shah concluded that to get the optimum estimation response and various activation functions for ANN and ELM; ANN will be useful for forecasting solar radiation in future studies. At the same time, Shah *et al*. claimed that Based on the values of statistical indicators like mean absolute percentage error (MAPE), root means square error (RMSE), mean bias error (MBE), and coefficient of determination (R2), ANN technique is more forgiving and simpler than the fuzzy logic technique for the prediction of solar radiation using many algorithms and models (Karaman *et al*., 2021; Shah *et al*., 2021).

Geetha *et al*. suggested that hourly average global radiation for the areas without meteorological data collection facilities would be accurately estimated and photovoltaic (PV) by implementing the ANN model (Geetha *et al*., 2022). Yu *et al*. found that solar energy consumption reduces demonstrate CO2 emissions at different quantiles for all selected countries except France (Yu *et al*., 2022; Yu *et al*., 2022). Furthermore, Hussain and khan studied the results of six machine learning models random forest, k-nearest neighbors, Gaussian process regression, support vector machine, multilayer perception, and XGBoost for global solar radiation (GSR) prediction (Husain and Khan, 2022). Li H. *et al*. estimate the monthly average daily diffuse solar radiation with multiple predictors (Li *et al*., 2011). At the same time, Faisal *et al*. proposed several neural networks trained using meteorological data to create a system to predict sun radiation. However, Gated Recurrent Unit (GRU) performed the best (Faisal *et al*., 2022). Qui *et al*. recommended the generalized XGBoost model. Daily solar radiation (Rs) can be estimated by incorporating sunshine/temperature data (Qiu *et al*., 2022). Mustapha Mushtaq suggested two-hybrid neural networks in terms of prediction performance for Africa (Mukhtar *et al*., 2022). Iqbal *et al*. claim that the constructed SRPM model could accurately predict solar radiation at every point in the world if it were precisely trained with all necessary data from the sites. (Iqbal *et al*., 2022). Shboul *et al*. concluded that the suggested ANN model could reach high levels of accuracy in forecasting solar radiation and wind speed, demonstrating that the generated prediction model may be used to construct solar/wind renewable energy systems (Shboul *et al*., 2021).

Choi proposed inverse distance weighting (IDW) to predict the solar radiation of an arbitrary area to improve the uncertainty caused by the large distance between the meteorological stations (Choi *et al*., 2022). Duan *et al*. intended to establish a coupling algorithm based on a bat algorithm (BA) and Kernel-based non-linear extension of the Arps decline (KNEA) for accurate forecasting of solar radiations (Duan *et al*., 2022). Zahraa E. Mohamed used ANN-based models to assess and forecast global solar radiation for three Egyptian cities using different inputs. He found that created ANN model can be the most accurate substitute for the conventional estimating approaches (Mohamed, 2019).

## 2. Materials and methods

### 2.1. Artificial neural network

Artificial neural networks (ANN) are data-processing systems; it has been developed to solve multiple problems in various fields of engineering, Natural Sciences, and Social sciences. ANN is a better option where the conventional modeling fails to generate the actual footprints of the system. The ANNs architecture is established with one or multiple node layers, including input layers, one or more hidden layers, and an output layer. Each layer is connected to its neighboring layer by various neurons. A neural network has at least one hidden layer where all the calculations at the back end are performed. Several nodes, known as neurons, characterize each layer. Each neuron is associated with particular weights, biases, and activation functions. In ANNs, the input data is divided into three sets; one set is used to train the model, the second is used for testing, and the third and final set is used to validate the model. In this research, the Levenberg-Marquardt algorithm was used to flow information through neurons in the forward direction. Once an ANN is tuned, it may be used to classify and predict input values (Malekian and Chitsaz, 2021). Two different architectures have been proposed for solar radiation prediction, shown in Figures 1 and 2.

The input layer may have one or several variables, and each is connected to the neurons in the hidden layer through some weights and a bias. These weights are known as the gradient or coefficient of the variable. The neuron receives data using the following equation

$$x_{hidden} = \sum_{i=1}^{n} w_i x_i + b_{input} \tag{1}$$

Here $x_i$ are the n, variables and $w_i$ are the n weight and $b_{input}$ is the input bias. A non-linear transformation through an activation function is applied to the eq. (1) for final information at neurons. One of the activation functions is a sigmoidal function; we used this function in the proposed ANN model.

$$f(x_{hidden}) = \frac{1}{1+e^{-x_{hidden}}} \tag{2}$$

The hidden layer is connected to the output layer and the neuron transfer information to the output layer. The output data is compared with the known data, and the error is calculated; if the error does not meet the convergence criterion, the process is repeated using backpropagation. In backpropagation, new weights are calculated till one gets optimal weights, which minimize the difference between ANN output and actual values.

Two different ANN models are used to calculate solar radiation; each model has one layer with ten neurons. The input and output have one variable in the first model (see Figure 1). In this model, Karachi's solar radiation data was used to find the solar radiation of three cities, Lahore, Multan, and Quetta. In the second model, three city data (Karachi, Lahore, and Quetta) were taken as input. These three cities are considered vertices of a triangular region formed by these cities. The second method finds the solar radiation of a city lying in this region. The Multan city lies in the triangular region formed by Karachi, Lahore, and Quetta; these three cities' solar radiation determines their solar radiation. All three types of solar radiation, Diffused, Direct Beam, and Global solar radiation, are found. The Latitudes and Longitudes of the cities are given in table 1.

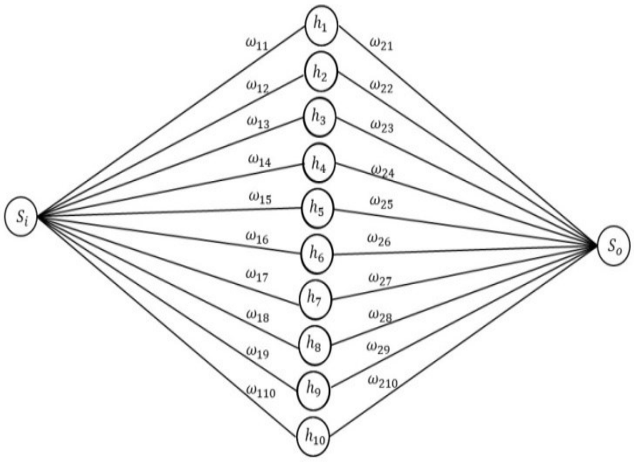



**Figure 1.** ANN model for solar radiaion output (So) determination of a city using single input Si

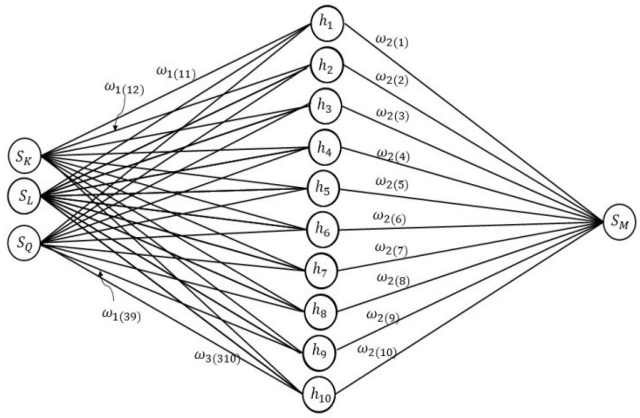



**Figure 2.** ANN model for solar energy determination of a city using three inputs. $S_K$, $S_L$, and $S_Q$ are input values of solar radiations for Karachi, Lahore, and Quetta, and $S_M$ is output solar radiation for the Multan

**Table 1.** The Latitude and Longitudes of the Lahore, Multan, Quetta, and Karachi

| City | Latitude | Longitude |
|---|---|---|
| Lahore | 31.5204° | 74.3587° |
| Multan | 30.1575° | 71.5249° |
| Quetta | 30.1798° | 66.9750° |
| Karachi, | 24.8607° | 67.0011° |

**Table 2.** Weights for single input ANN model for solar radiation determination

| Model I: Single input modle | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Weights for solar radiation calculation for Quetta | | | | | | Weights for solar radiation calculation for Multan | | | | | | Weights for solar radiation calculation for Lahore | | | | | |
| Diffused | | Direct Beam | | Gloabal | | Diffused | | Direct Beam | | Gloabal | | Diffused | | Direct Beam | | Gloabal | |
| w1 | w2 | w1 | w2 | w1 | w2 | w1 | w2 | w1 | w2 | w1 | w2 | w1 | w2 | w1 | w2 | w1 | w2 |
| -3.9482 | -2.4515 | -2.9988 | -3.1286 | -4.2989 | -3.1577 | -7.2629 | -4.6441 | -3.9671 | -3.7450 | -2.6627 | -1.8401 | -0.3314 | 0.3468 | -2.1756 | -1.9892 | -6.0965 | -4.3925 |
| -0.2830 | 0.1894 | -0.9111 | -1.0044 | 3.1595 | 2.2630 | 3.7727 | 3.3341 | -2.8048 | -2.5745 | -3.6184 | -2.4862 | -3.2495 | -1.7546 | -1.3588 | -1.1969 | -3.6100 | -2.4738 |
| -0.7315 | -0.1374 | 2.8706 | 2.8302 | -0.8567 | -0.7074 | -4.0224 | -2.2223 | -1.7945 | -1.5814 | 3.4806 | 2.6396 | -9.5685 | -6.4801 | 2.3868 | 2.5394 | 3.6624 | 2.8498 |
| -6.8247 | -4.5452 | 1.2037 | 1.1842 | 3.2160 | 2.2910 | -1.4504 | -0.4192 | 5.5235 | 5.8543 | -4.7633 | -3.3717 | -1.8014 | -0.6942 | 3.4324 | 3.6170 | 0.7769 | 0.7315 |
| -1.6865 | -0.8533 | -4.0437 | -4.1632 | -3.9978 | -2.9287 | -5.5454 | -3.3559 | -1.0362 | -0.8283 | 1.8688 | 1.4358 | -0.5491 | 0.1939 | -1.3501 | -1.2394 | -0.6292 | -0.2898 |
| 2.6191 | 2.2487 | -3.6374 | -3.7665 | 1.1946 | 0.8503 | -3.1627 | -1.6278 | -0.0192 | 0.2524 | -4.0296 | -2.8057 | -5.9078 | -3.6725 | -3.7807 | -3.6636 | -4.5451 | -3.1236 |
| -2.6624 | -1.4977 | 0.5313 | 0.4700 | -0.1676 | -0.0939 | -1.6659 | -0.5304 | -1.2392 | -1.0324 | -0.2610 | -0.0780 | 3.7507 | 3.2554 | -5.5768 | -5.5343 | 2.9020 | 2.2813 |
| 2.3558 | 2.0717 | 2.0060 | 1.9496 | -2.9223 | -2.1205 | -5.3159 | -3.2031 | -1.4669 | -1.1892 | -0.0896 | 0.0930 | 1.7746 | 1.8680 | 1.2878 | 1.4002 | -2.7814 | -1.7973 |
| -7.4603 | -5.0383 | 1.2000 | 1.1030 | -0.9693 | -0.7891 | 0.3370 | 0.8816 | -0.5589 | -0.3403 | 1.8366 | 1.3830 | -4.7529 | -2.8365 | -1.6562 | -1.5093 | -1.1387 | -0.5992 |
| 1.7521 | 1.6118 | -3.1604 | -3.2141 | -4.1168 | -3.0679 | 3.3971 | 3.0471 | -2.9937 | -2.7924 | -3.8341 | -2.7001 | 0.1528 | 0.7092 | -0.8822 | -0.7833 | -2.3524 | -1.4657 |

**Table 3.** Weights for three input ANN model for solar radiation determination

| Model II: Single input model | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Weights for solar radiation calculation for Multan | | | | | | | | | | | |
| Diffused | | | | Direct Beam | | | | Global | | | |
| **w11** | **w12** | **w13** | **w2** | **w11** | **w12** | **w13** | **w2** | **w11** | **w12** | **w13** | **w2** |
| -0.4807 | -1.1680 | -1.3903 | -1.9022 | -2.9879 | -2.4536 | -2.2238 | -4.0165 | -0.0962 | -0.3094 | -0.7094 | -1.1856 |
| -0.0219 | -0.7093 | -0.8878 | -1.1025 | 1.5965 | 1.3067 | 0.5805 | 1.5189 | -1.2527 | -2.5387 | -1.9534 | -4.1841 |
| -0.1509 | 0.4590 | 0.0032 | 0.1617 | -1.7260 | -0.9262 | -0.5634 | -2.2873 | 0.1013 | -0.6355 | -1.0205 | -1.5866 |
| 1.8683 | 2.6863 | 2.3435 | 4.0204 | 1.4826 | 0.6802 | 0.4850 | 1.1494 | 0.9910 | 1.1220 | 0.9285 | 1.1105 |
| -0.2330 | -1.0364 | -1.0467 | -1.5156 | 0.4147 | 0.1017 | 0.5713 | 0.0864 | -0.9163 | -1.4249 | -0.3368 | -2.1122 |
| -1.7649 | -2.2462 | -2.3242 | -3.8303 | -0.0641 | 0.0783 | 0.5003 | -0.1632 | 0.8632 | 0.7490 | 1.1755 | 1.0668 |
| -0.4301 | -0.9026 | -0.5094 | -1.1185 | 0.0834 | 0.3477 | 0.3340 | -0.0176 | 1.1619 | 0.8424 | 1.1146 | 1.2305 |
| -1.1082 | -2.2331 | -1.1352 | -2.8456 | -0.0406 | 0.5597 | -0.0374 | -0.2031 | -0.3322 | -0.7744 | 0.0537 | -1.1601 |
| -0.2616 | 0.3395 | 0.5011 | 0.2631 | 0.0057 | 0.1212 | 0.2735 | -0.3805 | 0.9332 | 1.0573 | 1.1028 | |
| -0.2388 | 0.3289 | 0.0441 | 0.0422 | -2.1958 | -1.1078 | -2.1026 | -3.2155 | 0.0640 | -0.4595 | -0.2837 | -1.0889 |

**Table 4.** Percentage Error in the calculation of solar radiation

| City | Diffuse Solar Radiation | Direct Solar Radiation | Global Solar Radiation |
|---|---|---|---|
| Lahore | 0.04 | 0.125 | 0.025 |
| Multan | 0.01 | 0.1 | 0.0125 |
| Quetta | 0.02 | 0.125 | 0.015 |
| Karachi, Lahore, Quetta | 0.015 | 0.15 | 0.01 |

| Coefficient of determination | 0.99 | 0.99 | 0.99 |
|---|---|---|---|

### 3. Results and conclusion

This research article is dealt with the structure and applicability of the ANN model to determine three types of solar radiation with two different architectures. The first architecture of the ANN model is built on the model of determination of solar energy radiation of three cities with the known of Karachi (see Figure 1). Hidden layers consist of ten neurons which help to evaluate solar radiations of Lahore, Multan, and Quetta. 60% data is used to train the ANN model; the remaining 40% is used to test the model. The three types of solar radiation, namely, direct beam radiation (BSR), diffused solar radiation (DSR), and global solar radiation (GSR) are determined for Multan, Lahore, and Quetta. ANN captures the effect of all three radiations. Random fifty percent data was selected to validate the model.

Another ANN architecture is built to estimate the solar radiation of a location through three different locations with known solar radiation. The city (Multan) whose solar radiations were to determine was lying in the triangular region, bounded by three cities: Karachi, Lahore, and Quetta (see Figure 2). In this model, we also used a hidden layer with ten neurons. The scheme to train, test, and validate the model was the same as in the first architecture.

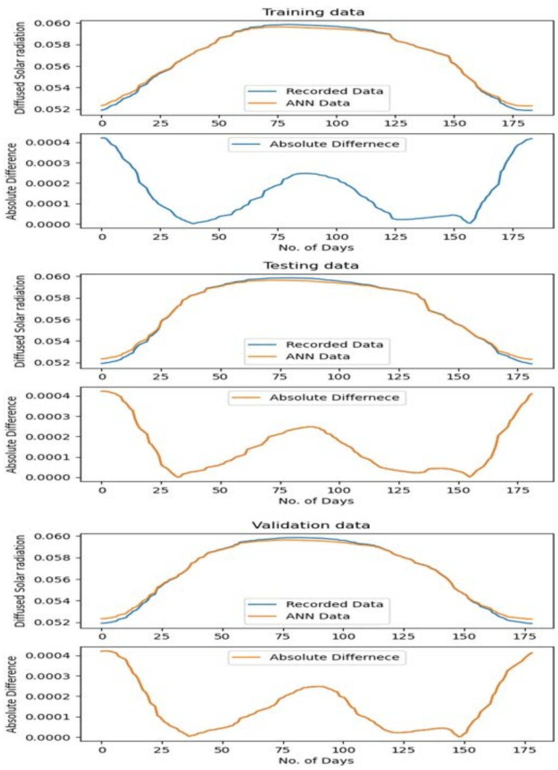



**Figure 3.** ANN modeling of Diffused solar radiation for Lahore

Figures 3–11 belong to ANN modeling of single input and a single output; one hidden layer has ten neurons. Each figure consists of three parts data training, testing, and validation. Each part has two subplots; one shows the recorded solar radiation and solar radiation determined by ANN modeling, and the second shows the absolute difference between them. Figures 3-5 show diffuse solar radiation for Lahore, Multan, and Quetta, respectively, determined by diffused solar radiation of Karachi. Figures 6-8 show direct beam solar radiation for Lahore, Multan, and Quetta. Figures 9–11 show global solar radiation for Lahore, Multan, and Quetta.

Figures 12–14 belongs to ANN modeling of three inputs and a single output, with one hidden layer, similar to the single-input case. These figures also consist of three parts corresponding to data training, testing, and validations parts. Each part has two subplots, like in Figures 3–11. Figures 12–14 show diffuse, direct beam, and global solar radiation for Multan, determined by three solar radiation inputs from Karachi, Lahore, and Quetta.

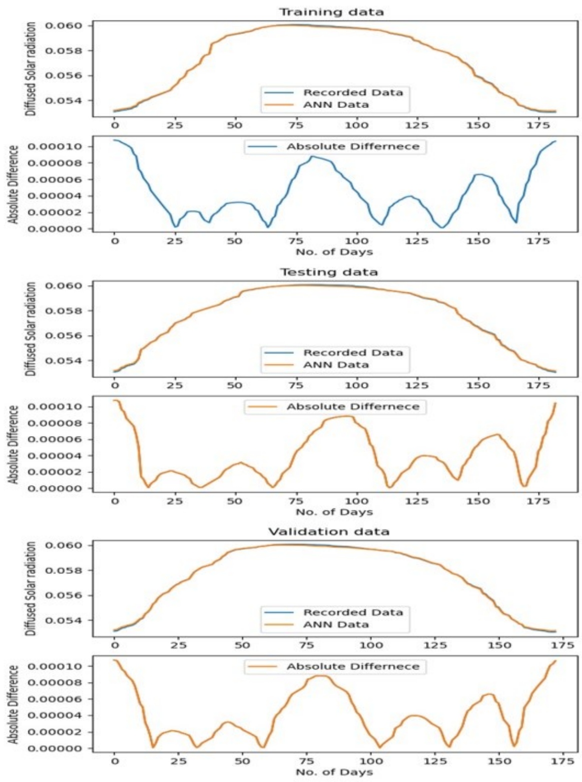



**Figure 4.** ANN modeling of Diffused solar radiation for Multan

Table 2 gives the weights for model I, the single input ANN model. There are three main columns for three cities, Lahore, Multan, and Quetta, with estimated solar radiation. Each city column is further divided into weights of three types of radiation; diffused, direct beam, and global solar radiation. Table 3 gives the weights for three input ANN models for the second model. The table structure is similar to table 2. Table 4 gives the percentage errors in the calculation through ANN. Small errors mean the ANN model determines the best values of all three types of radiation DSR, BSR, and GSR. The errors in the direct solar radiation estimation are higher than those in the other two; still, the error is negligible. The value of the coefficient of determination is 0.99 is each fitting.

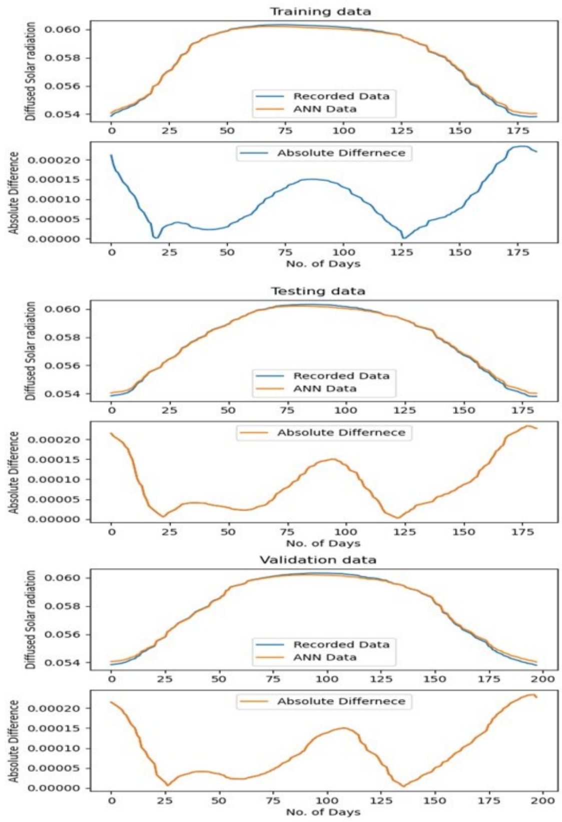



**Figure 5.** ANN modeling of Diffused solar radiation for Quetta

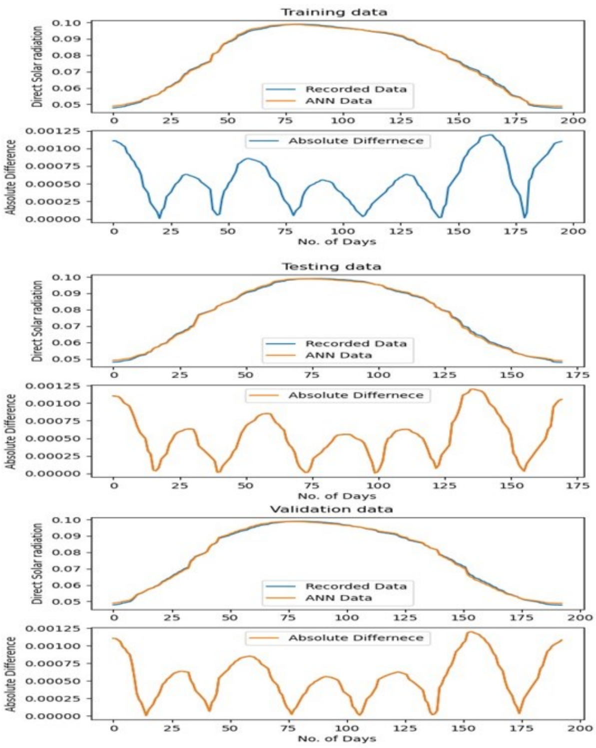



**Figure 6.** ANN modeling of Direct beam solar radiation for Lahore

## 4. Conclusion

We have used two different ANN architectures to estimate solar radiation for a particular city. In the first architecture (Figure 1), Karachi's solar radiation was used to find another city's solar radiation. Solar radiation of

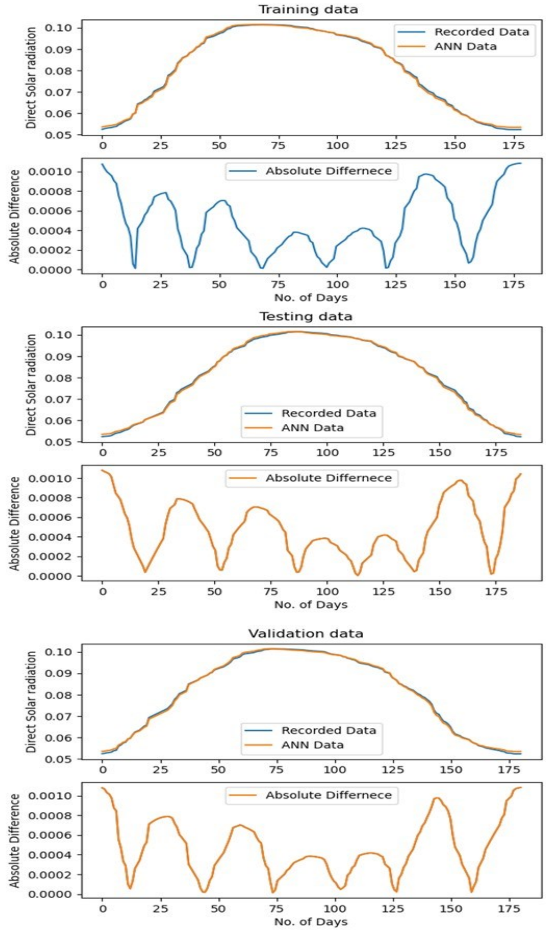



**Figure 7.** ANN modeling of Direct beam solar radiation for Multan

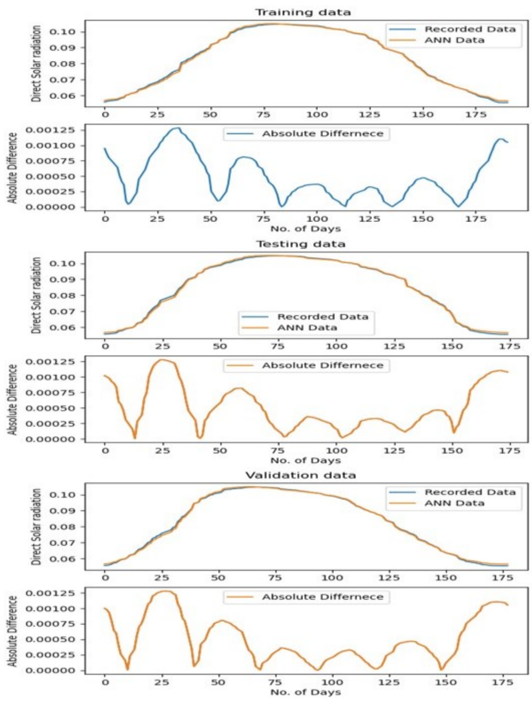



**Figure 8.** ANN modeling of Direct beam solar radiation for Quetta

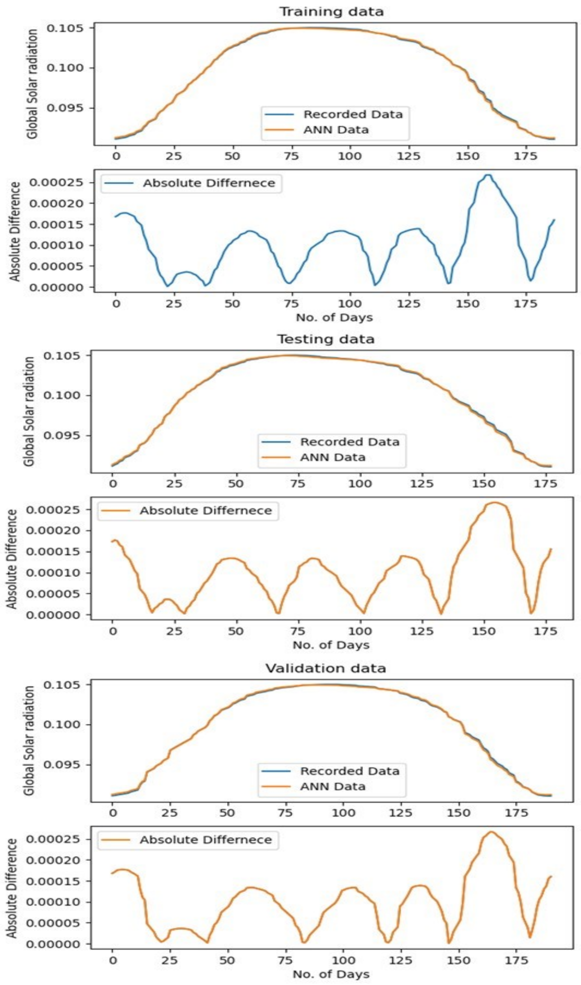



**Figure 9.** ANN modeling of Global solar radiation for Lahore

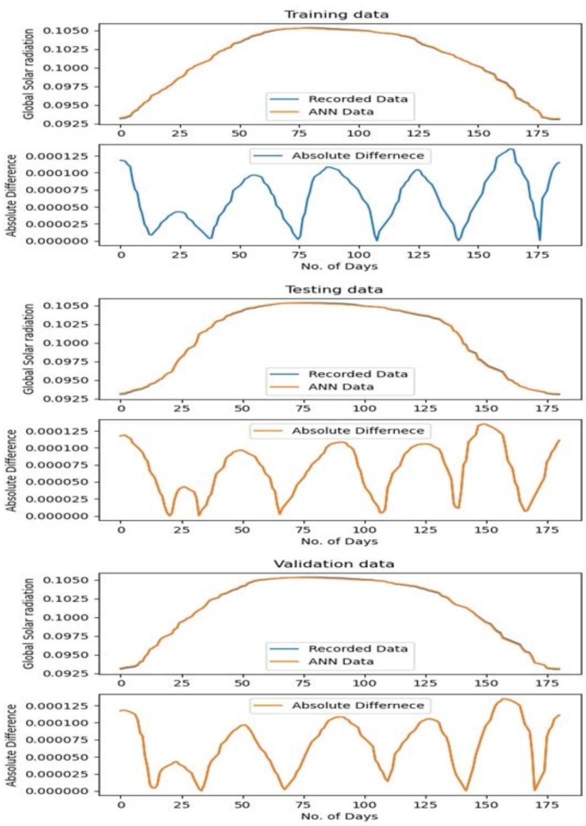



**Figure 10.** ANN modeling of Global solar radiation for Multan

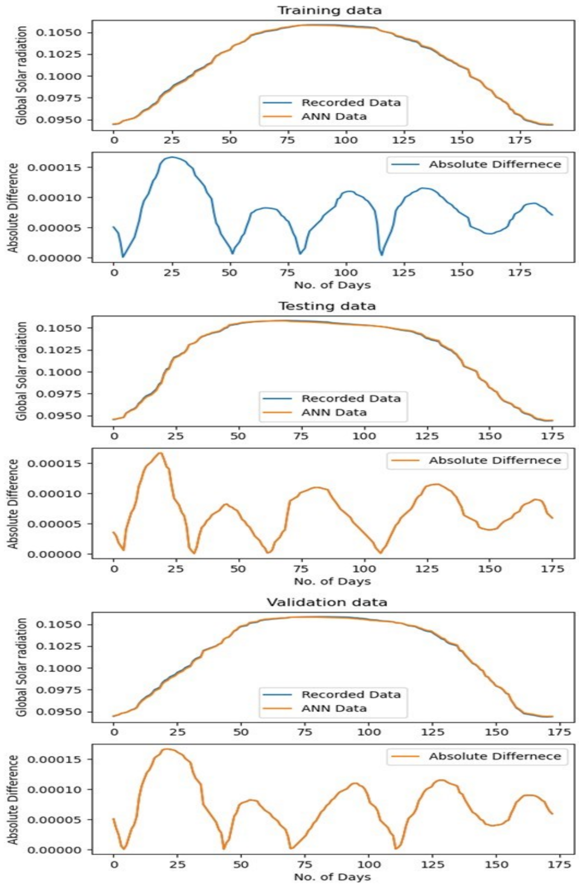



**Figure 11.** ANN modeling of Direct beam solar radiation for Quetta

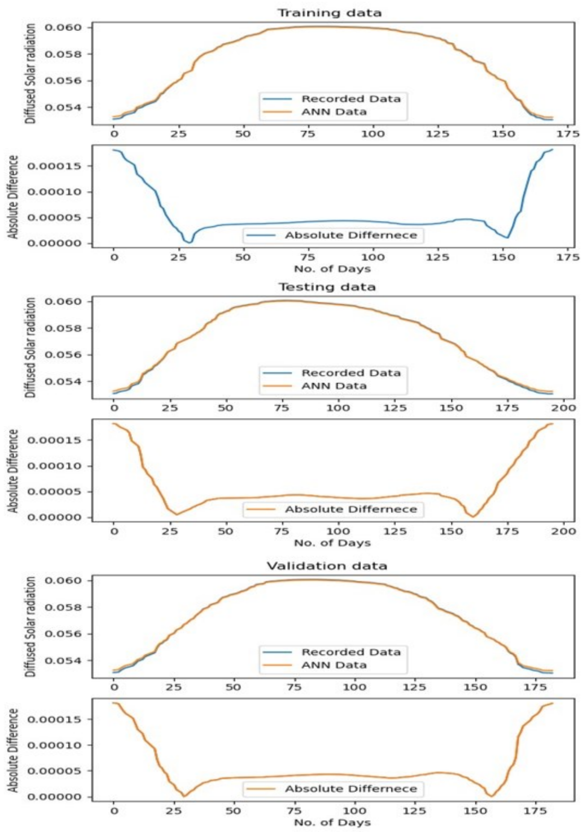



**Figure 12.** ANN modeling of Diffused solar radiation for Multan, using three inputs of solar radiation of Karachi, Lahore, and Quetta

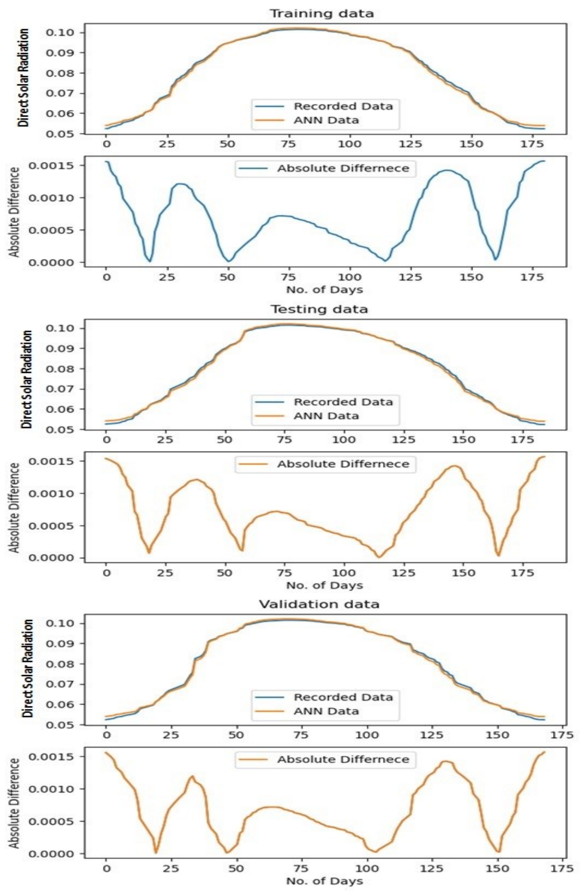



**Figure 13.** ANN modeling of Direct beam solar radiation for Multan, using three inputs of solar radiation of Karachi, Lahore, and Quetta

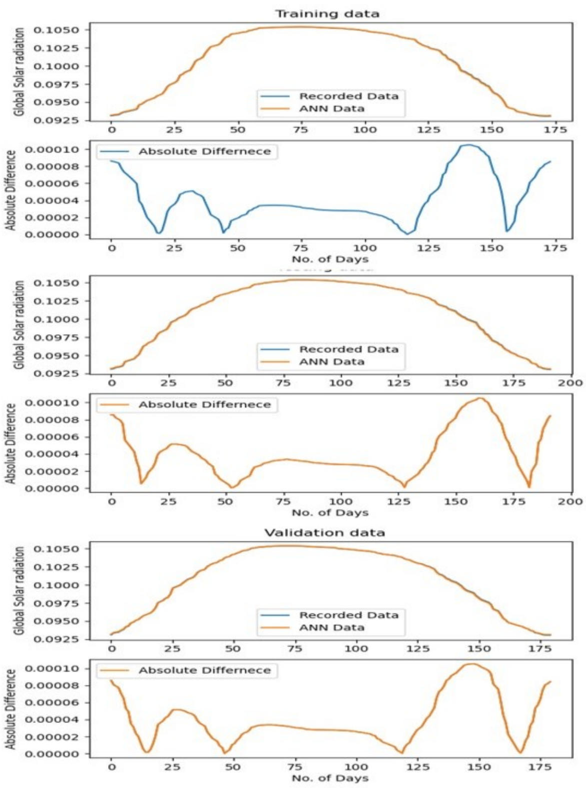



**Figure 14.** ANN modeling of Global solar radiation for Multan, using three inputs of solar radiation of Karachi, Lahore, and Quetta

three different cities (Multan, Quetta, and Lahore) is estimated in this model. In each case, all three types of radiations, DSR, BSR, and GSR, have been estimated (Figures 3-11). In the second architecture of the ANN method (Figure 2), we used a technique to find the solar radiation of a city in a triangular region formed by three cities lying at the vertices of the triangle. Here Multan lies in a triangular region formed by three cities Karachi, Lahore, and Quetta. In the second ANN model, there were three input variables compared to the first one, where only one input variable was used (Figures 12-14).

In each architecture, 60 percent of the data was used to train the network, and 40 percent was used for testing. Random 50 percent data was used to validate the network. The weights of models 1 and 2 are given in tables 2 and 3. Table 4 shows the percentage error in calculating three radiations using Model 1 and Model 2. The percentage error in each case is less than 0.2 percent for training, testing, and validation. Also, the coefficient of determination is 0.99 for both architectures. It shows the estimated data agree well with the known solar radiation. Therefore, both techniques may be used to estimate the solar radiation flux of any region (for solar energy conversion) where no direct measurements are carried.

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