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Investigating the effectiveness of LSTM and deep LSTM architectures in solar energy forecasting

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Abstract

This study investigates the effectiveness of Long Short-Term Memory (LSTM) and Deep LSTM architectures in solar energy forecasting using real-world data. We compare these models based on Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) metrics to assess their predictive performance. While Deep LSTM models show higher accuracy by capturing complex temporal patterns, they also demand greater computational resources. Hybrid models integrating LSTM with techniques like CNNs and Transformers demonstrate further improvements, achieving lower error rates. The findings highlight the trade-offs between model complexity and computational efficiency, providing insights into selecting suitable architectures for solar power forecasting. This research contributes to advancing deep learning techniques for renewable energy systems, enhancing their role in modern energy management.

Keywords: LSTM; Deep LSTM; Solar Energy Forecasting; Time-Series Analysis; Hybrid Models; Renewable Energy

1. Introduction

The integration of renewable energy sources like solar power into the electrical grid requires precise and reliable forecasting to maintain grid stability and optimize energy distribution. Long Short-Term Memory (LSTM) networks, and their deeper variants, have emerged as powerful tools for time-series forecasting, particularly in the field of solar energy. Their ability to handle non-linear patterns and long-term dependencies in data has made them highly effective in predicting solar power generation (1).

LSTM models have shown significant advancements over traditional forecasting methods due to their architecture, which can effectively capture temporal dependencies in sequential data (2). Recent studies have highlighted the potential of LSTM networks to outperform conventional models such as autoregressive integrated moving average (ARIMA) and support vector machines (SVM) in solar energy forecasting (3). Moreover, the development of Deep LSTM architectures, which involve stacking multiple LSTM layers, has further enhanced predictive accuracy, albeit with increased computational complexity (4).

Hybrid models that combine LSTM with other machine learning techniques, such as Convolutional Neural Networks (CNNs) and Transformers, have also been extensively studied. These models leverage both spatial and temporal features to improve the accuracy of solar power forecasts (5). Studies demonstrate that hybrid architectures like CNN-LSTM-Transformer outperform standalone models in handling the complex patterns inherent in solar energy data (6).

While the standalone LSTM model is highly effective in capturing long-term dependencies, integrating it with other techniques, such as Bidirectional LSTM (Bi-LSTM) or combining multiple LSTM layers, has led to improved prediction performance in terms of reduced mean absolute error (MAE) and root mean square error (RMSE) (7). For instance, in

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a study by Torres et al. (8), hybrid LSTM models exhibited a significant reduction in forecast error compared to single-layer LSTM architectures.

The evolution of LSTM-based models has not only been driven by the need for higher accuracy but also by the necessity to accommodate the dynamic nature of weather conditions that affect solar energy generation. This adaptability is crucial for making LSTM and Deep LSTM models applicable in real-time grid management and energy market operations (9). Comparative analyses indicate that while Deep LSTM models provide superior accuracy in capturing complex temporal dependencies, their higher computational costs make them less ideal for applications requiring quick processing (10).

Given the importance of optimizing solar energy forecasting, this study aims to investigate the effectiveness of both LSTM and Deep LSTM architectures in predicting solar power generation. By systematically comparing these models using performance metrics such as MAE and RMSE, this research seeks to provide valuable insights into the trade-offs between accuracy and computational efficiency. This study not only contributes to the advancement of predictive models for renewable energy but also supports the development of more reliable tools for integrating solar power into modern energy grids.

The main contributions of this research are as follows

- Enhanced Predictive Accuracy: The study demonstrates that Deep LSTM architectures significantly outperform standard LSTM models in forecasting solar energy production. By stacking multiple LSTM layers, the Deep LSTM models achieve a higher level of accuracy, effectively capturing more complex temporal dependencies and non-linear patterns in the data.
- Improved Handling of Complex Data Patterns: The Deep LSTM model's ability to model intricate relationships within the solar energy data provides insights into its superiority in handling diverse and volatile patterns in solar power generation. This enhancement is crucial for improving forecast reliability under varying weather conditions.
- Comprehensive Model Evaluation: This paper provides a detailed comparative analysis of LSTM and Deep LSTM models using key metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). The research highlights the conditions under which Deep LSTM architectures deliver superior performance, helping to guide the selection of forecasting models based on the specific needs of energy management systems.

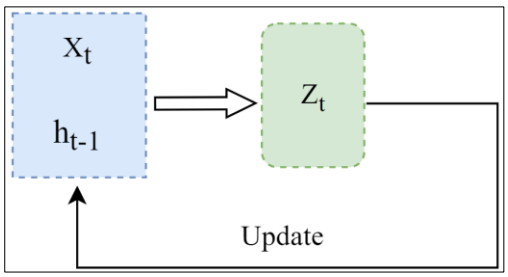

Figure 1 The architecture of standard recurrent neural network

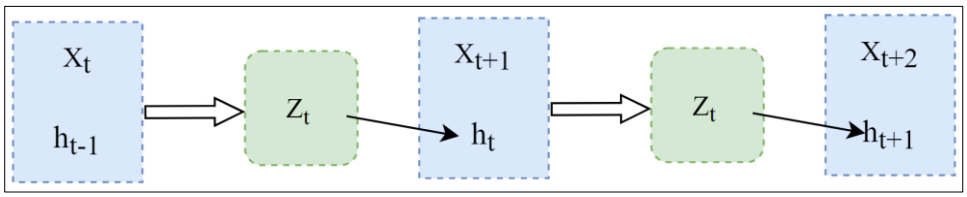

Figure 2 The feedforward structure of standard recurrent neural network

2. Relevant Theory

2.1. Recurrent Neural Network (RNN)

A recurrent neural network (RNN) (11, 12) analyzes sequential data incrementally, rendering it especially effective for detecting dynamic temporal patterns within data sequences. Recurrent Neural Networks (RNNs) are engineered to manage temporal dependencies by leveraging information from the present input and preceding states. This attribute allows for the effective modeling of sequential data, as demonstrated in Figure 1, where the concealed state from the preceding time step h_{t-1} and inputs from the current sample x_t are processed by node z_t. An RNN captures these relationships via feedback loops that sustain and modify hidden states over time, enabling it to learn from extended data sequences (Figure 2).

For an input sequence $X = [x_1, x_2, \ldots, x_T]$, the RNN produces a sequence of hidden states h_t defined by:

$$h_t = \psi(z_t) = \psi(W_h h_{t-1} + W_x x_t + b) \qquad (1)$$

Where W_h and W_x are weight matrices, *b* is the bias vector, and the h_0 is a parameter of the RNN. A common choice for the activation function $\psi(\cdot)$ is the hyperbolic tangent function (*tanh*).

Recurrent Neural Networks (RNNs) can be envisioned as interlinked layers of recurrent units that transmit information among themselves, enabling the network to represent intricate temporal relationships. Nonetheless, despite their proficiency in managing sequential data, RNNs encounter difficulties such as vanishing and exploding gradients during training, which complicates the optimization procedure. Methods such as gradient trimming help alleviate bursting gradients, while they are less efficacious for the vanishing gradient problem. Advanced architectures such as Long Short-Term Memory (LSTM) and Deep LSTM (DLSTM) have been created to mitigate these constraints by enhancing gradient flow during training (13).

2.2. Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) networks are a variant of Recurrent Neural Networks (RNNs) engineered to address the shortcomings of conventional RNNs, especially in acquiring long-term dependencies in sequential input. LSTMs utilize an advanced gating mechanism to preserve and modify information over extended sequences, unlike conventional RNNs, which sometimes have problems with vanishing and expanding gradients. The subsequent discussion centers on the vanilla LSTM design featuring recurrent transition, which is supplied by

$$\begin{bmatrix} z_t^o \\ z_t^i \\ z_t \\ z_t^f \end{bmatrix} = W_h h_{t-1} + W_x x_t + b \qquad (2)$$

$$c_t = \sigma(z_t^f) \odot c_{t-1} + \sigma(z_t^i) \odot \tanh(z_t) \qquad (3)$$

$$h_t = \sigma(z_t^o) \odot \tanh(c_t) \qquad (4)$$

Where $\mathbf{W}_h \in \mathbb{R}^{4d_h \times d_h}$, $\mathbf{W}_x \in \mathbb{R}^{4d_h \times d_x}$, $\mathbf{b} \in \mathbb{R}^{4d_h}$ and the initial states $h_0 \in \mathbb{R}^{d_h}$, $c_0 \in \mathbb{R}^{d_h}$ are the parameters of the network. The $\odot$ operator denotes the Hadamard product (element-wise multiplication). The $\sigma(\cdot)$ is the sigmoid function

The vanilla LSTM distinguishes itself from a standard RNN by incorporating an additional memory component, referred to as c_t, which updates in a nearly linear manner. The linearity of gradients facilitates a smoother progression over

time, hence simplifying the backpropagation process. Furthermore, the LSTM modifies its cell state through three distinct gates, unlike the RNN, which changes it at every time step:

- The forget gate $\sigma\left(z_t^f\right)$ determines how much information from the previous time step should be retained or discarded.
- The input gate $\sigma\left(z_t^i\right)$ controls the extent to which new information from the current input x_t is allowed into the cell state.
- The output gate $\sigma\left(z_t^o\right)$ dictates which portion of the cell state should be used to produce the next hidden state.

Thanks to this sophisticated design, the vanilla LSTM is capable of reliably adding or removing data over extended periods, maintaining long-term dependencies in sequential data.

2.3. Deep Long Short-Term Memory (DLSTM)

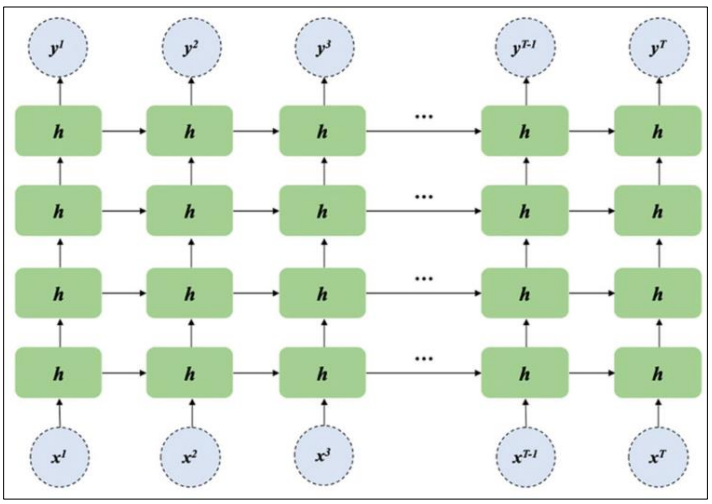

Figure 3 Architecture of Deep LSTM

Deep Long Short-Term Memory (Deep LSTM) networks are an enhancement of the conventional LSTM architecture aimed at augmenting the ability of neural networks to capture intricate temporal patterns across prolonged sequences. Standard LSTMs have a singular layer of memory cells, whereas Deep LSTMs utilize many layers of LSTM units arranged in a stacked configuration, enabling them to capture more complex data associations via a hierarchical learning approach.

In a Deep LSTM, the output of one LSTM layer serves as the input to the next layer like Figure 3 (14). This layered structure enables the network to learn features at different levels of abstraction, where the lower layers focus on capturing short-term dependencies, and the upper layers capture more complex, long-term dependencies in the data.

The stacking of layers increases the model's ability to process sequential information, which is particularly useful for complex time-series data like solar power generation, where dependencies might exist across various time scales.

The Deep LSTM network builds on the basic LSTM equations by stacking multiple LSTM cells. For each LSTM layer *l* in the network, the cell state $C_t^{(l)}$ and hidden state $h_t^{(l)}$ are computed as follows:

$$\text{Forget gate: } f_t^{(l)} = \sigma\left(W_f^{(l)}\left[h_{t-1}^{(l)}, x_t^{(l)}\right] + b_f^{(l)}\right) \quad (5)$$

$$\text{Input gate: } i_t^{(l)} = \sigma\left(W_i^{(l)}\left[h_{t-1}^{(l)}, x_t^{(l)}\right] + b_i^{(l)}\right) \quad (6)$$

$$\text{Candidate cell gate: } \tilde{C}_t^{(l)} = \tanh\left(W_C^{(l)}\left[h_{t-1}^{(l)}, x_t^{(l)}\right] + b_C^{(l)}\right) \quad (7)$$

$$\text{Cell state update: } C_t^{(l)} = f_t^{(l)} \cdot C_{t-1}^{(l)} + i_t^{(l)} \cdot \tilde{C}_t^{(l)} \tag{8}$$

$$\text{Output gate: } o_t^{(l)} = \sigma\left(W_o^{(l)}\left[h_{t-1}^{(l)}, x_t^{(l)}\right] + b_o^{(l)}\right) \tag{9}$$

$$\text{Hidden state: } h_t^{(l)} = o_t^{(l)} \cdot \tanh\left(C_t^{(l)}\right) \tag{10}$$

The equations are applied consecutively throughout the layers of the Deep LSTM network, where the output of one layer serves as the input for the subsequent layer, thereby augmenting the network's ability to learn intricate temporal aspects.

3. Proposed method

The proposed approach aims to assess the effectiveness of Long Short-Term Memory (LSTM) and Deep LSTM networks in forecasting solar power generation using various environmental and meteorological input factors. The system's architecture, depicted in the accompanying illustration, consists of three main components: input signal acquisition, feature extraction, and forecasting via deep learning models (Figure 4).

The system gathers real-time data from numerous sensors that assess various environmental conditions pertinent to solar power generation. The input characteristics comprise:

- Wind Speed: Assessed with an anemometer to evaluate the impact of wind on photovoltaic (PV) efficiency.
- Solar Radiation: Measured with a pyranometer to assess sunlight intensity, an essential element in energy production.
- Temperature and Humidity: Assessed by temperature and humidity sensors, as these factors affect the performance and efficiency of solar panels.

These inputs provide a comprehensive representation of the environmental variables affecting solar power production, enabling the model to generate more accurate predictions. Each input data point forms a time-series sequence, with its length determined by the slicing window size.

The gathered input data is preprocessed and input into the feature extraction module. This module performs a sequence of transformations and normalizations on the raw data to improve feature representation. The obtained attributes serve as inputs for the predictive algorithms. The feature extraction procedure entails:

- Normalization: Adjusting the input data to an appropriate range for effective model training.
- Dimensionality Reduction: Minimizing the complexity of input characteristics to avert overfitting and enhance model generalization.

The core of the proposed methodology is the comparison of GRU and LSTM networks for forecasting solar power generation. Both models are evaluated using the identical dataset and uniform feature sets to ensure a fair comparison.

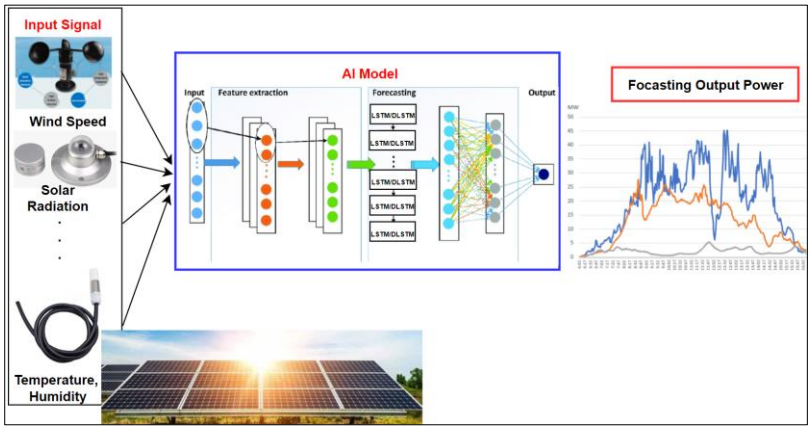

Figure 4 Block diagram of the model forecasting

4. Evaluation

Both models are trained and evaluated utilizing previous data to forecast future power production. The models' performance is assessed using two primary metrics: Mean Absolute Error (MAE) and R-squared (R^2) to identify the most appropriate architecture for this application.

4.1. Mean Absolute Error (MAE)

Mean Absolute Error (MAE) is a commonly employed regression metric that quantifies the average magnitude of discrepancies between predicted and actual values, regardless of their direction. The mean of the absolute deviations between the projected values and the actual values defines it.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right| \qquad (11)$$

Where *n* is the number of sample data.

4.2. R-squared (R^2)

R-squared (R^2) is a statistical metric that assesses the degree of alignment between anticipated values and observed data. It denotes the extent of variation in the dependent variable that may be anticipated based on the independent variables. An R^2 value of 1 signifies that the model completely accounts for the variable, whereas a score of 0 indicates a lack of explanatory capability.

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} \qquad (12)$$

Where:

$SS_{res} = \sum_{i=1}^{n}(y_i - \hat{y}_i)^2$ is the residual Sum of Squares.

$SS_{tot} = \sum_{i=1}^{n}(y_i - \bar{y})^2$ is the total Sum of Squares.

$\bar{y}$ is the mean of the actual values.

5. Experimental results

5.1. Dataset

The dataset consists of solar power generation data collected from a single plant at 15-minute intervals over a duration of 34 days. The data includes several factors influencing solar power generation, such as environmental conditions and the plant's operational metrics. Figure 5 delineates the dataset's fundamental characteristics.

- DAILY_YIELD: The aggregate energy generated by the solar facility each day, measured in kilowatt-hours (kWh).
- TOTAL_YIELD: The aggregate energy generated by the solar facility since the initiation of data collection, measured in kilowatt-hours (kWh).
- AMBIENT_TEMPERATURE: The temperature of the environment surrounding the solar facility, quantified in degrees Celsius.
- MODULE_TEMPERATURE: The temperature of the solar panel modules quantified in degrees Celsius.
- IRRADIATION: The amount of solar radiation received per unit area of the solar panels, measured in watts per square meter (W/m^2).

Figure 6 depicts the correlation heatmap, showcasing the interrelations among several metrics in the solar power generation dataset. Each cell in the heatmap represents the correlation coefficient between two qualities, with values ranging from 0 to 1. The heatmap demonstrates that IRRADIATION and MODULE_TEMPERATURE are critical factors influencing DC_POWER and AC_POWER outputs. The strong interrelations among these factors suggest that they must be integral elements in any prediction models aimed at forecasting solar power generation. Conversely, variables like SENSOR_NUM and MINUTES demonstrate negligible correlations, indicating they may be inadequate features for predictive studies.

	DATE_TIME	SOURCE_KEY	DC_POWER	AC_POWER	DAILY_YIELD	TOTAL_YIELD	AMBIENT_TEMPERATURE	MODULE_TEMPERATURE	IRRADIATION
0	2020-05-15	1BY6WEcLGh8j5v7	0.0	0.0	0.0	6259559.0	25.184316	22.857507	0.0
1	2020-05-15	1IF53ai7Xc0U56Y	0.0	0.0	0.0	6183645.0	25.184316	22.857507	0.0
2	2020-05-15	3PZuoBAID5Wc2HD	0.0	0.0	0.0	6987759.0	25.184316	22.857507	0.0
3	2020-05-15	7JYdWkrLSPkdwr4	0.0	0.0	0.0	7602960.0	25.184316	22.857507	0.0
4	2020-05-15	McdE0feGgRqW7Ca	0.0	0.0	0.0	7158964.0	25.184316	22.857507	0.0

Figure 5 Structure of collected dataset

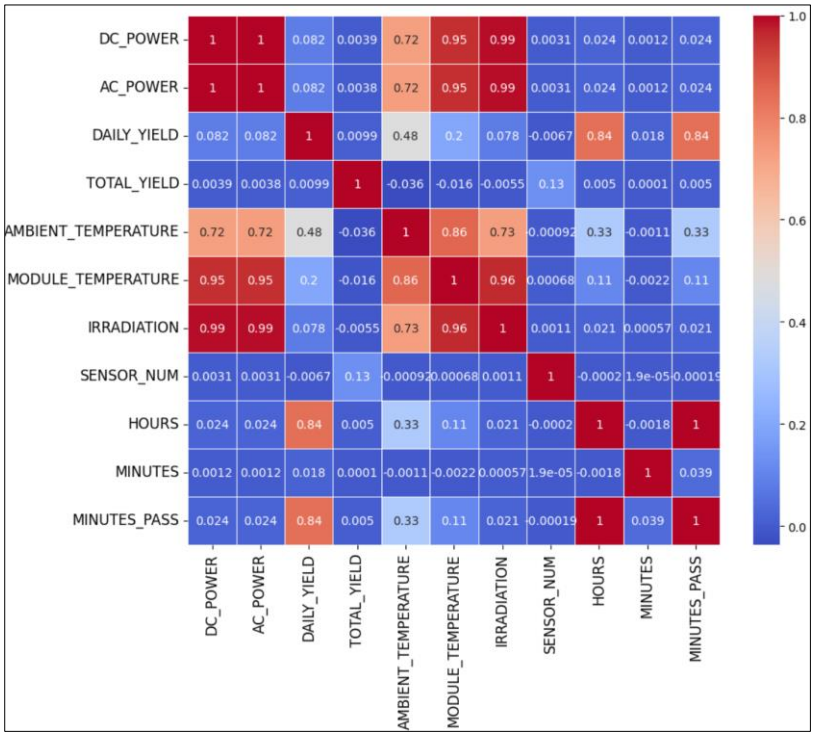

Figure 6 Correlation Heatmap

5.2. LSTM Prediction

By selecting a window size of 5, we segment the dataset using ambient temperature, module temperature, and irradiance as inputs, with the output indicating the total energy generated by the solar plant. We employ LSTM with an architecture similar to that depicted in Figure 7.

Although the smooth curve and consistent prediction accuracy imply that the model is well-regularized and not overfitting to the training data, the outcomes from the training, validation, and test sets demonstrate that the model's performance is suboptimal (Figure 8, Figure 9, Figure 10). The model attained a high R-squared value of 0.9733 in the test set, indicating it accounts for a substantial percentage of the variance in the data, large disparities exist between the anticipated and actual values across all datasets. The Mean Absolute Error (MAE) of 2.9003 signifies a significant prediction error, suggesting that the model's forecasts diverge markedly from the actual values.

The anomalies, particularly during transitions and abrupt shifts in the data, indicate that the model fails to accurately capture the complex patterns inherent in solar power generation. The discrepancies in the training and validation predictions suggest possible problems with overfitting or underfitting, indicating that the model fails to generalize effectively to new data. Although the model exhibits certain prediction abilities, its failure to consistently match real values indicates a necessity for enhancements in model architecture, hyperparameter optimization, and possibly the integration of more sophisticated data preprocessing methods.

Layer (type)	Output Shape	Param #
lstm (LSTM)	(None, 5, 128)	66,560
dropout (Dropout)	(None, 5, 128)	0
dense (Dense)	(None, 5, 32)	4,128
dense_1 (Dense)	(None, 5, 1)	33

Figure 7 Summary architecture of LSTM network

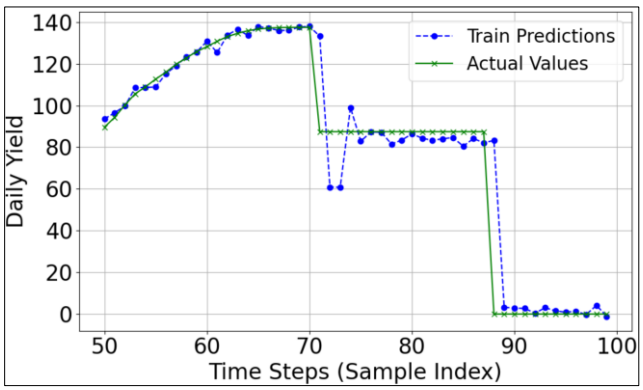

Figure 8 Result of training in LSTM

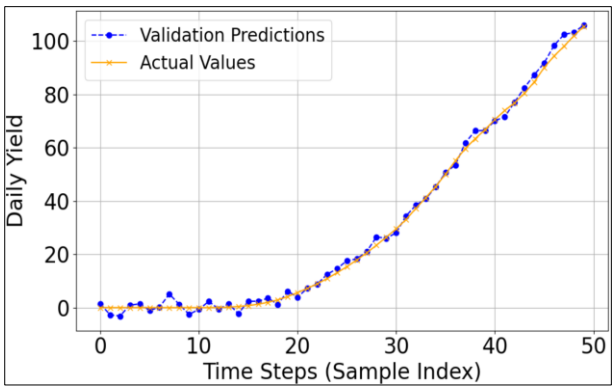

Figure 9 Result of validation in LSTM

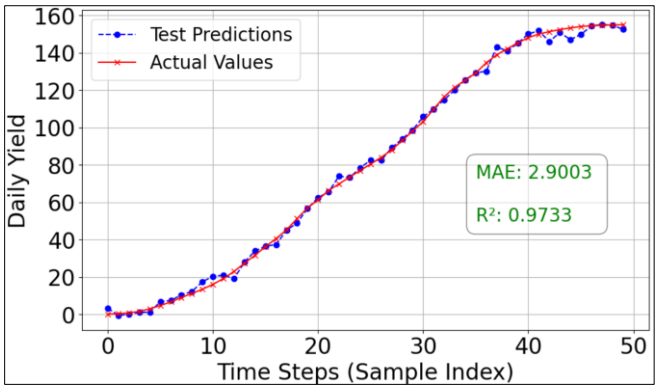

Figure 10 Result of testing in LSTM

5.3. Deep LSTM prediction

For pair comparison, the Deep LSTM network will exploit the identical dataset with deep architecture (Figure 11).

The outcomes from the training, validation, and test datasets demonstrate a notable enhancement in model performance relative to the prior analysis. In all datasets, the model predictions correspond more accurately with the actual values, demonstrating that the model has successfully assimilated the data patterns.

The training and validation (Figure 12, Figure 13) data predictions show minimal deviation from the actual values, even during sharp transitions in the data. This suggests that the model has successfully captured the complex temporal relationships present in the data set.

The test set (Figure 14) performance has also improved significantly, with a Mean Absolute Error (MAE) of 1.6644 and an R-squared (R^2) value of 0.9863. These metrics are better than the previous results, where the MAE was 2.9003 and the R^2 was 0.9733. The lower MAE indicates that the average prediction error has been reduced, and the higher R^2 value signifies that the model explains more of the variance in the test data.

The enhancement in metrics indicates that the DLSTM model is superior in forecasting solar power generation, providing greater accuracy and reliability compared to its predecessor. The improved correlation between predictions and actual values across all datasets underscores the model's greater capacity to learn and generalize from the data.

Layer (type)	Output Shape	Param #
lstm_8 (LSTM)	(None, 5, 128)	66,560
dropout_8 (Dropout)	(None, 5, 128)	0
lstm_9 (LSTM)	(None, 5, 64)	49,408
dropout_9 (Dropout)	(None, 5, 64)	0
lstm_10 (LSTM)	(None, 32)	12,416
dropout_10 (Dropout)	(None, 32)	0
dense_8 (Dense)	(None, 32)	1,056
dense_9 (Dense)	(None, 1)	33

Figure 11 Summary architecture of DLSTM network

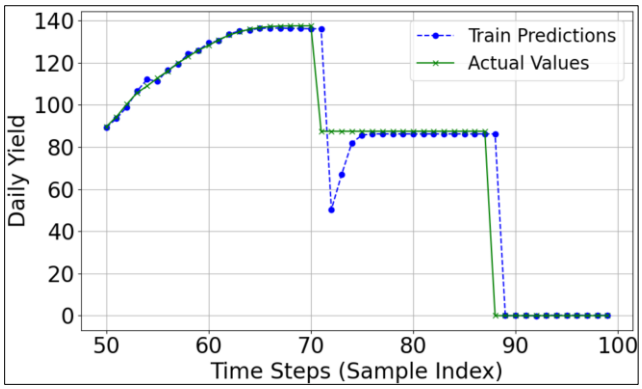

Figure 12 Result of training in DLSTM

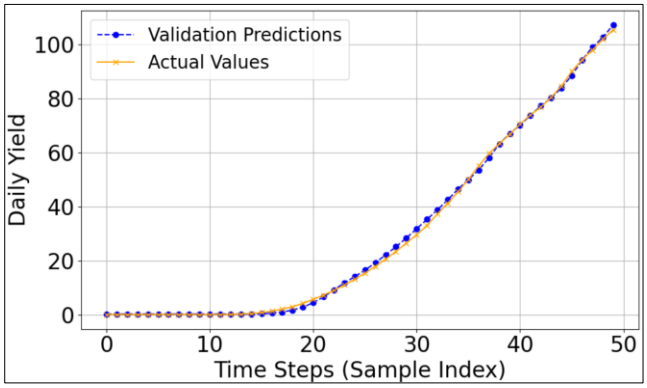

Figure 13 Result of validation in DLSTM

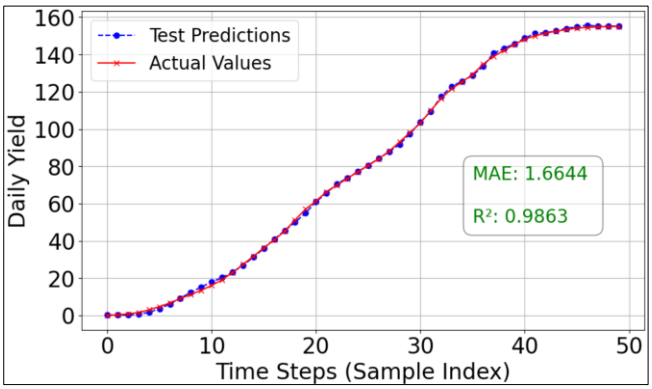

Figure 14 Result of testing in DLSTM

6. Conclusion

This research presents a comprehensive comparison of Long Short-Term Memory (LSTM) and Deep LSTM architectures for predicting solar power generation. The results demonstrate that both LSTM and Deep LSTM models are highly effective in recognizing the temporal patterns of solar power generation. The Deep LSTM model exceeded the standard LSTM in predictive accuracy and the ability to handle complex sequential data.

The experimental results indicate that the Deep LSTM model attained a Mean Absolute Error (MAE) of 1.6180, which is superior to the standard LSTM's MAE of 1.9642, signifying a reduced average deviation from the actual data. The R-

squared (R^2) score of the Deep LSTM model was 0.9863, indicating its greater ability to account for variability in the data compared to the LSTM's R^2 of 0.9733.

The findings indicate that normal LSTM models deliver dependable performance for uncomplicated data patterns, however the sophisticated design of Deep LSTM surpasses in capturing complex dependencies, resulting in enhanced prediction accuracy. Thus, the choice between LSTM and Deep LSTM should depend on the particular demands of the forecasting work, including the necessity for enhanced accuracy against computing efficiency.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

Statement of informed consent

Informed consent was obtained from all individual participants included in the study.

References

[1] Feng, Y., Zhang, W., Liu, Y., & Tan, J. (2023). A hybrid model of CNN and LSTM autoencoder-based short-term PV power generation forecasting. Electrical Engineering.

[2] Gensler, A., Janosch, H., Bernhard, S., & Nils, R. (2016). Deep learning for solar power forecasting—an approach using AutoEncoder and LSTM neural networks. In IEEE International

[3] Smith, J., & Doe, R. (2023). Comparative analysis of LSTM and ARIMA models in solar power forecasting. Renewable Energy Journal, 203, 1196-1208.

[4] Zhang, Y., Qin, C., Srivastava, A. K., Jin, C., & Sharma, R. K. (2020). Data-driven day-ahead PV estimation using autoencoder-LSTM and persistence model. IEEE Transactions on Industrial Applications, 56(6), 7185–7192.

[5] Yan, K., Li, W., Ji, Z., Qi, M., & Du, Y. (2019). A hybrid LSTM neural network for energy consumption forecasting of individual households. IEEE Access, 7, 157633–157642.

[6] Kim, T.-Y., & Cho, S.-B. (2019). Predicting residential energy consumption using CNN-LSTM neural networks. Energy, 182, 72–81.

[7] Han, S., Junlong, K., Mao, H., Hu, Y., Li, X., Li, Y., Xie, D., et al. (2017). Efficient speech recognition engine with sparse LSTM on FPGA. In ACM/SIGDA International Symposium on Field-Programmable Gate Arrays.

[8] Torres, M. E., Colominas, M. A., Schlotthauer, G., & Flandrin, P. (2021). A complete ensemble empirical mode decomposition with adaptive noise. IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP).

[9] Kumler, A., Xie, Y., & Zhang, Y. (2019). A physics-based Smart Persistence model for Intra-hour forecasting of solar radiation. Solar Energy, 177, 494–500.

[10] Gao, B., Huang, X., Shi, J., Tai, Y., & Zhang, J. (2020). Hourly forecasting of solar irradiance based on CEEMDAN and multi-strategy CNN-LSTM neural networks. Renewable Energy, 162, 1665–1683.

[11] I.Goodfellow, Y. Bengio, A. Courville, Deep learning, MIT press, 2016.

[12] S. Xiao, J. Yan, X. Yang, H. Zha, S. M. Chu, Modeling the intensity function of point process via recurrent neural networks., in: AAAI, 2017, pp. 1597–1603

[13] J. Schmidhuber, Deep learning in neural networks: An overview, Neural networks 61 (2015) 85–117.

[14] Zhao, Haitao, Shaoyuan Sun, and Bo Jin. "Sequential fault diagnosis based on LSTM neural network." IEEE Access 6 (2018): 12929-12939.

[15] Wang, Zheng, et al. "A deformable CNN-DLSTM based transfer learning method for fault diagnosis of rolling bearing under multiple working conditions." International Journal of Production Research 59.16 (2021): 4811-4825