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Modeling the Solar Radiation Parameter over Abuja using Neural Networks

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Abstract

Many computer simulation models which predict growth, development and yield of agronomic and horticultural crops require daily weather data as input. One of these inputs is daily total solar radiation, which in many cases is not available owing to the high cost and complexity of the instrumentation needed to collect the data. In this work, a neural network model of the solar radiation over Abuja, Nigeria is developed. The model is useful for predicting the solar radiation intensity over Abuja, and this prediction is very important for many solar radiation applications, including gathering and validating information on the potential of Abuja for location of a solar energy generating station. The model used was developed using the Levenberg-Marquardt back-propagation algorithm with data from the Campbell automatic weather station situated at the University of Abuja, Nigeria. Results show that the predictions from the model developed generally agree with the observations. Midday solar radiation values typically exceed 600 W/m^2 during equinoxes and sometimes drop below 500 W/m^2 during solstices. Two indices (the Solar Radiation Diurnal Index (SRDI) and the Solar Radiation Annual Index (SRAI)) were also introduced in this work to respectively characterize the amounts of solar radiations received in each day and in each year for a given location. Relevant information is also provided to guide stakeholders for the location of a solar energy generating station in the region.

Keywords: *Neural network, solar radiation, Abuja, prediction, solar radiation diurnal index, solar radiation annual index*

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INTRODUCTION

For life to survive on earth, it needs the sun's life-giving radiation, even though it has its side effects. Solar radiation affects the electron content of the ionosphere which in turn affects transmission and reception of radio frequency (RF) signals' use in telecommunications, the Global Positioning System (GPS) navigation systems and other high technology systems in space region. It can also affect air travel in the earth's polar region. Solar flares which are bursts of high energy release of typically 1×10^{20} J emanating from the sun are dangerous to living organisms. A large coronal mass ejection from our sun can also cause serious effects in electric power grids. The particle radiations ejected from the sun disturb the earth's magnetic field, causing magnetic storms. This can cause voltage surges in power lines and in extreme cases cause power blackout. The ionosphere is highly variable, and phenomena that occur in it are known to be controlled mainly by the solar radiation. Therefore it is needed to have precise knowledge of the solar radiation intensity and pattern over given locations on earth for our ability to make predictions of disaster and to device evasive actions. In the light of this, our research focus is on solving the problem of simulating the solar radiation intensity over Abuja.

The development of computer neural networks (also frequently referred to as neural networks or just NNs) dates back to the early 1940s. This was a result of the discovery of new techniques and developments and general advances in computer hardware technology. A neural network is a system of programs and data structures that approximate the operation of the human brain. It is a computing system made up of a number of simple highly interconnected processing elements that process information by their dynamic state responses to external inputs. It usually involves a large number of processors operating in parallel, each with its own small sphere of knowledge and access to data in its local memory. The processors are initially “trained” or fed large amount of data and rules about data relationships. A program can then tell the network how to behave in response to an external stimulus or can initiate activity on its own. The basic idea behind a neural network is to simulate i.e. copy in a simplified but reasonably faithful way lots of densely interconnected brain cells inside a computer so can get it to learn things, recognize patterns, and make decisions in a humanlike way [1]. Most NNs have some sort of training rule. In other words, NNs learn from examples (as children learn to recognize dogs from examples of dogs) and exhibit some capability for generalization beyond the training data.The amazing thing about a neural network is that you do not have to program it to learn explicitly: it learns all by itself, just like a brain.

Many researchers have used neural networks for characterization, modeling and prediction of solar radiation and other atmospheric parameters in many locations [2–9]. They used various data parameters (e.g., solar radiation, temperature, relative humidity, thunderstorm, and rainfall occurrence/intensity) collected from different stations to model the solar radiation and other atmospheric parameters over different regions. Results from the various studies indicate that neural networks are viable for both temporal and spatial modeling of solar radiation; results from the different studies show good agreements between the NN-estimated and actual values of the parameters for the areas under consideration. Krishnaiah *et al*. presented the development of neural network-based models for estimation of monthly mean daily and hourly values of solar global radiation [10]. Their results indicate that the neural network model showed promise for evaluating the solar radiation possibilities at other places where monitoring stations were not established. In Nigeria, Okoh *et al.* presented preliminary results on using artificial neural networks to model temporal surface temperature variations recorded at four stations in north-central Nigeria (7.29–9.93°N, 7.48–8.88°E) [11]. The study used the Levenberg-Marquardt back propagation algorithm, and the network was tested for interpolation and forecasting abilities. RMSE in the predictions were generally lower than 2°C, and over 88% of their predictions had better accuracies than 2°C. This study further demonstrated that neural networks are viable for modeling of atmospheric parameters in the Nigerian region.

The main purpose of this study is to develop a neural network model of the solar radiation over Abuja, Nigeria. This model will be used to predict the solar radiation parameter over Abuja, and the prediction is necessary for many solar applications, including pre-information on the potential of Abuja for the location of a solar energy generating station.

To characterize the diurnal amount of solar radiation received at a particular location, we introduce a quantity/parameter known as the Solar Radiation Diurnal Index (SRDI) which is a diurnal index for a given location. The SRDI for a given day and location is defined as the mean of hourly solar radiation values obtained in that location between sunrise and sunset for that day. The SRDI is therefore dimensionally equivalent to the solar radiation amount. The SRDI parameter provides a platform to compare the amounts of solar radiations received at different locations, and it is therefore particularly useful for making informed decisions on locations to install solar panels or other equipment that require large amounts of solar radiation for optimal performance. Occasionally, decision makers are faced with a task of choosing locations for sitting solar power plants; locations that receive more amounts of solar radiation are preferred. If typical SRDI values are known for different locations, the parameter could serve as criteria for deciding more efficient locations. The SRDI for a given location will change noticeably for the different seasons in a year. It is therefore necessary to introduce similarly defined longer-term indices. We introduce the Solar Radiation Annual Index (SRAI) which is an annual index for a given location. The SRAI for a given year and location is defined as the mean of the SRDIs for that location computed over all the days in that year. The SRAI is a longer-term index for a given location, and so it is more climatologic for given locations. Following this trend, even more longer-term indices can be defined to characterize the solar radiation property of locations over longer-terms like decades, centuries, etc.

DATA AND METHODS

Solar radiation data used in this study was obtained from the Campbell Scientific Automatic Weather Station installed at the University of Abuja main campus (9.07°N, 7.48°E, 536 m amsl). The Campbell Scientific Automatic Weather Stations are installed by the Centre for Atmospheric Research (CAR) of the National Space Research and Development Agency (NASRDA), at different locations in Nigeria for atmospheric research under a project known as TRODAN (Tropospheric Data Acquisition Network). A standard station is a fully configured, solar powered, multi-purpose and rugged automated weather station. The equipment consists of a weather-proof enclosure that contains a highly reliable Campbell Scientific CR1000 data logger, and equipped with a suite of standard calibrated weather sensors for measurements of barometric pressure, air temperature, relative humidity, wind speed and direction, soil temperature, moisture, rainfall and rain rate. The equipment is powered by a 12 V, 7 A battery, a 20 W solar panel and a charge controller for battery charging. The data logger is programmed for automatic sensor data acquisition using CR basic. When completely connected, the weather station will automatically start to take measurements through each of the parameter sensors outside of the box. The instrument is designed for long term unmanned or unattended operation and is ideal for meteorological, weather monitoring and climate study applications. The CR1000 data logger type is programmed for data acquisition at 5 min update interval/cycle. Different choices of communication options are available and they include GSM and GPRS, fixed line phone, phone modem, and direct RS232 connection using the computer RS232 port (Figure 1).

Data used in this work is for the period from year 2007 to 2012. The data was averaged in 1 h interval to reduce data spikes that were observed in the 5 min interval, and a total of 333,370 data points of solar radiation were obtained.

The Levenberg-Marquardt back-propagation algorithm was used in this work for the neural network training [12]. This algorithm is highly admired for its speed and efficiency in learning and as such was subsequently used for training [13, 14]. The neural network weights and bias values were updated according to the optimization method for this algorithm.

Three input neurons (namely, Year, Day of year, and Hour of day), representing the time for each data point, were used to learn the time series variation in the data. And there was one output neuron (the Solar Radiation parameter, in watts per meter squared, W/m^2) which the networks were trained to learn. We also used one hidden layer in this work since it has been shown that including more than one hidden layer does not lead to much difference in the accuracyof results [15], and even a drawback in using multiple hidden layers is that they are more prone to fall in bad local minima [16].

Fig. 1: *The Campbell Scientific Automatic Weather Station at the Abuja Location.*

There are also no specific and perfect rules for deciding the most appropriate number of neurons in a hidden layer. Using an excessive number of hidden layer neurons causes over-fitting while a fewer number leads to under-fitting. Either scenario greatly degrades generalization capability of the network with significant deviation in the prediction accuracy [17]. To decide an optimal number of neurons in our hidden layer, we simulated a system of networks, varying the number of hidden layer neurons in the networks from 1 to 30 in steps of 1. Finally, we considered the best of the 30 networks as the one which minimized the prediction error on the test data.

The data used in this work was split into three parts: a random 70% for training, a random 15% for validation, and the remaining 15% for testing. The last 15% (also called the test data) was never 'seen' by the networks until training was fully completed and the networks validated. To test the performance of each network, we simply require it to predict/simulate data corresponding to the period of the test data, and then we examine the error (that is, the difference between the predictions and the real observations in the test data). The RMSE (root-mean-square error) is used in this study as a measure of the difference between the predictions and the real observations from the Campbell equipment. The RMSE is computed using the formula in Eq. (1).

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} Errors^2}{n}} \qquad (1)$$

Where, Error = observation-prediction, and n = number of observations.

Figure 2 is an illustration of the RMSE values obtained on the test data for each of the 30 networks we trained, varying the number of hidden layer neurons in each.

We considered the best network to be that which minimized the RMSE values on the test data. Figure 2 shows that the best optimized number of hidden layer neurons for our training is 23; this is the one that shows the least RMSE value as evident in Figure 2. The neural network architecture for the optimal network in this work is therefore 3-26-1, meaning 3 input layer neurons, 23 hidden layer neurons, and 1 output layer neuron.

In this work, we compute the SRDIs and SRAIs as follows:

1. For each day, the SRDI was computed as the mean of the 1 h data starting from 06:00 LT to 18:00 LT.
2. For each year, the SRAI was computed as the mean of the SRDIs for all days in the year.

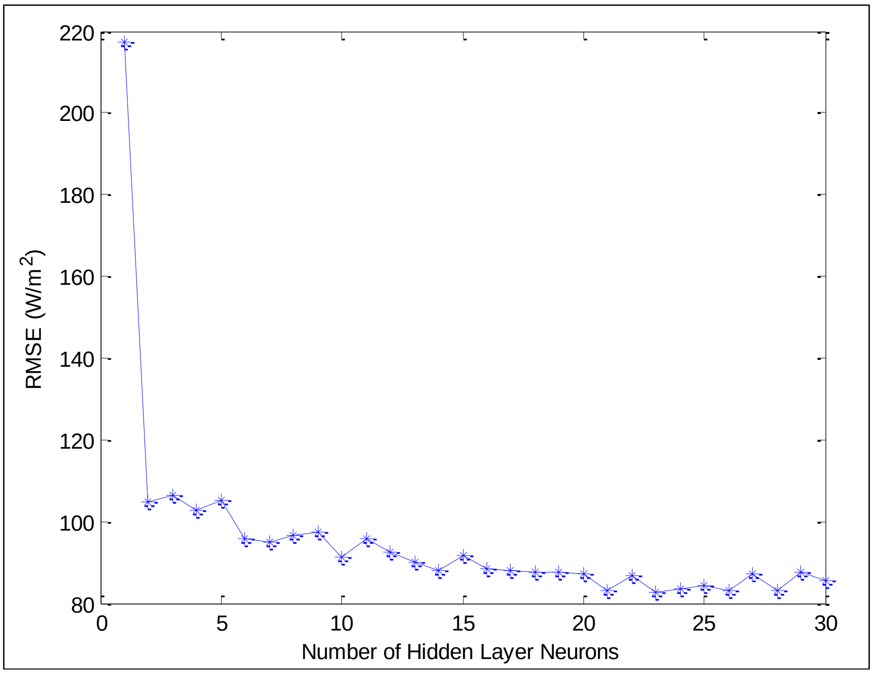

Fig. 2: *RMSEs on the Test Data for Different Number of Hidden Layer Neurons.*

RESULTS AND DISCUSSIONS

The optimal network obtained and described above is used here to illustrate how the predictions of the network compare with observations from the Campbell equipment. To investigate the performance of the neural network in predicting the solar radiation values, we simulated the network for six arbitrarily chosen days in a manner that the days cover different seasons of the years between 2007 and 2011. Figures 3(a)–(f) illustrate plots of the neural network predictions alongside the observations (or measurements) from the Campbell equipment. The plots are respectively for (a) day 250 of year 2007, (b) day 100 of year 2008, (c) day 50 of year 2009, (d) day 350 of year 2009, (e) day 150 of year 2010, and (f) day 1 of year 2011.

From the figures, it is evident that there is very good agreement between the model predictions and the observations. An observation that is expected is that the NN model predictions are smoother than in the physical observations, this is because the neural network models include smoothing operations in learning the transitions between the observations. Discussions in this paper are therefore mainly based on the neural network predictions.

Figure 4 was constructed to study the solar radiation variation over a typical year. The left-side axis of the figure (in blue color) is a plot of the solar radiation predictions from the neural network model developed in this work; it is a plot of the solar radiation values at local midday (that is, 11:00 UT, the local time in Nigeria is UT+1) for each day from day numbers 1 to 365 of year 2007. The right-side axis of the figure (in red color) is a plot of the SRDI for each day from day numbers 1 to 365 of year 2007.

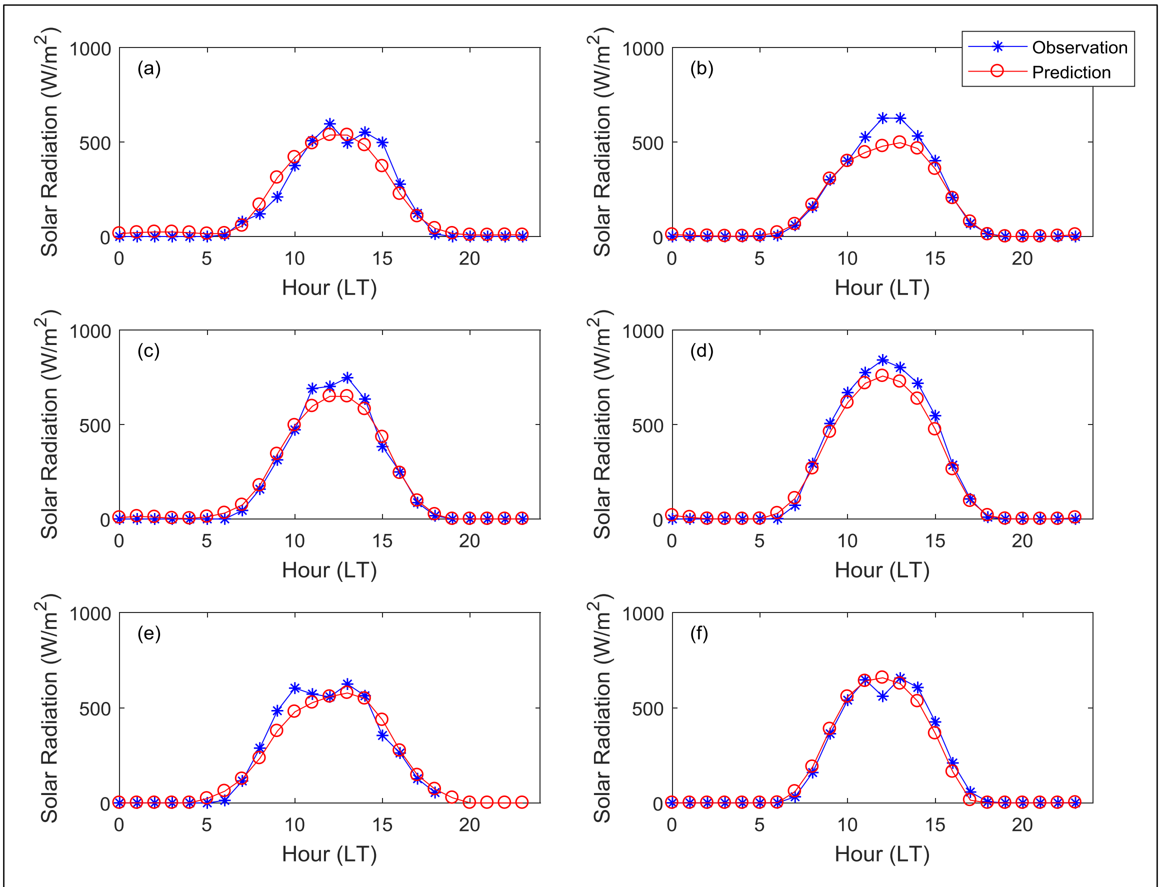

***Fig. 3:** Solar Radiation Predictions from the NN versus Observations from the Campbell Equipment for 6 days Arbitrarily Chosen to Cover All Seasons of the Years from Years 2007 to 2011: **(a)** day 250 of year 2007, **(b)** day 100 of year 2008, **(c)** day 50 of year 2009, **(d)** day 350 of year 2009, **(e)** day 150 of year 2010, and **(f)** day 1 of year 2011.*

Both plots reveal a similar pattern, that is, that the solar radiation values are maximum during the equinoxes (around the months of March and September) and minimum during the solstices (around the months of June and December). This is expected since the Abuja location for which solar radiation is modeled in this work is located close to the equator. During the equinoxes, the plane of the earth's equator passes through the center of the sun's disk and so, regions around the equator receive more direct radiation from the sun. On the contrary, during solstices, the sun reaches its most northerly and southerly excursions relative to the earth's equator, and so regions around the equator (like Abuja) receive less of the sun's radiation. This explains why the location of Abuja witnesses more of the solar radiation during the equinoxes, and least of it during the solstices. Figure 4 shows that during the equinoxes, the Abuja location receives as much as over 600 W/m^2 of the surface at midday, while in the solstices, the value drops to as low as below 500 W/m^2. Typically, a 1 m^2 size of solar panel installed in Abuja will receive more than 500 W of solar energy during most days in a year. The SRDI values are typically around 350 W/m^2; the values go beyond 400 W/m^2 during the equinoxes, and drop below 320 W/m^2 during the solstices. The computed SRAI value for year 2007 is 353 W/m^2. This means that at an equivalently constant rate, a 1 m^2 size of solar panel installed in Abuja will receive 353 W of the sun's energy throughout the periods between sunrise and sunset for each day in year 2017.

The solar radiation values also change from one year to another. Figures 5(a)–(d) were constructed to study year to year variations. The figures respectively represent solar radiation plots of both the neural network predictions and the Campbell equipment observations for day number 250 (arbitrarily chosen) of each of the years from 2007 to 2010.

Figures 5(a)–(d) reveal a general decline in the solar radiation values from years 2007 to 2010 (except for year 2008). The computed SRAIs for years 2007 to 2010 are respectively 353, 348, 342 and 341 W/m^2, which shows a consistent decrease in the annual values from year 2007 to 2010. This trend agrees with the solar activity cycle illustrated in Figure 6 wherein the solar activity levels decrease from years 2007 to a minimum at around year 2009/2010, and then the solar activity level starts increasing thereafter [18]. This correlation supports the fact that the level of activity in the sun has a direct effect on the amount of solar radiation we receive on earth.

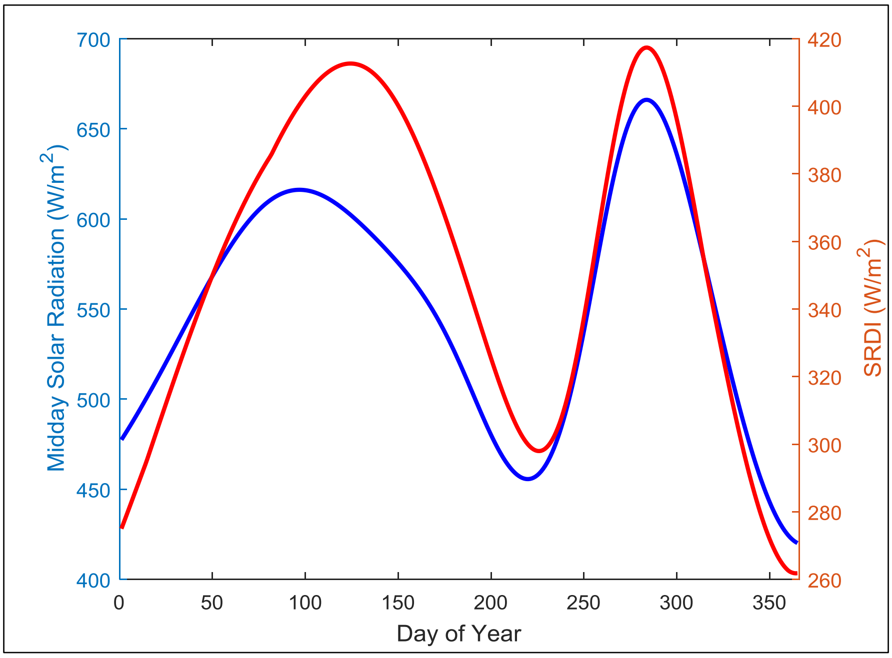

Fig. 4: *NN Simulation of the Solar Radiation for Local Midday, and Solar Radiation Diurnal Indices, for Day Numbers 1 to 365 of year 2007.*

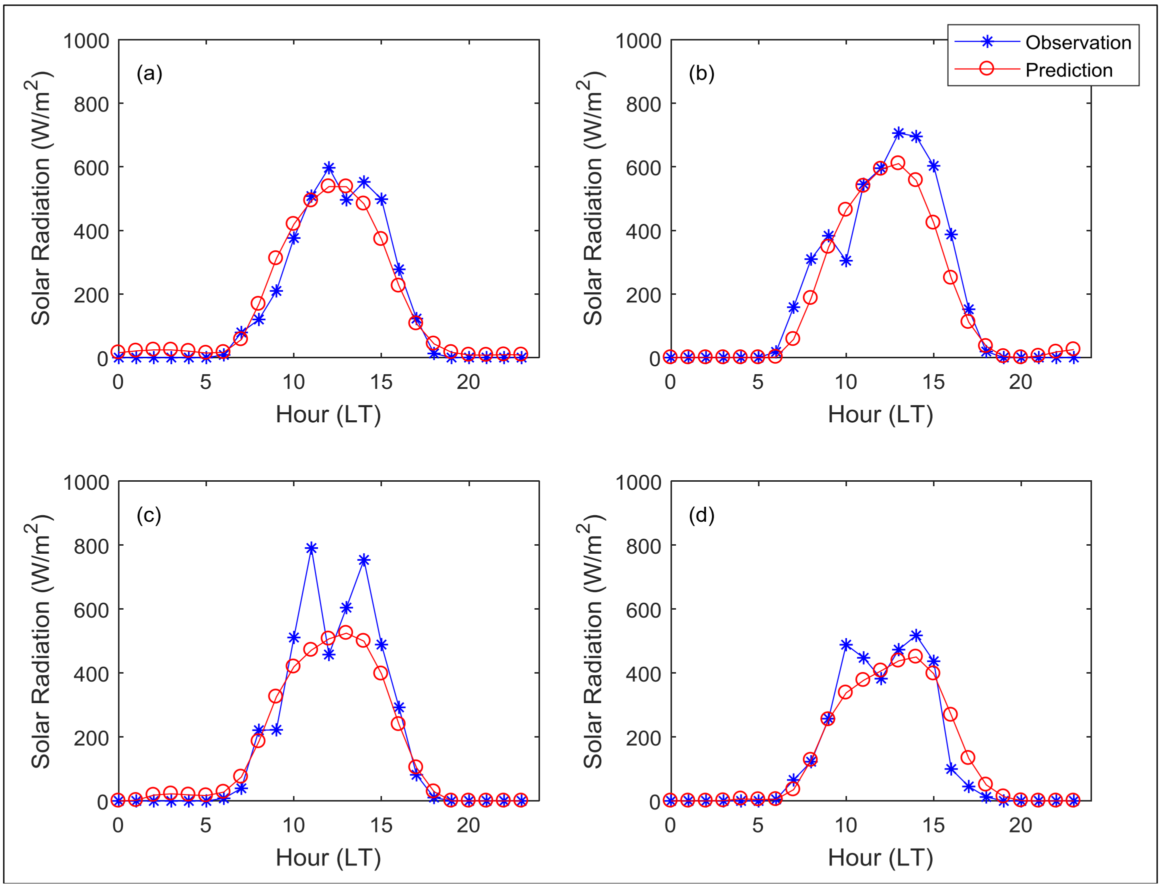

Fig. 5: *NN Predictions and Campbell Equipment Observations for Day Number 250 of* ***(a)*** *year 2007,* ***(b)*** *year 2008,* ***(c)*** *year 2009, and* ***(d)*** *year 2010.*

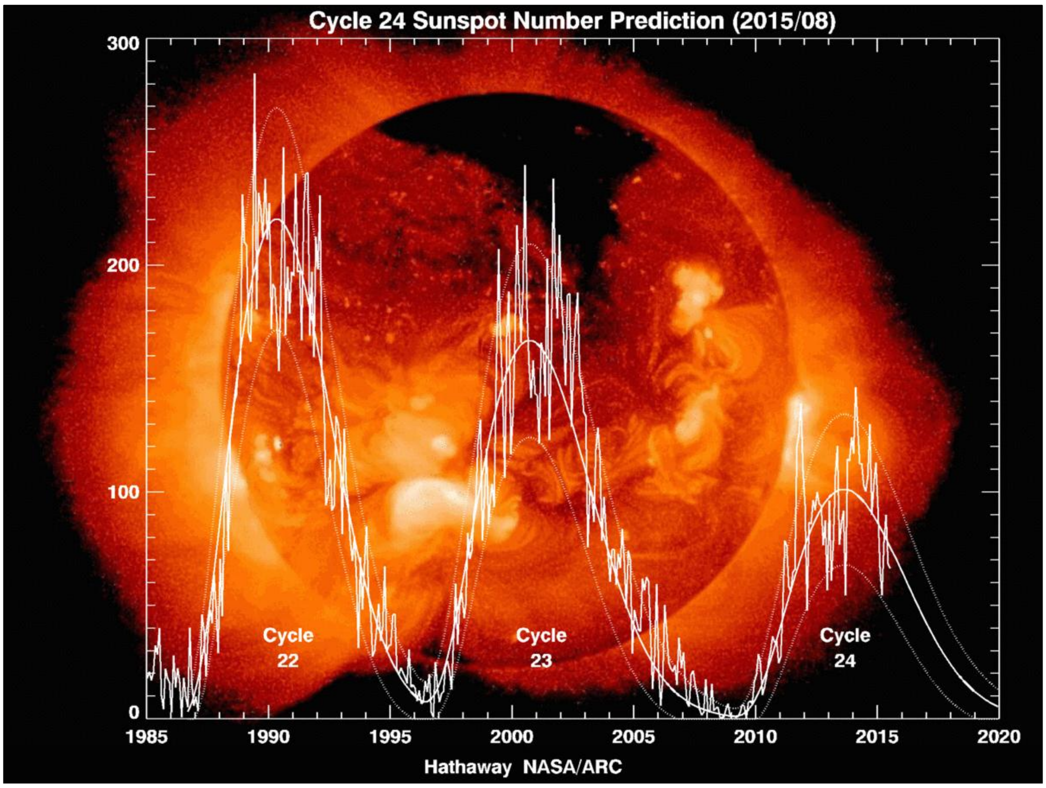

Fig. 6: *Solar Activity Cycle Prediction [18].*

Typical diurnal patterns of the solar radiation variation can be seen in Figures 3 and 5. Diurnal variations of the solar radiation are connected with events of the sunrise and sunset, which are in turn associated with the rotation of the earth about its axis. From the local midnight of each day, the solar radiation values are zero until sunrise (around 06:00 LT). The solar radiation values rise sharply thereafter following the rise of the sun to zenith position around local midday. The peak of the solar radiation is witnessed at around local midday, and thereafter a sharp drop in the radiation values are observed following the descent of the sun below the horizon. The solar radiation value returns to zero soon after sunset (around 18:00 LT) and remains at the zero level until sunrise in the following day.

CONCLUSION

In this study, computer neural networks have been used to train solar radiation observations over Abuja, Nigeria. A model that predicts and forecasts the solar radiation for the region was developed, and predictions from the model generally agree with the observations. This has further demonstrated that computer neural networks are good candidates for modeling the solar radiation parameter.

Two indices, the Solar Radiation Diurnal Index (SRDI) and the Solar Radiation Annual Index (SRAI)) were also introduced in this work to respectively indicate measures of the amounts of solar radiations received in each day and in each year for a given location. The SRDI for a given day and location represents a constantly equivalent amount of solar radiation that will be received on that location in the periods between sunrise and sunset of the day. The SRAI is similarly defined for an entire year.

Results from the study also indicate that the solar radiation values in Abuja are higher during equinoxes than at solstices. The highest amounts of solar radiations are received around the months of September/October and in March/April. Diurnal solar radiation values peak around midday, and they become zero in the periods between sunset and next sunrise. Year-to-year variations take a pattern similar to the solar activity cycle; the amount of solar radiation received during a year of higher solar activity is higher than for a year of lower solar activity, supporting the fact that the activities of the sun influence how much of the solar radiation we receive on earth.

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