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High-Accuracy Solar Energy Forecasting Using Hybrid AI Models: Optimizing Performance in Thermal and Mechanical Conversion Systems

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ABSTRACT: Accurate forecasting of solar photovoltaic (PV) energy generation remains a challenging task due to the strong variability and nonlinear influence of meteorological conditions, which directly affects the reliability of energy management systems. This paper proposed the comparative framework of models for highly accurate forecasting of solar photovoltaic (PV) energy generation, utilizing state-of-the-art machine learning (ML) and deep learning (DL) approaches to substantially boost forecasting reliability under varying environmental conditions. All five models, Multi-Layer Perceptron (MLP), Extreme Gradient Boosting (XGBoost), Long Short-Term Memory (LSTM) and families of models, gated recurrent unit (GRU) and bidirectional LSTM (BiLSTM) have been implemented and tested using realistic meteorological data and irradiance data directly retrieved from the GRIDouble project, supported in I-NERGY from the HORIZON 2020 program of the European Union. More specifically, the dataset consisted of hourly measurements of such variables as air temperature, cloud opacity, diffuse and direct irradiance, and global horizontal irradiance, coupled with solar energy production reading. To maximize the learning power of time-patterned data and to minimize its variance, a comprehensive pre-processing pipeline was implemented that included temporal features extraction, cyclical encoding, as well as min–max normalization. Experiments confirmed that XGBoost yielded the highest forecasting performance with $R^2 = 0.9478$, MSE = 3191.15, RMSE = 56.49, MSRE = 27.59. The remaining models, bidirectional LSTM and MLP, demonstrated $R^2 = 0.8662$ and $R^2 = 0.8581$, respectively, highlighting their substantial ability to model the temporal and nonlinear environment. In summary, XGBoost can be praised as the top model with the achieved the best performance in this experimental setting. It also presents incredible potential for smart-grid optimization and renewable energy forecasting.

Keywords: Solar Energy Forecasting, Photovoltaic Power Prediction, Deep Learning, Time Series Prediction, Renewable Energy Optimization, Smart Grid Management

1. INTRODUCTION

Due to the increasing demand for sustainable sources of energy, renewable energy generation has become an essential part of the modern power system [1]. Solar energy is one of the most promising of all renewable resources due to its abundance, sustainability, and decreasing installation costs. Photovoltaic systems are increasingly integrated into national power systems to satisfy electricity demand with reduced greenhouse gas emissions [2,3].

However, the variable and intermittent behavior of solar radiation, which is significantly affected by meteorological variables such as temperature, cloud opaqueness, and incident irradiance, makes the power system challenging to run safely and efficiently. Short-term solar energy forecasting is crucial for addressing these issues [4,5]. Reliable forecasts enable energy service providers to optimize generation scheduling, reduce dependency on backup power sources, and enhance overall grid stability.

Accurate short-term solar energy forecasts allow energy service providers to organize their electricity generation plans, limit their reliance on backup sources, and improve national power system performance. Traditional methods, such

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as linear regression or autoregressive models, are ineffective in capturing nonlinear and temporal dependent relationships [6]. As a result, their forecasting accuracy often deteriorates under highly dynamic weather conditions.

To overcome these limitations, developing ML- and DL-based forecasting methods has become popular for automatically learning complex patterns and long-term dependencies from multi-variate time-series data. Therefore, advanced ML and DL models, such as MLP, XGBoost, LSTM, GRU, and Bi-LSTM, can have an adequate solution for solar power generation forecasting. While MLP is capable of identifying nonlinear interactions between features, XGBoost can effectively determine feature relevance with structured data, and recurrent networks like LSTM and GRU are suitable for modeling temporal dependencies and long-range correlations. The combination of these methods will provide full-space modeling for the spatial and temporal aspects of solar power generation.

Implementation of a detailed preprocessing pipeline that includes temporal feature extraction, cyclical encoding, and generation of lag and rolling statistical features to enhance model learning and temporal awareness.

Development of a hybrid regression system that integrates both ML (MLP, XGBoost) and DL (LSTM, GRU, Bi-LSTM) models for comparative and analysis.

Comprehensive assessment of model accuracy using multiple metrics (MSE, MAE, R^2) and visual analysis through residual plots, correlation heatmaps, and feature importance graphs.

The paper is organized as follows: in Section 2, we provide the related work on ML and DL for solar forecasting. Section 3 outlines the dataset and its preprocessing and explain the models we proposed:, followed by experimentation and results in Section 4. The paper concludes with findings and possible future work in Section 5.

2. RELATED WORKS

Recently, highly accurate forecasting of PV power production has become vital to securing energy grid stability and optimal integration of renewable sources. Earlier projects have mainly utilized statistical predictive models heavily based on historical production data observations [7,8]. These models are more computationally efficient and ineffective at identifying the nonlinear relationships between various meteorological factors, irradiance, and the amount of energy produced by PV systems. Accordingly, scientists have used physical models, which integrate environmental factors, solar-ray weather data, and PV module signatures to increase prediction accuracy by learning the historical patterns of how these factors contribute to energy production [9]. Although physical models offer better interpretation of the significance of each factor involved in predicting the irradiance level, they do not guarantee high forecast precision due to issues of cloud cover, air mass movement rate, and aerosol factors that cause irradiance variation [10].

Thus, recent projects have harnessed the power of data-driven methodologies, such as ML and DL methodologies, in crafting business and projects forecasts due to their power to learn complex patterns from a dataset and since they do not have to learn the physics of irradiance variation with irradiance. In the early implementation of ML, M, and DL predictions to forecast energy production, researchers proposed SVMs, ANNs, and fuzzy logic systems [11,12]. However, it was demonstrated that all of these models could not effectively adapt to the vulnerability of power production from PV to varying weather conditions. Even with hybrid forecasting models, which combine optimization algorithms with the classic ML models to increase forecast precision, the performance of such models was not enough. For example, [13] employed Grey Wolf Optimization–General Regression Neural Network model since the GWO–GRNN model structure improves both computational efficiency and predictability of the model utilized. Similarly, [14] integrates DL forecasting alongside optimization techniques from swarm intelligence in creating a multi variable hybrid PV forecast due to increased maturity manifested over several seasons.

Ensemble learning models, such as Random Forest (RF), Extra Trees, and Extreme Gradient Boosting have recently evidenced their effectiveness due to the superior variability reduction power and the capability of multiple weak learners of enhancing prediction accuracy in comparison with a single robust learner. Several works confirm the high performance of ensemble frameworks in short-term PV forecasting, given the nonlinear dependencies between local irradiance and temperature and cloud opacity. A few results also confirm the high practical utility of boosting-based frameworks in comparison with traditional regression and SVM methods, owing to their high ability to learn high-order feature interactions [15-18]. However, these works indicate that ensemble approaches are disadvantaged by their static perception of temporal dependencies and fail to model sequential data patterns.

DL architectures, particularly Recurrent Neural Networks, and their “gated” type, which LSTMs belong to, allow modeling the complex temporal dependencies involved in PV generation. LSTMs solved the “vanishing gradient” challenge encountered by traditional RNNs, achieving notable success in both short-term and day-ahead forecasting. This work [19] validated that LSTM always outperforms feed-forward frameworks in long-term PV prediction using a multi-year dataset. Other work used deep RNNs with LSTM units to achieve 92% accuracy on ultrashort- and short-term prediction intervals. This paper [20] paper verified that LSTM surpasses classic ANNs and SVMs across all assessed short-term horizons. The recent works demonstrated that incorporating the Bi-LSTM and GRU network is fairly recent, it does qualify as a subsequent contribution [21,22].

However, their practicality is limited by the high computational cost and low performance in case of limited or noisy data due to their instinct to overfit. To mitigate these problems, several studies utilized hybrid ML–DL frameworks that aimed to combine the nonlinear feature learning offered by deep networks with the ensemble learners’ robustness and interpretability. For instance, [23,24] indicated that the R^2 performance is better where an XGBoost model is added to a neural network, as opposed to being employed as the only tool, which affirmed the value of structured feature learning combined with sequential modeling. Additionally, [25] tested deep feedforward and RNN models on PV data that explicitly depended on weather patterns. They discovered a vast improvement in one-day-ahead prediction results in comparison with the traditional ML approaches.

3. RESEARCH METHODOLOGY

The expected approach is to explore a novel solar energy production prediction framework, capable of ensuring high forecasting accuracy and comprising feature-rich preprocessing and a hybrid ML with DL regression ensemble. As illustrated in Fig. 1, the proposed method targets the dependencies between the production time intervals, meteorological data, and irradiance and the prediction of the PV power output based on this historical data domain. The whole workflow may be generally divided into five key stages, including: Data acquisition and preprocessing. Temporal, and domain feature engineering. Feature scaling and sequence generation. Regression engineering using a set of architectures. Visual validation and analytics.

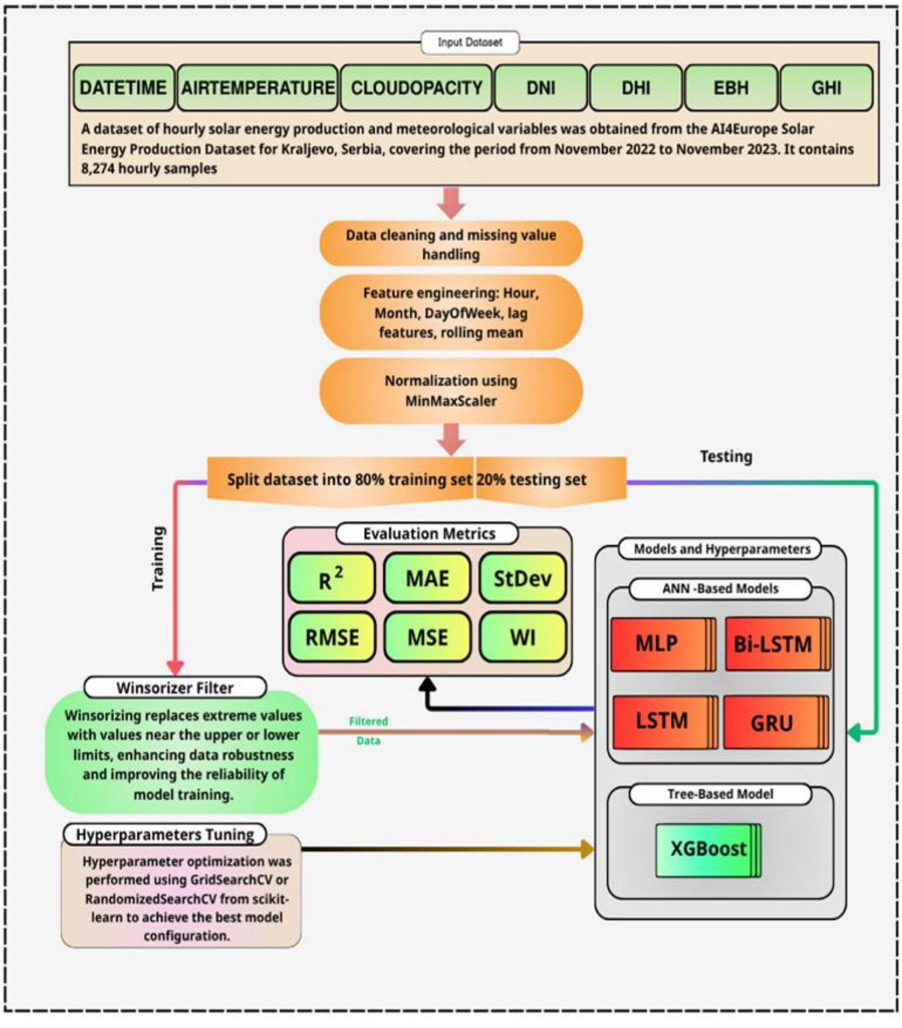

FIGURE 1 **proposed model**

3.1 DATASET DESCRIPTION

The dataset employed in this paper was obtained from the GRIDouble project within the European Union Horizon 2020 I-NERGY programme [26]. The dataset comprises hourly observations of essential meteorological and solar energy parameters gathered from numerous PV sites, comprising three locations and the Kraljevo station. Some of the environmental parameters comprised are follows: Air Temperature, Cloud Opacity, Diffuse Horizontal Irradiance, Direct Normal Irradiance, Extraterrestrial Horizontal Irradiance, and Global Horizontal Irradiance. In addition to this, the dataset includes hourly solar energy generation per location defined from the output of PV panels under varied weather conditions. Irradiance variables are treated as independent exogenous predictors measured prior to PV output, ensuring no information leakage. The combination of the meteorological and production parameters results in a rich multivariate time collection involving both spatial and temporal variations, rendering the dataset perfect for training and benchmarking MLP and DL models, such as XGBoost, LSTM, GRU, and Bi-LSTM.

3.2 DATA PREPROCESSING

To ensure data consistency and prepare it for temporal learning, some pre-processing steps were implemented:

3.2.1 DATETIME PARSING AND CLEANING

In order to facilitate concordance and sequencing, the Datetime column was transformed into the standardized datetime64 format. In addition, duplicate or deleterious timestamps have been labeled accordingly to eliminate them. This action guaranteed the even alignment of each observation in terms of time and resulted in a reliable basis for further studies because our sequenced model would be properly trained at the same time.

3.2.2 TEMPORAL FEATURE EXTRACTION

Temporal features such as hour, day, month, day of week, and the factor of being a day off during the week when appropriate were then extracted from the Datetime field. A cycle transformation of the hour and month components was conducted to encompass circulating patterns. The sine and cosine functions were utilized for the hour, whereas a circular transformation is not necessary for days or months.

3.2.3 LAG AND ROLLING FEATURES

Lag variables at 1-, 2-, 3-, 6-, 12-, and 24-hour intervals were generated to capture past dependencies in production patterns. Rolling mean features with 6-hour and 12-hour windows were calculated to smooth noise and emphasize local temporal trends, helping models learn gradual shifts in solar power output.

3.2.4 FEATURE SCALING

To standardize variable magnitudes, all input and target features were normalized to the [0,1] range using the Min–Max scaling technique. Chronological integrity was preserved via dividing the dataset into 80% training and 20% testing parts, ensuring realistic forecasting evaluation and preventing temporal information leakage during model training.

3.3 REGRESSION MODELS

To exploit both statistical and sequential dependencies, five regression approaches were implemented and compared:

3.3.1 MULTI-LAYER PERCEPTRON

The first DL regression model, the MLP, is used as the baseline model in this study to predict solar energy production based on irradiance, meteorological and temporal features. The MLP is implemented as a feed-forward neural network and consists of three dense layers with 128, 64, and 1 neurons. The Rectified Linear Unit activation function is applied to hidden layers for adding nonlinearity and preventing vanishing gradients. The dropout rate of 0.15 is applied to the hidden layers to increase stability and generalization. The nonlinearity in the MLP allows the model to learn the complex mapping of non-linear relationships between predictors and output energy values while minimizing the Mean-Squared Error loss and optimizing model parameters using the Adam optimizer that adaptively adjusts learning weights using the first and second moments. Given the flexibility of learning complex relationships between environmental conditions and PV output, the MLP can efficiently represent the nonlinear behavior of the solar power forecasting problem, which often involves complex dynamics and inter-correlations. MLP architecture is presented in Fig. 2.

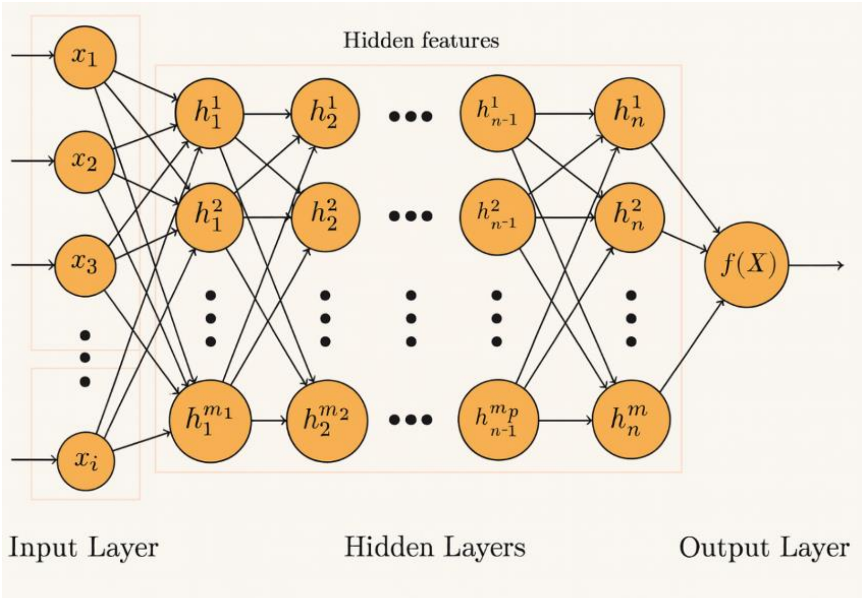

FIGURE 2 MLP architecture

3.3.2 XGBOOST REGRESSOR

XGBoost is a powerful ensemble learning algorithm that trains several decision trees in sequence. The algorithm constructs two trees in sequence. Each tree corrects the mistake of its immediate precursor. The model uses a regularized objective. It balances model performance with respect to modeling accuracy and robustness. The method draws first and second order gradient statistics based on gradient and hessian around the optimal split point. The approach efficiently approximates the loss function. The technique uses error minimization with MSE loss on prediction residuals to "shrink" tree weights. The technique uses gradient boosted second order trees that output the observation residuals. The iteration adds a new weak learner to the model, and it estimates the new residual. The XGBoost uses regularizations to control model sparsity through LASSO and Ridge condition such as and that penalizes overly complicated trees. The hyperparameters for XGBoost used in this study included 600 estimators, 0.03 learning rate, and 6 maximum tree depth. The method aggregates the weighted outputs of all trees and generates smooth and stable solar power forecasts. The machine learns data-driven methods that model non-linear relationships between irradiance levels, temperature, and weather-related variables, making the technique computationally efficient and interpretable. The Fig. 3 shows XG-boost design, while the Table 1. shows the hyperparameter used in XGBoost.

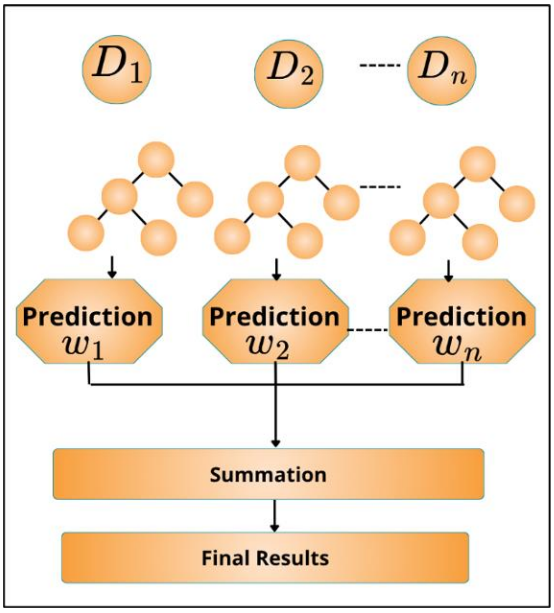

FIGURE 3 XGBoost Design

To achieve optimal forecasting accuracy while avoiding overfitting, the following tuned parameters were utilized:

Table 1 shows XGBoost parameters Used

Parameter	Description	Value
n-estimators	Number of boosting iterations	600
learning_rate	Shrinkage factor controlling update step size	0.03
max_depth	Maximum depth of individual trees	6
subsample	Fraction of samples used per tree	0.9
colsample_bytree	Fraction of features used per tree	0.9
reg_lambda	L2 regularization weight	1.0

These parameters ensure a balance among model complexity and computational efficiency, enhancing the generalization of the model across different temporal and weather conditions.

3.3.3 LONG SHORT-TERM MEMORY

An LSTM network is a specialized RNN that has essentially designed to model long-term temporal dependencies. The nature of the LSTM makes it perfectly suitable for solar energy production forecasting. In contrast to common networks, which update all memory cells across time steps, the LSTM includes gated cells - input, forget, and output gates – that govern whether and how information is initialized, discarded, or categorized depending on time. This manner useful whenese of the vanishing gradient dilemma. It allows the network for keeping crucial information while ignoring others from previous readings, resulting in a method that can model seasonal and behavior aspects. The LSTM model in this work forecasts the next-hour generation of solar power. It uses 24-hours' worth of past data to predict the future variations in multiple variables like temperature, irradiance, and temporal indicators. At the model level, this work includes an LSTM layer consisting of only one layer with 128 hidden cells. The LSTM layer is then followed by a Dense layer with 64 ReLU neurons and an output linear node. The Adam optimizer is utilized during training to minimize the Mean Squared Error loss, and an early stopping method is used to prevent overfitting. LSTM can capture nonlinear temporal correlations and learn daily and season patterns to achieve accurate predictions of PV generation within any weather conditions due to their ability to fit complex patterns. Fig. 4 LSTM architecture. Table 2 model summary.

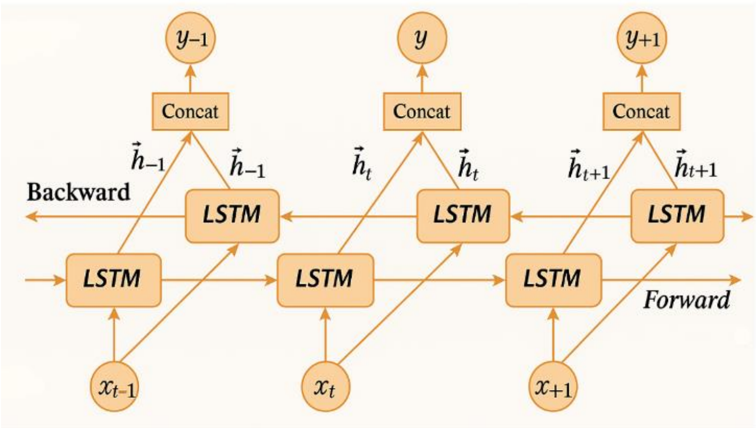

FIGURE 4 LSTM architecture

Table 2 LSTM Summary

Layer	Type	Units	Activation	Output
Input	LSTM	128	tanh / sigmoid (gated)	Sequence encoding
Hidden	Dense	64	ReLU	Nonlinear feature combination
Output	Dense	1	Linear	Predicted energy production

3.3.4 Gated Recurrent Unit

The GRU is a more streamlined variation of the LSTM and RNN. The GRU is a variation of the LSTM that condenses the hidden and cell states and does away with an output gate. The cell state is the state of memory in the network. It can contain memories that are short term, selective or long term. Like the LSTM, the GRU has the ability to selectively add or remove from the cell state. It accomplishes this by way of what is described as an update gate and a reset gate. The update gate and the reset gate control how much of the past information will be used to influence and how much of the new information will be added to the cell state. The meaning of GRU gates is:. Here, the GRU consumes a 24-hour window of the multivariate input series to predict the solar production for the next hour. The architecture includes a 128-unit GRU layer, followed by a Dense layer with 64 ReLU neurons, and a linear output layer. The GRU model is trained with the Mean Squared Error as loss and optimized by the Adam optimizer coupled with early stopping and learning rate reduction to ensure convergence. As the GRU has fewer gates than an LSTM cell, it has fewer parameters to learn, and fewer calculations need to be made. Gated mechanisms allow the GRU network to decide when and to what extent to retain memory easy to train if single time resolution is considered and there is a higher number of training signals. Furthermore, the GRU models are a good balance between speed and accuracy, making them well suited for active solar energy systems or smart grids where prediction needs to be rapid. As seen in Fig. 5, Table 3 shows the summary.

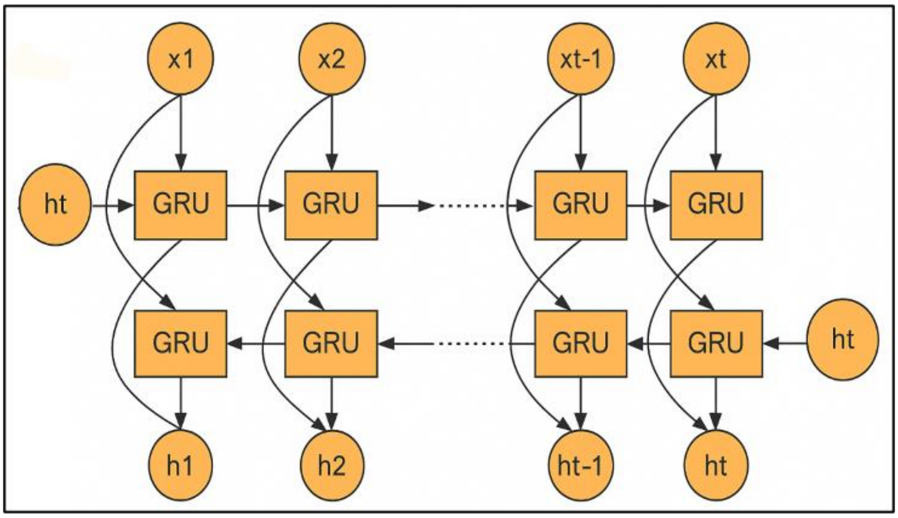

FIGURE 5 GRU architecture

Table 3 GRU summary

Layer	Type	Units	Activation	Description
Input	GRU	128	tanh / sigmoid	Sequence encoder
Hidden	Dense	64	ReLU	Nonlinear feature transformation
Output	Dense	1	Linear	Forecasted energy production

3.3.5 BIDIRECTIONAL LONG SHORT-TERM MEMORY

The Bi-LSTM network, an advanced form of LSTM designed to consider temporal dependencies in both directions, uses the forward and backward approach. Contrary to standard LSTMs that process the sequence in a particular order, the Bi-LSTM network considers two parallel layers regarding the past data and predicting the future context of the sequence. Bi-LSTM can understand more comprehensive temporal relationships, which is crucial for solar power forecasting as the solar power production becomes a function of previous irradiance performance and the present status of environmental factors. The Bi-LSTM model proposed, which predicts the solar power in the following hour, processes the 24-hour sequences of multivariate met and irradiance. The proposed Bi-LSTM network architecture is made up of 128-unit bidirectional LSTM layer and 64-neuron ReLU dense layer, then the linear output unit, varying in corresponding research. The model trains using Adam with Mean Squared Error loss via early stopping and a learning rate scheduling step. B i-LSTM model captures short- and long-term dependencies throughout the hourly fluctuations and evolution to reflect day-level continuity of the prediction. However, the bidirectional layer's incorporation enhances the performance of the machine learning model and outperforms both unidirectional LSTM and GRU network systems, mainly when the external factors evolve rapidly. Figure 6 Bi-LSTM architecture, while Table 4 shows Bi-LSTM summary.

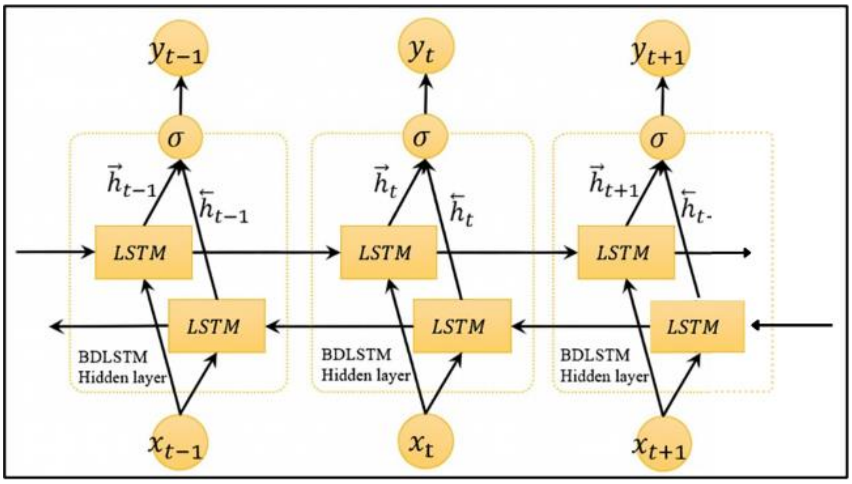

FIGURE 6 Bi-LSTM architecture

Table 4 Bi-LSTM summary

Layer	Type	Units	Activation	Description
Input	Bidirectional LSTM	128	tanh / sigmoid	Processes sequence in both directions
Hidden	Dense	64	ReLU	Nonlinear combination of temporal features
Output	Dense	1	Linear	Forecasted solar production

3.4 MODEL TRAINING AND EVALUATION

R-squared (R2) measures how well the model's predictions fit the actual data. It represents the proportion of variance in the dependent variable that is predictable from the independent variables [27].

$$R^2 = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \bar{y})^2} \qquad (1)$$

MSE measures the average squared difference among the actual and predicted values. It penalizes larger errors more heavily [28].

$$MSE = \frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}i)^2 \qquad (2)$$

MAE refer to the average magnitude of prediction errors, without considering their direction (positive or negative) [29].

$$\text{MAE} = \frac{1}{n}\sum i = 1^n |y_i - \hat{y}_i| \qquad (3)$$

RMSE is the square root of MSE, representing the error in the same units as the target variable (e.g., kWh) [30].

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (y_i - \hat{y}_i)^2} \qquad (4)$$

The Willmott Index (WI) assesses the degree of model prediction error relative to the variability in observed data. It ranges from 0 (no agreement) to 1 (perfect agreement) [31].

$$d = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (|\hat{y}_i - \bar{y}| + |y_i - \bar{y}|)^2} \qquad (5)$$

Standard Deviation (Std) measures the dispersion or variability of prediction errors around their mean. It quantifies the model's consistency[32] .

$$STD = \sqrt{\frac{1}{N-1}\sum(e_i - \bar{e})^2} \qquad (6)$$

4. Results and Discussion

This section presents a comprehensive comparison of the five regression and DL models (MLP, XGBoost, LSTM, GRU, and Bi-LSTM) based on different statistical performance metrics, counting the R^2, MSE, RMSE, MAE, Std, and WI as shows in Table 5. The results reflect each model's ability to accurately forecast hourly solar energy production under varying meteorological conditions.

Table 5 Proposed results

	R^2	MSE	RMSE	MAE	Std_Actual	Std_Pred	WI
MLP	0.858106	8679.424244	93.163428	53.755193	247.322760	196.174129	0.955565
XGBoost	0.947830	3191.146053	56.490230	27.595801	247.322760	234.826065	0.986114
LSTM	0.786711	13097.769932	114.445489	71.294927	247.807711	203.552728	0.934312
GRU	0.744140	15712.012837	125.347568	78.222019	247.807711	171.192441	0.910606
BiLSTM	0.866241	8213.933449	90.630753	53.277545	247.807711	234.067938	0.963532

The R^2 also establishes the capacity of the integrated models to accurately predict solar energy output. The XGBoost model achieved the highest R^2 value of 0.9478. The value indicates that the model is correctly capable of explaining about 95% of the variations in solar energy production. Other models such Bi-LSTM and MLP achieved 0.8662 and 0.8662 R^2, respectively. These values are considering given that are able to account for most of the all the nonlinear and temporal dependencies. More so, these values are slightly less compared to that of XGBoost since it integrates all the sequence together. On the other hand, LSTM and GRU achieved 0.7867 and 0.7441, respectively. This is an indicator of their lower performance under the evaluated configuration based on the similarity in the feature. Therefore, the current overall ranking; XGBoost > Bi-LSTM > MLP > LSTM > GRU confirms that XGBoost is the best model for predicting solar energy output due to enhanced accuracy and generalizability. Error-based evaluation also confirmed righteousness of the current findings all-around above. The model achieved the lowest MSE error, RMSE, and MAE of 3191.15, 56.49, and 27.59, respectively. It further demonstrated the model can predict with less deviation. The error is more significant for the model, an indication of less temporal learning. The more substantial error for the LSTM model also indicated the less ability of the model to adapt to lection diversity. The other model, namely, Bi-LSTM, and MLP, achieved moderate errors. These indicate a higher ability to recognize nonlinear dependencies, although it is slightly less accurate compared to XGBoost. Standard deviation and Willmott's Index also confirmed the ability of the model to accurately predict solar energy output. R^2 assessed how much the predicted model can explain the variation in the predicted variables. WI obtained 0.9861, is the highest, which is more accurate compared to other models. Other integrated models Bi-LSTM, and MLP achieved 0.9635 and 0.9556. These values are also indicating that based on the hybrid ensemble tree model, the current developed model is better.

Figure 7 shows the comparative ranking of all predictive models based on their R^2 values, highlighting XGBoost as the most accurate model with the highest explanatory power.

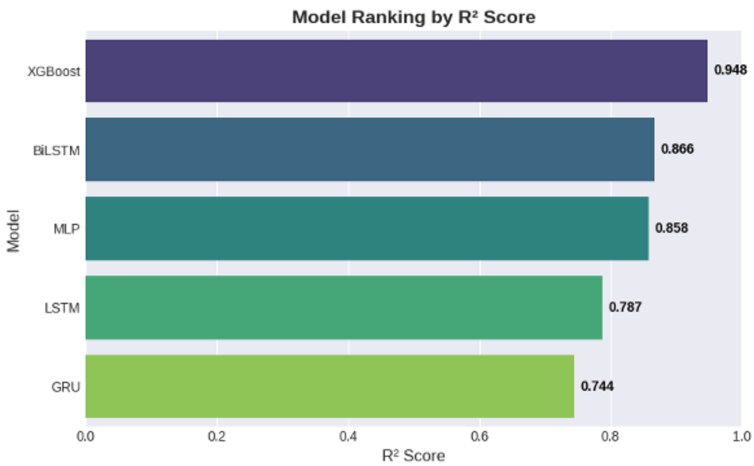

FIGURE 7 Ranking of Models Based on R^2

Figure 8 shows the trade-off among R^2 and MAE, revealing XGBoost's balance among precision and low error.

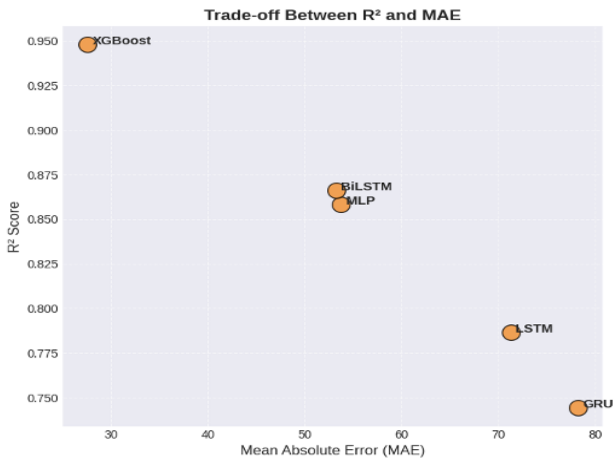

FIGURE 8 Trade-off Between R^2 and MAE

Figure 9 shows residual distributions; XGBoost and Bi-LSTM exhibit the narrowest, most centered errors, indicating superior prediction accuracy.

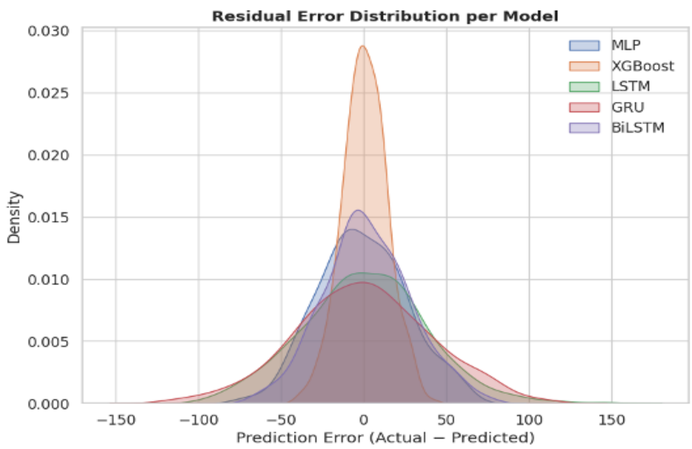

FIGURE 9 Residual Distribution of Prediction Errors Across Different Models

Figure 10 shown a normalized radar chart comparing overall model performance across multiple metrics, confirming XGBoost's dominance in prediction accuracy and stability.

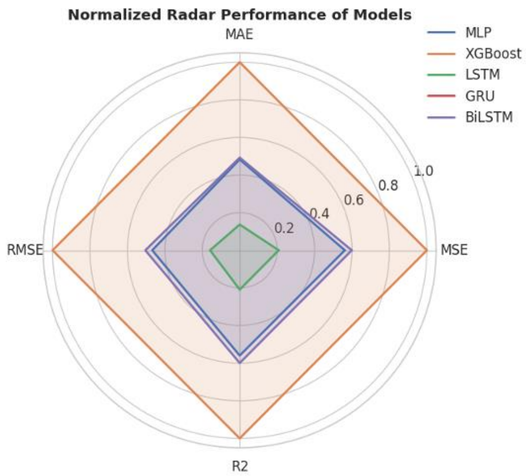

FIGURE 10 Normalized Radar Chart of Model Performance Metrics

Figures 11–15 shows the regression fit between actual and predicted solar energy values. Among all models, XGBoost and BiLSTM exhibit the closest alignment to the ideal prediction line.

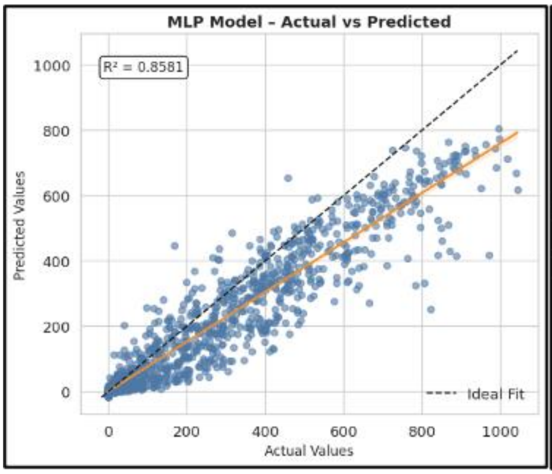

FIGURE 11 **Actual vs Predicted for MLP**

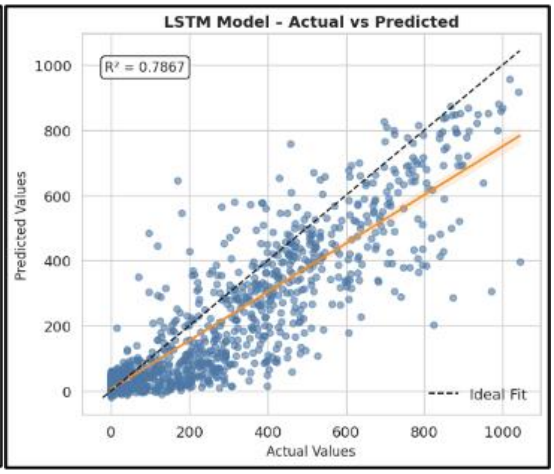

FIGURE 12 **Actual vs Predicted for LSTM**

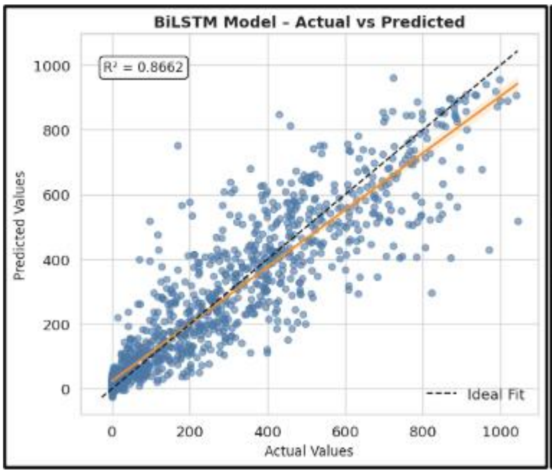

FIGURE 13 **Actual vs Predicted for BiLSTM**

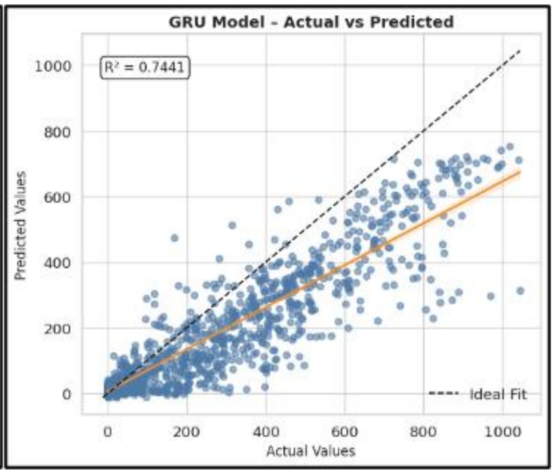

FIGURE 14 **Actual vs Predicted for GRU**

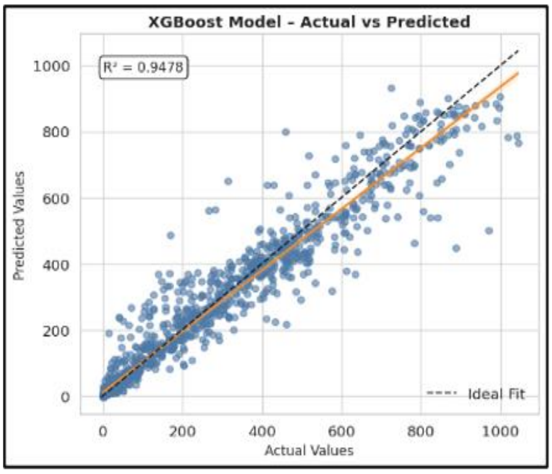

FIGURE 15 **Actual vs Predicted for XGBoost**

5. Conclusions

The promising results of the present study are condensed for the first time in Table 5, summarizing a holistic evaluation of the five predictive models for solar energy forecasting based on multilayer meteorological and irradiance data. Results indicated that the highest R^2 value of 0.9478 is achieved by XGBoost, and the highest median is indicated for BiLSTM and MLP, reiterating the strong capacity of these models in simultaneously modelling both the heavy and non-heavy lineal dependencies of weather factors on PV energy production within the evaluated dataset, within the scope of the current experimental setup. Deep learning models, mostly BiLSTM, are successful in capturing time-dependent long-term dependencies and the day-normalized residual effect precision, in contrast to the extra computational resources of the tree-based method. In light of the above, the findings demonstrate that combining gradient boosting with meteorological variables enables reliable and practical solar power predictions while maintaining ease of implication to the community. Future research may extend this framework by incorporating satellite-based irradiance data, atmospheric aerosol indices, and longer-term datasets to further enhance forecasting reliability. Additionally, hybrid architectures integrating deep learning and ensemble methods, such as CNN–BiLSTM–XGBoost, may be explored to better capture spatiotemporal characteristics. Real-time deployment and adaptive learning strategies, including continuous model retraining under evolving atmospheric conditions, also represent promising directions for advancing intelligent renewable energy management systems.

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CONFLICTS OF INTEREST

The authors declare no conflict of interest

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