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Performance Evaluation of Artificial Neural Networks in Estimating Global Solar Radiation, Case Study: New Borg El-Arab City, Egypt

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Abstract

The most sustainable source of energy with unlimited reserves is the solar energy, which is the main source of all types of energy on earth. Accurate knowledge of solar radiation is considered to be the first step in solar energy availability assessment, and it is the primary input for various solar energy applications. The unavailability of the solar radiation measurements for several sites around the world leads to proposing different models for predicting the global solar radiation. Artificial neural network technique is considered to be an effective tool for modelling nonlinear systems and requires fewer input parameters. This work aims to investigate the performance of artificial neural network-based models in estimating global solar radiation. To achieve this goal, measured dataset of global solar radiation for the case study location (lat. 30° 51 N and long. 29° 34 E) are utilized for modelestablishment and validation. Mostly, common statistical indicators are employed for evaluating the performance of these models and recognizing the best model. The obtained results show that the artificial neural network models demonstrate promising performance in the prediction of global solar radiation. In addition, the proposed models provide superior consistency between the measured and estimated values.

Keywords

Artificial Neural Networks (ANN); Solar energy; Solar radiation models; Statistical indicators; Temperature-based models; Egypt

1. Introduction

Affordable and clean energy is the 7^{th} goal in the Sustainable Development Goals (SDGs), which not only satisfies the sustainability but also saves the climate and environment. The most sustainable source of energy with unlimited and infinity reserves is the solar energy, which is the main source of all types of energy on earth. Accurate knowledge of solar radiation is considered to be the primary step in solar energy availability assessment and serves as the first input for various applications of solar energy (Janjai, Pankaew & Laksanaboonsong, 2009; Wong & Chow, 2001; Hassan, Ali & Youssef, 2017). The unavailability of the solar radiation measurements for several sites around the world, because of the high cost and equipment calibration and maintenance requirements (El-Sebaii, Al-Hazmi, Al-Ghamdi & Yaghmour, 2010; Hassan, Youssef, Ali, Mohamed & Hanafy, 2017), leads to proposing different models for predicting the global solar radiation. Angström (1924) introduced the primary sunshine-based model, which was modified by Prescott (1940) and has become the most widely used model around the world for evaluating solar radiation (Besharat, Dehghan, Faghih & 2013; Almorox, Benito & Hontoria, 2005). The study of investigating the performance of 31 non-sunshine-based models for predicting the monthly average of daily global solar radiation on a horizontal surface was carried out by (Youssef, Hassan, Youssif & Ali, 2016). The models that have the most accurate estimations are recognized, and the best model among all models is also identified. Similarly, (Hassan, Youssef, Mohamed, Ali & Hanafy, 2016) presented a new temperature-based model for estimating global solar radiation. The results showed that the new suggested models have accurate and excellent predictions for global solar radiation at different locations, especially at coastal sites. Furthermore, the new presented formulas of the best temperature-based model also provide better results compared with those for the most accurate sunshine-based models from the literature. In addition, the issue of assessing the performance of different day-of-the-year-based models to estimate global solar radiation - Case study: Egypt was carried out by (Hassan et al., 2016). The obtained results illustrated that the hybrid sine and cosine wave model and the 4^{th} order polynomial degree model have the best estimations for global solar radiation on a horizontal surface. Jiang (2009) proposes study of computation of the monthly average daily global solar radiation using artificial neural networks and comparison with other empirical models in China. The developed ANN model used feed-forward back propagation algorithm in the analysis. Şenkal & Kuleli (2009) evaluated solar radiation in Turkey using artificial neural networks and satellite data. The ANN model used Scale Conjugate Gradient (SCG) and Resilient Propagation (RP) learning algorithms and logistic sigmoid transfer function.

This study aims to investigate the performance of artificial neural network models for estimating the monthly average daily global solar radiation on a horizontal surface, (G), at study location as a case study. For achieving this purpose, the measured global solar radiation data at New Borg El-Arab, Egypt (Lat. 30° 51 N and long. 29° 34 E) are utilized for establishing and validating the proposed models. Moreover, the most commonly statistical indicators, such as Root Mean Square Error (RMSE) and coefficient of determination (R^2), are calculated to evaluate the performance of these models (Besharat et al. 2013; Li, Ma, Lian & Wang, 2010).

2. Material and Methods

2.1. Data Collection

The measured dataset of ambient temperature and global solar radiation between 1^{st} of July 1983 and 30^{th} of June 2005 are used for establishing and validating the applicability of models to predict the monthly average daily global solar radiation on a horizontal surface. These data are retrieved from the NASA Surface meteorology and Solar Energy website (Youssef et al., 2016; Hassan et al., 2016), ("NASA Surface meteorology and Solar Energy", n.d.).

2.2. Artificial Neural Network (ANN)

ANN is a type of artificial intelligence (AI) technique, which is a non-linear mapping computational algorithm based on a black-box modelling technique. It is designed to deal with training data set in order to learn, store and recall the data to perform a multidimensional transformation between the input and output spaces without understanding the dynamic relation between them. ANN is efficient and less time-consuming in modelling different complex engineering problems, such as control systems, classification, speech, vision and pattern recognition compared to other mathematical models, such as regression regression (Fadare, 2009; Kalogirou, 2001; Lin, Bhattacharyya & Kecman, 2003).

The ANN model consists of multiple connected processing elements called artificial neurons. Figure (1) shows the five basic components of the artificial neuron, which are input, weight and biases, summing junction, transfer (activation) function, and output. For each artificial neuron, every input is multiplied with individual weight. In the middle part of the model, the sum function is applied to all weighted inputs and bias. At the exit of artificial neuron, the sum of previously weighted inputs is passing through the transfer function. A simple ANN with multiple connected artificial neurons distributed in three multiple layers called input, hidden, and output layer is shown in Fig. (1).

The network weights are updated and adjusted during the training process through different algorithms until the desired output is reproduced from a set of inputs. The training process is based on either supervised or unsupervised learning depending on whether the expected targets are involved in the training process or not. The ANN training topology can allow the feed-forward and back-propagation of the information flow in order to minimize the difference between the output and the desired target. Considerable computational resources are required to perform a sufficient training session. A non-linear relation between input and output variables is associated with the trained ANN in order to be used to predict the output for any new input data set, which is not a part of the training data. More detailed theories and applications can be found in Picton (2000).

2.3. Design of the Artificial Neural Network (ANN) Model

Proposed ANN models are trained under MATLAB neural network toolbox, and the weights' adjustment is performed by LM algorithm. For the output layer, a linear activation function "Purelin" is used. For the training of network, the algorithm "TRAINLM" is used. TANSIG transfer function is used in the hidden layer. The input layer and the output layer, with two (Extra-terrestrial solar radiation and temperature) and one (Global solar radiation) neurons are used in the layers, respectively. On the other side, the number of neurons in the single hidden layer varies from three neurons to five neurons in order to reach the best performance. In order to suit the consistency of the model, all source data are normalized in the range 0 to 1 and then returned to original values after the simulation (Rahimikhoob, 2010). .

3. Performance Evaluation

The performance of the models is evaluated using the most commonly statistical indicators, namely: Mean Percentage Error (MPE), Mean Bias Error (MBE), Root Mean Square Error (RMSE) and Coefficient of Determination (R^2) (Hassan et al., 2016). The value of MPE between $\pm 10\%$ is considered an acceptable value, and it is clarified by (Eq. 1). The values of mean bias error (MBE) (Eq. 2) give information about the long-term performance of the developed model, where the positive MBE value refers to overestimation in the calculated value, and the negative MBE value refers to under-estimation in the calculated value. The smaller MBE value refers to the better model performance, and the small value is desired. The values of RMSE (Eq. 3) give information about the short-term performance of the model and are always positive values. A smaller value refers to a better performance of the model, and zero represents the ideal case. The values of (R^2) (Eq. 4) illustrate information about the goodness of fit; R^2 values are between zero and one ($0 \leq R^2 \leq 1$), and the largest value is the desired value. The accepted range of RMSE, MPE, MBE is between $\pm 10\%$ MJ/m^2 day^{-1}[22]. The values of these statistical indicators are calculated using equations:

$$MPE = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{G_{i,c} - G_{i,m}}{G_{i,m}}\right)x100 \tag{1}$$

$$MBE = \frac{1}{n}\sum_{i=1}^{n}\left(G_{i,c} - G_{i,m}\right) \tag{2}$$

$$RMSE = \left[\frac{1}{n}\Sigma_{i=1}^{n}\left(G_{i,c} - G_{i,m}\right)^2\right]^{\frac{1}{2}} \tag{3}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (G_{i,m} - G_{i,c})^2}{\sum_{i=1}^{n} (G_{i,m} - G_m)^2} \tag{4}$$

where $G_{i,c}$ is the i h calculated value, and $G_{i,m}$ is the i the measured value is the average value of the measured and calculated values; and n is the number of observations.

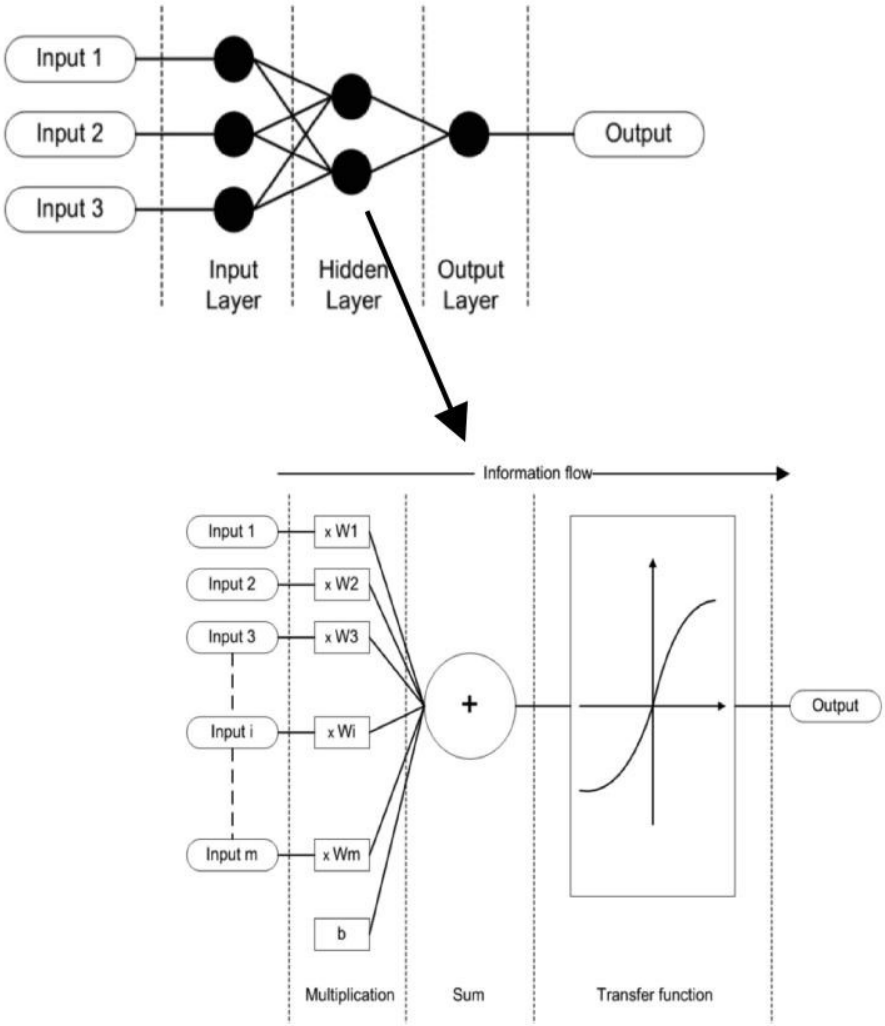

Figure 1. Simple Artificial Neural Network (ANN) with thebasic components of arificial neuron [23].

4. Results and Discussion

The measured data of daily global solar radiation and air temperature are divided into two data sets and averaged to acquire the monthly average daily values. The first data set from 1^{st} July 1983 to 31^{st} December 2002, is used to establish models. The second data set, from 1^{st} January 2003 to 30^{th} June 2005, is employed for evaluating and validating the developed models using statistical indicators. The predictions of three ANN models are compared with the measured data of global solar radiation. The values of statistical indicators for three ANN models (2-3-1, 2-4-1, 2-5-1) are computed using equations Eqs. (1-4). The obtained values of different statistical indicators (RMSE, MPE, MBE and R^2) are summarized in Table 1. The acceptable models are recognized, and the most accurate model is identified by comparing the statistical indicators associated with three models. The best ANN model is recognized in bold, as illustrated in Table 1.

Table 1. Statistical indicators for three developed models

Model	MPE	MBE	RMSE	R^2
ANN Model_HdN3	0.7150	-0.0963	0.6573	0.9916
ANN Model_HdN4	0.7754	-0.0575	0.7433	0.9892
ANN Model_HdN5	0.1765	-0.1850	0.6794	0.9910

According to the obtained results, the three ANN models have excellent estimations for the monthly average of daily global solar radiation, with good statistical indicators values in the acceptable range. The predictions of the three developed ANN models are compared with the measured data as illustrated in **Fig. 2(a)**. Similarly, **Fig. 2(b)** demonstrates the prediction of the best ANN model (Model 1; 2-3-1) compared with the measured data. The statistical indicators graphs for the estimated values of monthly average of daily global solar radiation using three ANN models at New Borg El-Arab are clarified in **Fig. 3**.

For MPE, all the models have values within the acceptable range and less than 1 %, with the lowest value of 0.18 for Model 3. All the three models give negative small values for MBE, which indicates a good long-term performance for the models with slight under-estimation in the calculated value. As shown in Fig. 2(a), all the three models accurately predict the global solar radiation for the period from January to April and from September to October. For November and December, the global solar radiation is slightly predicted. During the months from May to August, both Model 1 and Model 3 under predict the global solar radiation while Model 2 over predicts the global solar radiation during May.

These results are consistent with the values of MBE, which have small negative values with the lowest value of 0.0575 for Model 2, as shown in **Fig. 3**. For RMSE, all the three models give small values, which indicate good short-term performance for the models with the smallest RMSE value of 0.657 and the best short-term performance for Model 1.

The R^2 values for three models are higher than 0.989 %, which indicate good fitting. In addition, all ANN models show a slight variation in their performance with excellent R^2 values, higher than 0.989 %. On the other hand, Model 1, which has three neurons in the hidden layer, provides the best performance with the highest R^2 value (Ajayi, Ohijeagbon, Nwadialo & Olasope, 2014), followed by Model 3 that has five neurons in the hidden layer. For Model 1, the statistical indicators RMSE and R^2 are 0.66 MJ/m^2 and 0.9916%, respectively.

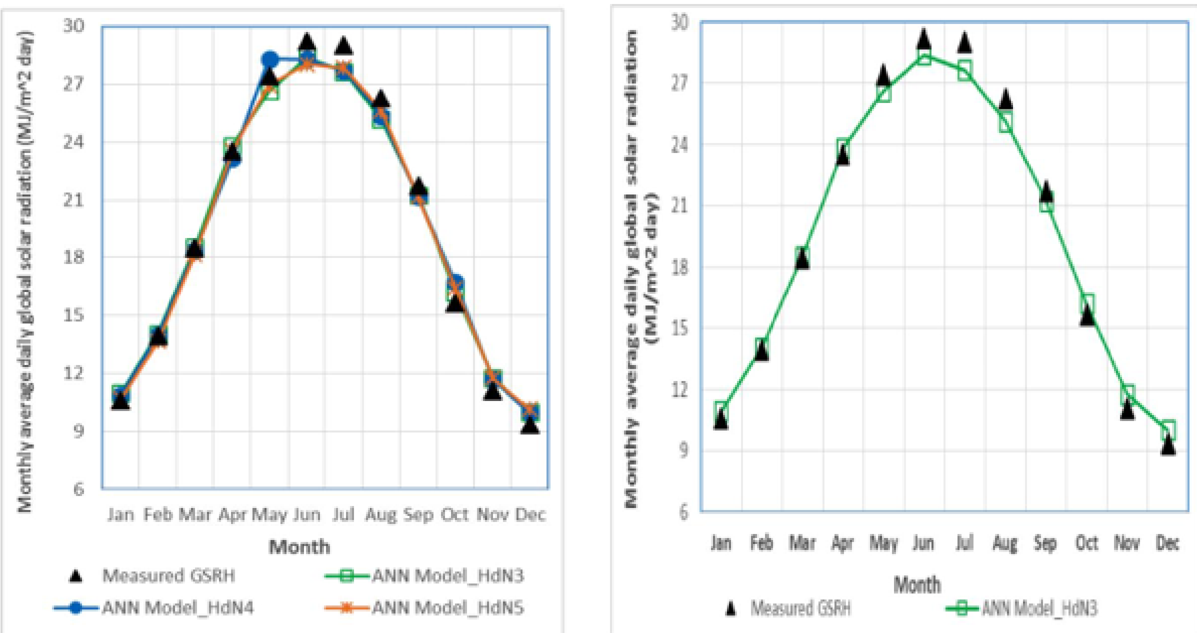

Figure 2. Performance of the ANN models compared with the measured data at New Borg-El-Arab, (a) all models, (b) best model (Model 1; 2-3-1)

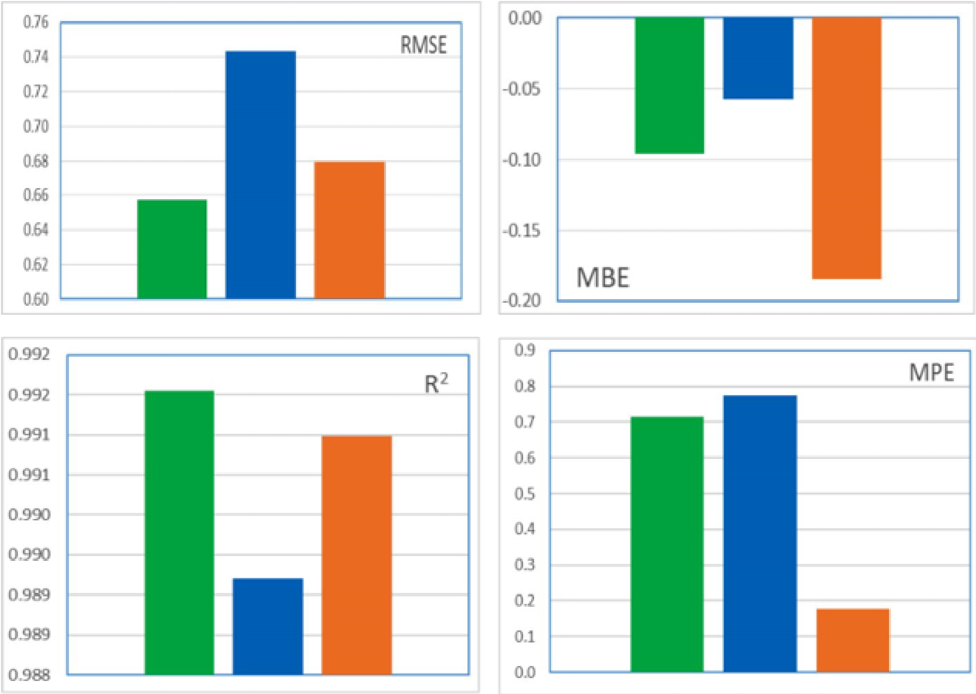

Figure 3. Statistical indicators (RMSE, R^2, MBE, MPE) graph forthree ANN models at New Borg El-Arab.

From the above discussion, it can be concluded that the developed models in this study can be employed for estimating global solar radiation with high accuracy. Consequently, the presented models are adequate for estimating monthly average daily global solar radiation on a horizontal surface. In addition, the proposed models indicate that the artificial neural network models demonstrate promising predictions of monthly mean daily global solar radiation by using commonly available data of extra-terrestrial solar radiation and temperature.

5. Conclusion

This work aims to investigate the performance of artificial neural network models for estimating the monthly average daily global solar radiation on a horizontal surface. To achieve this goal, the measured data of extra-terrestrial solar radiation, temperature and global solar radiation at study location are utilized for establishing and validating the proposed ANN models. According to the obtained results, the presented ANN models are applicable and significant for the quick and accurate prediction of the monthly average daily global solar radiation on a horizontal surface.

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