FUDMA Journal of Sciences (FJS)
ISSN online: 2616-1370
ISSN print: 2645 - 2944
Vol. 10 No. 11, June, 2026, pp 167 – 175
DOI: https://doi.org/10.33003/fjs-2026-1011-5158

A Multiple Optimizer Based Long Short-Term Memory Models for the Efficient Prediction of Solar Radiation

Mohammed Abdulaziz Usman, Yahaya Isah Shehu,
Shehu Malami Sarkin -Tudu and Anas Tukur Balarabe

Faculty of Computing, Department of Computer Science, Sokoto State University, Sokoto State.

*Corresponding authors' email: Jeezoo99@gmail.com

ABSTRACT
To ensure energy security and environmental sustainability, transition to renewable energy sources is required, one of the most important and sustainable renewable energy is solar energy, However, in developing predicting system, accurate solar radiation is essential for optimizing solar energy systems particularly in regions with limited ground based infrastructures including Northwest Nigeria, To address this challenge a time series dataset of daily solar radiation measurements from available meteorological parameter, several previous studies have used various methods including ARIMA, SARIMA, Machine learning and Deep leaning models with static hyperparameter optimization approach, Meanwhile optimization of forecasting systems is necessary for developing accurate energy predicting systems. Deep learning is effective in solar radiation forecasting. To evaluate the performance of deep learning method for daily solar prediction, an optimized Long Short-Term Memory (GWO-LSTM and BO-LSTM) based deep learning models were developed in the study, The optimized models were created using daily solar radiation data from Nigerian Meteorological Agency for a period of 20 years, in three states in Northwest Nigeria: Kaduna, kano and katsina, This models were evaluated using two forecasting performance metrics: R^2 coefficient of determination and Root Mean Square Error (RMSE), The models results shows both optimized models outperformed baseline LSTM model, The LSTM-BO indicates performance with training $R^2 = 0.8500$, RMSE=0.3876 and testing of $R^2 = 0.8205$, RMSE = 0.4309 while GWO-LSTM achieves training of $R^2 = 0.8358$, RMSE = 0.4054 and testing of $R^2 = 0.8190$, RMSE = 0.4340 respectively. The LSTM-BO achieves slightly better predicting accuracy than LSTM-GWO.

Received: 22 Jan. 2026

Accepted: 12 Feb. 2026

Published: 14 June 2026

Keywords: Solar Radiation Prediction, Long Short-Term Memory, Grey Wolf Optimizer, Bayesian Optimizer, Deep Learning, Dynamic Hyperparameter Tuning

INTRODUCTION

The primary focus of the energy industry in recent years has been on reducing carbon emissions by shifting to renewable energy sources (Gielen et al., 2019). Excessive carbon emissions negatively affect the environment, leading to further global warming and climate change(Yoro & Daramola, 2020). Furthermore, industrial development has considerably accelerated the global energy demand, resulting in the supply of non-renewable energy sources, such as natural gas, coal, and petroleum, being increasingly constrained(Ahmad & Zhang, 2020). Given this circumstance, many countries have crafted and subsequently implemented policies and strategies associated with the energy sector (Lindberg et al., 2019). In(Falcone, 2023), there is an emphasis on new domestic policy commitments aimed at achieving 100% dependency on renewable energies. Considering the integration of renewable energy sources into grids, most studies focused on the development of photovoltaic (PV) systems rather than the incorporation of other types of renewable energy, such as biomass, wind energy, and other forms. Solar energy is one of such sources and has been given considerable attention because of its abundance and sustainability (Olugbenga et al., 2026). The characteristics of solar energy, such as uncertainty, fluctuation, and randomness, may lead to dynamic instability and unpredictability of solar PV power output (Chen & Chang, 2021). Given this difficulty, techniques for accurately predicting the amount of solar irradiance should be pursued to provide important decision support to power-dispatching systems. More importantly, the search for appropriate methods can considerably minimize the running cost of power systems(Varganova & Khramshin, 2022). Solar energy is gaining popularity as a renewable energy source due to its environmental benefits and abundance(Rabaia et al., 2021).

The expanding demand for feasible energy sources has made solar energy a really attractive alternative due to its abundance, adaptability and reliability(Jia et al., 2024). In any case, creating solar energy framework requires adequate data on solar radiation in an area or region. Solar radiation information is vital for the design and usage of solar energy technologies(Kumar et al., 2020a). Ground estimations give the foremost exact solar radiation data; however, it isn't readily accessible primarily due to the starting investment and maintenance cost of the measuring instruments(Chave et al., 2019). The challenges and instability experienced within the ground estimation of solar radiation information have come about into the improvement of solar radiation forecasting models and algorithms(Aguiar et al., 2016). Estimating of solar radiation information is vital before the establishment of solar systems in order to analyse and asses the capacity and potential of the solar control plant framework for viable utilization (Gürel et al., 2020).

Consequently, precise forecasting of solar irradiance is paramount for furnishing critical decision-making support to power-dispatching systems and for significantly reducing the operational costs associated with power systems(Jia et al., 2024).A principal obstacle to the accurate forecasting of solar radiation is the pervasive inadequacy in the availability and accessibility of reliable ground based solar radiation datasets(Kumar et al., 2020b). Although ground measurements provide the most precise data, their acquisition is frequently constrained by the considerable initial capital investment and the ongoing maintenance expenses associated with the requisite measuring instruments(Chave et al., 2019). This economic barrier results in a significant deficiency of comprehensive, reliable, and localized historical solar radiation and correlated meteorological datasets(Bloomfield et al., 2022). As a result, researchers are frequently forced to depend on less rigorously investigated methodologies, such as treating solar radiation as basic time-series data, which complicates the development and validation of highly accurate predictive models specifically tailored to local atmospheric variability(Gürel et al., 2020). For example, in Northwest Nigeria, the absence of measurement instruments restricts access to vital meteorological parameters, thereby obstructing effective forecasting of solar radiation(Idogho et al., 2025).

Solar radiation forecasting methodologies are broadly categorized into physical, statistical, and machine learning approaches(Methods & Trends, 2024). Physical models rely on numerical weather predictions and atmospheric physics, while statistical methods including ARIMA and its seasonal variant (SARIMA) utilize historical time series patterns(Bhatti et al., 2021), also demonstrated ARIMA(1,1,2) for daily solar radiation with reasonable accuracy, though such linear models struggle with nonlinear meteorological dynamics(Hossain et al., 2025).

The failure of ordinary time series strategies in capturing nonlinear data designs has driven to the wide utilization of neural networks for estimating non-linear systems(Jia et al., 2024), Thus, neural systems have been connected to time-series forecast. For instance, A Versatile Neuro-Fuzzy Inference Framework (ANFIS) model was created by (Kumar et al., 2020b), to predict the monthly mean solar radiation in Nigeria. Air temperature of monthly mean least temperature, maximum temperature and relative humidity were utilized as input parameters by (Owura et al., 2023) to utilized a hybrid approach which combined an ANFIS with Particle Swarm Optimization (PSO) and Wavelet Transform (WT) algorithms for solar radiation forecast in Nigeria. Results appeared that the hybrid WT-ANFIS demonstrated a superior performance over the PSO-ANFIS model by 65% RMSE and 9% R^2, Also ANN models for solar irradiance forecasting in Nigeria were also created by(Salisu et al., 2019), while the optimization approach adopted is static

A deep learning regression model built on Levenberg-Marquardt back propagation algorithm was utilized to train and test solar radiation model by(Chave et al., 2019). ANN models were created for four areas in Keras python using all the input parameters. The R-value for all the areas considered extend from 0.9046–0.9777 for solar irradiance. (Science & Analytics, n.d.) compared the forecasted result of machine learning models with that of deep learning models for both global solar radiation (GSR) and diffuse solar radiation (DSR) forecast in parts of Nigeria. Their results appeared that the application of RNN for GSR forecast in Yobe (with an R^2 value of 0.9546 and RMSE of 82.22 W/m^2) had the best performance when compared with ANN and CNN models used in their findings, with no optimization.

Also, Deep learning architectures, particularly Recurrent Neural Networks (RNN) and LSTM networks, have gained prominence for time series forecasting applications(Law, 2024). LSTM networks address the vanishing gradient problem inherent in conventional RNNs through specialized gating mechanisms (input, forget, and output gates) that regulate information flow(Ramachandran, 2024), with no optimization.

Recent studies by (Isma'il & Aliyu, 2023), have demonstrated LSTM effectiveness for solar radiation forecasting addresses the significant data deficit in solar radiation records across Northwest Nigeria by using LSTM deep learning architecture. Utilizing meteorological datasets from the Nigerian Meteorological Agency (NiMet), the study demonstrates the efficacy of recurrent neural networks in modeling daily solar fluctuations. The model exhibited predictive accuracy, yielding an R^2 of 0.79 for training and 0.78 for testing, with a Root Mean Square Error (RMSE) of approximately 0.46 to 0.47. This research underscores the potential of advanced deep learning to mitigate data scarcity in regional renewable energy planning.

Existing literature reveals that many studies employ static hyperparameter values, with no optimization, which is potentially suboptimal for specific geographic and climatic conditions. Furthermore, comparative studies often utilize different datasets across varying locations, complicating performance assessments. As a result of these, daily solar radiation information collected was utilized as a time Series information, an approach not considered in most of the literature. The main contribution of the present study is to make a comparative analysis on integrating an LSTM Deep Learning Model with both Grey Wolf Optimizer (GWO-LSTM) and Bayesian Optimizer (BO-LSTM), to dynamically improve accuracy of the proposed Models.

The rest of this paper include the following sections: brief description of study area, the methodology used for model development and techniques used for evaluating the developed model, result obtained with discussions, followed by concluding remarks on the present study.

The Study Area

The study area consists of states like, kano, kaduna and Katsina state in Northwest Nigeria. estimating land covering area of 90 388km^2,the area located between Latitudes 9^{o}01' – 13^{o}31'N, and 6^{o}00' – 9^{o}30'E as shown in figure 1 , the area is bordered by Zamfara state to the west, Abuja to the south, Bauchi to the east and Niger Republic to the north, this study area is located on the ' High plains of North Nigeria' at an altitude of 450m -745m above sea level, is also underlain by the Precambrian basement complex rocks, with climate of the area describes as Aw based on Koppen's classification characterized by alternating wet and dry seasons, the dry season is accompanied by dust laden wind from Sahara desert known as harmattan , which is as a result of Tropical continental Air mass while the wet season is influenced by Tropical maritime from the Atlantic Ocean occurring between April and May and September to October, the temperature in the area, alternates between hot and cold seasons with the occurrence of harmattan (a very cold season) between November and February, the Harmattan seasons greatly affected and reduces Solar Radiation within this areas, the average minimum and maximum temperature of the area is 21.4 $\pm$ 3.44^{o}C and 32.8 $\pm$ 3.37^{o}C respectively, the location also characterized by leached ferruginous soil developed on deeply weather Precambrian Basement rock Below represent the depicted study area.

Figure 1: The Study Area from Northwest Nigeria. Sources: Adopted from the Administrative Map of Nigeria(Isma'il & Aliyu, 2023)

MATERIALS AND METHODS

Data Used

For this study, a daily average solar radiation dataset is provided by the Nigerian Meteorological Agency (NIMET) in millijoules per square meter per day (MJ/m2/day). The Dataset comprises a univariate time series of daily solar radiation measurements covering 20 years (1994 to 2014), with a total of 43,800 temporal observations after precise quality control procedures. After cleaning, the dataset was divided using a chronological 80/20 split, allocating the first 34,963 observations (1994 - 2010) for training while the remaining 8,737 observations (2011-2024) for Testing. This temporal splitting approach preserves the sequential dependencies essential for time series prediction, while the details of the data features such as Date (Calendar dates of observation, with Datetime) and Radiation (Daily average solar Radiation MJ/m^2/day with floating values). Statistical descriptions and sample of the Dataset is as follows respectively.

Table 1: Complete Dataset Statistics from (1994 – 2014) for the 3 States. (Kano, Kaduna and Katsina)

Statistics	Value (kwh/m^2/day)	Value (MJ/m^2/day)
Count	43,800 Observations	43,800 Observations
Mean	5.07	18.24
Standard Deviation	1.58	5.67
Standard Error of the Mean	0.0075	0.0271
Minimum	0.89	3.21
5th Percentile	2.45	8.82
10th Percentile	3.12	11.23
25th Percentile(Q1)	3.86	13.89
Median (50th Percentile)	5.16	18.56
75th Percentile (Q3)	6.37	22.91
90th Percentile	7.12	25.63
95th Percentile	7.68	27.65
Maximum	8.29	29.84
Range	7.40	26.63
Inter Quartile Range (IQR)	2.51	9.02
Variance	2.49	9.02
Skewness	-0.21	-0.21
Kurtosis	-0.87	-0.87
Coefficient of Variation	31.16%	31.09%
Sum(Total hourly Energy) = Mean x Count	222,066.00 kwh/m^2/day	799,632.00 MJ/m^2/day

Table 2: Below is a Sample of the Solar Radiation Dataset

Date	Time	Radiation (MJ/m^2/day)	Radiation (kwh/m^2/day)
01/01/1994	06:00	3.21	0.89
01/01/1994	12:00	15.43	4.28
01/01/1994	18:00	8.56	2.38
02/01/1994	06:00	2.98	0.83
02/01/1994	12:00	12.87	3.58
02/01/1994	18:00	7.23	2.01
03/01/1994	06:00	3.45	0.96
03/01/1994	12:00	14.56	4.04
03/01/1994	18:00	8.12	2.26
04/01/1994	06:00	17,23	4.79

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

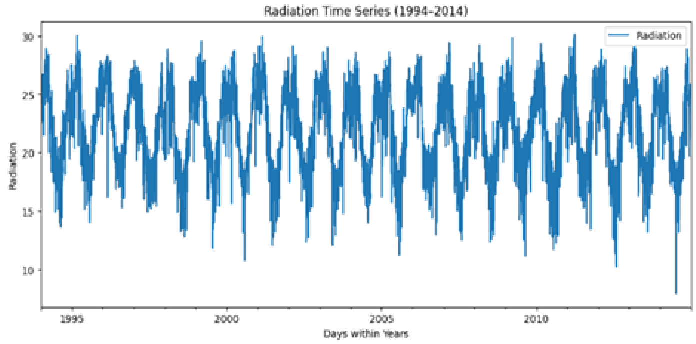

Figure 2: Daily Sunshine Radiation from 1994 – 2014 in kwh/m^2 in the Study Area

Data is pre-processed to handle missing values, outliers, and normalization of features, Although the Dataset was initially checked for missing values, no missing values were identify in the 43,800 Observations, however any potential missing values would have been handled using linear interpolation, which estimate missing values based on neighbouring data points and preserving the temporal continuity of the time series while method used in identify the Outliers is the Interquartile Range (IQR) method, where values falling below Q1 -1.5 x IQR or above Q3 +1.5 were considered outliers, no significant outlier found in the Dataset. The dataset is split into training sets 80% and testing sets 20%, with the training set used for model development and the testing set used for evaluation.

The experiments were conducted on an equipped Personal Computer with a 16-core processor AMD Ryzen 9, 64 GB DDR – 3200 RAM and 24 GB GPU NVIDIA RTX 3090.

Software environment includes Python 3.9.1 6, Scikit Optimize 0.9.0, TensorFlow 2.11.0, mealy and customize GWO implementation, every configuration evaluated during the process of optimization was limited to 100 epochs with initial stopping of 10 to balance up computational flexibility, thoroughness following similar configurations, the proposed model was retrained with 200 epochs and 10 stopping patience.

Long Short-Term Memory

An LSTM (Lond Short-Term Memory) network is designed with stacked LSTM layers to capture the temporal dependencies in solar radiation data. The output layer will be a fully connected layer that predicts the solar radiation value, moreover, According to (Hewamalage et al., 2021), 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(Rao et al., 2018). 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(Zhang et al., 2019). Compared with traditional RNN, LSTM can store long-term information. A typical LSTM unit is depicted below.

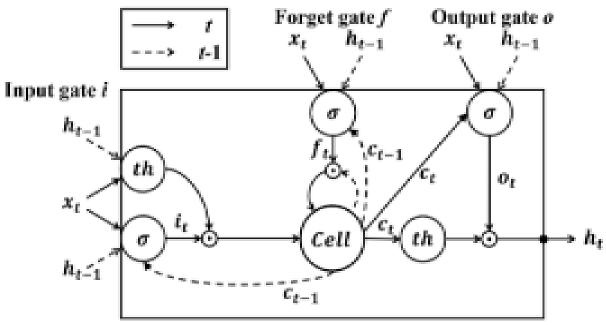

Figure 3: A long Short-Term Memory unit (Isma'il & Aliyu, 2023)

Where:

X = Daily Average Solar Radiation-(1)

X*t* is the external input vector fed into the LSTM cell at the current time step t.

h_{t-1} is the hidden state vector produced by the LSTM cell at the previous time step $t-1$.

i. ***Solid lines (⟶):*** Flow of information at the current time step t.

ii. ***Dashed lines (⇢):*** Flow of information from the previous time step $t-1$.

iii. ***Circle with crosshair (⊗):*** Element-wise multiplication.

iv. ***Circle with plus (⊕):*** Element-wise addition.

The solid arrows in the Fig 3 shows the value at the current time t, and the dash arrow indicates the values at t-1, while memory cell is writing, forgetting and outputting operations are determined by three gates, input gate i, forget gate f and output gate o, at the beginning of each time t, the unit first calculates the activation function $\{I_t, F_t\}$of the input and forgot gate and then update the memory cell from C_{t-1} to C_t, then also calculates the output gate activation function O_t , In the input gate is where the Optimizers (GWO or BO) , that is the best set of hyperparameter Values will be placed, where the final model will learn the temporal patterns in the historical dataset to predict future values, then calculates and writes a new state value based on current input x_t and the previously hidden layer output h_{t-1} so that output gate will finally calculates the hidden layer output h_t according to the current input x_t , the previous hidden layer output $h_{t-1,}$ and current state c_t of memory unit. The LSTM model was developed using the keras library based on python 3.7

The LSTM network architecture incorporates stacked LSTM layers with the following mathematical formulation [17]:

1. *Forget Gate (f_t)*

Determines what to discard from the previous cell state $\mathbf{c}_{t-1}$.

$$\mathrm{f}_t = \sigma\left(\mathrm{W}_f \mathrm{x}_t + \mathrm{U}_f \mathrm{h}_{t-1} + \mathrm{b}_f\right)$$

- Output range: [0, 1] per element.
- 0= "forget completely", 1= "keep completely"

2. Input Gate (i_t)

Decides which new information to store in the cell state.

$$\mathrm{i}_t = \sigma(\mathrm{W}_i \mathrm{x}_t + \mathrm{U}_i \mathrm{h}_{t-1} + \mathrm{b}_i)$$

3. Candidate Cell State ($\tilde{c}_t$)

Creates candidate values that could be added to the memory.

$$\tilde{\mathrm{c}}_t = \tanh(\mathrm{W}_c \mathrm{x}_t + \mathrm{U}_c \mathrm{h}_{t-1} + \mathrm{b}_c)$$

- Output range: $(-1,1)$

4. Cell State Update (c_t)

Combines forget gate, previous cell state, input gate, and candidate state:

$$\mathbf{c}_t = \underbrace{\mathbf{f}_t \otimes \mathbf{c}_{t-1}}_{\text{discard}} \oplus \underbrace{\mathbf{i}_t \otimes \tilde{\mathbf{c}}_t}_{\text{add new}}$$

- $\mathbf{f}_t \otimes \mathbf{c}_{t-1}$: removes irrelevant past memory.
- $\mathbf{i}_t \otimes \tilde{\mathbf{c}}_t$: adds selected new information.

5. Output Gate (o_t)

Controls how much of the cell state is exposed as the hidden state.

$$\mathrm{o}_t = \sigma(\mathrm{W}_o \mathrm{x}_t + \mathrm{U}_o \mathrm{h}_{t-1} + \mathrm{b}_o)$$

6. Hidden State (h_t)

Final output of the LSTM cell at time t.

$$\mathbf{h}_t = \mathbf{o}_t \otimes \tanh(\mathbf{c}_t)$$

- Passed to the next time step and used for prediction

σ *is Sigmoid activation:* $\sigma(x) = \frac{1}{1+e^{-x}}$

tanh is Hyperbolic tangent activation

W and b are weight matrices and bias vectors, respectively (subscripts denote gate-specific parameters) respectively.

Optimization Techniques

i. ***Hyperparameter Tuning Using Grey Wolf Optimization (GWO)***

GWO is applied to tune the hyperparameters of LSTM models. The hyperparameters that is optimized has included the number of layers, LSTM unit, learning rate, batch size and the number of epochs

ii. ***Bayesian Optimizer will also be applied to tune the hyperparameter of LSTM***

The hyperparameters that is optimized has included the number of layers, number LSTM units, learning rate, batch size and the number of epochs.

For equal comparison between optimization algorithms, identical hyperparameter bounds were employed, the search space was put to dimensions that significantly impact model capacity (LSTM Units), convergence behaviour which is the learning rate and gradient estimation stability, the batch size.

Table 3: Display Optimization Search Space from the Results

Metric	LSTM-GWO	LSTM-BO
LSTM Units	35	22
Learning Rate	0.00742	0.00189
Batch Size	64	49
Dropout Rate	0.22	0.30
Number of Layers	2	2
Epochs	200	200
Validation Error	0.4275	0.4300

Evaluation calls for LSTM-GWO include 10 iterations with 8 wolves = 80 iterations (though many are position updates within the pack), while LSTM-BO includes 20 iterations (20 evaluations of different hyperparameter sets). The objective functions (Validation error) is 10 epochs per evaluation, including validation error during the optimization process of 0.4275 for GWO and 0.4300 for BO, which makes GWO slightly better during training. Bayesian optimization demonstrates superior sample efficiency, achieving comparable or better results with 75% fewer evaluations.

Evaluation Metrics

In this study, we use 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 is performed on an 80% training set to 20% test data split.

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

I) The coefficient of determination or R^2 refers to a measure that provides information about the goodness of fit of a model, it takes values between 0 and 1, meaning the larger this indicator the better the performance of the model, so the bigger the R^2 value the better the estimation ability of the model, this indicator is expressed mathematically as:

$$R^2 = 1 - \frac{\sum(y_a - y_p)^2}{\sum(y_a - \overline{y_p})} (2)$$

Where:
n = number of observation
y_a= actual value
y_p= predicted value
$\overline{y_p}$= mean of predicted values

ii) Root Mean Square Error (RMSE) : This will measure the average magnitude of error between the predicted and actual values, providing an assessment of model accuracy, 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,

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

Where:
n = number of observations
$y_{i,e}$ = the i[th] estimated value
$y_{i,m}$ = the i[th] measured value

RESULTS AND DISCUSSION

In this paper, two optimized models were developed to predict daily solar radiation, the prediction performance was evaluated by predicting the daily solar radiation of 20% of the total dataset from 1994 – 2014, where both optimization techniques are used separately in Figure 3, The first result below represent the predicted values from the optimized developed model (Grey Wolf Optimizer-LSTM) versus the actual data values is as shown in Figure 4.

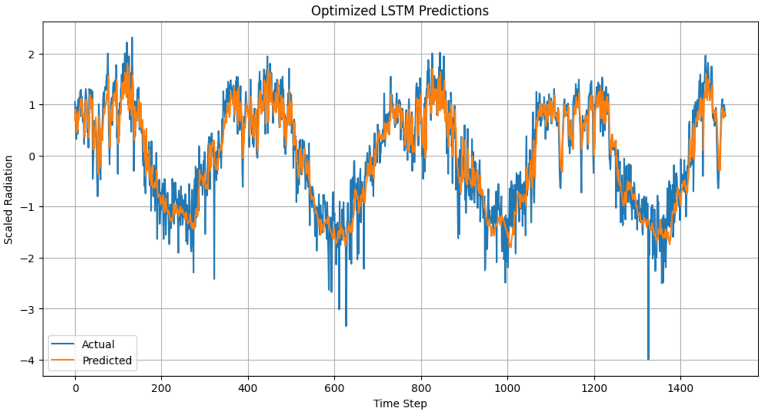

Figure 4: Grey Wolf Optimizer -LSTM Prediction Versus Actual Daily Solar Radiation

While the Second Result represent the predicted values from the optimized developed model (Bayesian optimizer-LSTM) versus the actual data values is as shown in Figure 5

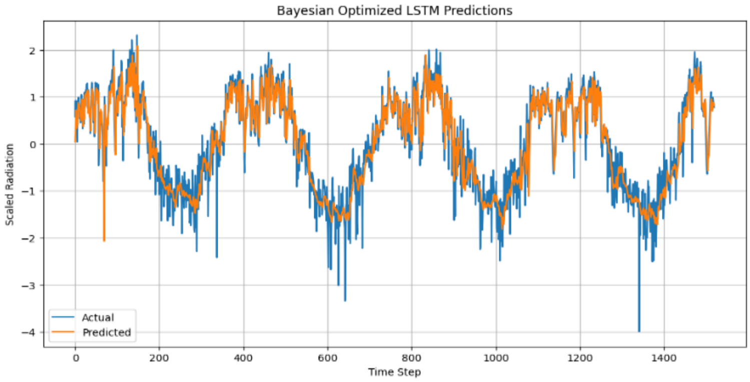

Figure 5: BO-LSTM Prediction Versus Actual Daily Solar Radiation

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 4 below summarizes the results obtained using the collected dataset.

Table 4: Performance Statistics of Prediction on the Dataset Between the Two Optimizers

Prediction Metrics	**GWO-LSTM Train set Test set**		**BO-LSTM Train set, Test set**	
R^2 Score	0.8358 /	0.8190	0.8500	0.8205
RMSE	0.4053 /	0.4340	0.3876	0.4309

Table 5, Overall Comparison performance Results Between the Two proposed Models and Baseline Model (unoptimized model)

Prediction Metrics	**GWO-LSTM Train set/ Test set**		**BASELINE LSTM Train set/ Test set**		**BO-LSTM Train set/ Test set**	
R^2 Score	0.8358 /	0.8190	**0.79**	**0.78**	0.8500 /	0.8205
RMSE	0.4053/	0.4340	**0.46**	**0.47**	0.3876 /	0.4309

The statistical significance indicates that the improvements are meaningful with GWO-LSTM: 7.7% improvement in test R^2, 7.7% reduction in RMSE and BO-LSTM: 8.1% improvement in test R^2, 8.3% reduction in RMSE.

From table 5, both proposed models outperformed the previous work, indicating integration based on the new model's evaluations and predicting accuracy. The application of GWO and BO results demonstrated that, by automating the design of a neural network, they can create accurate solar radiation prediction models that learn complex temporal patterns directly from datasets.

Comparison of results of the prediction for the Optimized LSTM models adopted in this study, base work(Isma'il & Aliyu, 2023) and other unoptimized models adopted in the literature, from the table results below, we can observe that the proposed models perform well when compared with the ANFIS was used by (Salisu et al., 2018), to predict the Global Solar radiation on a horizontal surface in Nigeria, it can also be seen from below that the prediction strength of the optimized models 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 predict irradiance and solar photovoltaic multi-parameter forecast.

Table 6: Performance Results Between Proposed Models and Unoptimized Models

Algorithm	Dataset	RMSE	R^2
GWO-LSTM	Training	0.41	0.84
	Testing	0.43	0.82
BO-LSTM	Training	0.39	0.85
	Testing	0.43	0.82
LSTM(Isma'il & Aliyu, 2023)	Training	0.46	0.79
	Testing	0.47	0.78
ANFIS (Salisu et al., 2018)	Training	0.81	0.87
	Testing	1.69	0.74
PSO-ANFIS (Salisu et al., 2019)	Training	0.68	0.91
	Testing	1.38	0.81
WT-ANFIS (Salisu et al., 2019)	Training	0.24	0.99
	Testing	0.87	0.86
ANN (Bamisile et al., 2020)	Training	0.73	0.97
	Testing	0.76	0.98

The result of this study indicate minimum error in terms of predicting accuracy (RMSE) , which showed that optimized LSTM performs better than several Alternative models, such as PSO-ANFIS, FFNN, which has been the most widely used for solar energy forecasting(Bamisile et al., 2020), also established that the deep learning models have better performance than machine learning models, and are therefore more suitable for solar radiation predictions.

Discussion

The results obtained from the study are proof that Dynamic Hyperparameter optimization significantly improves the predictive accuracy for the LSTM Models, for solar Radiation forecasting in the 3 Northwest States in Nigeria. The implication of this findings is necessary, since accurate Solar prediction is the primary driver for photovoltaic(PV) energy generation, however, variability nature of solar radiation is influenced by atmospheric conditions, cloud cover and seasonal changes, which presents significant challenges for Grid integration and Energy Management, where solar energy is substantial but ground measurement equipment is limited, accurate prediction systems or Models are important for Grid Stability and power dispatch , Energy Storage Optimization. Performance comparison with unoptimized models from table 5 (benchmark LSTM Model) and table 6 with other unoptimized models demonstrate that both GWO and BO optimized models Outperformed the models in the literature, which uses static hyperparameter values (unoptimized models). The improvement of GWO (R^2 = 5.0% improvement with RMSE = 7.7% reduction and BO (R^2 = 5.2% improvement with RMSE = 8.3% reduction) against the base work model. These improvements are significantly and practically meaningful for solar radiation prediction, The unoptimized LSTM, while exhibiting the applicability of deep learning in data scare region, left significant gains unrealized due to the use of static hyperparameters, while the optimized models automatically identified the optimal balance between the model's parameters.

CONCLUSION

Two predicting model based on Optimized Long Short-Term Memory Models were developed to predict the average solar radiation for some North western region of Nigeria, the developed models were a target for the Solar installation and for estimating the amount of energy that can harnessed. The performances of the developed models were determined using the coefficient of determination and root mean square error, these results obtained showed that the developed Optimized LSTM predicting is accurate and reliable for predicting solar radiation in North western Nigeria, but the limitations are Combining predictions from multiple optimized models (e.g., LSTM-GWO and LSTM-BO ensembles) could potentially yield better performance than any single model, as ensemble methods can reduce prediction variance and also While this study compared GWO and BO, other optimization algorithms (e.g., particle swarm optimization, genetic algorithms, Ant colony and Bat optimization Algorithms) warrant investigation for this application.

The result of this study indicate minimum error in terms of predicting accuracy (RMSE) , which showed that optimized LSTM performs better than several Alternative models, such as PSO-ANFIS, FFNN, which has been the most widely used for solar energy forecasting(Bamisile et al., 2020), also established that the deep learning models have better performance than machine learning models, and are therefore more suitable for solar radiation predictions.

Discussions of Results

The results obtained from the study are proof that Dynamic Hyperparameter optimization significantly improves the predictive accuracy for the LSTM Models, for solar Radiation forecasting in the 3 Northwest States in Nigeria. The implication of this findings is necessary, since accurate Solar

prediction is the primary driver for photovoltaic(PV) energy generation, however, variability nature of solar radiation is influenced by atmospheric conditions, cloud cover and seasonal changes, which presents significant challenges for Grid integration and Energy Management, where solar energy is substantial but ground measurement equipment is limited, accurate prediction systems or Models are important for Grid Stability and power dispatch , Energy Storage Optimization. Performance comparison with unoptimized models from table 5 (benchmark LSTM Model) and table 6 with other unoptimized models demonstrate that both GWO and BO optimized models Outperformed the models in the literature, which uses static hyperparameter values (unoptimized models). The improvement of GWO (R2 = 5.0% improvement with RMSE = 7.7% reduction and BO (R2 = 5.2% improvement with RMSE = 8.3% reduction) against the base work model. These improvements are significantly and practically meaningful for solar radiation prediction, The unoptimized LSTM, while exhibiting the applicability of deep learning in data scare region, left significant gains unrealized due to the use of static hyperparameters, while the optimized models automatically identified the optimal balance between the model's parameters.

CONCLUSION

Two predicting model based on Optimized Long Short-Term Memory Models were developed to predict the average solar radiation for some North western region of Nigeria, the developed models were a target for the Solar installation and for estimating the amount of energy that can harnessed. The performances of the developed models were determined using the coefficient of determination and root mean square error, these results obtained showed that the developed Optimized LSTM predicting is accurate and reliable for predicting solar radiation in North western Nigeria, but the limitations are Combining predictions from multiple optimized models (e.g., LSTM-GWO and LSTM-BO ensembles) could potentially yield better performance than any single model, as ensemble methods can reduce prediction variance and also While this study compared GWO and BO, other optimization algorithms (e.g., particle swarm optimization, genetic algorithms, Ant colony and Bat optimization Algorithms) warrant investigation for this application.

REFERENCES.

Aguiar, L. M., Pereira, B., Lauret, P., Díaz, F., & David, M. (2016). Combining solar irradiance measurements , satellite-derived data and a numerical weather prediction model to improve intra-day solar forecasting. 97. https://doi.org/10.1016/j.renene.2016.06.018

Ahmad, T., & Zhang, D. (2020). A critical review of comparative global historical energy consumption and future demand: The story told so far. Energy Reports, 6, 1973–1991. https://doi.org/10.1016/j.egyr.2020.07.020

Bamisile, O., Oluwasanmi, A., Obiora, S., Osei-Mensah, E., Asoronye, G., & Huang, Q. (2020). Application of deep learning for solar irradiance and solar photovoltaic multi-parameter forecast. Energy Sources, Part A: Recovery, Utilization and Environmental Effects, 00(00), 1–21. https://doi.org/10.1080/15567036.2020.1801903

Bhatti, U. A., Yan, Y., Zhou, M., Ali, S., Hussain, A., Qingsong, H. U. O., Yu, Z., & Yuan, L. (2021). Time Series Analysis and Forecasting of Air Pollution Particulate Matter (PM 2 . 5): An SARIMA and Factor Analysis Approach. https://doi.org/10.1109/ACCESS.2021.3060744

Bloomfield, H. C., Wainwright, C. M., & Mitchell, N. (2022). Characterizing the variability and meteorological drivers of wind power and solar power generation over Africa. June, 1–19. https://doi.org/10.1002/met.2093

Chave, J., Davies, S. J., Phillips, O. L., Lewis, S. L., Sist, P., Schepaschenko, D., Armston, J., Baker, T. R., Coomes, D., Disney, M., Duncanson, L., Hérault, B., Labrière, N., Meyer, V., Réjou-méchain, M., Scipal, K., & Saatchi, S. (2019). Ground Data are Essential for Biomass Remote Sensing. Surveys in Geophysics, 0123456789. https://doi.org/10.1007/s10712-019-09528-w

Chen, H., & Chang, X. (2021). Photovoltaic power prediction of LSTM model based on Pearson feature selection. Energy Reports, 7, 1047–1054. https://doi.org/10.1016/j.egyr.2021.09.167

Falcone, P. M. (2023). Sustainable Energy Policies in Developing Countries : A Review of Challenges and Opportunities.

Gielen, D., Boshell, F., Saygin, D., Bazilian, M. D., Wagner, N., & Gorini, R. (2019). The role of renewable energy in the global energy transformation. Energy Strategy Reviews, 24(June 2018), 38–50. https://doi.org/10.1016/j.esr.2019.01.006

Gürel, A. E., Ağbulut, Ü., & Biçen, Y. (2020). Assessment of machine learning, time series, response surface methodology and empirical models in prediction of global solar radiation. Journal of Cleaner Production, 122353. https://doi.org/10.1016/j.jclepro.2020.122353

Hewamalage, H., Bergmeir, C., & Bandara, K. (2021). Recurrent Neural Networks for Time Series Forecasting: Current status and future directions. International Journal of Forecasting, 37(1), 388–427. https://doi.org/10.1016/j.ijforecast.2020.06.008

Hossain, M. L., Shams, S. M. N., & Ullah, S. M. (2025). Time-series and deep learning approaches for renewable energy forecasting in Dhaka : a comparative study of ARIMA , SARIMA , and LSTM models.

Idogho, C., Owoicho, E., Joy, A., Onuhc, O., Harsito, C., & Omenkaf, K. (2025). Machine Learning - Based Solar Photovoltaic Power Forecasting for Nigerian Regions. 1922–1934. https://doi.org/10.1002/ese3.70013

Isma'il, M., & Aliyu, S. (2023). Daily Solar Radiation Forecasting for Northwest Nigeria Using Long Short-Term Memory. International Journal of Science for Global Sustainability, 9(1), 8. https://doi.org/10.57233/ijsgs.v9i1.407

Jia, K., Yang, X., & Peng, Z. (2024). Design of an integrated network order system for main distribution network considering power dispatch efficiency.

Kumar, D. S., Yagli, G. M., Kashyap, M., & Srinivasan, D. (2020a). Solar irradiance resource and forecasting : a comprehensive review. 14, 1641–1656. https://doi.org/10.1049/iet-rpg.2019.1227

Kumar, D. S., Yagli, G. M., Kashyap, M., & Srinivasan, D. (2020b). Solar irradiance resource and forecasting: a comprehensive review. IET Renewable Power Generation, 14(10), 1641–1656. https://doi.org/10.1049/iet-rpg.2019.1227

Law, K. L. E. (2024). Deep Learning Models for Time Series Forecasting : A Review. IEEE Access, 12(July), 92306–92327. https://doi.org/10.1109/ACCESS.2024.3422528

Lindberg, M. B., Markard, J., & Andersen, A. D. (2019). Policies, actors and sustainability transition pathways: A study of the EU's energy policy mix. Research Policy, 48(10), 1–15. https://doi.org/10.1016/j.respol.2018.09.003

Methods, C., & Trends, E. (2024). Solar Radiation Forecasting : A Systematic Meta-Review of. 1–27.

Olugbenga, G., Akeem, A. O., & Enitan, O. (2026). A GEOSPATIALLY-ENHANCED MACHINE LEARNING FRAMEWORK FOR SOLAR RADIATION. 10(4), 290–298.

Owura, K., Opoku, R., Boahen, S., & Yaw, G. (2023). Analysis of indoor set-point temperature of split-type ACs on thermal comfort and energy savings for office buildings in hot-humid climates. 4(October 2021), 368–376. https://doi.org/10.1016/j.enbenv.2022.02.006

Rabaia, M. K. H., Abdelkareem, M. A., Sayed, E. T., Elsaid, K., Chae, K. J., Wilberforce, T., & Olabi, A. G. (2021). Environmental impacts of solar energy systems: A review. Science of the Total Environment, 754, 141989. https://doi.org/10.1016/j.scitotenv.2020.141989

Ramachandran, K. K. (2024). THE EVOLUTION OF RECURRENT NEURAL NETWORKS IN HANDLING LONG-TERM. 1(1), 1–10.

Rao, G., Huang, W., Feng, Z., & Cong, Q. (2018). LSTM with sentence representations for document-level sentiment classification. Neurocomputing, 308, 49–57. https://doi.org/10.1016/j.neucom.2018.04.045

Salisu, S., Mustafa, M. W., & Mustapha, M. (2018). Predicting Global Solar Radiation in Nigeria Using Adaptive Neuro-Fuzzy Approach. 2. https://doi.org/10.1007/978-3-319-59427-9

Salisu, S., Mustafa, M. W., Mustapha, M., & Mohammed, O. O. (2019). Solar radiation forecasting in Nigeria based on hybrid PSO-ANFIS and WT-ANFIS approach. International Journal of Electrical and Computer Engineering, 9(5), 3916–3926. https://doi.org/10.11591/ijece.v9i5.pp3916-3926

Science, D., & Analytics, A. (n.d.). Master of Science Data Science and Advanced Analytics Effective Use of Numerical Weather Predictions for Solar Energy Forecasting.

Varganova, A. V, & Khramshin, V. R. (2022). Improving Efficiency of Electric Energy System and Grid Operating Modes : Review of Optimization Techniques. 1–16.

Yoro, K. O., & Daramola, M. O. (2020). CO2 emission sources, greenhouse gases, and the global warming effect. In Advances in Carbon Capture: Methods, Technologies and Applications. Elsevier Inc. https://doi.org/10.1016/B978-0-12-819657-1.00001-3

Zhang, B., Zhang, S., & Li, W. (2019). Bearing performance degradation assessment using long short-term memory recurrent network. Computers in Industry, 106, 14–29. https://doi.org/10.1016/j.compind.2018.12.016