DLSTM with Adam Lyrebird optimization for solar irradiance prediction using time series data

*Abstract\_* In a variety of fields including climatology, energy, and engineering, precise solar irradiance measurement is crucial. For most studies, the model outputs are the irradiance values, and the model inputs are meteorological parameters. Although there have been many recent developments in solar irradiation techniques, computation error and achieving high prediction accuracy continue to be major challenges. In this work, a novel Adam Lyrebird Optimization Algorithm\_ Deep Long ShortTerm Memory (ALOA\_DLSTM) method for solar irradiance prediction is proposed. Primarily, input time series solar irradiance data is gained from the database. Further, technical indicator extraction is carried out, where indicators, like Relative Strength Index (RSI), Simple Moving Average (SMA), Linear Regression Forecast (LRF) and Weighted Moving Average (WMA)is extracted. Then the solar irradiance prediction is carried outemploying DLSTM trained with proposed ALOA. Moreover, ALOA is introduced by integrating Adam Optimizer and the Lyrebird Optimization Algorithm (LOA).Furthermore, supremacy of proposed ALOA\_ DLSTM is investigatedconcerning Root Mean Square Error (RMSE), Mean Average Percentage Error (MAPE), MSE, and Relative Absolute Error (RAE) and is found to have gained values of 0.270, 0.138, 0.073, and 0.203.

*Keywords\_* solar irradiance, time series data, Deep Long Short-Term Memory, Adam optimizer, Lyrebird Optimization Algorithm

# Introduction

I

n the current and upcoming decades, renewable energy and green infrastructure are largely regarded as the most important elements supporting the sustainable growth of intelligent cities [1]. Climate change and environmental pollution are major concerns, and solar energy is experiencing unprecedented growth as a sustainable renewable energy source [2] [3]. A potential energy source for the world's sustainable development goals is solar energy engineering. The main factor accelerating the rise in solar power generation is photovoltaic (PV) panels [4]. Reducing the environmental impact of civilization can be achieved by converting to solar PV electricity from fossil fuels. PV modules and inverters are used in solar PV power plants to produce electricity from sunlight. PV cells, which use the photovoltaic effect to turn sunlight into electricity, make up PV modules, commonly referred to as solar panels [5]. Nevertheless, the characteristics of PV are stochastic, intermittent, and variable due to their susceptibility to environmental factors like sunlight, season, and geographic location [4]. The continual development of PV technology is necessary for the constant improvement of PV module power. As a result of the complex factors that affect solar radiation intensity, solar energy output differs from other manageable energy sources in that it exhibits high nonlinearity, strong randomness, and large intermittency [3]. Reducing resource waste and unnecessary expenses is made possible by highly accurate irradiance prediction [5].

Precise prediction of solar irradiance across various temporal scales is essential for efficient solar energy utilization and a crucial phase in the grid incorporation and supervision of solar farms. The economics of PV power generation are enhanced by accurate solar forecasting tools, and the adverse impacts of PV uncertainty on grid stability are minimized [6][7]. Three main categories of solar irradiance prediction methods are identified in the literature currently in publicationand they include statistical, Machine Learning (ML) and physical framework. The physical model describes the physical state of meteorological conditions and the dynamic movement of the atmosphere using mathematical equations, which allows one to derive the mathematical relationship among physical state and solar irradiance [8]. The purpose of statistical models is to determine mathematical relationship among historical solar irradiance and meteorological indicators by analyzing the trend of historical time-series data. Autoregressive (AR), autoregressive moving average, and autoregressive integrated moving average (ARIMA) are commonly employed statistical techniques in the prediction of solar irradiance [4]. The application of ML methods and Deep Learning (DL) in the renewable energy industry has significantly increased in the past few years. Sequence prediction problems have been effectively addressed by Recurrent Neural Networks (RNNs). As a result, compared to the preceding two approaches, there is less framework bias and less need to make assumptions about the initial model. Nevertheless, numerical issueslike vanishing gradients may give rise to long historical connections. RNNs typically use Long-Short-Term Memories (LSTMs) and Gate Recurrent Units (GRUs) to avoid this issue [9] [5].

The primepurposeof this manuscript is to build a novelDL-based solar irradiance prediction techniqueregarding hybrid optimization approaches. The input time series solar irradiance data is attained from database. Afterwards, technical indicators like RSI, WMA, SMA and LRF are extracted. Finally, solar irradiance is predicted using DLSTM, which is trained using proposed ALAO. Moreover, ALAO is formed by combining Adam optimizer and LOA.

The key influence of this paper is explicated as follows:

* ***Established ALAO\_DLSTM for solar irradiance prediction:*** A novel optimization technique called ALAO is devised for effectively training the DLSTM technique to predict solar irradiance. The proposed ALAO is introduced by combining Adam optimizer and LAO.

The arrangement for the residual sections of this paper is explicated here: section 2 analysespreceding solar irradiance prediction techniques with its challenges, section 3 elucidates ALAO\_DLSTM demonstrated in this paper, section 4 investigates experimental outcomes of the novel technique, and section 5 provides the conclusionand future researchof devisedapproach.

# Motivation

On a cloudy day, estimating the solar irradiance at ground level is a difficult and error-prone task. For the purpose of power scheduling and future solar energy production measurement, solar irradiance prediction is very helpful. Accurately predicting solar power generation has become a significant and difficult issue in present intelligent grid schemes due to rapid development of solar energy facilities in recent years. Furthermore, the current solar irradiance prediction frameworks and the difficulties they face are reviewed.

1. *Literature survey*

Yu, Y., Hu, *et al*. [4] devised Hybrid Quantum Long Short-Term Memory (QLSTM) to predict solar irradiance 1 hour in advance. This method had reduced error, better prediction, and good processing capacity. However, this method was unsafe, complex, and had a high time consumption. Girimurugan, R., *et al.* [5] developed Imputed Gate Recurrent Units (IGRU) for the prediction of solar irradiance. The IGRU was very flexible, had little computational complexity, and didn't need an extra imputation step during data pre-processing. Nevertheless, this method was not generalizable and required different imputation procedures for different datasets. Zhang, L., *et al*. [7] established Vision Transformer-E (ViT-E) for very short-term solar irradiance forecasting. The attention model ViT-E achieved a more balanced qualitative and quantitative outcome and exhibited good interpretability. However, this technique failed to utilize in real-world applications and had minimum accuracy.Thaker, J., *et al*. [10] devised Hybrid+Satellite+Numerical Weather Prediction (Hyb+SAT+NWP) for short-term solar irradiance prediction. The method was consistent and exhibited reliability and model’s predictions were precise in terms of minimalizingtotal error. However, this model did not consider the combination of additional meteorological variables likewind speed, relative humidity, and temperature, as exogenous features to improve performance. Li, Q., et *al*. [3] introduced Complete Ensemble Empirical-Wasserstein Generative Adversarial Network-Long Short-Term Memory (CEE-WGAN-LSTM) for two-channel solar irradiance forecasting. In addition to effectively reducing data complexity, the method reduced fitting error to a minimum value and predictedvariations in real irradiance data with accuracy. However, this model's performance was affected by the numerous attempts it made to choose the model parameters.

1. *Major challenges*

The majordrawbacks faced by the prevailing methods of solar irradiance are listed below,

* The performance obtained by the hybrid QLSTM in [4] was limited by the noise and errors of scheme, and attainingvaluableoutcomes required important optimization and error correction methods.
* The main challenge faced by the Vit-E in [7] was that it did not consider using RNN model in amalgamation with Transformer model for Seq2sqe techniques with dynamic image data streams as a technique to enhance prediction efficiency.
* The CEE-WGAN-LSTM in [3] had superior accuracy and faster efficacy in predicting data with minimum complexity. However, it did consider optimizing model measures to enhance applicability of the technique.
* The majority of earlier research concentrated on creating forecasting models, which are inaccurate, especially for extreme weather conditions, and utilize small datasets that provide insufficient representative training examples for Deep Neural Networks.

# Proposed ALOA\_ DLSTM for prediction of solar irradiance

This paperintroducesaninnovativemethod for the prediction of solar irradiance using a DL method. Primarily, input time series solar irradiance data is taken from database. Afterwards, technical indicator extraction is carried out, where indicators, like RSI, WMA, SMA, and LRF are extracted. Then the solar irradiance prediction is carried outemploying DLSTM with proposed ALOA. In this case, ALOA is established by incorporating Adam Optimizer and LOA. Figure 1 represents schematic structure of proposed ALOA\_ DLSTMfor the prediction of solar irradiance.

Input time series solar irradiance data

Extraction of technical indicator

Solar irradiance prediction

Deep Long Short-Term Memory(DLSTM)

Proposed Adam Lyrebird Optimization Algorithm (ALOA)

Adam Optimization

Lyrebird OptimizationAlgorithm (LOA)

Predicted output

Fig. 1. Schematic structure for the proposed ALOA\_DLSTM for the prediction of solar irradiance

1. *Data acquisition*

Continuous data collected over an extended period of time is called a time series data. The important features from a specified time series data must be refined to apply DL frameworks. Let's assume that the datasethascount of time series data samples and it is demonstrated as follows,

 (1)

In the above equation, dataset is indicated as, total number of time series data is signified as, andspecifies time-series data positioned atindex of database.

1. *Technical indicator extraction*

The technical indicators extraction phase receives input datain order to mine technical features connected to the time-series data. The efficacy of the proposed ALOA\_ DLSTM technique can be greatly and more precisely increased by mining technical indicators from the data.Several technical indicators [11], such as RSI, WMA, SMA, and LRF, that are mined from input time series data are explained below.

*Relative strength index*

This indicator uses the difference between the solar irradiance in the past and the current solar irradiance to determine the basic strength of the variation in the solar irradiance. The solar irradiance value remains at a constant percentage between 0 and 100. RSI is measured as follows,

 (2)

wherein, represents the ratio of average of solar irradiance level of -periods are high to the absolute value of the average solar irradiance level of -periods are low. Also, RSI indicator is indicated as .

*Weighted Moving Average*

WMA gives current data more weight and previous data less weight. This is achieved by multiplying every value of solar irradiance by a weighting factor. Below is the expression for WMA,

 (3)

Here,signifies the weights assigned to the corresponding time period and specifies the solar irradiance values for the corresponding time periods. Moreover, time period signified by and WMA is designated by the term .

*Simple moving average*

SMA is defined as the ratio of solar irradiance values for the corresponding time period to the total time period. The formula for computing SMA is articulatedas below;

 (4)

where, SMA indicator is specified by the term .

*Linear Regression forecast*

A statistical method called linear regression is employed to forecast future solar irradiance values based on historical solar irradiance values.It is frequently used as a measurable method to identify overextended solar irradiance and the underlying trend. The formula for measuring LRF is stated asfollows;

 (5)

Here,signifies forecast solar irradiation, indicates intercept, represents coefficient of the predictor variables . Furthermore, the prediction variation based on time of day, time of year is denoted by and LRF is signified by the term .

The total feature vector is represented as , and it is statedbeneath,

 (6)

1. *Solar irradiance prediction*

Accurately predicting solar power generation has become a significant and difficult issue in current intelligent grid schemes due to the rapid growth of solar energy plants in the last few years.An efficient and reliable DLSTM [12] model is used to predict solar irradiation in order to increase the forecasting accuracy of solar energy generation. The process has been enhanced by using the ALOA to train the DLSTM. Additionally, the DLSTM model receives the feature vector as input.

*Architecture of DLSTM*

DLSTM [12] is an advanced Recurrent Neural Network (RNN) that selectively updates its contents with the use of a memory cell and a long time to effectively learn dependencies in the input data. The issue of vanishing gradient, which typically develops during long-term Neural Network (NN) memorization is effectively addressed by the DLSTM. In addition to a memory cell, the DLSTM contains three various kinds of gates include input, output, and forget gates. The forget cell controls the information that is entered into the memory cell, whereas input gate controls flow of information into memory cell. Moreover, flow of information from memory cell is controlled by the output gate. The feature vector is considered to DLSTM model together with a value of past hidden state.The expressions for input gate and forget gateare expressed below,

 (7)

 (8)

Thereafter, cell state at previous time interval is utilized for updating present cell state as specified beneath,

 (9)

Further, the output gate operation is modeled as follows,

 (10)

The expression for corresponding outcome response is articulated as follows,

 (11)

wherein, element-wise product is designated by, sigmoid function is denoted as, signifies bias, weight matrix is specified by, feature vector is specifiedby, input gate is representedby, forget gate is denoted by, memory cell is designated by , and output gate is signified as . The output acquired from DLSTM is denoted by . The schematiclayout of DLSTM model is illustrated in figure 2.

Input



LSTM

Dropout

Dense

Dense

Output









Fig. 2. Layout of the DLSTM model

*Training of Deep LSTM*

The LOA [13] and Adam optimizer [14] are incorporated to form the ALOA algorithm. An algorithm known as the LOA [13] is a bio-inspired metaheuristic that resembles the way lyrebirds naturally behave in the wild. By leveraging its members' collective search power in the problemsolving space, LOA is able to offer appropriate solutions for optimization issues in an iteration-based procedure. Also, LOA handled real world application effectively. The Adam optimizer [14] was created to optimize probabilistic objective functions in the first order using gradients. The method is simple to use, efficient in computation, and requires little memory. Moreover, it is well suitable for a wide variety of ML non-convex optimization issues. By incorporating LAO with Adam optimizer, the proposed ALOA technique attains high prediction accuracy with minimum error. The following describes the steps in the ALOA algorithm.

*Step i) Initialization*

The population of the algorithm is consisting of LOA members, and it can be mathematically described utilizing a matrix as shown by equation (12).

 (12)

Equation (13) is used to initialize the main location of LOA members arbitrarily in the problem solvingspace.

 (13)

where, population matrix of LOA is designatedby, representscandidate solution, specifiessize in search space, amount of lyrebirds are signifiedby, amount of decision variables are denotedby, specifies random number in interval [0, 1],  and represents lower bound and upper bound of decision variable.

*Step ii) Fitness function*

The fitness function is used to find the optimum solution and also it is known as the minimization issue. Moreover, MSE represents average squared difference between original and actual values. The expression for MSE is expounded as beneath,

 (14)

Here, signifies Mean Square Error, expectedoutcome is specifiedby, overall count of data is represented by , and acquiredoutcome from DLSTM is designatedby.

*Step iii) Mathematical modeling of LOA*

The population updation technique consists of two phases include (a) hiding and (b) escaping, which is based on the lyrebird's decision in this scenario. Equation (15) is used in design of LOA to simulate lyrebird's decision-making procedure when deciding between hiding or escaping during danger. Thus, in every iteration, the location of every member of LOA is updated only concerning one of the initial or secondary phases.

 (15)

where, indicates random number in the interval [0,1].

*Step iv) Escaping strategy (phase 1)*

Every member's location relative to other population members with higher objective function values is regarded as a secure location in the LOA design. As a result, equation (16) can be used to find set of safe regions for every LOA member.

 (16)

wherein, indicates set of safe regions for  lyrebird and representsrow of matrix . It is considered in LOA design that lyrebird occasionally makes its way to one of these safeplaces. Equation (17) is utilized to determine each LOA member's new location based on the lyrebird movement modeling finalized in this stage.

 (17)

 (18)

 (19)

Applying Adam optimizer, whichenhances the efficiency of LOA, and according to Adam optimizer [14],

 (20)

Applying equation (20) in equation (19), the updated equation of ALOA is obtained as below,

 (21)

where, parameter is denoted as , states random number at range [0,1], step size is denoted as , gradient’s moving average is indicated as , squared gradient is signified as , parameter is represented as and is the randomly selected [1,2].The lyrebird's position is updated during the exploration phase using the equation mentioned above.

*Stage v) Hiding strategy (phase 2)*

Equation (22) is employed in LOA design to determine a novel location for every LOA member concerning modeling of the lyrebird's movement towards adjacent optimal region for hiding.

 (22)

where, iteration counter is designated as .

*Stage vi) Re-evaluation of fitness function*

Equation (12) is used to calculate the members' fitness after the lyrebird's location has been modified, and the lyrebird with the minimum fitness is chosen as thefinest solution.

*Step vii) Termination*

The above-mentioned procedures are repeatedly performed until maximum iteration value is attained. Pseudocode for ALOA algorithm is demonstrated in algorithm 1.

|  |  |
| --- | --- |
| Algorithm 1. Pseudocode of ALOA algorithm | |
| Start ALOA | |
| 2. | Input problem information such as objective function, constraints and variables |
| 3. | Set LOA population sizeand iterations () |
| 4. | Create initial population matrix at random employingequation (13) |
| 5. | Assess objective function |
| 6. | Regulatefinest candidate solution |
| 7. | For to |
| 8. | For to |
| 9. | Regulatecategory of lyrebird defense approach against predator attack utilizingequation (15) |
| 10. | If (select phase 1) |
| 11. | Control candidate safe zones forLOA member utilizing equation (16) |
| 12. | Computenovellocation of LOA member employing equation (21) |
| 13. | Else (select phase 2) |
| 14. | Analyze new location of LOA member by means of equation (22) |
| 15. | End if |
| 16. | End (for to ) |
| 17. | Save optimum candidate solution so far |
| 18. | End (for to ) |
| 19. | Output finest quasi-optimal solution acquired with LOA |
| End ALOA | |

Thus, ALOA algorithm introduced by combining LOA and Adam optimizer efficiently improved the convergence rate and generated the optimum weights and bias of DLSTM in minimum time, thereby improving the efficiency of DLSTM in solar irradiance prediction.

# Results and discussion

The ALOA\_DLSTM proposed in this work for predicting solar irradiance is examined for its efficacycontemplatingseveralparameters, such as MSE, RMSE, MAPE, and RAE.

1. *Experimental set-up*

The execution of ALOA\_DLSTM model for predicting solar irradiance is accomplished on a system with Python.

1. *Description about dataset*

Daily Total Solar Irradiance (TSI) averages are available in the Total Solar Irradiance–Daily Average dataset [15]. Variations in the amount of sunlight that enters the Earth's atmosphere are tracked by the TSI measurement.The predicted absolute accuracy of the Total Irradiance Monitor (TIM)'s TSI measurement is 350 ppm, or 0.035%. The Sun's output can be estimated because the relative variations in solar irradiance are quantified to be less than 10 ppm/yr (0.001%/yr).

1. *Evaluation measures*

Numerousparameters, likeRAE, MAPE, RMSE, and MSE are utilized to assess the performance of ALOA\_DLSTM technique.

***a) MSE:*** MSE factor is employed to calculate mean of the squared deviation amongpredicted and actual outcome, and it is stated in equation (12).

***b) RMSE:***RMSEmeasure is computed by taking the square root of MSE, and the expression is articulatedbeneath,

 (23)

***c) MAPE:*** MAPE is also known as Mean Absolute Percentage Deviation (MAPD) is a measure of prediction accuracy of a solar irradiation prediction model and the formula is articulatedbelow,

 (24)

***d) RAE:*** RAE is a commonparameter of precision or accuracy. RAE is defined as the ratio of average value of real errors to the average of absolute measure of expected errors.

 (25)

1. *Comparative techniques*

The ALOA\_DLSTM developed in this paper for predicting the solar irradiation is inspected for its performance by comparing it with approaches, like QLSTM [4], IGRU [5], Hyb+SAT+NWP [10], and CEE-WGAN-LSTM [3].

1. *Solar irradiance prediction*

The solar irradiation prediction-based assessment of the ALOA\_DLSTM is illustrated in Figure 3). By contemplating year as 2020, the solar irradiance prediction values attained by QLSTM is 740.3333265, IGRU is 680.3063, Hyb+SAT+NWP is 800.3603529, and CEE-WGAN-LSTM is 1044.869861. The original solar irradiance value is 1360.6126, and the proposed ALOA\_DLSTM technique attained solar irradiance value is 1133.843833, which is almost nearby the original value.

|  |
| --- |
|  |

Fig. 3. Valuation based on solar irradiance prediction

*Comparative analysis*

The ALOA\_DLSTM is estimated for its effectivenesscontemplatingseveralmetrics, namely MSE, RMSE, MAPE, and RAE, which is explicated in Figure 4. Figure 4a) depictsvaluation of ALOA\_DLSTM with respect to MSE. The ALOA\_DLSTM model figured a minimum MSE of 0.073, with delay of 5000sec. Moreover, a higher MSE of 0.357, 0.255, 0.208, and 0.147 is achieved by QLSTM, IGRU, Hyb+SAT+NWP, and CEE-WGAN-LSTM, which demonstrates the efficiency of ALOA\_DLSTM method. The investigation of ALOA\_DLSTM based on RMSE is displayed in Figure 4b). When considering 5000sec delay, the RMSE value quantified by QLSTM, IGRU, Hyb+SAT+NWP, CEE-WGAN-LSTM and ALOA\_DLSTM is 0.597, 0.505, 0.456, 0.383, and 0.270. Similarly, the examination of ALOA\_DLSTM in terms of MAPE is explicated in Figure 4c). In this case, the ALOA\_DLSTM measureslowestMAPE of 0.138 for delay of 5000sec and the prevailingapproachesattainedMAPE of 0.450 by QLSTM, 0.329 by IGRU, 0.294 by Hyb+SAT+NWP, and 0.208 by CEE-WGAN-LSTM. The analysis of ALOA\_DLSTM utilized for predicting solar irradiance by employing RAE is illustrated in Figure 4d). The RAE measured by ALOA\_DLSTM model is 0.203 and RAE calculated by conventionalmethods, such asQLSTM is 0.543, IGRU is 0.403, Hyb+SAT+NWP is 0.379, and CEE-WGAN-LSTM is 0.268for delay of 5000sec.

|  |  |
| --- | --- |
|  |  |
| **(a)** | **(b)** |
|  |  |
| **(c)** | **(d)** |

Fig. 4. Comparative examination of ALOA\_DLSTM in terms of a) MSE, b) RMSE, c) MAPE, and d) RAE

1. *Comparative discussion*

The supremacy of the ALOA\_DLSTM is evaluated with regard to variousparameters, includeRAE, MAPE, RMSE, and MSEby comparing it with conventional solar irradiance approaches, and this is illustrated in table 1. The values in table 1 are attained when delay of 5000sec is concerned. The ALOA\_DLSTM figuredlowest value of MSE at 0.073, RMSE at 0.270, MAPE at 0.138 and RAE at 0.203. The ALOA\_DLSTM achieved a superior prediction accuracy and minimum MSE due to utilization of DLSTM for solar irradiation prediction, and thus resultant in minimal loss. Moreover, enhancement in performance is realized in the devised ALOA\_DLSTM because of the usage of new ALOA method and utilization of DLSTM for solar irradiance prediction.

Table 1

Comparative discussion of ALOA\_DLSTM

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Variation | Metrics | QLSTM | IGRU | Hyb+SAT+NWP | CEE-WGAN-LSTM | Proposed ALOA\_DLSTM |
| *Delay as 5000sec* | *MSE* | 0.357 | 0.255 | 0.208 | 0.147 | 0.073 |
| *RMSE* | 0.597 | 0.505 | 0.456 | 0.383 | 0.270 |
| *MAPE* | 0.450 | 0.329 | 0.294 | 0.208 | 0.138 |
| *RAE* | 0.543 | 0.403 | 0.379 | 0.268 | 0.203 |

# Conclusion

A precise prediction of solar irradiance is required in order to increase the degree of integration of renewable energy sources into the controls of current power system. With the widespread availability of data, data driven algorithms could be utilized to improve solar generation predictions. In this manuscript, DLSTM model enhanced with ALOA algorithm is established for predicting solar irradiance efficiently with help of time series data gained from specified database. Additionally, technical indicators are excerpted, where the indicators mined are RSI, WMA, SMA and LRF. The DLSTM model predicts solar irradiance based on the indicators that were extracted. The proposed ALOA algorithm was utilized to tune the DLSTM classifier. The ALOA model incorporates the LAO technique with the Adam optimizer. The ALOA\_DLSTM model proved its superiority in solar irradiance prediction with a minimum MSE of 0.073, RMSE of 0.270, MAPE of 0.138, and RAE of 0.203. In future, the performance will be enhanced by integrating hybrid DL techniques. In addition, considering efficient features can be incorporated to further enhance the prediction accuracy. Further, incorporating data imputation methods is also worth pursuing.

# References

1. J. D. Sachs, G. Schmidt-Traub, M. Mazzucato, D. Messner, N. Nakicenovic, and J. Rockström, “Six transformations to achieve the sustainable development goals”, *Nature sustainability*, vol. 2, no. 9, pp.805-814, 2019.
2. E. Miranda, J. F. G. Fierro, G. Narváez, L. F. Giraldo, and M. Bressan, “Prediction of site-specific solar diffuse horizontal irradiance from two input variables in Colombia”, *Heliyon*, vol. 7, no.12, 2021.
3. Q. Li, D. Zhang, and K. Yan, “A Solar Irradiance Forecasting Framework Based on the CEE-WGAN-LSTM Model”, *Sensors*, vol. 23, no.5,pp.2799, 2023.
4. Y. Yu, G. Hu, C. Liu, J. Xiong, and Z. Wu, “Prediction of solar irradiance one hour ahead based on quantum long short-term memory network”, *IEEE Transactions on Quantum Engineering*, 2023.
5. R. Girimurugan, P. Selvaraju, P. Jeevanandam, M. Vadivukarassi, S. Subhashini, N. Selvam, S. K. Ahammad, S. Mayakannan, and S. K. Vaithilingam, “Application of Deep Learning to the Prediction of Solar Irradiance through Missing Data”, *International Journal of Photoenergy*, 2023.
6. S. Dunnett, A. Sorichetta, G. Taylor, and F. Eigenbrod, “Harmonised global datasets of wind and solar farm locations and power”, *Scientific data*, vol.7, no.1, pp.130, 2020.
7. L. Zhang, R. Wilson, M. Sumner, and Y. Wu, “Advanced multimodal fusion method for very short-term solar irradiance forecasting using sky images and meteorological data: A gate and transformer mechanism approach”, *Renewable Energy*, vol. 216, pp.118952, 2023.
8. Y. Hao, and C. Tian, “A novel two-stage forecasting model based on error factor and ensemble method for multi-step wind power forecasting”, *Applied energy*, vol.238, pp.368-383, 2019.
9. G. Narvaez, L. F. Giraldo, M. Bressan, and A. Pantoja, “Machine learning for site-adaptation and solar radiation forecasting”, *Renewable Energy*, vol. 167, pp.333-342, 2021.
10. J. Thaker, R. Höller, and M. Kapasi, “Short-Term Solar Irradiance Prediction with a Hybrid Ensemble Model Using EUMETSAT Satellite Images”, *Energies,* vol. 17, no.2, pp.329, 2024.
11. Technical indicators was taken from "<https://library.tradingtechnologies.com/trade/chrt-technical-indicators.html>", accessed on February 2024.
12. W. Zhu, C. Lan, J. Xing, W. Zeng, Y. Li, L. Shen, and X. Xie, “Co-occurrence feature learning for skeleton based action recognition using regularized deep LSTM networks”, *In Proceedings of the AAAI conference on artificial intelligence*, vol. 30, no. 1, March 2016.
13. M. Dehghani, G. Bektemyssova, Z. Montazeri, G. Shaikemelev, O. P. Malik, and G. Dhiman, “Lyrebird Optimization Algorithm: A New Bio-Inspired Metaheuristic Algorithm for Solving Optimization Problems”, *Biomimetics*, vol. 8, no. 6, pp.507, 2023.
14. D. P. Kingma, and J. Ba, “Adam: A method for stochastic optimization”, *arXiv preprint arXiv: 1412.6980*, 2014.
15. Total Solar Irradiance – Daily Average dataset was taken from “<https://lasp.colorado.edu/lisird/data/sorce_tsi_24hr_l3>”, accessed on February 2024.