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Original Article

Solar Power Forecasting Using Deep Learning Model Based Improved Particle Swarm Optimization Method

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Abstract - *Accurately forecasting solar power is essential for secure and efficient operations of contemporary power systems, particularly in the smart grid and renewable energy integration context. In this paper, we present a new hybrid deep learning model, the BiLSTM Model using Improved PSO (BiLSTM-IPSO), for improved short-term prediction of solar power, which incorporates the Bidirectional Long Short-Term Memory (BiLSTM) model with an Improved Particle Swarm Optimization (IPSO) algorithm. The IPSO algorithm successively arranges the BiLSTM hyperparameters with chaotic initialization, adaptive inertia weights, and velocity clamping, to converge globally and avoid stagnating locally. The proposed BiLSTM-IPSO model performance is compared with various state-of-the-art techniques, including TLBO-DL, CNN-LBO, BiLSTM-AADC, and HCLN, using standard indicators, such as MSE, RMSE, MAE, MBE, and* R^2*. Results show that our model consistently performs better than all the baselines, and the lowest RMSE and the highest* R^2 *are 0.0565 and 0.955, respectively, on the 0.5-hour horizon. The excellent generalization performance of the framework in all of its forecast horizons indicates its feasibility for applications in real-time deployment in solar energy management systems and smart-grid operations.*

Keywords - *Solar Power Prediction, Deep Learning Methods, MAE, BiLSTM, IPSO.*

1. Introduction

The worldwide transition to renewable energy sources highlights the need for accurate renewable energy forecasting models. Among them, solar energy, recognized as one of the most plentiful and environmentally friendly energy sources, is regarded as an optimal alternative renewable energy solution [1]. Solar power is inherently variable and intermittent, influenced by changing various weather conditions like cloud cover, temperature, and moisture content in the air. This timelessness will seriously challenge grid balancing, energy management, and operational scheduling in smart grid systems [2]. Thus, precise forecasting for solar energy has been necessary for the operative combination of solar power into the main grid [3, 4].

The deep learning approaches, such as the LSTM framework, have shown the potential for time-series data with temporal dependency and nonlinear behaviour [5, 6]. BiLSTM models can aggregate context information from previous and coming sequences, which is more appropriate for predicting highly volatile energy generation data. However, the success of BiLSTM is very sensitive to the choice of hyperparameters [7].

General grid search-based approaches for model hyperparameter optimization are time-consuming and inefficient [8]. To cope with these problems, the PSO metaheuristic algorithms have been used because of their simplicity, fast convergence rate, and ability to explore a large search space [9] successfully. However, the traditional PSO methods still have defects in premature convergence, the trap in local extreme value, and the insufficient exploration capability in complicated high-dimensional spaces [10, 11].

To address these problems, this paper proposes an IPSO-based BiLSTM for solar power prediction, so-called BiLSTM-IPSO. The IPSO improves the traditional PSO, which utilizes chaotic initialization to ensure more diverse particles, and dynamic change of inertia weight seeking a middle ground between over-exploration and under-exploitation, and that of velocity clip to avoid the premature convergence of particles in BiLSTM optimization. The presentation of the suggested BiLSTM-IPSO model is assessed using metrics like RMSE, MSE, MAE, MBE, and R^2. Experimental results confirm the superiority in prediction accuracy and generalization ability of BiLSTM-IPSO, which has potential in improving the operation efficiency of renewable-integrated smart grids.

The principal contributions of this work :

- To use BiLSTM's strong temporal modelling capabilities only to capture complex dependence in solar power generating patterns.
- Improve the performance of the BiLSTM by proposing an effective hyperparameter optimization approach based on IPSO.
- To enhance the prediction performance and robustness of existing methods, like TLBO-DL, BiLSTM-AADC, CNN-LBO, and HCLN.

This study is structured as follows: a literature survey of various methods is included in section 2. In Section 3, the suggested BiLSTM-IPSO approach is shown. Section 4 describes the experimental design and analysis. The article is concluded, and discussed future research in Section 5.

2. Literature Review

The ability to forecast solar energy is vital for effective grid maintenance and the safe incorporation of photovoltaic and other renewable energy sources into the electrical grid. [12]. Raju et al. [13] proposed a novel hybrid Deep Learning (DL) model with LSTM & CPSO. applied to short-term solar irradiance prediction.

Their model also significantly outperformed traditional LSTM and optimization techniques, including Firefly Algorithm (FA) and conventional PSO, regarding smaller MAE, MSE, and RMSE values. This paper demonstrated the significance of intelligent hyperparameter tuning in improving LSTM network capabilities in solar forecasting.

Molu et al. [14] suggested a mixed DL model combining Bayesian optimization with Savitzky-Golay filtering for improved short-term solar radiation prediction accuracy. The study obtained excellent forecasting accuracy by combining sophisticated attention mechanisms and dilated convolutional layers with a BiLSTM network. The Bayesian optimization was a game-changer in tuning hyperparameters and preprocessing filters. It improved greatly over (sMAPE/n) scores, thus demonstrating the strengths of the hybrid framework in combination with probabilistic optimization.

Sulaiman et al. [15] applied optimization methods and the deep learning framework to wind power prediction, in which the Teaching-Learning-Based Optimization (TLBO) method was combined with deep learning models.

While the wind-oriented nature of their work was their initial focus, the directed hyperparameter exploration for metaheuristics discussed is highly relevant for solar forecasting. TLBO-DL succeeded in providing better prediction results when compared to PSO, BMO, BBO, and FA, proving that TLBO can enhance the performance of renewable energy predictions in diverse weather scopes. Their study emphasizes the need for optimization in improving deep learning model robustness in renewable energy domains.

Saadati et al. [16] concentrated on Machine-Learning (ML), Deep-Learning (DL), and chaotic model-based methodologies to enhance the prediction of solar energy. They compared EL with LSTM and chaotic ESN. They showed that incorporating exogenous variables, such as ambient temperature, in addition to the endogenous solar generation data, had a major impact on predicting performance. This study has identified the necessity of combining multiple sources of data and optimization methods (Tree-structured Parzen Estimator of hyperparameter optimization) to deal with the nonlinearity and unpredictability of solar energy production. It achieved a R^2 of more than 0.97.

Lee et al. [17] produced a prediction model for small-scale solar power systems with limited data availability; they proposed to develop a prediction system based on TSMixer and Transfer Learning. Their framework provided a high prediction rate on a few datasets with transfer learning using Dynamic Time Warping (DTW) data similarity. They exhibited lower values of MSE and MAE compared to the standard LSTM and Transformer models, which indicated that their models were lower. Transfer learning is utilized to enhance the prediction accuracy of solar energy due to limited data.

Bhutta et al. [18] suggested utilizing hybrid DL models, such as Hybrid Convolutional-LSTM Net (HCLN), to maximize solar power efficiency in smart grids. They demonstrated that the combination of CNN and RNN methods enables them to achieve the lowest error rate in predicting solar generation systems (the minimum RMSE and MAE) in terms of prediction, as opposed to other models. The model hybridization gave the model the capability to address better the nonlinearities and temporal variability of the solar irradiance, and be applied to support the plans to integrate smart grids [19].

Comparison literature in Table 1 gives clear indications that application of DL models with sophisticated metaheuristic optimization frameworks (such as CPSO, TLBO, and Bayesian optimization) will be a fruitful approach in achieving accurate and strong solar energy forecasting [20-22]. Nevertheless, there exist issues on convergence rate, the inability to withstand different weather conditions and extrapolating to other geographical locations. To bridge those gaps, the BiLSTM-IPSO seeks improvement of the accuracy in the prediction of solar power generation by developing an enhanced PSO-based BiLSTM model for dynamic solar power prediction. In contrast, the excellent adaptability and prediction precision in dynamic solar power environments are guaranteed.

Table 1. Comparison study on several deep learning models to predict solar power

Reference	Method	Objective	Metrics	Advantages	Research Gaps
Demir et al. [23]	LSTM, BiLSTM, GRU, BiGRU	Solar radiation prediction in the Konya region	MAE, RMSE, RÂ²	Deep learning (BiLSTM, LSTM) showed the highest accuracy, robust to temporal variations.	Traditional methods (Bagging, RF) are less accurate in nonlinear datasets.
Chang et al. [24]	TESDL method	Solar power generation prediction for distributed grids	Accuracy factor improvement	27% improvement over conventional VM-based forecast models	Only focused on a single data source; lacks hybrid ensemble methods
Ibrahim et al. [25]	CNN with the LSTM method	PV power prediction short-term	RMSE, MAE	5%-25% RMSE & MAE improvement; 70% reduced training time	Limited application to larger time horizons beyond 2 hours
Elsaraiti et al. [26]	LSTM and MLP	Short-term PV power forecasting for grid operation	MAE, MAPE, RMSE, RÂ²	LSTM outperforms MLP in handling sequential solar data	The study focused only on basic architectures; no hybrid optimization was used
Sharma et al. [27]	LSTM and Nadam Optimizer	Long-term PV power forecasting (case study India)	RMSE, MAE, Accuracy Improvement %	Nadam optimizer enhanced LSTM performance by 30%-58%	Focused mainly on a single-location (India) dataset; scalability not discussed
Al-Shahri et al. [28]	ML/DL review on PV optimization	Comprehensive review of solar PV optimization	General (Descriptive)	Broad survey of techniques (ANN, SVM, RNN, CNN)	No specific model proposal; mainly a review paper
Parida et al. [29]	CNN and LBO	Solar power generation prediction	MAE, RMSE, MAPE, RÂ²	Hybrid model enhanced CNN with effective hyperparameter tuning	LBO model performance in highly noisy datasets needs further validation
Demir et al. [23]	LSTM, BiLSTM, GRU, BiGRU	Solar radiation prediction in the Konya region	MAE, RMSE, RÂ²	Deep learning (BiLSTM, LSTM) showed the highest accuracy, robust to temporal variations.	Traditional methods (Bagging, RF) are less accurate in nonlinear datasets.
Chang et al. [24]	TESDL method	Solar power generation prediction for distributed grids	Accuracy factor improvement	27% improvement over conventional VM-based forecast models	Only focused on a single data source; lacks hybrid ensemble methods

3. Methodology

3.1. BiLSTM Design Architectur

BiLSTM improves the LSTM network by learning long-range dependence forward and backward. For solar power prediction, the BiLSTM model can effectively model unfathomable temporal dependencies among solar irradiance, weather features, and historical power generations.

Let $\overrightarrow{h_t}$ and $\overleftarrow{h_t}$ be the hidden states of the forward LSTM and backward LSTM cells, respectively, at each time step t. Equation (1) represents the total output at time step t, equivalent to the concatenation of previous and current hidden states. In Equation (2-7), the "forget gate," denoted by F_t, is responsible for discarding data from the cell state C_{t-1}. I_t is the symbol for the input gate that controls the addition of fresh data to the cell state. $\tilde{C}_t$ denotes the possible candidate state for adding new data to the cell, and C_t stands for the updated cell state that incorporates the candidate state's choice and the forget gate.

Y_t represents the output gate, which will pass the information to the next hidden state and lastly, at time step t, the final hidden state h_t is passed to the next layer. V_f, V_i, V_c, and V_o, represent each gate's weight matrix and the corresponding biases, denoted as b_f, b_i, b_c, and b_o, respectively [30].

$$h_t = Concate\,(\overrightarrow{h_t}, \overleftarrow{h_t}) \quad (1)$$

$$F_t = \sigma\big(V_f \cdot [h_{t-1}, x_t] + b_f\big) \quad (2)$$

$$I_t = \sigma(V_i \cdot [h_{t-1}, x_t] + b_i) \quad (3)$$

$$\tilde{C}_t = tanh(V_C \cdot [h_{t-1}, x_t] + b_C) \quad (4)$$

$$C_t = F_t * C_{t-1} + I_t * \tilde{C}_t \quad (5)$$

$$Y_t = \sigma(V_o \cdot [h_{t-1}, x_t] + b_o) \quad (6)$$

$$h_t = Y_t * \tanh(C_t \quad (7)$$

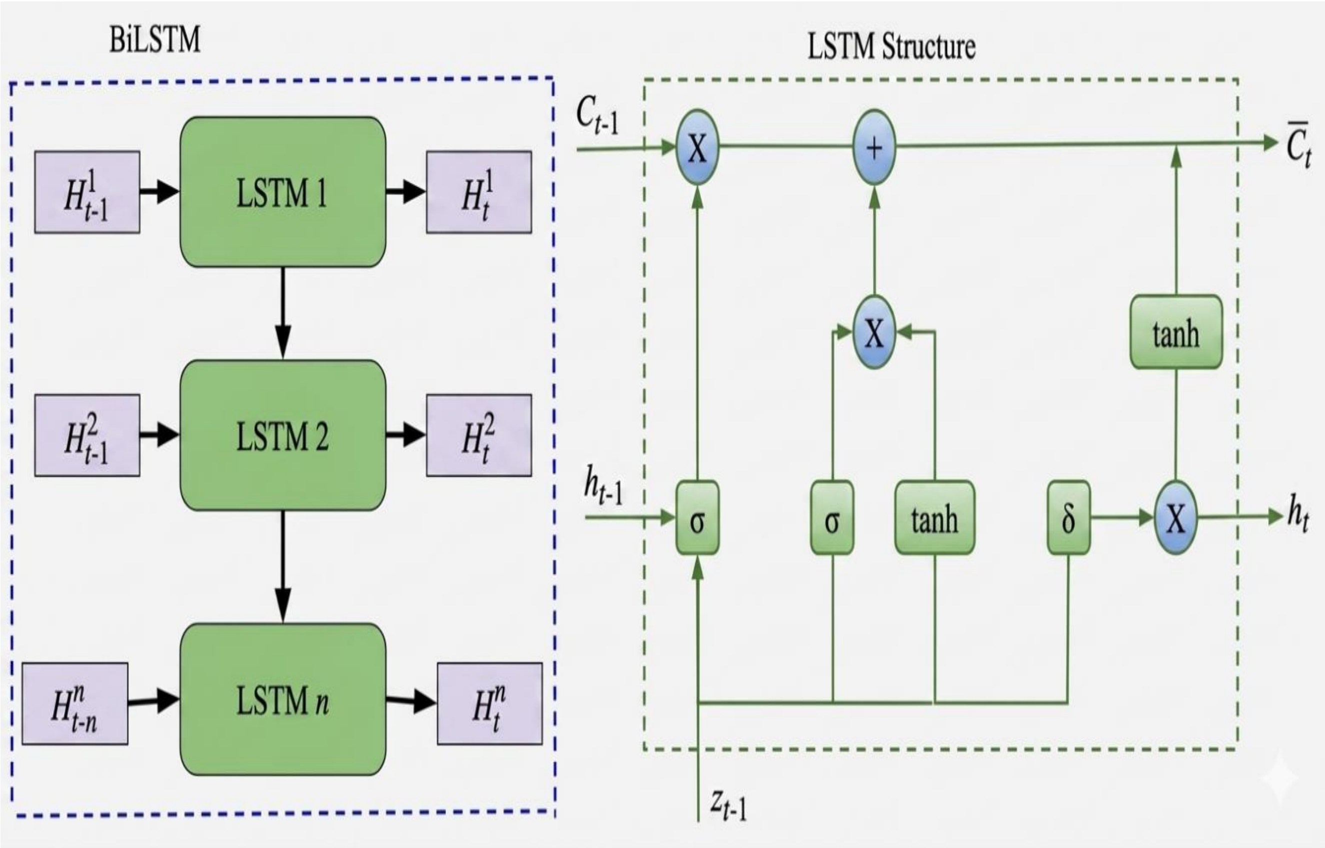


Fig. 1 BiLSTM design architecture

3.2. Improved Particle Swarm Optimization

Although conventional (PSO) is commonly used for hyperparameter tuning, it tends to encounter premature convergence and get trapped in local minima. To handle these problems, utilize the Improved PSO (IPSO) in this paper.

In improved PSO, each particle is a potential output solution (set of hyperparameters of the BiLSTM). The particles update their position by the pbest and gbest solutions.

The classic rules for updating particle movement and positional updates are :

$$v_i^{(t-1)} = w.v_i^{(t)} + c_1 \cdot r_1 \cdot \big(p_{best,i} - x_i^{(t)}\big) + c_2 \cdot r_2 \cdot (g_{best,i} - x_i^{(t)}) \quad (8)$$

$$x_i^{(t-1)} = x_i^{(t)} + v_i^{(t-1)} \quad (9)$$

Each particle's velocity (v_i), location (x_i), inertia weight (w), acceleration coefficients ($c_1$and c_2), and two random values ($r_1$and r_2) between 0 and 1 make up the equation.

$$w = w_{max} - \frac{(w_{max}-w_{min})\times t}{t_{max}} \quad (10)$$

$$z_{i-1} = \mu \cdot z_i \cdot (1 - z_i) \quad (11)$$

$$v_i \in [-v_{max}, v_{max}] \quad (12)$$

$$\text{Fitness} = \tfrac{1}{n}\textstyle\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (13)$$

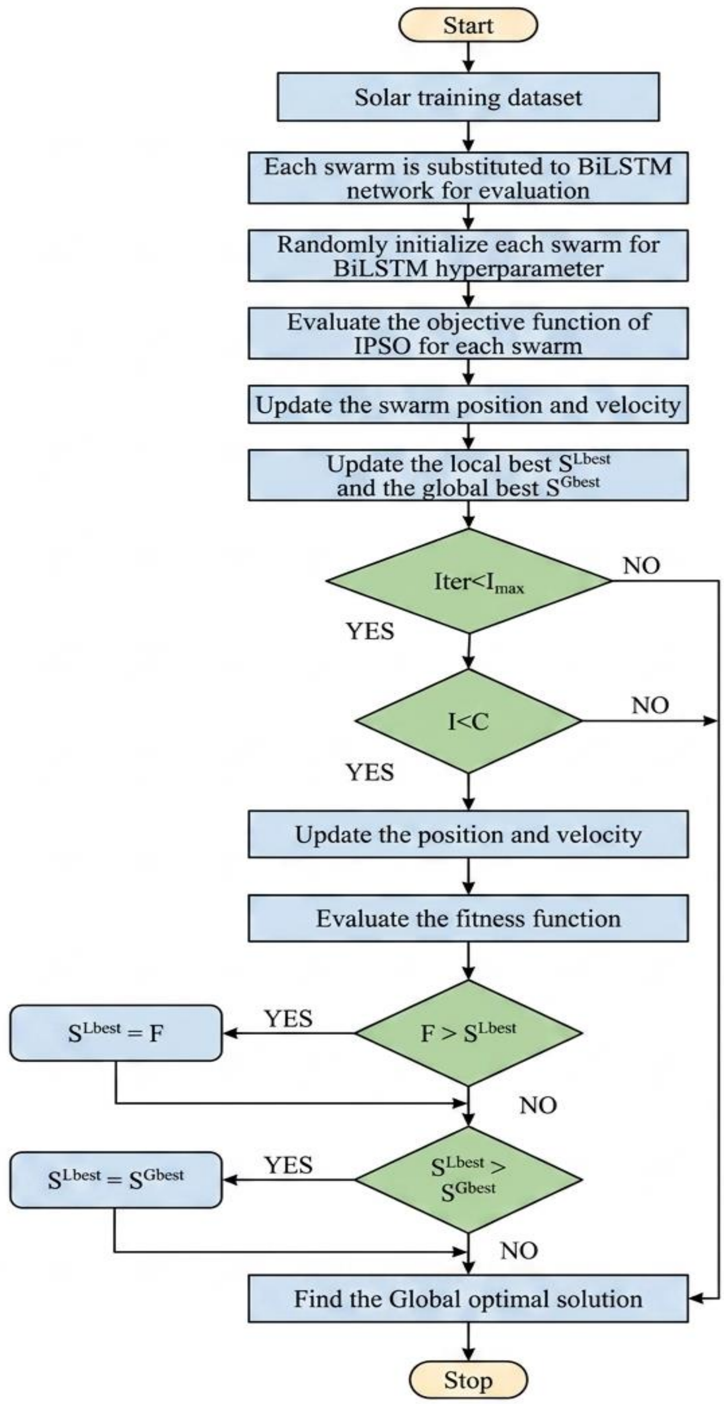


Fig. 2 BiLSTM-IPSO solar power forecasting working process

3.3. BiLSTM-IPSO Solar Power Forecasting Framework

The paper introduces a new model called BiLSTM-IPSO that will enhance predictive precision of solar energy generation through the combination of the BiLSTM framework and an IPSO algorithm. The major reason for this combination is to employ BiLSTM ability to train in steps to represent temporal data and IPSO to find the appropriate hyperparameters that will improve prediction accuracy. The process begins with pre-treatment of the data, i.e. the collection of historical data on solar power and the weather. The dataset is normalized before being placed into the network so that the input features are scaled into a constant interval, usually [0,1], hence supporting the convergence of the network during the training.

A missing value is addressed appropriately depending on the interpolation or mean imputation in order to accomplish the input data consistent and complete. The BiLSTM model is generated following preprocessing, and it has two layers of LSTM, which are in both temporal directions to capture both preceding and subsequent context patterns. Top hyperparameters are randomly initialized, hidden neuron count, batch size, learning rate, and dropout rates and BiLSTM layers are only a few of these factors. These initial settings, however, are not fixed, but are tuned to optimum predictive behaviour. The benefits of IPSO over classical PSO include adaptive inertia weight update, use of chaos as an initializer to diversify better the population and velocity clamping, which helps to prevent overt motion. All these improvements will ensure that there is a quicker convergence and counteract the premature halting of the local minimum. The benefits of IPSO over classical PSO include adaptive inertia weight update, use of chaos as an initializer to diversify better the population and velocity clamping, which helps to prevent overt motion. All these improvements will ensure that there is a quicker convergence and counteract the premature halting of the local minimum.

Algorithm-1: BiLSTM-IPSO solar power forecasting framework

Input: solar irradiance, temperature, humidity, wind speed.
Output: Forecasted solar power
Step 1: Problem formulation, solar power forecasting

$$\hat{y}_t = f(x_{t-n} \dots . x_t)$$

Where x_t is the feature vector at time t and $\hat{y}_t$ is the predicted solar power.
Step 2: Normalize all features to the [0.1] range.
Step 3: Initial BiLSTM Model Configuration
3.1 Set initial hyperparameter ranges:
Learning rate $\in [10^{-5}, 10^{-2}]$
Number of neurons ∈[32, 256]
Dropout rate ∈ [0.1, 0.5]
Batch size ∈ [16, 128]
Step 4: IPSO-Based Hyperparameter Optimization
4.1 Initialize IPSO parameter:
Swarm size P, maximum iterations $I_{max}, w_{max}, w_{min}, c_1, c_2$
4.2 Initialize each particle using the chaotic logistic map:

$$z_{i+1} = \mu . z_i . (1 - z_i), \qquad \mu = 4$$

4.3 For each particle:
Map position $x_i$to BiLSTM hyperparameters
Train BiLSTM model with the corresponding hyperparameters
Evaluate using Validation MSE:

$$\text{Fitness} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

4.4 Update particle velocity and position:

$$v_i^{(t-1)} = w . v_i^{(t)} + c_1 \cdot r_1 \cdot \left(p_{best,i} - x_i^{(t)}\right) + c_2 \cdot r_2 \cdot (g_{best,i} - x_i^{(t)})\text{ax}$$

$$x_i^{(t-1)} = x_i^{(t)} + v_i^{(t-1)}$$

Apply velocity clamping and update. p_{best}, g_{best}.
4.5 Adjust inertial weight:

$$w = w_{max} - \left(\frac{w_{max} - w_{min}}{I_{max}}\right) . t$$

Repeat steps 4.3 to 4.5 until convergence or max iterations.
Step 5: Final BiLSTM model training
5.1 Select optimal hyperparameters from IPSO output.
Step 6: Test the trained BiLSTM-IPSO model on the unseen test set.
6.2 Compute all the metrics
6.3 Compare with baseline models
Step 7: End

After the best hyperparameters are determined via IPSO, retrain the BiLSTM network with the tuned settings. Training is done for several epochs, and the early stopping procedure reduces the chance of overfitting. Optimizer: utilize the Adam optimizer, which helps convergence by updating learning rates in real time during backpropagation.

4. Experimental Setup and Result Discussion

To assess the effectiveness of the proposed framework, a series of comprehensive experiments was conducted with the real-life solar Photovoltaic (PV) power generation data. The data was obtained from a 5 MW site based in Southern UK, and consists of regular 30-minute time intervals between 3 November 2017 and 17 December 2019. This dataset, which consists of 37,200 data entries, was downloaded from the Western Power Distribution Open Data Hub and contains solar power generation and meteorological parameters. The missing values were interpolated, and the data was min-max normalized to bring all the features in the interval [0, 1] before training.

To guarantee balanced learning and testing, this dataset was further sliced into training (70%), validation (15%) and testing (15%). This experiment was done at the rate of 0.5-hour, 1-hour and 2-hour under two conditions with and without meteorological input data. A simple neural network was a BiLSTM network that was optimized using hyperparameter optimization using the IPSO algorithm. The IPSO introduced chaotic initialization, adaptive inertia weight, and velocity amplitude bracing to reinforce global exploration and convergence. Parameters, including the layer depth, count of neurons, step size, regularization dropout and mini- batch size, had been optimized by IPSO with the minimum of validation Mean Squared Error (MSE) as a criterion.

The result of the suggested BiLSTM-IPSO contrasts with several state-of-the-art methods (TLBO-DL, CNN-LBO, BiLSTM-AADC, and HCLN). The evaluation metrics were the MSE, RMSE, MAE, MBE, and R^2. The experiments were conducted on an "Intel Core i7 CPU and 32 GB of memory, running Python version 3.9 with the Keras deep learning toolkit". The statistical performance was calculated at all forecast lead times for every competing model.

4.1. Performance Evaluation

The predictive ability of the BiLSTM-IPSO model was assessed using different statistics, including average MSE, average RMSE, average MAE, average MBE, and R^2. These measures give a joint sense of the model's accuracy, robustness, and bias features over different forecast horizons. The test was carried out with 0.5-hour, 1-hour, and 2-hour-ahead prediction under realistic circumstances, and the comparison was made against four benchmark models, namely TLBO-DL, CNN-LBO, BiLSTM-AADC, and HCLN. Equation (14-17) computes the evaluation of the suggested method.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{14}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{15}$$

$$\mathrm{MBE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i) \tag{16}$$

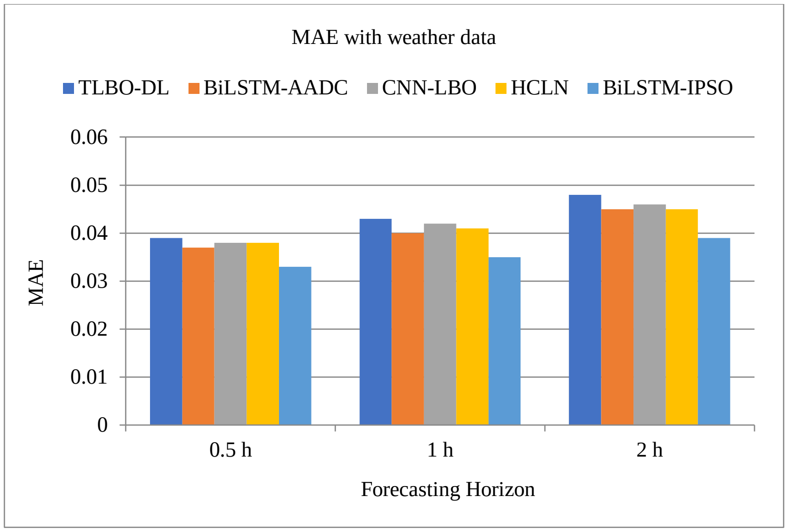
$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \tag{17}$$

Figure 3 shows the MAE of our models at a few forecasting horizons under two situations: (a) with weather and (b) without weather. It notes that the BiLSTM-IPSO performs consistently with the smallest MAE over all horizons, in particular outperforms all other models at 2-hour, where others present larger errors. All models then benefit from including weather data, although BiLSTM-IPSO is the more robust even in the absence of the additional inputs. CNN-LBO and TLBO-DL perform moderately, although HCLN and BiLSTM-AADC achieve better accuracy than the baseline, but are inferior to our proposed method.

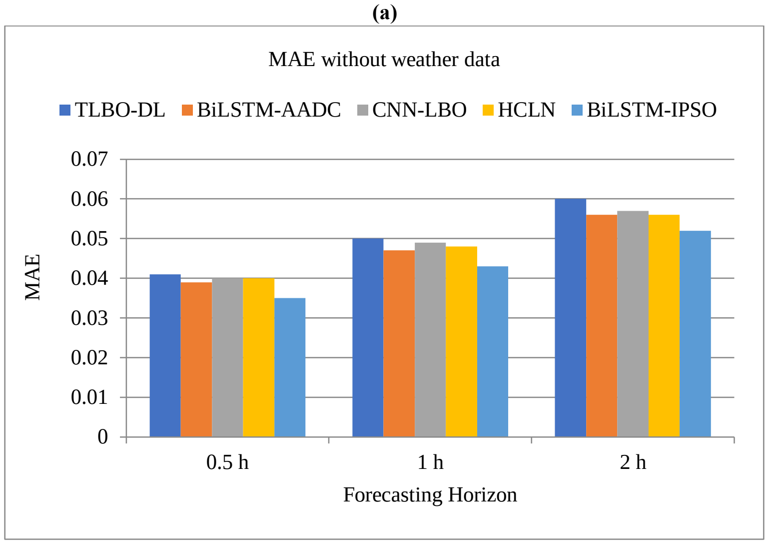
Figure 4 shows the RMSE comparison with the same set of models and conditions. The conclusions confirm the previous finding, where BiLSTM-IPSO obtains the least RMSE values in both including and excluding weather data experiments, elucidating its superior generalization and prediction accuracy. With the increase of forecast horizon from 0.5h to 2h, error margins get larger for all models, while BiLSTM-IPSO experiences a rather flat error profile. High RMSE spikes for TLBO-DL and CNN-LBO suggest little capacity for long-horizon forecasting without fine-tuned tuning.

Figure 5, it is observed that the 2-hour forecasting of the solar power, while modelled as a function of solar irradiation, is best represented in the form of the proposed BiLSTM-IPSO model by keeping the first peak closer to the original solar power value and maintaining the sharpness and height of the peak directly consistent with the actual trend. The other models (TLBO-DL, CNN-LBO, and BiLSTM-AADC) have flat or delayed peaks and clearly underpredict power generation around noon, showing a poor performance concerning long duration times.

In Figure 6, the results of 2-hour ahead prediction confirm that the actual power curve and BiLSTM-IPSO are highly relevant, and that BiLSTM-IPSO is superior to HCLN and CNN-LBO, which underestimate the peak generation. The spread in model outputs is smaller than that in the 2-hour case, but BiLSTM-IPSO always has better matching to the profiles and better identification of rise and fall behavior.

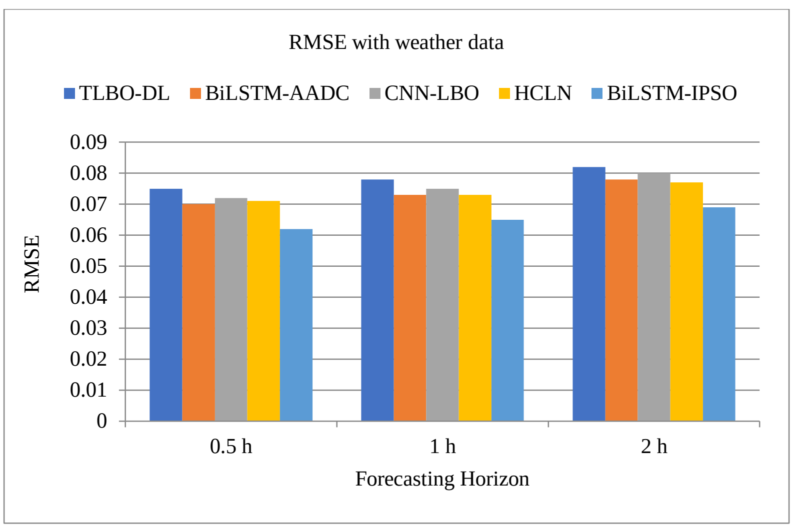


(a)

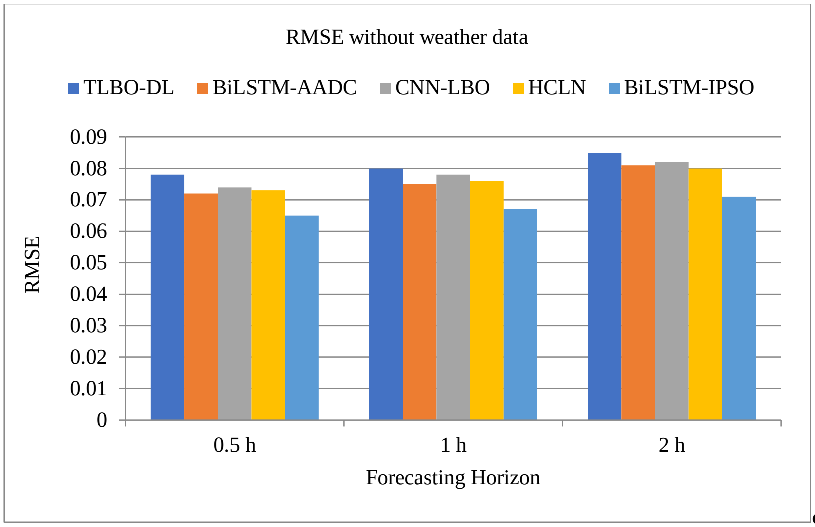


(b)

Fig. 3 Error analysis on various methods (a) MAE including weather data, and (b) MAE excluding weather data.



(a)



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(b)

Fig. 4 Error analysis on various methods (a) RMSE including weather data, and (b) RMSE excluding weather data.

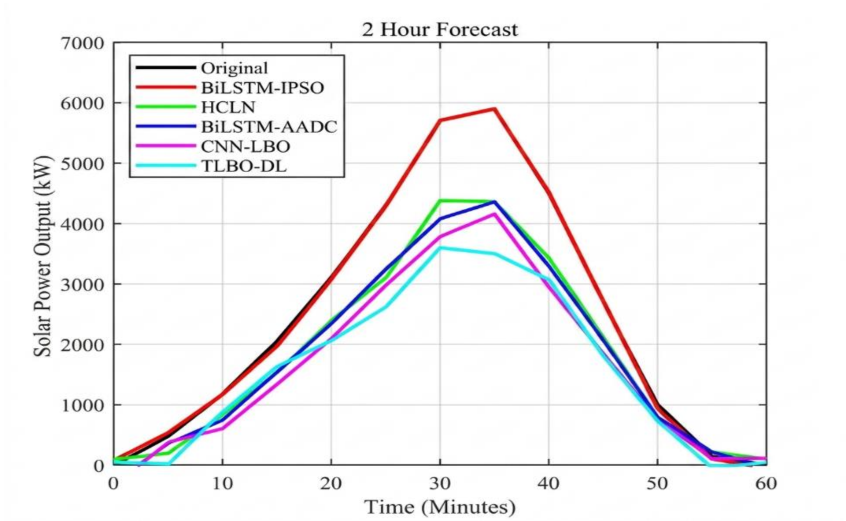

Fig. 5 Solar power forecasting in various methods on a 2-hour horizon

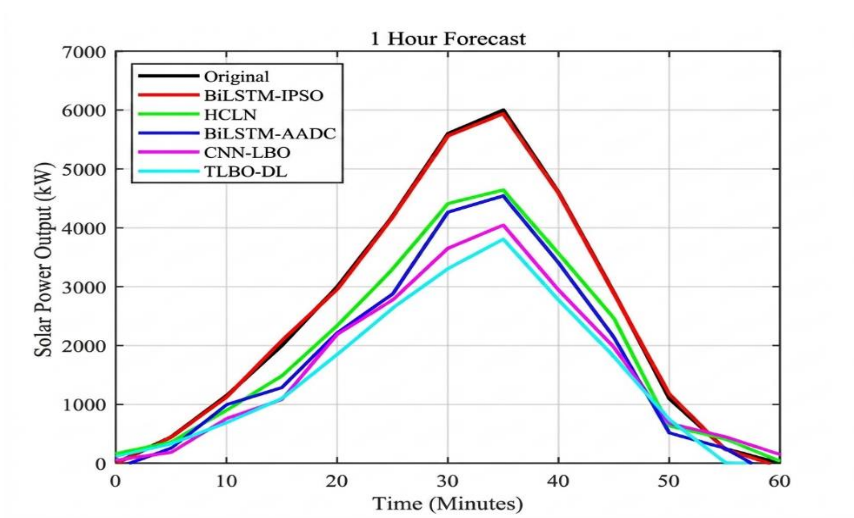

Fig. 6 Solar power forecasting in various methods on a 1-hour horizon

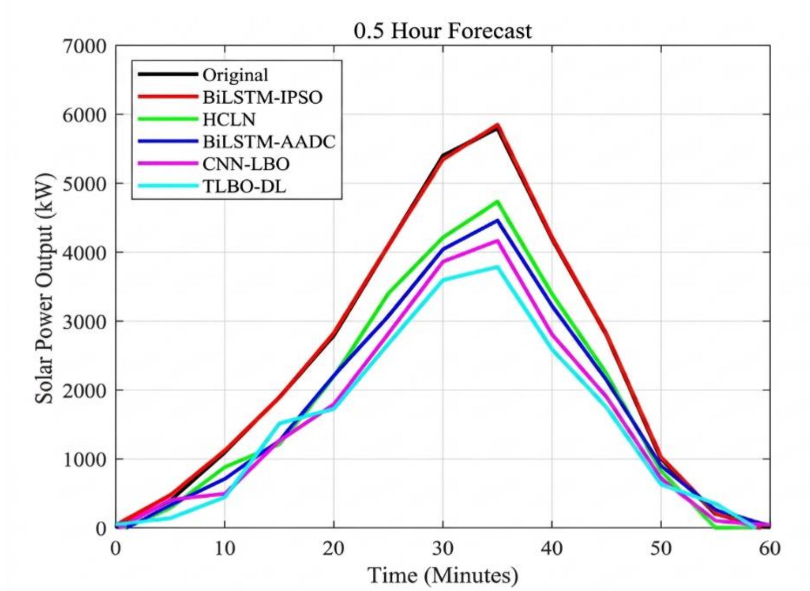

Fig. 7 Solar power forecasting in various methods on a 0.5-hour horizon

Figure 7, at a 0.5-hour (30-minute) prediction horizon, shows that all the models have high short-term prediction accuracy; however, IPSO still gives the best aggregate forecasting performance as it is closer to the ground truth.

Its path follows the truth very well, even in rapid transitions, while two other models, including TLBO-DL and CNN-LBO, have an appreciable delay and underestimate during peaks.

Table 2. Performance analysis of various methods on a 0.5-hour horizon

Methods	MSE	RMSE	MAE	MBE	R^2
TLBO-DL	0.0048	0.0693	0.0512	-0.0021	0.928
CNN-LBO	0.0045	0.0671	0.0495	-0.0019	0.932
BiLSTM-AADC	0.0042	0.0648	0.0471	-0.0018	0.939
HCLN	0.004	0.0632	0.0463	-0.0017	0.942
BiLSTM-IPSO	0.0032	0.0565	0.0394	-0.0009	0.955

The performance comparison results of Tables 1, 2, and 3 indicate the effective predictive ability of the proposed BiLSTM-IPSO model in the three forecasting periods: 0.5 h, 1 h, and two h. As shown in Table 1 (0.5-hour horizon), BiLSTM-IPSO reaches the lowest MSE (0.0032), RMSE (0.0565), and MAE (0.0394), and the highest R^2 (0.955), reflecting high accuracy and low bias compared with TLBO-DL, CNN-LBO, and other models. The same tendencies are seen in Table 2 (1-hour horizon), with BiLSTM-IPSO still leading, with an RMSE value of 0.0574 and R^2 of 0.953. While HCLN and BiLSTM-AADC have acceptable performance, the error scores have continuously worsened.

Table 3. Performance analysis of various methods on a 1-hour horizon

Methods	MSE	RMSE	MAE	MBE	R^2
TLBO-DL	0.0051	0.0714	0.053	-0.0023	0.921
CNN-LBO	0.0047	0.0685	0.0502	-0.002	0.93
BiLSTM-AADC	0.0043	0.0655	0.048	-0.0019	0.938
HCLN	0.0041	0.064	0.047	-0.0018	0.944
BiLSTM-IPSO	0.0033	0.0574	0.0412	-0.001	0.953

It is observed from Table 3 (2-hour horizon) that the RMSE value and R^2 value of BiLSTM-IPSO still rank in first place, even under the scenario of solely increasing the prediction uncertainty, which demonstrates the effectiveness of BiLSTM-IPSO in long-horizon forecasting.

Meanwhile, traditional methods, including TLBO-DL, fall into the obvious performance decay with higher MSE and lower R^2. These findings collectively verify that the BiLSTM-IPSO algorithm minimizes error and ensures forecasting stability and generalization over different forecasting horizons.

Table 4. Performance analysis of various methods on a 2-hour horizon

Methods	MSE	RMSE	MAE	MBE	R^2
TLBO-DL	0.0055	0.0742	0.055	-0.0026	0.914
CNN-LBO	0.005	0.0707	0.0515	-0.0023	0.926
BiLSTM-AADC	0.0045	0.067	0.049	-0.002	0.934
HCLN	0.0042	0.0648	0.0476	-0.0019	0.94
BiLSTM-IPSO	0.0036	0.06	0.0435	-0.0011	0.949

5. Conclusion and Future Scope

In this paper, an improved hybrid forecasting model, termed BiLSTM-IPSO, is presented, which aims to further enhance the short-term forecasting accuracy of solar output prediction based on the BiLSTM network and an IPSO algorithm. The method of the proposed model is that it overcomes the shortcomings of the fixed hyperparameter selection in deep learning models using a dynamical swarm-based optimization, which enhances the convergence and forecast accuracy.

The model was tested on real data in various conditions (time-horizon of 0.5-hour, 1 hour, and 2 hours ahead) and under various input settings (including or not the weather). Experimental results reveal that BiLSTM-IPSO significantly outperforms conventional and existing forecasting methods such as TLBO-DL, CNN-LBQ, BiLSTM-AADC, and HCLN. The proposed model, on average, recorded better predictability scores, in terms of MSE, RMSE, MAE, and MBE, and produced higher R^2 values, suggesting better generalization and temporal learning performance. In particular, BiLSTM-IPSO presented RMSE values at 0.0565, 0.0574, and 0.0600 on the 0.5-hour, 1-hour, and 2-hour prediction horizons, which are significantly superior to its counterparts.

BiLSTM-IPSO suggests a possible real-time tool for solar power prediction in smart grids, energy management systems, and renewable integration systems. Moreover, this model could be extended to future research to be applied to multistep forecasting, hybrid deep learning to apply ensembles, or real-time adaptive systems, which could offer edge computing-based onsite decision-making with the aid of prediction.

Conflicts of Interest

No conflicts of interest.

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References

[1] Lingyun Jia et al., "Improving Short-term Forecasting of Solar Power Generation by using an EEMD-BiGRU Model: A Comparative Study based on Seven Standalone Models and Six Hybrid Models," *International Journal of Green Energy*, vol. 21, no. 14, pp. 3135-3158, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[2] Wencheng Liu, and Zhizhong Mao, "Short-term Photovoltaic Power Forecasting with Feature Extraction and Attention Mechanisms," *Renewable Energy*, vol. 226, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[3] Xuhui Hu, Huimin Li, and Chen Si, "Improved Composite Model using Metaheuristic Optimization Algorithm for Short-Term Power Load Forecasting," *Electric Power Systems Research*, vol. 241, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[4] Wei Liu, Qian Liu, and Yulin Li, "Ultra-Short-Term Photovoltaic Power Prediction based on Modal Reconstruction and BiLSTM-CNN-Attention Model," *Earth Science Informatics*, vol. 17, no. 3, pp. 2711-2725, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[5] Mengyao Chao et al., "An Improved Hybrid Neural Network Algorithm for Predicting Photovoltaic Output Power: Considering the Seasonal Output Characteristics of Solar Energy," *Journal of Renewable and Sustainable Energy*, vol. 17, no. 2, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[6] Manel Marweni et al., "Forecasting of Solar Irradiance and Power in Uncertain Photovoltaic Systems using BiLSTM and Bayesian Optimization," *Arabian Journal for Science and Engineering*, vol. 50, no. 14, pp. 10763-10777, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[7] Bing Li, Haizheng Wang, and Jinghua Zhang, "Short-term Power Forecasting of Photovoltaic Generation based on CFOA-CNN-BiLSTM-Attention," *Electrical Engineering*, vol. 107, no. 8, pp. 10335-10347, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[8] Yaxi Liu et al., "Multi-Layer BiLSTM Photovoltaic Prediction Study based on Improved PSO," *2023 5th International Conference on Circuits and Systems (ICCS)*, Huzhou, China, pp. 273-278, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[9] Nguyen Thi Hoai Thu, Phan Quoc Bao, and Nguyen Vu Nhat Nam, "Multiple Step Ahead Forecasting of Rooftop Solar Power Based on a Novel Hybrid Model of CEEMDAN-Bidirectional LSTM Network with Structure Optimized by PSO Method," *2022 11th International Conference on Control, Automation and Information Sciences (ICCAIS)*, Hanoi, Vietnam, pp. 522-528, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[10] Shuaiyu Zhuv, Hong Qing, and Tingting Yang, "Research on Ultra-Short-Term Photovoltaic Power Prediction based on Improved Dung Beetle Algorithm Optimization for BiLSTM," *Smart Grid and Cyber Security Technologies: 8th International Conference on Life System Modeling and Simulation, LSMS 2024 and 8th International Conference on Intelligent Computing for Sustainable Energy and Environment, ICSEE 2024*, Suzhou, China, vol. 2217, pp. 61-75, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[11] Mingyue Zhang et al., "Ultra-Short-Term Photovoltaic Power Prediction based on Similar Day Clustering and Temporal Convolutional Network with Bidirectional Long Short-term Memory Model: A Case Study using DKASC Data," *Applied Energy*, vol. 375, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[12] Di Wang, Sha Li, and Xiaojin Fu, "Short-Term Power Load Forecasting based on Secondary Cleaning and CNN-BILSTM-Attention," *Energies*, vol. 17, no. 16, pp. 1-23, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[13] V. Ashok Gajapati Raju et al., "Short-Term Solar Irradiance Forecasting Model based on Hyper-Parameter Tuned LSTM Via Chaotic Particle Swarm Optimization Algorithm," *Case Studies in Thermal Engineering*, vol. 69, pp. 1-22, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[14] Reagan Jean Jacques Molu et al., "Advancing Short-term Solar Irradiance Forecasting Accuracy Through a Hybrid Deep Learning Approach with Bayesian Optimization," *Results in Engineering*, vol. 23, pp. 1-16, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[15] Mohd Herwan Sulaiman, and Zuriani Mustaffa, "Enhancing Wind Power Forecasting Accuracy with Hybrid Deep Learning and Teaching-Learning-based Optimization," *Cleaner Energy Systems*, vol. 9, pp. 1-12, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[16] Taraneh Saadati, and Burak Barutcu, "Optimized Solar Energy Forecasting for Sustainable Development using Machine Learning, Deep Learning, and Chaotic Models," *International Journal of Energy Economics and Policy*, vol. 15, no. 1, pp. 110-120, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[17] Younjeong Lee, and Jongpil Jeong, "TSMixer-and Transfer Learning-based Highly Reliable Prediction with Short-Term Time Series Data in Small-Scale Solar Power Generation Systems," *Energies*, vol. 18, no. 4, pp. 1-21, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[18] Muhammad Shoaib Bhutta et al., "Optimizing Solar Power Efficiency in Smart Grids using Hybrid Machine Learning Models for Accurate Energy Generation Prediction," *Scientific Reports*, vol. 14, no. 1, pp. 1-25, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[19] J. Faritha Banu et al., "Artificial Intelligence with Attention based BiLSTM for Energy Storage System in Hybrid Renewable Energy Sources," *Sustainable Energy Technologies and, Assessments*, vol. 52, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[20] Min Yu et al., "Short-term Photovoltaic Power Point-interval Forecasting based on Double-layer Decomposition and WOA-BiLSTM-Attention and Considering Weather Classification," *Energy*, vol. 275, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[21] Neethu Elizabeth Michael et al., "A Cohesive Structure of Bi-Directional Long-Short-Term Memory (BiLSTM)-GRU for Predicting Hourly Solar Radiation," *Renewable Energy*, vol. 222, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[22] Wenshuai Lin, Bin Zhang, and Renquan Lu, "A Novel Hybrid Deep Learning Model for Photovoltaic Power Forecasting based on Feature Extraction and BiLSTM," *IEEJ Transactions on Electrical and Electronic Engineering*, vol. 19, no. 3, pp. 305-317, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[23] Vahdettin Demir, "Evaluation of Solar Radiation Prediction Models using AI: A Performance Comparison in the High-Potential Region of Konya, Türkiye," *Atmosphere*, vol. 16, no. 4, pp. 1-23, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[24] Rui Chang, Lei Bai, and Ching-Hsien Hsu, "Solar Power Generation Prediction based on Deep Learning," *Sustainable Energy Technologies and Assessments*, vol. 47, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[25] Mohamed Sayed Ibrahim, Sawsan Markos Gharghory, and Hanan Ahmed Kamal, "A Hybrid Model of CNN and LSTM Autoencoder-based Short-Term PV Power Generation Forecasting," *Electrical Engineering*, vol. 106, no. 4, pp. 4239-4255, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[26] Meftah Elsaraiti, and Adel Merabet, "Solar Power Forecasting using Deep Learning Techniques," *IEEE Access*, vol. 10, pp. 31692-31698, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[27] Jatin Sharma et al., "A Novel Long Term Solar Photovoltaic Power Forecasting Approach using LSTM with Nadam Optimizer: A Case Study of India," *Energy Science and Engineering*, vol. 10, no. 8, pp. 2909-2929, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[28] Omar A. Al-Shahri et al., "Solar Photovoltaic Energy Optimization Methods, Challenges and Issues: A Comprehensive Review," *Journal of Cleaner Production*, vol. 284, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[29] Raj Kumar Parida et al., "Enhanced Solar Power Prediction using CNN and Ladybug Beetle Optimization Algorithm," *Intelligent Decision Technologies*, vol. 18, no. 3, pp. 2133-2144, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[30] Sheo Kumar, and Amritpal Singh, "An Enhanced Deep Learning Predictive Framework for Drug Target Indications in Alzheimer's Disease," *Current Bioinformatics*, vol. 21, no. 8, pp. 644-655, 2026. [CrossRef] [Google Scholar] [Publisher Link]