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Daily Solar Radiation Forecasting for Northwest Nigeria Using Long Short-Term Memory

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ABSTRACT

In order to ensure energy security and environmental sustainability, transition to renewable energy sources is required. One of the most viable and sustainable renewable energy sources is solar. However, developing solar energy systems requires solar radiation data which is scarce for most locations including Northwest Nigeria. In order to address this challenge, solar radiation is usually estimated from the available meteorological parameters. Several previous studies have used various methods including geospatial techniques and machine learning to predict monthly and yearly solar radiation, while few studies have focused on the estimation of daily solar radiation. Meanwhile, providing daily solar radiation data is necessary for the development of solar energy systems. Deep learning has been shown to be effective in solar radiation forecasting. To evaluate the performance of the deep learning method for daily solar radiation prediction, a Long Short-Term Memory (LSTM) based deep learning model was developed in this study. The forecasting model was created using daily solar radiation data collected over a 21-year period by the Nigerian Meteorological Agency in three major towns in North West Nigeria: Kano, Kaduna, and Katsina. The model was evaluated using two statistical indicators: coefficient of determination (R^2) and Root Mean Square Error (RMSE). Results showed that R^2 of 0.79 and 0.78 were obtained for the training and testing datasets respectively, while RMSE of 0.46 and 0.47 were obtained for the training and testing datasets respectively. Overall, the LSTM deep learning model has been proven to be effective in forecasting daily solar radiation.

Keywords: Deep Learning, LSTM, Solar Radiation, Time Series.

1. INTRODUCTION

Renewable energy resources have several advantages which include minimizing environmental pollution, reduction in greenhouse gas emission and combating climate change in order to achieve sustainable growth and development. Renewable resources include solar, wind and geothermal energy. Solar energy is one of the most important renewables because it has several advantages over other sources. It is among the most abundant and adaptable renewable energy sources that can be used directly or indirectly (Fraihat *et al.*, 2022).

The increasing demand for sustainable energy sources has made solar energy a very attractive alternative due to its abundance, flexibility and reliability. However, developing solar energy system requires adequate information on solar

radiation in an area or region. Solar radiation data is indispensable for the design and implementation of solar energy technologies. Ground measurements provide the most accurate solar radiation data; however, it is not readily available mainly due to the initial investment and maintenance cost of the measuring instruments (Notton *et al.*, 2019). The difficulties and uncertainty encountered in the ground measurement of solar radiation data have resulted into the development of solar radiation prediction models and algorithms. Forecasting of solar radiation data is crucial before the installation of solar systems in order to analyze and estimate capacity and potential of the solar power plant system for effective utilization (Üstün *et al.*, 2020).

The inability of conventional time-series methods in capturing nonlinear data patterns has led to the wide usage of neural networks for forecasting non-linear systems (Jung. *et al.*, 2020). Hence, neural networks

have been applied to time-series prediction. For instance, An Adaptive Neuro-Fuzzy Inference System (ANFIS) model was developed by Salisu (2017) to predict the monthly average solar radiation in Nigeria. Air temperature of monthly mean minimum temperature, maximum temperature and relative humidity were used as input parameters. Salisu *et al.* (2019) employed a hybrid approach which combined an ANFIS with Particle Swarm Optimization (PSO) and Wavelet Transform (WT) algorithms for horizontal solar radiation prediction in Nigeria. Results showed that the hybrid WT-ANFIS model performed better than the PSO-ANFIS model by 65% RMSE and 9% R². Also, ANN models for solar irradiance forecasting in Nigeria were developed by Bamisile *et al.* (2020). A deep learning regression model built on Levenberg-Marquardt back propagation algorithm is used to train and test the model for all the locations considered. The ANN models were developed for four locations in Keras python using all the input parameters. The R-value for all the locations considered range from 0.9046–0.9777 for solar irradiance. Bamisile *et al.* (2021) compared the predictive performance of machine learning models with that of deep learning models for both global solar radiation (GSR) and diffuse solar radiation (DSR) prediction in parts of Nigeria. Their results showed that the application of RNN for GSR prediction in Yobe (with an r value of 0.9546 and RMSE of 82.22 W/m²) had the overall best model performance when compared with ANN and CNN models used in their study.

The ANN and ANFIS are among the machine learning methods used for solar energy forecasting and modeling (Akter *et al.*, 2022). However, the prediction model's performance depends not only on the selection of the input but also on the model framework playing an essential role in prediction accuracy. Through the use of data-driven models, it is possible to capture the underlying mapping of solar irradiance (Madhiarasan and Louzazni, 2022).

Recently, deep learning techniques have been used in various fields in order to overcome the limitations of the traditional neural networks and other machine learning methods (Akter *et al.*, 2022). Deep learning algorithms are computational models that are made up of multiple processing layers for the extraction

of features from complex data representations (Pandey and Janghel, 2019). Recent developments in deep learning technology has included Recurrent Neural Networks (RNNs), a special type of neural network with strong interdependencies and meaningful representation preserving data about occurrences in previous time steps (Pandey and Janghel, 2019). In addition, unlike the ANN which lacks a correlation approach and performs direct mapping between input and output data, the RNN builds up sequence to sequence mapping by adding up cyclic connections to neurons. This makes the RNN more suitable for application in time series forecasting (Akter *et al.*, 2022). Recently, the RNN performance has been improved by the introduction of Long Short-Term Memory (LSTM) networks based on RNNs trained using back-propagation through time, which overcomes the vanishing gradient problem (Liu *et al.*, 2019) that arises during training conventional RNNs.

The LSTM models have emerged as valuable models for forecasting time-series. They are deep learning-based model specifically designed to handle sequence data and they can memorize long temporal relationships in data (Malakar *et al.*, 2021). The architecture of LSTM unit comprises of an input gate, forget gate, output gate, and a cell unit. The cell functions as a memory and remembers values over an arbitrary time interval. The input gate, forget gate, and output gate control information flow into and out of the cell (Husein and Chung, 2019). The cell adds an extra weight to the passing-through data, giving the model the capability to 'forget' irrelevant data and predict temporal sequence data (Carutasu, *et al.*, 2021).

Recently, researchers have developed interests in the LSTM of time series and sequence database, which have been used for diverse applications (Madhiarasan and Louzazni, 2022). For instance, Husein and Chung (2019) developed an LSTM-RNN model for hourly day-ahead solar irradiance forecasting. They compared the results with a Feed Forward Neural Network (FFNN), a method with a proven record of success in solar irradiance forecasting. The LSTM-RNN model was found to perform better than that of the FFNN.

Similarly, de Araujo (2020) used a combination of Weather Research and Forecasting (WRF) model and LSTM network for solar radiation forecasting in Dili Timor Leste based on 12-month solar radiation data. Results showed good performance of the combined method which can be applied to simulate any other weather variable for relevant applications.

Also, a high-precision forecasting model based on deep LSTM and machine learning techniques using global horizontal irradiance (GHI) ground measurements as well as satellite-derived data has been developed by Benamrou *et al.* (2020). The simulation and results showed that the proposed method performed better than the other benchmark approaches.

Alharbi and Csala (2021) designed a prediction model based on bidirectional long short-term memory (BI-LSTM). The model was able to estimate the future performance of solar irradiance, including global horizontal irradiance (GHI), direct normal irradiance (DNI), and diffuse horizontal irradiance (DHI), with the wind speed and ambient temperature values based on time series. The GHI, DNI and DHI are important parameters in determining solar energy potentials and in the design of solar energy systems.

From the above review, it will be observed that there are two major categories of estimating solar radiation: Monthly daily average solar radiation (MDASR) and daily solar radiation (DSR). MDASR suffers from anomaly in the process of data reduction that can affect the result. This is because the data used cannot reflect the condition of an actual day and if used means that the solar radiation condition does not change between adjacent years. The daily solar radiation on the other hand and the hourly radiation data has proven to be much more useful for developing solar energy systems, but the meteorological parameters used by most studies in the literature are not readily available in Northwest Nigeria. Since sunshine hours has been found to be the most influential parameter, the present study hence focuses on the estimation of the daily solar radiation from measured sunshine hours using LSTM. It is also worth noting that in the context of Northwest

Nigeria, data on other variables that influences solar radiation as attainable in other literature are unavailable largely due to inadequate or absence of measuring instruments. As a result of these, the daily solar radiation data collected was used as a time series data, an approach not considered in most of the literature. The main contribution of the present study is the demonstration of the viability of building a deep learning model (LSTM) for a single time series data input.

The rest of this paper comprises of the following sections: brief description of the study area and data collection for the study; the methodology used for the model development and strategies used for evaluating the developed model; results obtained and discussion; followed by concluding remarks on the present study.

2. THE STUDY AREA

The study area comprises of Katsina, Kano, and Kaduna states in Northwest Nigeria, covering an area of 90,376 km². The area is located between Latitudes 9°00' – 13°30'N, and Longitudes 6°00' – 9°30'E as shown in Fig. 1. The area is bordered by Niger Republic to the north, Bauchi State to the east, Abuja to the south and Zamfara State to the west. The study area is located on the “High Plains of Northern Nigeria” which lies on altitude of between 450 to 745m above sea level (Udo, 1970). The area is underlain by the Precambrian Basement Complex Rocks. The climate of the area is described as Aw based on Koppen’s classification, characterized by alternating wet and dry seasons. The dry season is accompanied by a dust laden wind from the Sahara Desert, known as Harmattan, which is brought by the Tropical Continental air mass, while the rainy season is heavily influenced by the Tropical Maritime from the Atlantic Ocean, occurring between April/May and September/October (Eludoyin, 2011). The temperature in the area interchanges between hot and cold seasons with the occurrence of Harmattan (a very cold season) between November and February. The Harmattan greatly reduces the amount of solar radiation received in the area. The average minimum temperature in the area is 21.4±3.43°C. The mean maximum temperature in the area is 32.8±3.37°C (Eludoyin, 2011). The area

is characterized by leached ferruginous tropical soil developed on deeply weathered Precambrian Basement Complex rock. The projected population of the area in 2016 was about twenty-seven million.

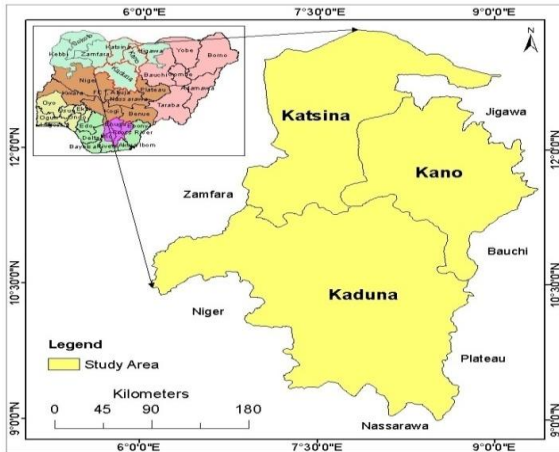


Fig. 1. The Study Area in Northwestern Nigeria
 Source: Adapted from the Administrative Map of Kaduna State

3. MATERIALS AND METHODS

3.1 Data Used

For this study, daily average solar radiation data for a period of 21 years were provided by the Nigerian Meteorological Agency (NIMET) in millijoule per meter square per day (MJ/m²/day). The data were converted into kilowatt per hour per meter square per day (kWh/m²/day) using the International Energy Agency (IEA) General Converter for Energy. This is because solar radiation values are generally expressed in kWh/m²/day. The measured values of daily sunshine radiation are shown in Fig. 2.

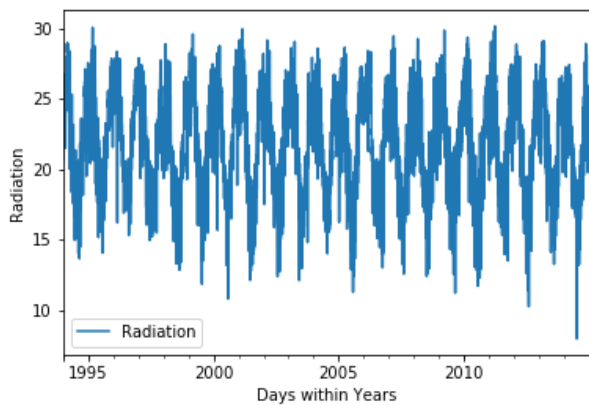


Fig. 2. Daily sunshine radiation from 1995 to 2014 in kWh/m²/day in the study area

3.2 Long-Short Term Memory (LSTM)

According to Cui (2018), LSTM which is based on the traditional RNN can solve the gradient disappearance problem in RNN thereby improving its forecasting accuracy. LSTM replaces each hidden layer neuron with a memory cell with a forgetting mechanism in addition. The status information of the memory unit does not change with time, but is updated by the forgetting mechanism to retain useful information for the prediction results. Compared with traditional RNN, LSTM can store long-term information. A typical LSTM unit is depicted in Fig. 3.

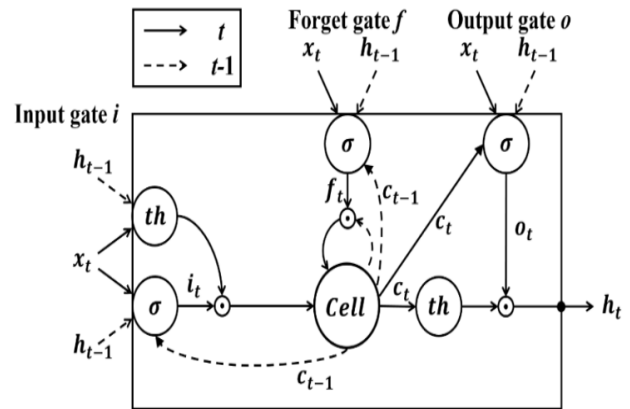


Fig. 3. A Long Short Term Memory unit (Cui, 2018).

Where:

x_t denotes the current input layer vector

h_{t-1} denotes the hidden layer vector at the previous moment.

The solid arrow in Figure 3 indicates the value at the current time t , and the dashed arrow indicates the value at time $t-1$. The memory cell's writing, forgetting, and outputting operations are determined by three gates: input gate i , output gate o , forget gate f . At the beginning of each time t , the unit first calculates the activation function $\{i_t, f_t\}$ of the input gate and the forget gate, and updates the memory cell from c_{t-1} to c_t . Then the unit calculates the output gate activation function o_t , and the hidden layer outputs h_t . The input gate calculates and writes a new state value based on the current input x_t and the previously hidden layer output h_{t-1} . The output gate finally calculates the hidden layer output ht according to the current input x_t , the previous hidden layer output h_{t-1} , and the current state c_t of the memory unit. The LSTM model was developed using the Keras library based on Python 3.7.

A. Evaluation Metrics

In this study, we used the train/test split model evaluation procedure to estimate how well a model will generalize to out-of-sample data and two evaluation metrics to quantify the model's performance. The experiment was performed on a 70% training set to 30% test data split as shown in Fig. 4. This was chosen as the train/test split for it is common in the literature. The train/test approach was also considered because of its simplicity, speed and flexibility.

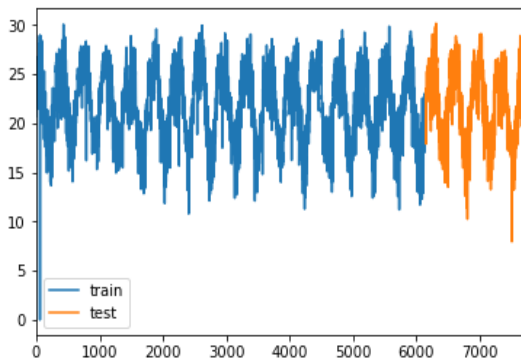


Fig. 4. Train/Test Dataset Distribution

Two statistical indicators: coefficient of determination (R^2) and Root Mean Square Error (RMSE) which are mostly used in the literatures for comparing the performance of different ANN models was used as the evaluation metrics in the present study.

1) The coefficient of determination, or R^2 , is a measure that provides information about the goodness of fit of a model. It takes values between 0 and 1. The larger this indicator is the better the performance of the model. So the closer the R^2 is to unity, the better the estimation ability of the model. This indicator is expressed mathematically as:

$$R^2 = 1 - \frac{\sum(y_a - y_p)^2}{\sum(y_a - \bar{y}_p)^2} \quad (2)$$

Where:

- n = number of observation
- y_a = actual value
- y_p = predicted value
- \bar{y}_p = mean of predicted values

2) RMSE describes information about the short term performance by comparing the actual

deviation one by one between the estimated and the measured values. It is to some extent the mean absolute deviation error. RMSE is mathematically expressed as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (y_{i,e} - y_{i,m})^2}{n}} \quad (3)$$

Where:

- n = number of observations
- $y_{i,e}$ = the i^{th} estimated value
- $y_{i,m}$ = the i^{th} measured value

4. RESULTS AND DISCUSSION

In this paper, an LSTM was developed to predict daily solar radiation. To demonstrate the merit of these models, its prediction performance was evaluated by predicting the daily solar radiation of 30% of the total dataset from 1994-2014. The predicted daily solar radiation values using the developed LSTM model versus the actual data values is as shown Fig. 5.

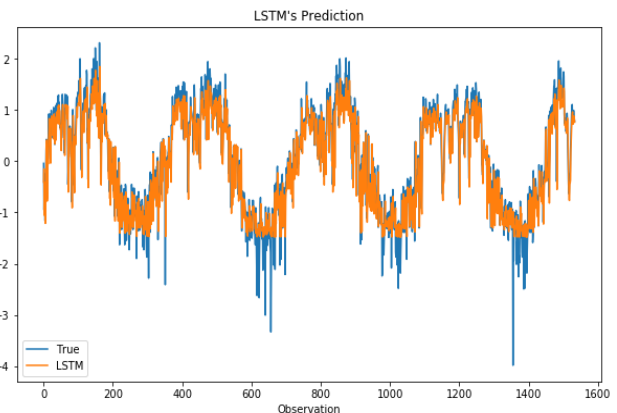


Fig. 5. LSTM Predicted versus actual daily solar radiation

The performance of the developed models was measured using the coefficient of determination (R^2) and an error evaluation metric, namely, the root mean square error (RMSE). Table 1 summarizes the results obtained using the collected dataset.

Table 1. Performance Statistics of Prediction on the Dataset

Algorithm	Dataset	RMSE	R^2
LSTM	Training	0.46	0.79
	Testing	0.47	0.78

From Table 1, it can be deduced that the LSTM model performs well and hence can be adopted for daily solar radiation prediction. Table 2 shows comparison of the results of the prediction of the LSTM model adopted in this study and other models adopted in the literature. It can be observed from Table 2, that the LSTM performs well when compared with ANFIS which was used by Salisu *et al.* (2018) to predict the global solar radiation on horizontal surface in Nigeria from measured meteorological data. It can also be seen from Table 2 that the predictive power of LSTM is outstanding when compared with PSO-ANFIS and WT-ANFIS used by Salisu *et al.* (2019) to forecast global horizontal solar radiation in Nigeria as well as the ANN used by Bamisile *et al.* (2020) to forecast solar irradiance in Sokoto State, Nigeria.

Table 2. Comparison of Performance with Other Models

Algorithm	Dataset	RMSE	R ²
LSTM	Training	0.46	0.79
	Testing	0.47	0.78
ANFIS (Salisu <i>et al.</i> , 2018)	Training	0.81	0.87
	Testing	1.69	0.74
PSO-ANFIS (Salisu <i>et al.</i> , 2019)	Training	0.68	0.91
	Testing	1.38	0.81
WT-ANFIS (Salisu <i>et al.</i> , 2019)	Training	0.24	0.99
	Testing	0.87	0.86
ANN (Bamisile <i>et al.</i> , 2020)	Training	0.73	0.97
	Testing	0.76	0.98

The results of this study also corroborate with the findings of Srivastava and Lessmann (2018) which showed that the LSTM performs better than several alternative methods such as the FFNN which has been the most widely used for solar energy forecasting. Bamisile *et al.* (2021) also established that the deep learning models have better performance than the machine learning models, and are therefore more suitable for solar radiation prediction.

5.0 CONCLUSION

A forecasting model based on Long Short-Term Model (LSTM) was developed to predict the average daily solar radiation for the North Western region of Nigeria. The developed model is targeted to be an assessment tool for predicting the solar installation and for estimating the amount of energy that can be harnessed. The performance of the developed models was determined using the coefficient of determination and the root mean square error. The results obtained showed that the developed LSTM forecasting model is accurate and reliable for predicting solar radiation in North Western Nigeria.

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