# Estimating Global Solar Energy Using Multilayer Perception Artificial Neural Network

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*Abstract*— This paper presents a global solar energy estimation method using artificial neural networks (ANNs). The clearness index is used to calculate global solar irradiations. The ANN model is based on the feed forward multilayer perception model with four inputs and one output. The inputs are latitude, longitude, day number and sunshine ratio; the output is the clearness index. Based on the results, the average MAPE, mean bias error and root mean square error for the predicted global solar irradiation are 5.92%, 1.46% and 7.96%.

***Keywords***— Solar energy, solar energy prediction, artificial neural network, Malaysia .

## I. Introduction

SOLAR energy is the portion of the sun's energy available at the earth's surface for useful applications, such as raising the temperature of water or exciting electrons in a photovoltaic cell, in addition to supplying energy to natural processes like photosynthesis. This energy is free, clean and abundant in most places throughout the year. Its effective harnessing and use are of importance to the world, especially at a time of high fossil fuel costs and the degradation of the atmosphere by the use of these fossil fuels. Solar radiation data provide information on how much of the sun's energy strikes a surface at a location on the earth during a particular time period. These data are needed for effective research into solar-energy utilization. Due to the cost of and difficulty in solar radiation measurements, these data are not readily available; therefore, alternative ways of generating these data are needed. A comprehensive solar radiation database is an integral part of an energy efficiency policy [1, 2]. In Malaysia, there are cities/regions that do not have measured solar radiation data; therefore, a predication tool should be developed to estimate the potential of solar energy based on location coordinates.

In recent years, ANNs have been used in solar radiation modeling work for locations with different latitudes and climates, such as Saudi Arabia, Oman, Spain, Turkey, China, Egypt, Cyprus, Greece, India, Algeria and the UK [3-34]. Little work regarding solar energy prediction has been done for Malaysia. The only significant prediction methods have been proposed in [35, 36] in 1982 and 1992. The authors in [35] have only proposed solar radiation data for three locations without any prediction algorithms, while the authors in [36] have proposed a prediction algorithm for monthly solar radiation based on the least square linear regression analysis using eight data locations. Consequently, an ANN model for solar energy prediction should be developed to provide a comprehensive database for the solar energy potential in Malaysia. Moreover, the proposed ANN model will be more accurate than the proposed methods in [35, 36], and it will provide hourly, daily and monthly solar radiation predictions for many different locations in Malaysia because the location coordinates are provided.

The main objective of this research is divided into two sub objectives: develop a feed forward ANN model to predict the clearness index ($K_T$) based on the number of sunshine hours, day number and location coordinates, and calculate the global ($E_T$) \ solar irradiation for Malaysia. This work has been based on long term data for solar irradiations (1984-2004) taken from the 28 sites in Malaysia. These data were provided by the Solar Energy Research Institute (SERI) of Universiti Kebangsaan Malaysia (UKM).

## II. Solar Energy Modeling

Solar radiation is classified in two main parts, the extraterrestrial solar irradiation ($E_{extra}$) and the global solar irradiation ($E_T$). The variable $E_{extra}$ stands for the total solar energy above the atmosphere while $E_T$ is the total solar energy under the atmosphere. The value for $E_{Extra}$ is given by

$$E_{extra} = \left\{ I_o\left[1+.034\cos\left(\frac{2\pi N}{365}\right)\right]\right\} * Day\ length \tag{1}$$

where $I_o$ is the solar constant, 1,367 $W/m^2$, and N is the number of the day. The day length is calculated by

$$Day\ length = \frac{2}{15}\ cos^{-1}(-\tan L \tan \delta) \tag{2}$$

where L is the latitude and $\delta$ is the angle of declination, given by

$$\delta = 23.45 \sin\left[\frac{360\ (284+N)}{365}\right] \tag{3}$$

The global solar irradiation ($E_T$) on a tilted surface consists of three parts

$$E_T = E_B + E_D + E_R \tag{4}$$

where $E_B, E_D\ and\ E_R$ are beam (direct), diffused and reflected solar irradiation, respectively. On a horizontal surface, $E_R$ is equal to zero; therefore, $E_T$ on a horizontal surface is given by

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$$E_T = E_B + E_D \tag{5}$$

The global ($E_T$) can be calculated using $E_{extra}$ as below,

$$\frac{E_T}{E_{extra}} = K_T \tag{6}$$

## III. Artificial Neural Network for Clearness Index Prediction

Artificial neural networks (ANNs) are information processing systems that are non-algorithmic, non-digital and intensely parallel [37]. They learn the relationship between the input and output variables by studying previously recorded data. An ANN resembles a biological neural system, composed of layers of parallel elemental units called neurons. The neurons are connected by a large number of weighted links, over which signals or information can pass. A neuron receives inputs over its incoming connections, combines the inputs, generally performs a non-linear operation and outputs the final results. MATLAB was used to train and develop the ANNs for clearness index prediction. The neural network adopted was a feed forward, multilayer perception (FFMLP) network, among the most commonly used neural networks that learn from examples. A schematic diagram of the basic architecture is shown in Figure 1. The network has three layers: the input, hidden and output layers. Each layer is interconnected by connection strengths, called weights.

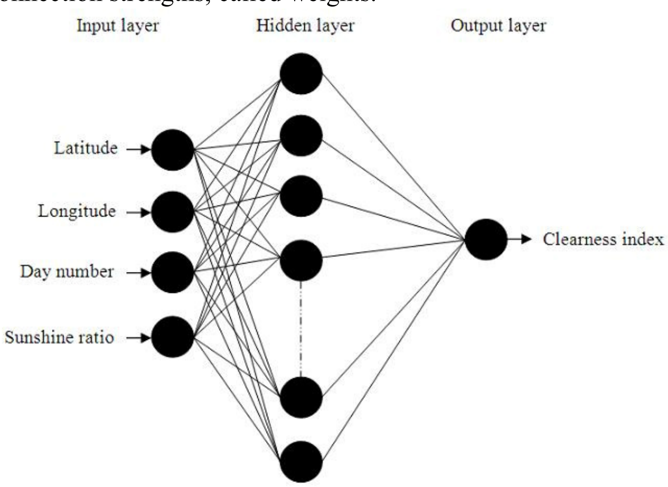


Figure 1 Topology of the FFMLP ANN used to predict the clearness index

Four geographical and climatic variables were used as input parameters for the input nodes of the input layer. These variables were the day number, latitude, longitude and daily sunshine hours ratio (i.e., measured sunshine duration over daily maximum possible sunshine duration). A single node was at the output layer with the estimated daily clearness index prediction as the output. The transfer function adopted for the neurons was a logistic sigmoid function $f(zi)$

$$f(zi) = \frac{1}{1+e^{-z_i}} \tag{7}$$

$$zi = \sum_{j=1}^{4} w_{ij} x_j + \beta_i \tag{8}$$

where $zi$ is the weighted sum of the inputs, $xj$ is the incoming signal from the jth neuron (at the input layer), $wij$ the weight on the connection directed from neuron $j$ to neuron $i$ (at the hidden layer) and $\beta_i$ the bias of neuron $i$. Neural networks learn to solve a problem rather than being programmed to do so. Learning is achieved through training. In other words, training is the procedure by which the networks learn, and learning is the end result. The most common methodology was used, supervised training. Measured daily clearness index data were given, and the network learned by comparing the measured data with the estimated output. The difference (i.e., an error) is propagated backward (using a back propagation training algorithm) from the output layer, via the hidden layer, to the input layer, and the weights on the interconnections between the neurons are updated as the error is back propagated. A multilayer network can mathematically approximate any continuous multivariate function to any degree of accuracy, provided that a sufficient number of hidden neurons are available. Thus, instead of learning and generalizing the basic structure of the data, the network may learn irrelevant details of individual cases.

In this research, 28 weather stations' data were used, 23 stations' data were used to train the network and 5 sites were used to test it.

## IV. Results and Discussion

To ensure the efficacy of the developed network, five main sites were chosen out of the 28 sited in Malaysia. The chosen sites are Kuala Lumpur, Ipoh, Alor Setar, Kuching and Johor Bharu. These sites span Malaysia and have been chosen to check the efficacy of the developed network over all of Malaysia.

Figure 2 shows the predicted clearness indexes compared with the measured values for the five chosen stations. The figure shows good agreement between the measurements and the predictions. The best fit appears in the Johor Bharu and Kuching stations, while the worst is in the Alor Setar station. The fittings are all acceptable due to the low calculated error, as will be discussed later.

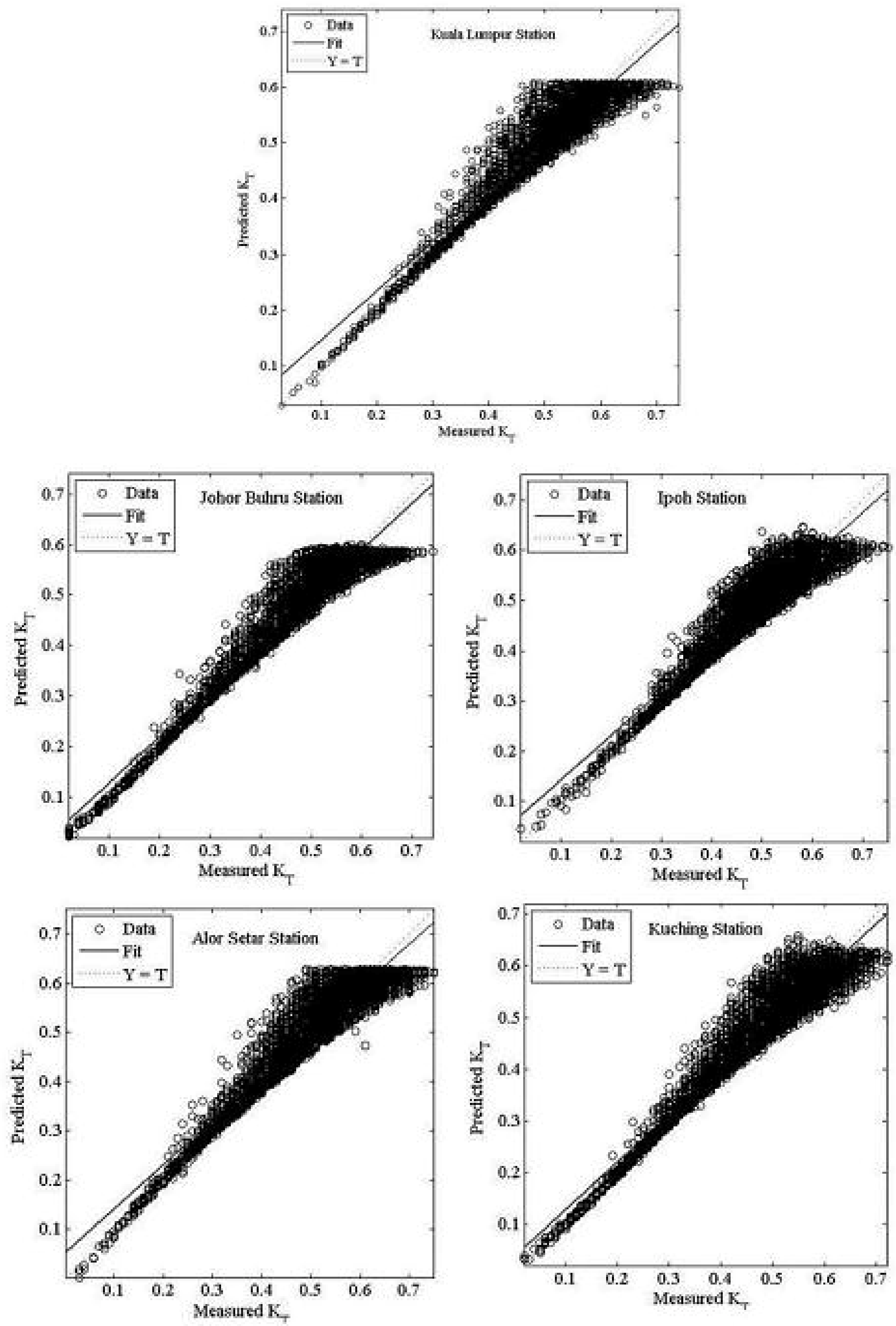


Figure 2 Comparison between measured and predicted clearness indexes

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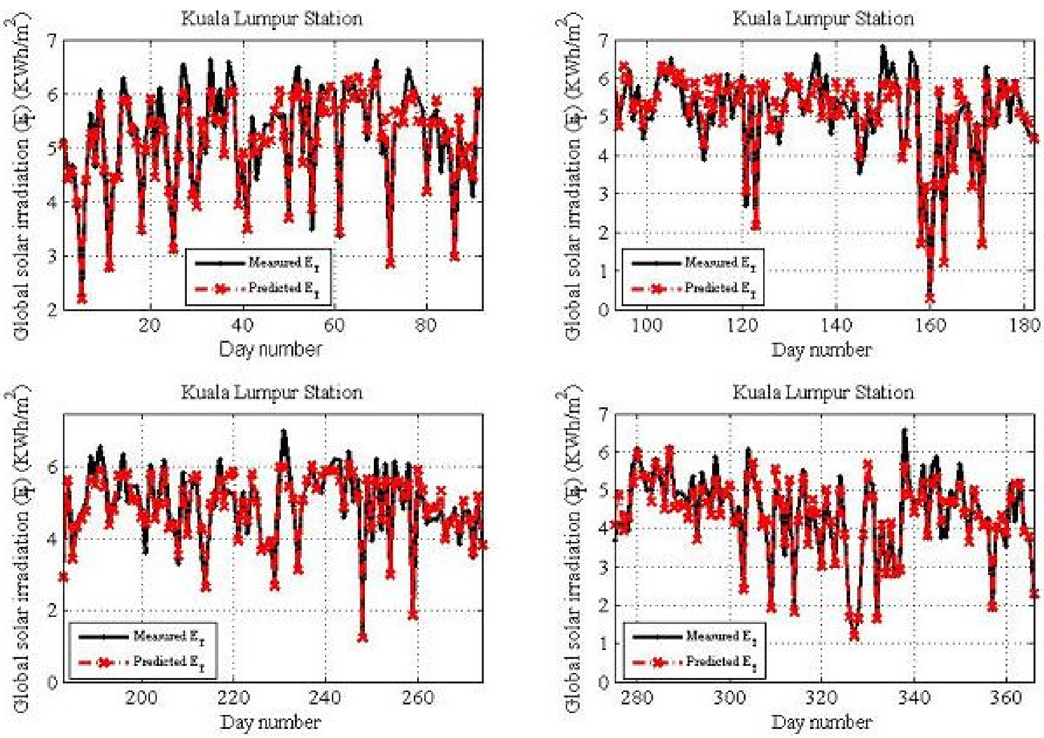
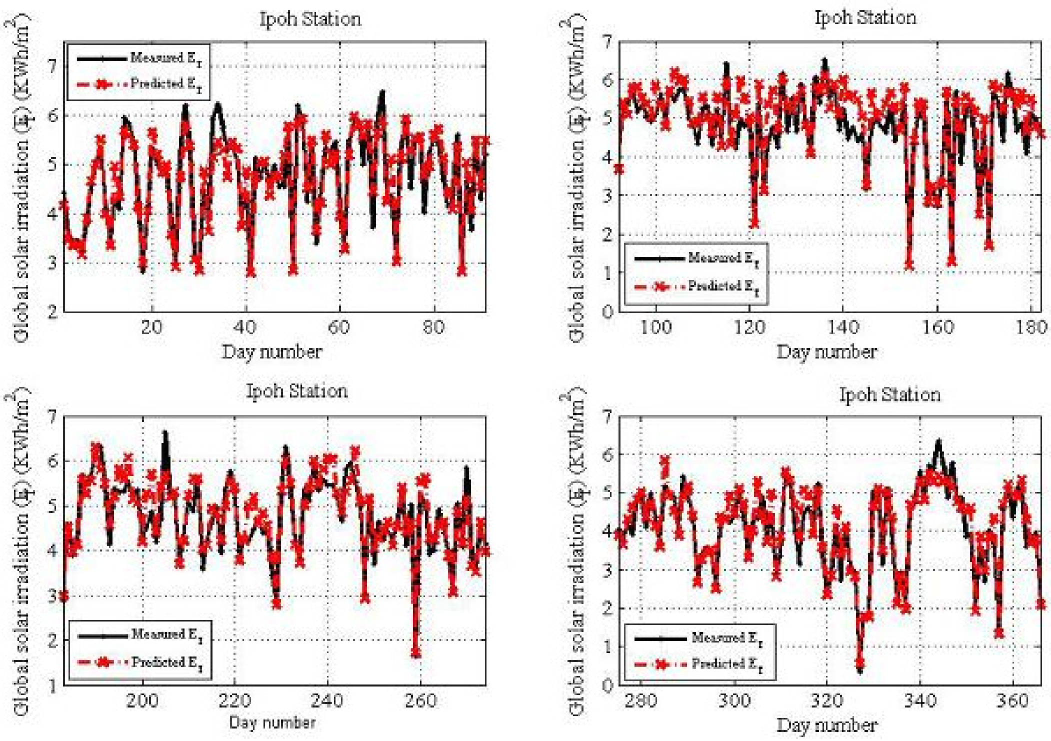
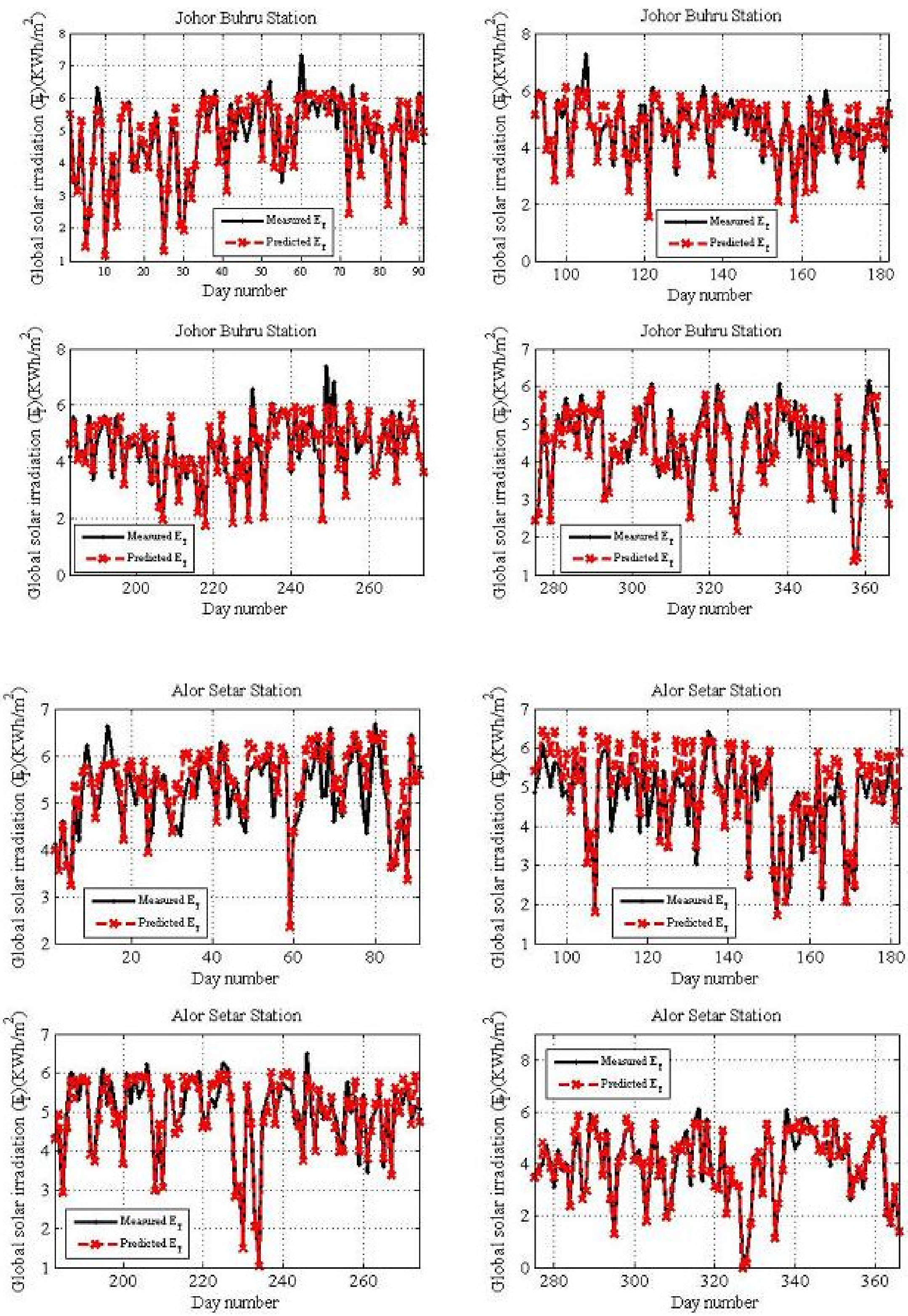
To evaluate the developed network, the measured values of the sunshine ratio for the year 2000 in each of the chosen sites have been used to predict the global solar radiation for this year. The predicted data were then compared with the measured data, which were also taken from the chosen sites for the same year. Figure 3 shows a comparison between the measured and predicted daily global solar radiation of the chosen sites.


Kuala Lumpur Station
Global solar irradiation (E_T) (KWh/m^2)
Day number
Measured E_T
Predicted E_T


Ipoh Station
Global solar irradiation (E_T) (KWh/m^2)
Day number
Measured E_T
Predicted E_T


Johor Buhru Station
Johor Buhru Station
Johor Buhru Station
Johor Buhru Station
Alor Setar Station
Alor Setar Station
Alor Setar Station
Alor Setar Station
Global solar irradiation ($E_T$)(KWh/m$^2$)
Day number
Measured $E_T$
Predicted $E_T$

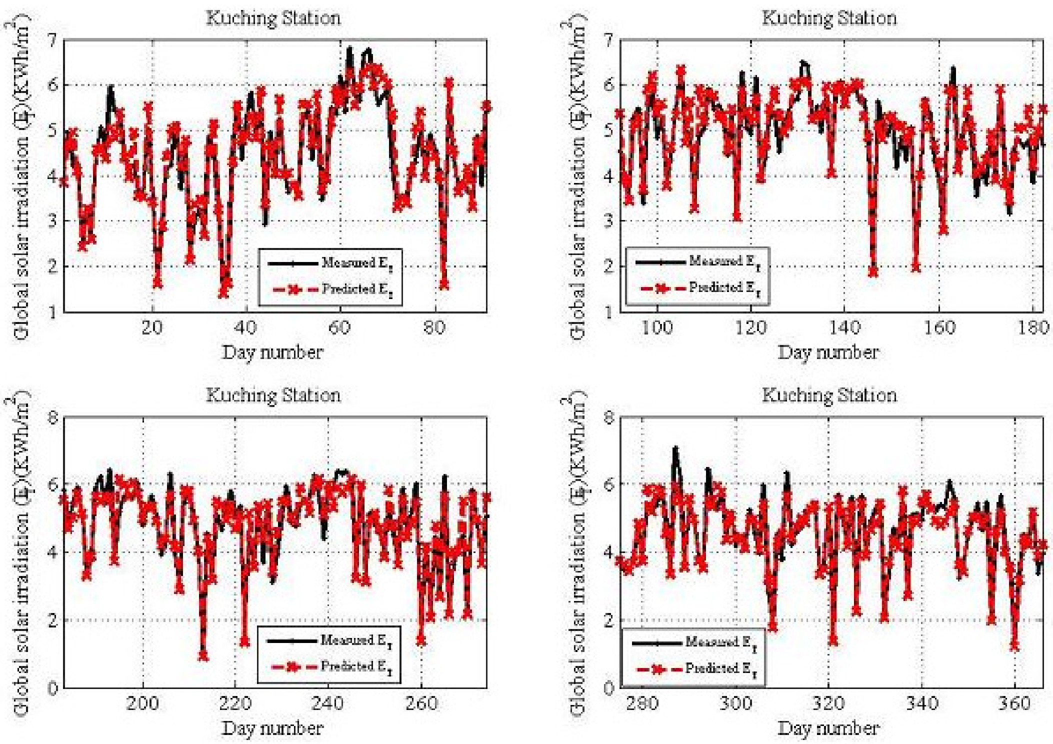



Figure 3 Comparison between the measured and predicted daily global radiation for the chosen five sites

In general, the prediction of the global radiation was acceptable and accurate. Based on the results, it is clear that Malaysia has a stable climate throughout the year. Cloud cover generally reduces the radiation by 50%, so the global irradiation fluctuated in the range of 2 to 6 $KWh/m^2$. The second part of the year (October to February) saw more cloud cover, and consequently, poorer solar potential compared with the first part of the year (March to October). Table 1 shows the yearly average global solar irradiation for the five sites. From the table, the best prediction is at the Kuala Lumpur station, while the worst is at Alor Setar. The Kuala Lumpur region has the highest solar potential.

Table 1 Annual global solar radiation averages for five different sites in Malaysia

| Site | Average $E_T$ per annum (Measured) ($KWh/m^2$) | Average $E_T$ per annum (Predicted ) ($KWh/m^2$) |
|---|---|---|
| **Kuala Lumpur** | 4.84 | 4.83 |
| **Johor Bharu** | 4.51 | 4.55 |
| **Ipoh** | 4.54 | 4.64 |
| **Alor Setar** | 4.66 | 4.8 |
| **Kuching** | 4.62 | 4.66 |

To get an idea of the monthly solar irradiation profile in Malaysia, the chosen five sites' weather data were used again to predict the daily global solar irradiations at the five sites for five years (1999-2004). The monthly average global solar irradiations were then calculated and compared with the monthly averages of the measured data. Figure 4 shows the monthly average of the predicted global solar irradiations compared with the measured values.

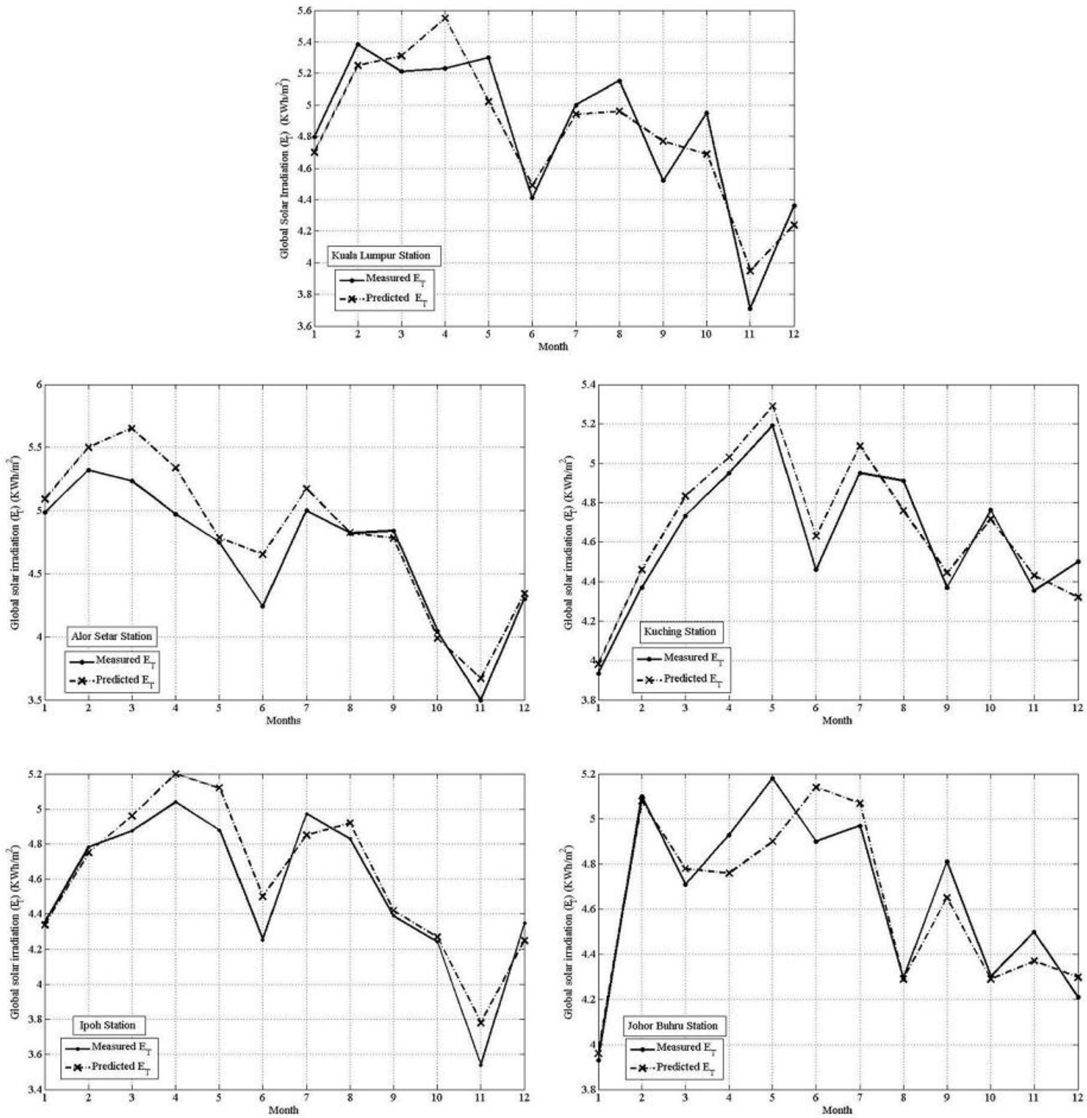



Figure 4 Comparison between the monthly average of the predicted and the measured global solar irradiations

As mentioned previously and also from Figure 4, the global solar irradiation values were clearly degraded in the wet season (October to February) due to the heavy cloud cover and rains; however, most of the monthly

As mentioned above, predicted values (daily global and diffused irradiations) have been compared with measured values to calculate the mean absolute percentage error (MAPE). The MAPE is defined as

$$MAPE = \frac{Measured\ Value - Predicted\ Value}{Measured\ Value} x\ 100\% \qquad (9)$$

The MAPE values of the chosen sites are listed in Table 2. The average error in predicting the global solar irradiation was 5.86%.

Additionally, most authors who have worked in this field evaluated the performance of the utilized ANN models quantitatively, and ascertain whether there is any underlying trend in the performance of the ANN models in different climates using statistical analysis involving mean bias error (MBE) and root mean square error (RMSE). These statistics were determined as

$$MBE = \frac{1}{n}\sum_{i=1}^{n}(I_{P\,i} - I_i) \qquad (10)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(I_{P\,i} - I_i)^2} \qquad (11)$$

where $I_{P_i}$ is the predicted daily global irradiation on a horizontal surface, $I_i$ is the measured daily global radiation on a horizontal surface and n is the number of observations.

MBE is an indication of the average deviation of the predicted values from the corresponding measured data and can provide information for the long term performance of the models. A positive MBE value indicates the amount of overestimation in the predicted global solar radiation and vice versa. RMSE provides information on the short term performance and is a measure of the variation of the predicted values around the measured data, indicated by the scattering of data around the linear lines shown in Figure 2. Table 6 shows the MBE and RMSE values for the chosen sites.

Table 2 MBE and RMSE for the five sites

| Site | MBE ($KWh/m^2$) | MBE (%) | RMSE ($KWh/m^2$) | RMSE (%) |
|---|---|---|---|---|
| **Kuala Lumpur** | -0.0087 | -0.18% | 0.348 | 7.2% |
| **Alor Setar** | 0.161 | 3.45% | 0.419 | 9% |
| **Johor Bharu** | 0.043 | 0.95% | 0.342 | 7.6% |
| **Kuching** | 0.036 | 0.78% | 0.353 | 7.6% |
| **Ipoh** | 0.105 | 2.3% | 0.380 | 8.4% |

From Table 2, the MBE of the Kuala Lumpur station was -0.18%, meaning the predicted values are underestimated by 0.018%, while every others station showed a slight overestimation. The average MBE for the developed network is 0.673 $KWh/m^2$, meaning the predicted values were overestimated by 1.46%.

The RMSE shows the efficiency of the developed network in predicting future individual values. A large positive RMSE means a large deviation in the predicted value from the real value. The average RMSE for the developed network is 0.3684 $KWh/m^2$, meaning a deviation of 7.96% is possible in a predicted individual value.

## I. CONCLUSION

A prediction of global solar irradiation using ANN is developed. This prediction was based on collected data from 28 sites in Malaysia. The developed network predicted the clearness indexes. The clearness indexes were then used to predict the global solar irradiation. Additionally, estimations of the diffused solar radiation were proposed using an equation developed for Malaysia. This equation calculates the diffused solar irradiation as a function of the global solar irradiation and the clearness index. Five main sites in Malaysia have been used to test the proposed approach. The average MAPE, MBE and RMSE for the predicted global solar irradiation are 5.92%, 1.46% and 7.96.

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