Solar Irradiance Forecasting Based on Deep Learning for Sustainable Electrical Energy in Cameroon

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Abstract- Solar energy is indeed a promising source of clean and renewable electricity generation. It is worth noting that there has been a growing interest in the utilization of solar photovoltaic energy as a sustainable energy source. The integration of renewable energy into large-scale power grids poses challenges to grid security and stability due to the intermittent nature of power generation resulting from meteorological parameters. As a result, accurate solar irradiance forecasting is gradually becoming more crucial for system planning as a means of minimizing solar irradiance fluctuations. Increasingly more models are being taken into consideration for forecasting as artificial intelligence technologies, particularly deep learning, advance owing to their greater capacity to handle challenging nonlinear issues. Our team has developed a cutting-edge forecasting model that utilizes Long Short-Term Memory (LSTM) to accurately predict solar radiation. The accuracy of the forecast is being evaluated using meteorological parameters obtained from the city of Douala in Cameroon. Based on the experimental results presented, it appears that the LSTM model may offer superior prediction performance, as evidenced by the reported RMSE of 0.47W/m^2 and MAE of 5.2813W/m^2.

Keywords: forecasting, deep learning, Long Short-Term Memory (LSTM), solar irradiance, renewable energy.

1. Introduction

The depletion of fossil fuels and the phenomenon of global warming has prompted a surge in the utilization and advancement of Renewable Energy Sources (RES) in recent times. Renewable energy sources, namely solar, wind, hydro, and geothermal power, have been acknowledged as innovative solutions to the aforementioned issues and are indicative of the future of energy progress [1]. Solar and wind power have gained widespread popularity as alternative sources of energy, and are being increasingly adopted in numerous countries worldwide, surpassing other conventional sources. Renewable energy sources, namely solar and wind power, are increasingly being recognized as the most viable options for power generation in various settings, including residential, commercial, and industrial applications.

Nevertheless, the variability of RES remains high and is significantly influenced by geographical location and weather patterns [2]. The incorporation of RES into the pre-existing energy infrastructure is presenting a significant obstacle. The integration in question has garnered significant attention owing to its capacity to produce electrical energy. Renewable energy plants are frequently utilized in smart grids, but their integration into grid-connected sources has presented notable challenges for power grids. These challenges include issues related to system stability, reliability, power balance, reactive power compensation, and frequency response, as noted in sources [3], [4]. Therefore, it seemed that forecasting the potential of these systems would be a promising approach to address these issues.

Numerous scholars have directed their attention towards enhancing the energy output of said systems by optimizing various factors such as the number of modules, storage capacity, inverter, and controller type [5]. The appropriate planning of storage systems has the potential to enhance the functioning of electrical networks that rely on renewable energies [6]. The process of determining the appropriate dimensions is a critical aspect of designing models in such systems. The RES modeling approach encompasses not only the determination of appropriate plant sizes but also incorporates the consideration of planning these facilities in the face of fluctuating weather patterns [7]. The sporadic nature of renewable energy sources may result in a significant equilibrium challenge between the generation of electricity and the demand for power. Consequently, it is imperative to program the production systems during the planning phase to align the production process with the anticipated load profile.

The provision of dependable forecasting data from these sources enables network operators to anticipate instances of generation scarcity or surplus. The utilization of RES could be optimized through the implementation of power forecasting techniques. The accurate forecasting of solar irradiance is crucial for the effective operation, management, and control of real-time electric power systems, as it enables the prediction of photovoltaic power variability [8]. The accurate solar forecast mentioned here serves to mitigate the effects of production variability, enhance the reliability of the system, facilitate greater integration of renewable energy sources, and lower the expenses associated with maintaining auxiliary equipment [9]. The accuracy of prediction models is significantly influenced by factors such as spatial and temporal resolutions, weather variability, input parameter selection, and learning algorithms. The forecast performance is subject to the influence of the training modes.

The subject of solar forecasting is currently of great interest, and a number of methods for predicting short-term solar irradiances have been recently proposed. In a general sense, the act of predicting can be categorized into five distinct groups according to the methods used for forecasting, as outlined in the reference [10]. The five methods discussed are time series analysis, regression analysis, numerical weather prediction, image-based forecasting, and machine learning. A time series refers to a collection of observations that are recorded in chronological order. This type of data is typically analyzed using forecasting models that are categorized as either stationary or nonstationary. The Autoregressive (AR), Moving Average (MA), and Autoregressive Moving Average (ARMA) models are frequently employed for the purpose of predicting stationary trends. On the other hand, Integrated Moving Average (IMA), Autoregressive Integrated Moving Average (ARI-MA), Seasonal Autoregressive Integrated Moving Average (SARIMA), and other models are utilized for predicting non-stationary trends [11]–[13]. In [14], the use of Artificial Neural Networks (ANN) and Particle Swarm Optimisation (PSO) in a forecasting model is described. Regression analysis is a statistical technique utilized to estimate the associations between variables. It is a useful tool for describing the correlation between solar irradiance and exogenous variables, as indicated by sources [15], [16]. Numerical weather prediction (NWP) models simulate irradiance fluxes at various atmospheric levels, distinguishing between the shortwave and longwave components of the solar spectrum [17], [18]. In this study, a hidden Markov model (HMM) that has been genetic algorithm-optimized is used to create a dependable power prediction model.

The method of Image-based forecasting employs satellite cloud images and all-sky images as either a primary or supplementary data source for the purpose of predicting irradiance. The aforementioned practice has the potential to significantly enhance one's forecasting abilities by offering advance notice of incoming cloud formations with a time frame ranging from several minutes to a few hours [19], [20]. As a subdivision of artificial intelligence, the technique of machine learning has the ability to acquire knowledge from datasets and establish a nonlinear correlation between the input and output data. Currently, machine learning (ML) is widely utilized as a prevalent methodology for solar forecasting and load forecasting, as indicated by recent research [10]. Whilst ANNs and SVMs remain fundamental machine learning methods for solar irradiance prediction, numerous alternative approaches have been employed in recent times. These include k-nearest neighbors (kNN), random forest (RF), gradient-boosted regression (GBR), hidden Markov models (HMMs), fuzzy logic (FL), wavelet networks (WNN), and LSTM. The aforementioned methods have not been presented in an exhaustive manner. Numerous additional implementations of machine learning algorithms for the purpose of solar radiation forecasting can be observed in contemporary scholarly works [21].

Long Short-Term Memory (LSTM) has demonstrated efficacy as a novel machine-learning technique in the domain of solar irradiance prediction, as evidenced by prior research [22], [23]. Owing to its distinctive cellular configuration, the memory system is capable of retaining crucial attributes that are pertinent to the learning experience and enhancing overall efficacy. Consequently, the utilization of LSTM for irradiance prediction enables the acquisition of correlation over consecutive hours and the identification of long-term trends, such as seasonal patterns. Chu et al [24] introduced a new method for predicting solar irradiance that incorporates a dataset based on images and employs the LSTM model. The model under consideration has been formulated with the aim of predicting solar irradiance for a time horizon ranging from 5 to 60 minutes in advance. The present study introduces two distinct methodologies that rely on input variables provided by the LSTM model. The initial approach involves utilizing solar irradiance values from 5 minutes prior, current solar irradiance, and a central value as input parameters. The second approach incorporates various input parameters, including solar irradiance values from five minutes prior, the most recent solar irradiance reading, the central value, the variance value, the red-blue comparison method, and the three-step search method. The LSTM model that was trained using the second method exhibited superior predictive outcomes. Fuel availability and consumption are impacted by pandemic-related difficulties, demanding predictive techniques like artificial intelligence. In order to forecast future oil consumption and access in the European Union area and candidate nations, this research employs decision trees, Naive Bayes, SVM, k-NN, and Ensemble Boosted trees [25].

Justin et al. [26] introduced a modified version of the LSTM model, specifically a stacked LSTM model that incorporates Principal Component Analysis (PCA), in order to improve the accuracy of solar irradiance prediction. Data was gathered over a six-month period spanning from September 2019 to February 2020 from a weather station located in Morong, Rizal. The dataset utilized in this study comprises various meteorological variables, including humidity, ambient temperature, location altitude, station temperature, sea level pressure, wind speed, illuminance, and absolute pressure. The study conducts a comparative analysis of the efficacy of the proposed stacked LSTM model vis-à-vis other deep learning models such as Convolutional Neural Network (CNN) and Bidirectional LSTM. The model under consideration has demonstrated a high degree of accuracy, as evidenced by its Normalized Root Mean Square Error (MMSE) value of 0.953 and Mean Absolute Error (MAE) value of 41.738 W⁄m2. In their study, Yu et al. [27] utilized the LSTM model to forecast solar irradiance for a one-hour period in three distinct regions of the United States, namely Atlanta, New York, and Hawaii. The model under consideration has incorporated various input parameters, including but not limited to clear sky index, relative humidity, cloud type, dew point, solar zenith angle, temperature, precipitable water, wind speed, and wind direction. Solar data was gathered between 2013 and 2017 from the National Solar Radiation Data Base (NSRDB). According to their report, the LSTM model under consideration exhibits an RMSE that falls within the range of 45.84 W⁄m2 to 41.37 W⁄m2 across the designated locations. Chandola et al. [28] constructed a deep LSTM network to forecast solar irradiance at various time horizons (specifically, 3, 6, and 24 hours in advance) in the arid regions of India. The LSTM network is fed with historical data pertaining to Global horizontal irradiance (GHI), Diffuse Horizontal Irradiance (DHI), Direct Normal Irradiance (DNI), temperature, pressure, wind speed, relative humidity, dew point, and wind direction. The validation of the model was conducted utilizing a dataset spanning five years (2010-2014) from four distinct cities situated in the Thar desert, which was procured from the NSRB. The model that was developed has demonstrated outstanding performance, as evidenced by the MAPE values that fall within the range of 6.79% to 10.47%.

Srivastava et al [29] employed a LSTM model for the purpose of predicting solar irradiance for the following day, utilizing satellite data. The model's performance is assessed based on the remote-sensing data collected from 21 distinct locations. Among these locations, 16 are situated in mainland Europe, while the remaining 5 are located in the United States. Various atmospheric parameters such as air pressure, coverage of clouds, maximum and minimum temperature, and particular humidity, among others, are utilized as input variables. The empirical findings indicate that the LSTM model developed outperformed the other models that were taken into consideration. Furthermore, the LSTM model has exhibited superior performance compared to the persistence model, as evidenced by a mean forecast skill measurement of 52.2%.

As per the literature presented above, it has been observed that forecasts which are not precise tend to occur, and the level of accuracy is contingent upon the weather forecast. Consequently, the present study employs an LSTM-based methodology to make long-term forecasts, utilizing past weather data as input. The objective of this study was to create a solar irradiance forecasting model that could optimize the operation of small dwellings and renewable energy generators. To accomplish this, we utilized the LSTM model, which has demonstrated exceptional predictive capabilities in prior research.

The present document is structured in the following manner. The second section of the document outlines the LSTM Approach for forecasting, encompassing a comprehensive analysis of the data, the LSTM network, and its utilization in addressing the structured output forecasting problem. The study's findings are presented in Section 3, while Section 4 provides the concluding remarks.

2. LSTM-Based Temporal Feature Learning

2.1. LSTM Network

The Long Short-Term Memory (LSTM) technique is designed to retain information over extended periods by employing specialized memory units that facilitate the updating of the previous hidden state. This feature enables the comprehension of temporal associations within a prolonged sequence. The proposed recurrent neural network in 1997 was the time recurrent neural network by Hochreiter and Schmidhuber [30]. The inbuilt memory unit and gate process of Recurrent Neural Networks (RNN) effectively address the issue of gradient disappearance during training, which is commonly encountered in conventional RNNs. Figure 1 depicts the memory channel and the gate mechanism, comprising the forget gate, input gate, update gate, and output gate. According to reference [23], the architecture of LSTM can be delineated as follows:

- The output value of the forget gate is denoted by f_t is given by equation (1) while the sigmoid activation function is represented by the symbol σ.

$$f_t = \sigma \tag{1}$$

- Equation (2) denotes that i_t represents the output value of the input gate, where σ is the corresponding mathematical symbol.

$$i_t = \sigma \tag{2}$$

- Equation (3) denotes the hyperbolic tangent func tion applied to the input variable c_t, which represents the resulting output value of the update gate.

$$c_t = tanh \tag{3}$$

- Equation (4) represents the product of i_t and $\tilde{c}_t$, where c_t denotes the memory cell.

$$c_t = f_t \times c_{t-1} + i_t \times \tilde{c}_t \quad (4)$$

- The variable o_t expressed in equation (5), represents the output value of the output gate.

$$o_t = \sigma \quad (5)$$

The output vector result of the memory cell at time t, denoted as h_t is determined by equation (6). Where w_f, w_i, w_c, and w0 are the weight matrices. The variables b_f, bi, b_c, and b_o represent bias vectors commonly used in energy analysis.

$$h_t = 0_t \times tanh\,(c_t) \quad (6)$$

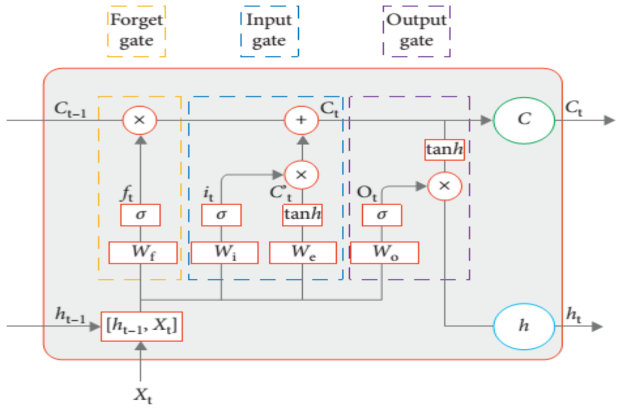

Fig. 1. Long-Term Memory Organizational Diagram.

2.2. Performances metrics

The evaluation of forecasting accuracy involves the consideration of two performance metrics, namely the Root Mean Square Error (RMSE) and the Mean Absolute Error (MAE), along with their corresponding forecast skills. The equations (7) and (8), respectively. Here, N represents the total number of observations, and I_x denotes the value of the target variable for x belonging to the set of predicted and measured values.

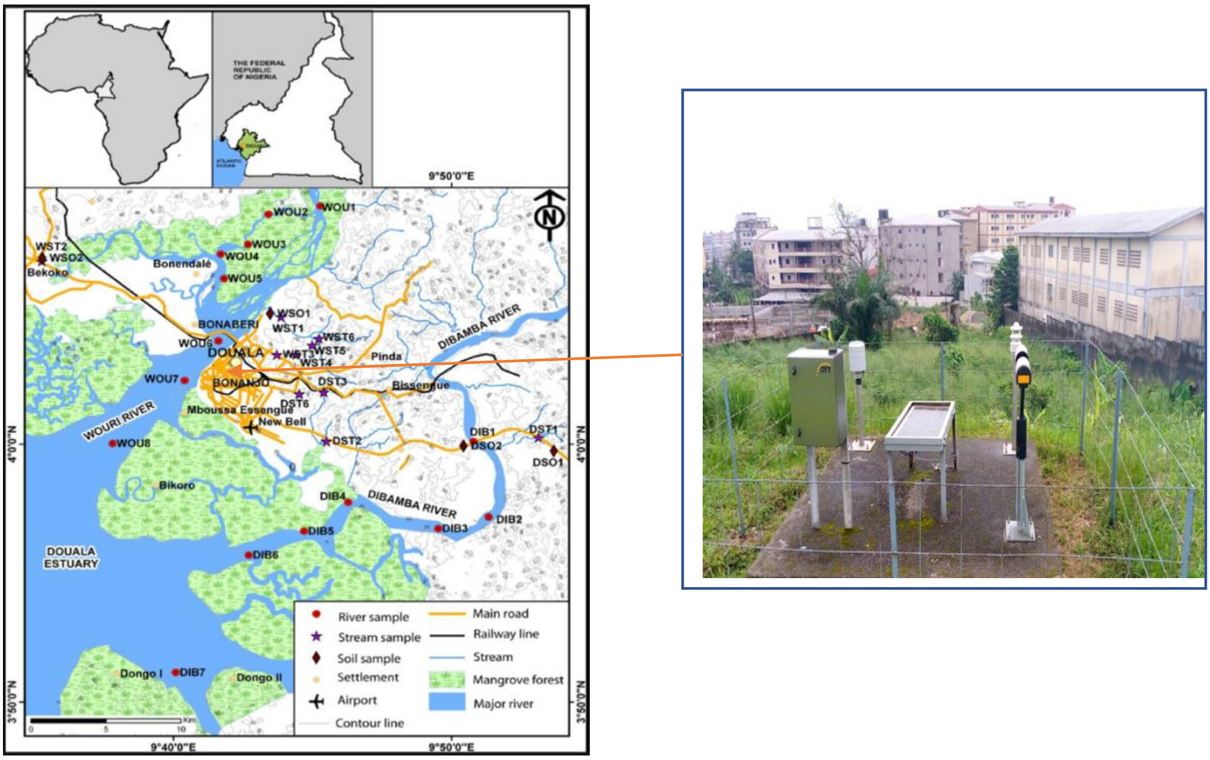

Fig. 2. Meteorological Station IUT Douala

RMSE exhibits greater sensitivity toward significant deviations that may exist between the forecasted values and the actual values. The MAE metric is deemed appropriate in cases where it is assumed that the discrepancies between actual and predicted values are directly proportional to the associated energy expenditures. The equations for calculating the Root Mean Squared Error RMSE and MAE are expressed as

$$RMSE = \frac{1}{\sqrt{N}}\sqrt{\sum_{i=1}^{N}(I_{pred,i}) - (I_{meas,i})} \quad (7)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|(I_{meas,i}) - (I_{pred,i})\right| \quad (8)$$

The RMSE is a statistical metric utilized to evaluate the performance of a model. Its value is always non-negative, where zero represents the optimal case [31], [32], [33], [34].

2.3. Study of the location and data processing

Douala's metrological station served as our study's experimental prototype at the Institute of Technology. Douala is a coastal city that is 4°3′53.77″ north of the equator and 9°41′15.41″ east of the Greenwich meridian. It is elevated 13 meters above sea level on the Wouri Stream. This meteorological station, whose readings are seen in Fig. 2, served as the data source. To better understand rainfall data and the hydrological regime of the drains in the Tongo Bassa catchment area, the Douala Institute University of Technology and the Institute for Research and Development (IRD) collaborated to set up this station. Supported by the Douala Urban Community (CUD), the French Fund for the World Environment, and the French Development Agency, the Douala Sustainable City Project is the vehicle for this effort. Solar irradiance (in W/m^2), temperature (in °C), wind speed (in m/s), humidity (in %), and Atmospheric pressure (in Pa) are all examples of such information. For the time being, we have a year's worth of information gathered every 30 minutes from January 1, 2020, to December 31, 2020. The main statistical features of solar irradiance in this data collection are shown in Table 1.

Table 1. Properties of the dataset's statistics

Samples	Statistical indicators GHI(W/m^2)			
	Number of samples	Max	mean	std
Training sample (90%)	15811	1.2952 E+03	146.7763	227.0141
Testing samples (10%)	1757	934.7000	142.6466	209.7131
All samples	17569	1.952 E+03	146.3524	225.3424

3. Results and Discussions

The computations are performed using MATLAB R2022a on a MacBook Pro equipped with a Core i5 processor clocked at 2.30Ghz and 8GB of RAM. The implementation of the LSTM model in this research was made possible by the use of the deep learning toolbox offered by MATLAB R2022a and the definition of numerous hyperparameters and methods that influence learning performance. The Adaptive Moment Estimation (ADAM) algorithm, which was built using MATLAB, served as the optimization method in this research. By adaptively adjusting the learning rate, the ADAM algorithm's use offers a beneficial method for quickly identifying the most effective solution [28]. An in-depth description of the ADAM computation procedure and mathematical framework may be found in earlier works [29]. Due to its capacity for quick computations, the ADAM algorithm was selected. There were no clear recommendations for the best settings when the learning model adjusted the hidden layer and unit weight to reduce model error. Instead, depending on the user's experience, such settings were chosen. The normalization procedure was employed to stop any data utilized for learning from being diverted. A central processing unit (CPU) was used to carry out the computation. The specified parameters for the training options models are represented by the stated values. Adam is the selected optimization method, with a maximum of 250 iterations. The initial learning rate is set to 0.01 and the gradient threshold is set to 1. The learning rate is piecewise, with a 200-day drop period and a drop factor of 0.

The temporal data flow for a certain input parameter is as follows:

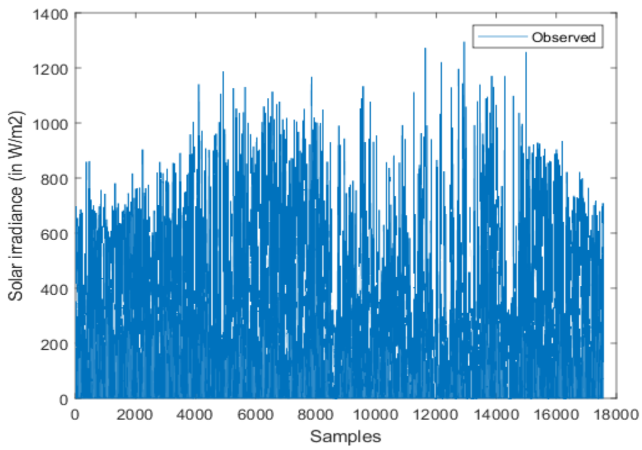

Fig. 3. Time series representation of a solar irradiance

Figure 4 displays the LSTM network's training results.

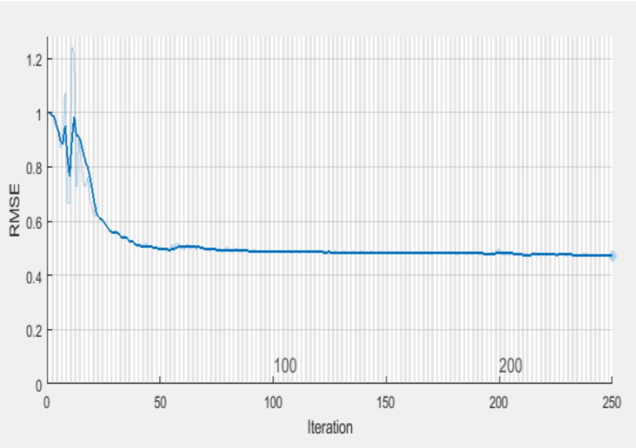

Fig. 4. Training progress of the LSTM.

The training process is stopped after 100 repetitions. Therefore, the following are the best possible outcomes for the forecast performance indicators: MAE = 5.4537W/m^2 and RMSE = 0.47W/m^2. Predicted values are shown in Fig. 5 along with the training time series.

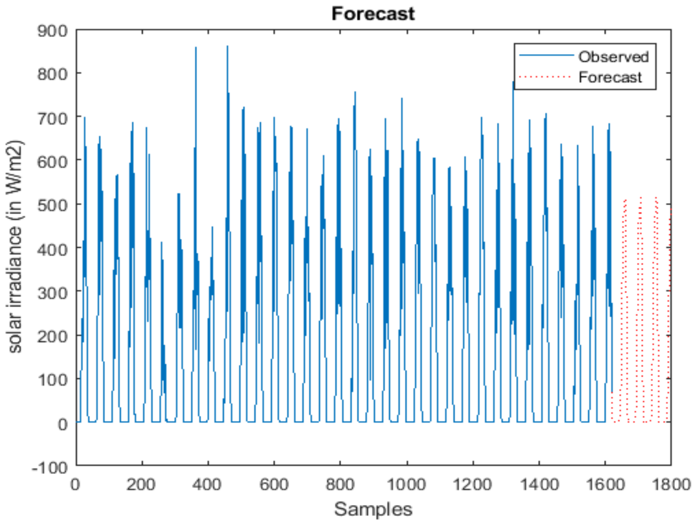

Fig. 5. Solar irradiance with forecasted values

Figure 6 displays the results of an analysis of the test data in relation to the predicted values.

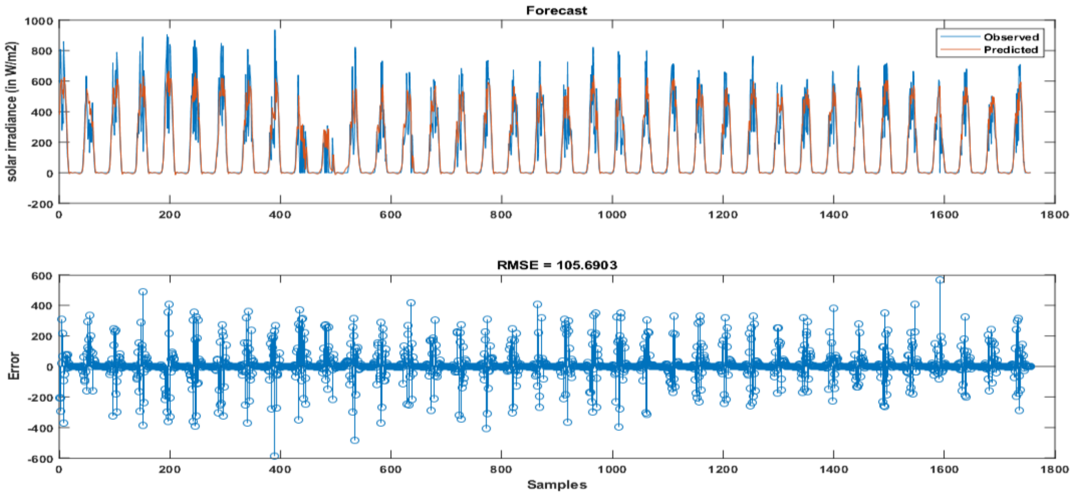

Fig. 6. Prediction of solar irradiance

The contrast between the actual and predicted values is seen in Fig. 6. Both results are close enough to one another, validating the precision of our model.

4. Conclusion

Accurate solar forecasting over extended periods is critical for maximizing the operational efficiencies of intelligent power grids. The power systems are becoming increasingly uncertain, spanning from generation to demand-side domains. Various techniques and tools have been devised to forecast solar energy production, with varying degrees of accuracy. The primary constraint of the existing methodologies is their restricted applicability to a particular time and/or location. The study proposes an LSTM-based learning model for solar irradiance prediction. The utilized model incorporates past GHI data as a feature input. Based on the analysis conducted, the investigated models for the given location exhibit feasibility and adaptability with an RMSE of 0.47W/m^2 and MAE of 5.2813W/m^2. The LSTM's significant discovery is its ability to establish a straightforward and comprehensible input-output mapping correlation within the predictive model.

Credit authorship contribution statement

Reagan Jean Jacques Molu: Conception and design of study, Data acquisition, Analysis, and interpretation of data, Drafting the manuscript, Programming. **Wulfran Fendzi Mbasso**: Data acquisition, Analysis, Drafting the manuscript. **Serge Raoul Dzonde Naoussi**: Methodology, Reviewing the manuscript, Approval of the version of the manuscript to be published. **Patrice Wıra**: Methodology, Reviewing the manuscript, Approval of the version of the manuscript to be published. **Saatong Kenfack Tsobze**: Methodology, Reviewing the manuscript, Approval of the version of the manuscript to be published.

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Declaration of competing interest

The authors declare that they have no competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

References

[1] Oymak, Aysenur, and Mehmet Rida Tur. "A Short Review on the Optimization Methods Using for Distributed Generation Planning." International Journal of Smart Grid-ijSmartGrid 6, no. 3 (2022): 54-64.

[2] J. Wang, H. Zhong, X. Lai, Q. Xia, Y. Wang, and C. Kang, “Exploring Key Weather Factors From Analytical Modeling Toward Improved Solar Power Forecasting,” IEEE Trans. Smart Grid, vol. 10, no. 2, pp. 1417–1427, Mar. 2019, doi: 10.1109/TSG.2017.2766022.

[3] C. Wan, J. Zhao, Y. Song, Z. Xu, J. Lin, and Z. Hu, “Photovoltaic and solar power forecasting for smart grid energy management,” CSEE Journal of Power and Energy Systems, vol. 1, no. 4, pp. 38–46, Dec. 2015, doi: 10.17775/CSEEJPES.2015.00046.

[4] S. Koohi-Kamali, N. A. Rahim, H. Mokhlis, and V. V. Tyagi, “Photovoltaic electricity generator dynamic modeling methods for smart grid applications: A review,” Renewable and Sustainable Energy Reviews, vol. 57, no. C, pp. 131–172, 2016.

[5] S. Koohi-Kamali, N. Abd Rahim, and H. Mokhlis, “Smart power management algorithm in microgrid consisting of photovoltaic, diesel, and battery storage plants considering variations in sunlight, temperature, and load,” Energy Conversion and Management, vol. 84, pp. 562–582, Aug. 2014, doi: 10.1016/j.enconman.2014.04.072.

[6] S. Ferlito, G. Adinolfi, and G. Graditi, “Comparative analysis of data-driven methods online and offline trained to the forecasting of grid-connected photovoltaic plant production,” Applied Energy, vol. 205, pp. 116–129, Nov. 2017, doi: 10.1016/j.apenergy.2017.07.124.

[7] G. Graditi, S. Ferlito, G. Adinolfi, G. Tina, and C. Ventura, “Energy yield estimation of thin-film photovoltaic plants by using physical approach and artificial neural networks,” Solar Energy, vol. 130, pp. 232–243, Jun. 2016, doi: 10.1016/j.solener.2016.02.022.

[8] I. Majumder, P. K. Dash, and R. Bisoi, “Variational mode decomposition based low rank robust kernel extreme learning machine for solar irradiation forecasting,” Energy Conversion and Management, vol. 171, pp. 787–806, Sep. 2018, doi: 10.1016/j.enconman.2018.06.021.

[9] M. G. De Giorgi, P. Congedo, and M. Malvoni, “Photovoltaic power forecasting using statistical methods: Impact of weather data,” Science, Measurement & Technology, IET, vol. 8, pp. 90–97, May 2014, doi: 10.1049/iet-smt.2013.0135.

[10] D. Yang, J. Kleissl, C. Gueymard, H. Pedro, and C. Coimbra, “History and trends in solar irradiance and PV power forecasting: A preliminary assessment and review using text mining,” Solar Energy, vol. 168, Feb. 2018, doi: 10.1016/j.solener.2017.11.023.

[11] W. Ji and C. Chan, “Prediction of hourly solar radiation using a novel hybrid model of ARMA and TDNN,” Solar Energy - SOLAR ENERG, vol. 85, pp. 808–817, May 2011, doi: 10.1016/j.solener.2011.01.013.

[12] C. Voyant, M. Muselli, C. Paoli, and M. L. Nivet, “Numerical Weather Prediction (NWP) and hybrid ARMA/ANN model to predict global radiation,” Energy, vol. 39, no. 1, pp. 341–355, Mar. 2012, doi: 10.1016/j.energy.2012.01.006.

[13] J. Hassan, “ARIMA and regression models for prediction of daily and monthly clearness index,” Renewable Energy, vol. 68, pp. 421–427, Aug. 2014, doi: 10.1016/j.renene.2014.02.016.

[14] Dahlan, Nofri Yenita, Syafiq Zamri, Muhammad Ikram Ahmad Zaidi, Azlin Mohd Azmi, and Ramlan Zailani. "Forecasting Generation of 50MW Gambang Large Scale Solar Photovoltaic Plant Using ANN-PSO." International Journal of Renewable Energy Research (IJRER) 12, no. 1 (2022): 10-18.

[15] Z. Dong, D. Yang, T. Reindl, and W. Walsh, “A novel hybrid approach based on self-organizing maps, support vector regression and particle swarm optimization to forecast solar irradiance,” Energy, vol. 82, pp. 570–577, Mar. 2015, doi: 10.1016/j.energy.2015.01.066.

[16] H. Jiang, Y. Dong, and L. Xiao, “A multi-stage intelligent approach based on an ensemble of two-way interaction model for forecasting the global horizontal radiation of India,” Energy Conversion and Management, vol. 137, pp. 142–154, Apr. 2017, doi: 10.1016/j.enconman.2017.01.040.

[17] H. Verbois, W. Walsh, and R. Huva, “Solar irradiance forecasting in the tropics using numerical weather prediction and statistical learning,” Solar Energy, vol. 162, Mar. 2018, doi: 10.1016/j.solener.2018.01.007.

[18] R. Perez et al., “Comparison of numerical weather prediction solar irradiance forecasts in the US, Canada

and Europe," Solar Energy, vol. 94, pp. 305–326, Aug. 2013, doi: 10.1016/j.solener.2013.05.005.

[19] J. Kamadinata, T. Lit Ken, and T. Suwa, "Sky Image-Based Solar Irradiance Prediction Methodologies Using Artificial Neural Networks," Renewable Energy, vol. 134, Nov. 2018, doi: 10.1016/j.renene.2018.11.056.

[20] Y. Chu, H. T. C. Pedro, M. Li, and C. F. M. Coimbra, "Real-time forecasting of solar irradiance ramps with smart image processing," Solar Energy, vol. 114, pp. 91–104, Apr. 2015, doi: 10.1016/j.solener.2015.01.024.

[21] C. Voyant et al., "Machine Learning methods for solar radiation forecasting: a review," Renewable Energy, vol. 105, Jan. 2017, doi: 10.1016/j.renene.2016.12.095.

[22] P. Huang, W. Chao, L. Fu, Q. Peng, and Y. Tang, "A deep learning approach for multi-attribute data: A study of train delay prediction in railway systems," Information Sciences, vol. 516, pp. 234–253, Dec. 2019, doi: 10.1016/j.ins.2019.12.053.

[23] M. Madondo and T. Gibbons, "Learning and Modeling Chaos Using LSTM Recurrent Neural Networks".

[24] Bakiri, Hussein, Hellen Maziku, K. Nerey Mvungi, Ndyetabura Hamisi, and Massawe Libe. "A novel load forecasting model for automatic fault clearance in secondary distribution electric power grid using an extended-multivariate nonlinear regression." International Journal of Smart Grid 5, no. 2 (2021).

[25] G. Harman, "Destek Vektör Makineleri ve Naive Bayes Sınıflandırma Algoritmalarını Kullanarak Diabetes Mellitus Tahmini," European Journal of Science and Technology, Dec. 2021, doi: 10.31590/ejosat.1041186.

[26] H. Calinao, E. Sybingco, R. Concepcion II, E. Dadios, J. De Guia, and J. Alejandrino, Using Stacked Long Short Term Memory with Principal Component Analysis for Short Term Prediction of Solar Irradiance based on Weather Patterns. 2020. doi: 10.1109/TENCON50793.2020.9293719.

[27] Y. Yu, J. Cao, and J. Zhu, "An LSTM Short-Term Solar Irradiance Forecasting under Complicated Weather Conditions," IEEE Access, vol. 7, pp. 1–1, Oct. 2019, doi: 10.1109/ACCESS.2019.2946057.

[28] D. Chandola, H. Gupta, V. Tikkiwal, and M. Bohra, "Multi-step ahead forecasting of global solar radiation for arid zones using deep learning," Procedia Computer Science, vol. 167, pp. 626–635, Jan. 2020, doi: 10.1016/j.procs.2020.03.329.

[29] S. Srivastava and S. Lessmann, "A comparative study of LSTM neural networks in forecasting day-ahead global horizontal irradiance with satellite data," Solar Energy, vol. 162, Feb. 2018, doi: 10.1016/j.solener.2018.01.005.

[30] S. Hochreiter and J. Schmidhuber, "Long Short-term Memory," Neural computation, vol. 9, pp. 1735–80, Dec. 1997, doi: 10.1162/neco.1997.9.8.1735.

[31] H. Khorasanizadeh and K. Mohammadi, "Prediction of daily global solar radiation by day of the year in four cities located in the sunny regions of Iran," Energy Conversion and Management, vol. 76, pp. 385–392, Dec. 2013, doi: 10.1016/j.enconman.2013.07.073.

[32] G. Hassan, E. Youssef, M. Ali, Z. Mohamed, and A. Hanafy, "Evaluation of different sunshine-based models for predicting global solar radiation – case study: New Borg El-Arab city, Egypt," Therm sci, vol. 22, no. 2, pp. 979–992, 2018, doi: 10.2298/TSCI160803085H.

[33] Dukkipati, Sudha, V. Sankar, and P. Srinivasa Varma. "Forecasting of solar irradiance using probability distributions for a PV system: a case study." International Journal of Renewable Energy Research (IJRER) 9, no. 2 (2019): 741-748.

[34] Pani, Alok Kumar, and Niranjan Nayak. "Forecasting solar irradiance with weather classification and chaotic gravitational search algorithm based wavelet kernel extreme learning machine." International Journal of Renewable Energy Research (IJRER) 9, no. 4 (2019): 1650-1659.