Forecasting Solar Power Generation in Tay Ninh Province Using Deep Learning and Statistical Models: A Comparative Evaluation

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ABSTRACT

In this study, a method was proposed for an accurate prediction of the rooftop PV power output at a specific power unit located in Tây Ninh province, Vietnam, employing six machine learning models: Artificial Neural Network (ANN), Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), Bidirectional LSTM (Bi-LSTM), and Linear Regression (LR). Data preprocessing was conducted before partitioning the dataset into training and testing sets. The results indicated that the Bi-LSTM model exhibited superior performance compared to other models, achieving the lowest Mean Absolute Error (MAE) of 32.29, Root Mean Squared Error (RMSE) of 56.20, and normalized RMSE (n-RMSE) of 12.19%. GRU and LSTM also yielded favorable results, while ANN, CNN, and LR displayed slightly higher prediction errors. In conclusion, the Bi-LSTM model emerged as the most effective approach for precise rooftop solar power output forecasting, surpassing other models, including the conventional LR model. This method was realized and promising.

1. INTRODUCTION

The prediction of solar energy generation is critically important within the field of renewable energy, contributing significantly to efficient grid management, optimal energy utilization, and well-informed decision-making. A particular trend can be seen around the world, involving the heightened connection of concentrated solar power within the distribution network, which renders theaccurate prediction of this energy source's output increasingly imperative. In recent times, Tây Ninh province, Vietnam, has witnessed a surge in rooftop solar installations, adding substantial pressure to the distribution grid. Consequently, a reliable forecasting system is now essential for guaranteeing the operational effectiveness of the grid. A major challenge when forecasting rooftop solar energy lies in the availability and quality of historical weather data. To achieve precise predictions, a reliable historical weather model, encompassing solar radiation, temperature, and cloud cover, is of utmost importance. Collecting such data can be challenging, particularly in remote areas or regions with limited weather monitoring infrastructure.

Another significant challenge arises from the variability in the characteristics of solar panels. Different types of solar panels exhibit varying efficiencies and output capacities, directly influencing energy production. Accurate information about installed solar panels, including their age, condition, and operational characteristics, is crucial for precise forecasting. However, this data is not always readily available or consistently updated. Geographical factors also play a decisive role in photovoltaicproduction. The location of solar panels, their tilt angle, the impact of shading from surrounding structures or vegetation, and the overall landscape can significantly affect energy generation. Integrating these specific location-based factors into forecasting models requires accurate geographical data, necessitating additional efforts for collection and integration. With these distinctive challenges, accurately forecasting the power output of rooftop solar installations is far from straightforward. Therefore, there is a need for research into various forecasting methods to identify effective solutions tailored to different types of data and regions.

There have been various research studies focused on forecasting PV power capacity, which can be broadly classified into two categories: indirect prediction based on physical models and direct prediction based on historical data. The direct prediction method involves the development of a nonlinear forecasting model that utilizes historical meteorological information and PV generation figures to directly output the PV power capacity. On the other hand, indirect models follow a two-stage approach involving an initial prediction of solar irradiance, after which a physical model is utilized to connect irradiance levels to the PV system's power capacity. However, this two-step prediction

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and calculation process in indirect models introduces uncertainties and errors, making the forecasting of PV power capacity more complex and computationally expensive, while reducing its accuracy.

Direct forecasting models for PV power capacity can be broadly categorized into two main groups: conventional statistical methods and contemporary intelligent techniques. Traditional methods, such as linear regression [1], AR-MA [2], and ARIMA models [3], have demonstrated their effectiveness in predicting PV power capacity by analyzing statistical relationships based on historical data. Yet, their strong reliance on linearity and need for stationary data restricts their utility for complex, nonlinear time series predictions. To overcome the challenges presented by the inhenrent nonlinearity of PV power output data, modern intelligent methods have emerged and garnered significant attention. These advanced techniques include artificial neural networks (ANN) [5], [6], conventional neural networks, support vector regression (SVR) [7], support vector machines (SVM) [8], and extreme learning machines (ELM) [9].

In recent times, the field of PV power capacity forecasting has witnessed a surge in popularity and progress due to deep learning technology. Deep learning methods, such as convolutional neural networks (CNN) [10], [11], [12], recurrent neural networks (RNN) [13], long short-term memory networks (LSTM) [14], [15], [16], bidirectional long short-term memory network (Bi-LSTM) [17], [18], [19], and gated recurrent units (GRU) [20], have been proposed and rigorously evaluated. The application of these deep learning approaches has shown considerable potential in substantially improving the precision of PV power capacity prediction. By adeptly capturing complex patterns and temporal dependencies in the data, these models stand as formidable tools to enhance the forecasting accuracy of PV power capacity.

The use of deep learning in PV power capacity forecasting has demonstrated strong potential in enhancing predictive performance. These approaches are particularly effective due to their ability to model intricate data behaviors and temporal trends within historical PV datasets. By capturing such dynamics, they offer a robust solution for improving prediction reliability. As researchers continue to explore and refine these AI-based model approaches, we expect further breakthroughs in the domain of solar energy forecasting, ultimately contributing to the sustainable and efficient utilization of solar power resources. Hence, in this study, our aim is to evaluate the effectiveness of representative forecasting models, built on well-established techniques,for application in data-constrained environments, such as in Vietnam.

The next parts of this study cover are organized as follows: Section 2 explains the techniques employed in the proposed approach. Section 3 presents and discusses the results. Lastly, Section 4 concludes the findings and suggests potential future work.

2. METHODOLOGY

2.1 Linear regression (LR)

Linear Regression (LR) is a widely acclaimed and effective statistical technique utilized in the fields of forecasting and estimation. Its primary objective is to establish a straight-line relationship between a dependent outcome and one or more independent predictors. This approach has gained traction due to its simple structure and ease of use. By uncovering patterns in data, LR offers useful insights across multiple domains such as economics, healthcare, social sciences, finance, and information systems.

Fundamentally, LR fits a straight-line model to observed data by minimizing the gap between the predicted values and the actual observations. This linear replationshipis represented as:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n \qquad (1)$$

In this equation, y represents the dependent variable, the x terms (x_1, x_2, ..., x_n) are the independent variables, and the β terms (β_0, β_1, β_2, ..., β_n) denote model coefficients. LR determines optimal coefficient values to produce the line best reflecting the fundamental connection between variables.

Various methods are employed to estimate the coefficients in LR, with Ordinary Least Squares (OLS) and Maximum Likelihood Estimation (MLE) being the most common. The OLS method works by reducing the total squared error between actual outcomes and model predictions, essentially minimizing the residuals. MLE, conversely, selects coefficients maximizing the probability of observing the actual data under the LR model. The versatility of LR extends beyond simple linear relationships. It can handle more complex scenarios, such as Multiple Linear Regression, where multiple independent variables contribute to the prediction of the dependent variable. Additionally, Nonlinear Regression techniques allow LR to capture nonlinear relationships between the variables, further enhancing its applicability in diverse datasets. Moreover, LR is widely employed in Time Series Regression, enabling the forecasting of future values based on past observations. However, LR has multiple limitations, including sensitivity to influential data points and susceptibility to outliers, which may impact the model's forecasting abilities.

2.2 Artificial Neural Network (ANNs)

The Artificial Neural Network (ANN) is a widely recognized and powerful computational models inspired by how the human brain functions. They are extensively applied in machine learning tasks to address a wide range of complex and large-scale problems.. Within ANNs, data is processed as it moves through a hierarchy of interconnected layers – initially from inputs, then through intermediate layers where computations occur, and finally to output nodes that produce predictions. Each node processes signals using weighted sums, followed by activation functions that introduce non-linearity. During learning, the system modifies internal parameters – commonly referred to as weights and offsets/biases – so that its predicted results increasingly align with actual observations.

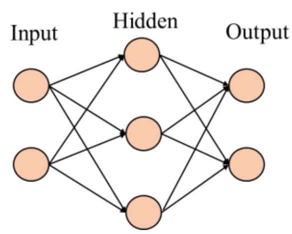


Fig. 1. Structure of ANN model.

Thanks to their ability to manage large and varied datasets, ANNs are used in many domains including pattern recognition, language understanding, and financial analytics. Their flexibility and strong generalization ability make them effective for tackling difficult real-world problems. However, to achieve good performance, careful attention must be given to the model's architecture and training process, including hyperparameter tuning to avoid issues like overfitting.

2.3 Convolutional Neural Network (CNN)

Convolutional Neural Networks (CNNs) represent a tailored type of neural architecture designed primarily for handling visual information. These networks are particularly well-suited for extracting meaningful patterns from images due to their ability to compress data while retaining essential features. CNNs are a standard in image recognition tasks across industries such as medicine, healthcare, automotive, and security.

A Convolutional Neural Network (CNN) employs a structured sequence of operations to process visual data. Initially, it identifies essential patterns such as edges or textures using filters and activation functions—this stage is handled by what is known as the convolutional layer. The resulting feature maps are then simplified to reduce dimensionality and computational complexity by selecting the most informative parts; this function is performed by the pooling layer. Finally, the extracted and compressed information is passed through a densely connected system that combines features to make predictions—this is managed by the fully connected layer.

CNN's architecture has proven highly effective in image recognition and classification tasks, particularly in applications related to healthcare, automotive technology, and energy due to its ability to condense data while retaining crucial information.. The CNN architecture is illustrated in Fig.2.

2.4 Long short term memory network (LSTM)

Long Short-Term Memory network (LSTM) is a specialized form of recurrent neural network (RNN) created to effectively retain and process information over extended sequences. Unlike the original RNN model that often face limitations like gradient vanishing when handling long-range dependencies, LSTM utilize specialized memory cells to store and control information flow.

Each memory unit in an LSTM network contains internal mechanisms that regulate information flow. One mechanism filters incoming data to determine how much should be written to memory – this is known as the input gate. Another identifies outdated or irrelevant content for removal, referred to as the forget gate. The final mechanism evaluates what stored data should be passed on to the next time step, which is handled by the output gate. The architecture of a typical LSTM cell is illustrated in Fig. 3.

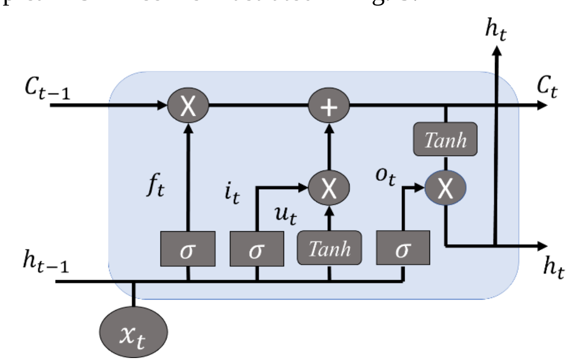


Fig. 2. The architecture of LSTM.

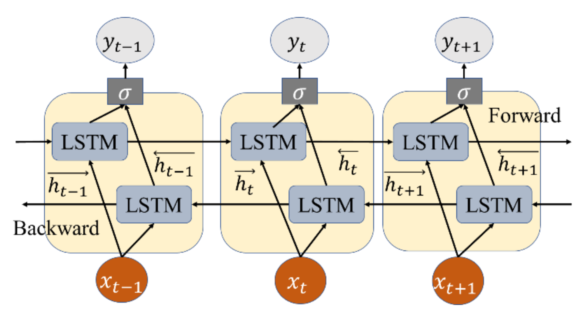


Fig. 3. The architecture of Bi-LSTM model.

Mathematically, the operations within an LSTM unit can be described using the following equations:

$$i_t = tanh.(W_i.[h_{t-1}, x_t] + b_i) \quad (2)$$

$$f_t = \sigma.(W_f.[h_{t-1}, x_t] + b_f) \quad (3)$$

$$o_t = \sigma.(W_o.[h_{t-1}, x_t] + b_o) \quad (4)$$

$$\tilde{C}_t = tanh.(W_C.[h_{t-1}, x_t] + b_c) \quad (5)$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \quad (6)$$

$$h_t = o_t.\tanh(C_t) \quad (7)$$

2.5 Bidirectional long short term memory network (BiLSTM)

The Bidirectional Long Short-Term Memory (Bi-LSTM) is another variation of the LSTM architecture, where one unidirectional LSTM layer is split into two bidirectional layers: Backward and Forward. Each layer shares the same structure. The input sequence is sent into the input layer, and the forward path processes the input from the beginning to the end of the sequence to retain outputs at each time step. The reverse sequence is calculated backward and forward along time t to capturethe output at each time step. Both the forward and reverse sequences are computed in parallel. Each sequence then undergoes its respective activation function. In the final step, outputs from the two directions are merged to generate the complete output. Fig. 4 provides a visual representation of the Bi-LSTM network.

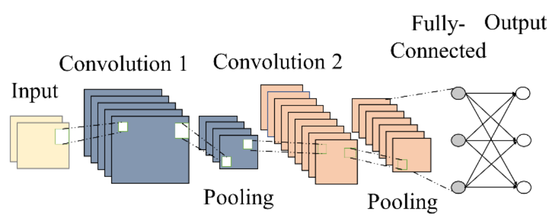


Fig. 4. The block diagram of CNN model.

2.6 Gated recurrent unit (GRU)

The Gated Recurrent Unit (GRU) is a streamlined variant of the recurrent neural network (RNN), recognized for its computational efficiency and ability to model dependencies over extended time steps. Similar to LSTM, GRU is engineered to mitigate the vanishing gradient issue, thereby enhancing the network's capacity to retain and learn information over long sequences.

At the core of a GRU are two internal control mechanisms that manage information flow through the network. One mechanism is responsible for adjusting how much of the previous hidden state should be reset, allowing the unit to discard irrelevant past information – this is referred to as the reset gate. The other mechanism determines how much of the incoming input should be merged with the existing state to form the new hidden state, a process governed by the update gate. The operation of GRU was shown in Fig.5.

Mathematically, the operations within a GRU unit can be described as follows:

$$r_t = \sigma(W_r.x_t + U_r h_{h-1} + b_r) \quad (8)$$

$$z_t = \sigma(W_z.x_t + U_z h_{h-1} + b_z) \quad (9)$$

$$\tilde{h}_t = \tanh[(W_h.x_t + U_h(r_t * h_{h-1})] \quad (10)$$

$$h_t = (1 - z_t)h_{h-1} + \tilde{h}_t * z_t \quad (11)$$

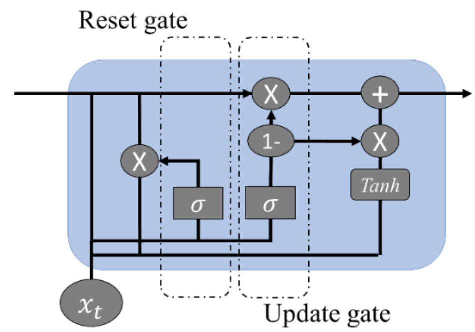


Fig. 5. The operation of GRU model.

The simplicity of the GRU architecture, with its reduced number of gates compared to LSTM, results in fewer parameters to optimize during training. This advantage makes the GRU well-suited for hyperparameter optimization in various applications..

2.7 Forecasting accuracy measures

The assessment of forecast errors is fairly important in selecting the appropriate forecasting method. Three metrics was applied for this study, described as follows:

- Mean Absolute Error (MAE):

$$MAE = \frac{1}{n} * \sum |y_{true} - y_{pred}| \quad (12)$$

- Root Mean Square Error (RMSE)

$$RMSE = \sqrt{\frac{1}{n} * \sum (y_{true} - y_{pred})^2} \quad (13)$$

- Normalized Root Mean Square Error (n-RMSE)

$$n\text{-}RMSE = \frac{RMSE}{\max(y_{true}) - \min(y_{true})} * 100\% \quad (14)$$

where, y_{true} denotes the measured data, and y_{pred} denotes the forecasting values.

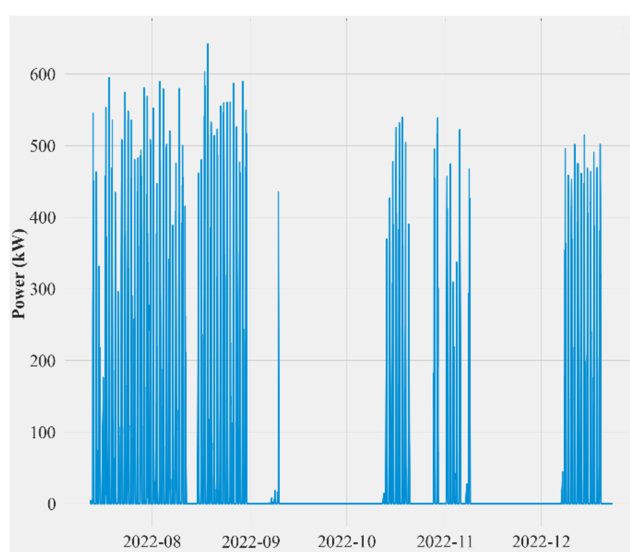
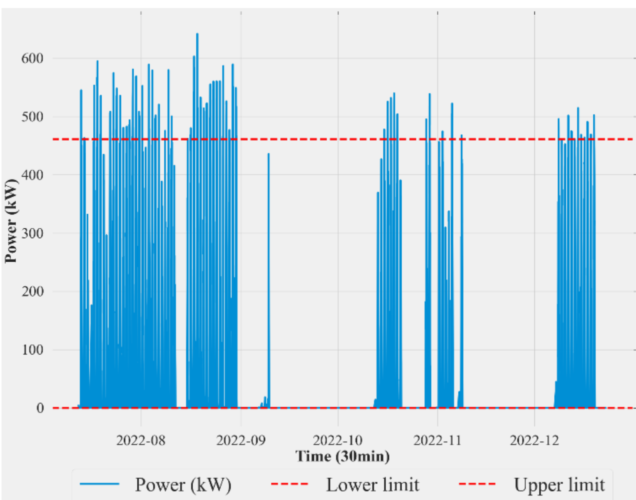


Fig. 6. The original dataset obtained from Inverter 157.

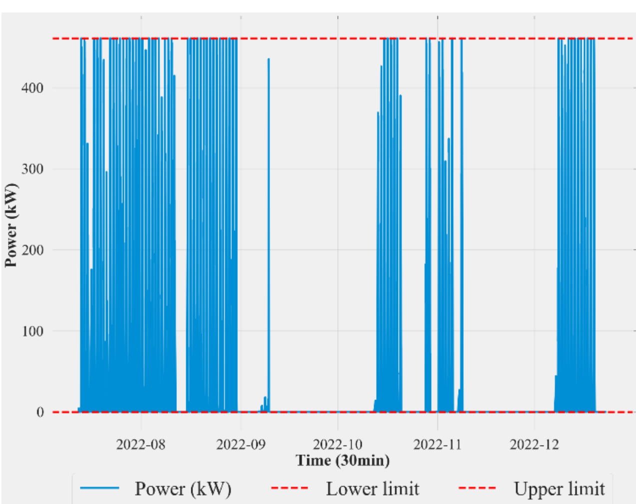
3. RESULTS AND DISCUSSION

3.1 Data collection

The data on rooftop solar energy production has been collected from the rooftop PV system which installed at Tây Ninh, Vietnam, utilizing the output signal from Inverter ID 157 to gather power generation data. This dataset encompasses values recorded from July 2022 to December 2022, with a time resolution of 30 minutes, expressed in kilowatts (kW). The raw, unprocessed dataset is illustrated in Fig. 6.



a. Dataset before being processed.



b. Dataset after being processed

Fig. 7. Data preprocessing using IQR.

3.2. Data pre-processing

Data preprocessing has become extremely crucial as it ensures the accuracy of the forecasting model. Proper handling of missing values is of utmost importance to avoid potential biases in the forecasted results. Additionally, the identification and elimination of outliers, which may arise from measurement errors, extreme weather conditions, or system malfunctions, is fairly significant in effective data preprocessing. By carefully execute these preprocessing steps, the consistency and reliability of the dataset are guaranteed, ultimately enhancing forecasting performance and practical applications in solar energy management and utilization. During the data analysis, it was evident that there were numerous instances of missing values and significant fluctuations, leading to irregular variations in the data. To address this, the data was subjected to an algorithm that removed missing values and merged reliable data into continuous sequences. Subsequently, the cyclical nature of solar radiation was utilized to remove inaccurately merged segments. After the data sequences were merged, outlier data was processed using the IQR method. The preprocessing process using IQR was presented using Fig. 7a and Fig. 7b. Fig. 7a depicts the initial dataset with red dotted lines indicating the upper and lower limits, while Fig. 7b shows the dataset after the outliers have been removed. After the dataset was preprocessed, it was separated into training set and the testing setwith a proportion of 80/20. These sets then became the inputs for the forecasting models.

3.3 Models parameters and hyperparameters

In the linear regression model, the parameters utilized here are the coefficients $\beta_0, \beta_1, \ldots, \beta_8$ metioned in Eq. 1. These coefficients are automatically calculated based on the input data. Notably, there are no hyperparameters associated with the linear regression model.

Table 1 presents the hyperparameters for four models: ANN, Bi-LSTM, LSTM, and GRU. The ANN model includes a dense layer with 32 units. In the LSTM architecture, a dense layer with 16 units is followed by two stacked LSTM layers containing 100 and 50 units respectively. The Bi-LSTM and GRU models were configured using the same hyperparameters: a 16-unit dense layer and two LSTM layers, each having 50 units. All models were trained for 30 epochs with a lookback period of 5.

Table 1. Hyperparameters for four forecasting models

Model	Dense layer	LSTM layer 1	LSTM layer2	Epoch	Lookbac k
ANN	32	X	X	30	5
Bi-LSTM	16	50	50	30	5
LSTM	32	100	50	30	5
GRU	16	50	50	30	5

3.4 Forecasting results

In this research, the predictive performance of various models was systematically compared by employing them to forecast the succeeding 30-minute intervals within the Tây

Ninh dataset. The forecasting methodology utilized in the experiment pertains to the one-step ahead prediction process. The outcomes, delineated in Fig. 8 and Fig. 9, respectively portraying a specific day within the test set and the entire test dataset, accentuated the superior accuracy exhibited by deep learning models in closely approximating actual data. Table 2 illustrates the error calculated in MAE, RMSE and n-RMSE for further analysis.

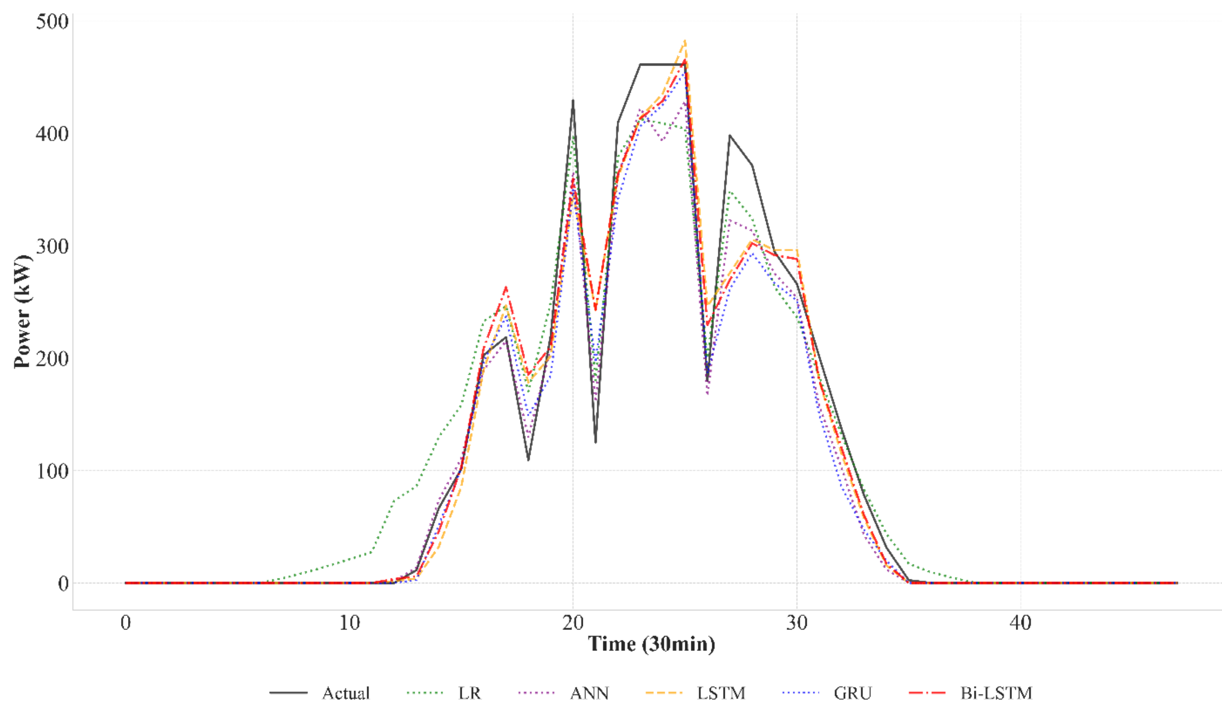


Fig. 8. The forecasted results for a random day in the test set

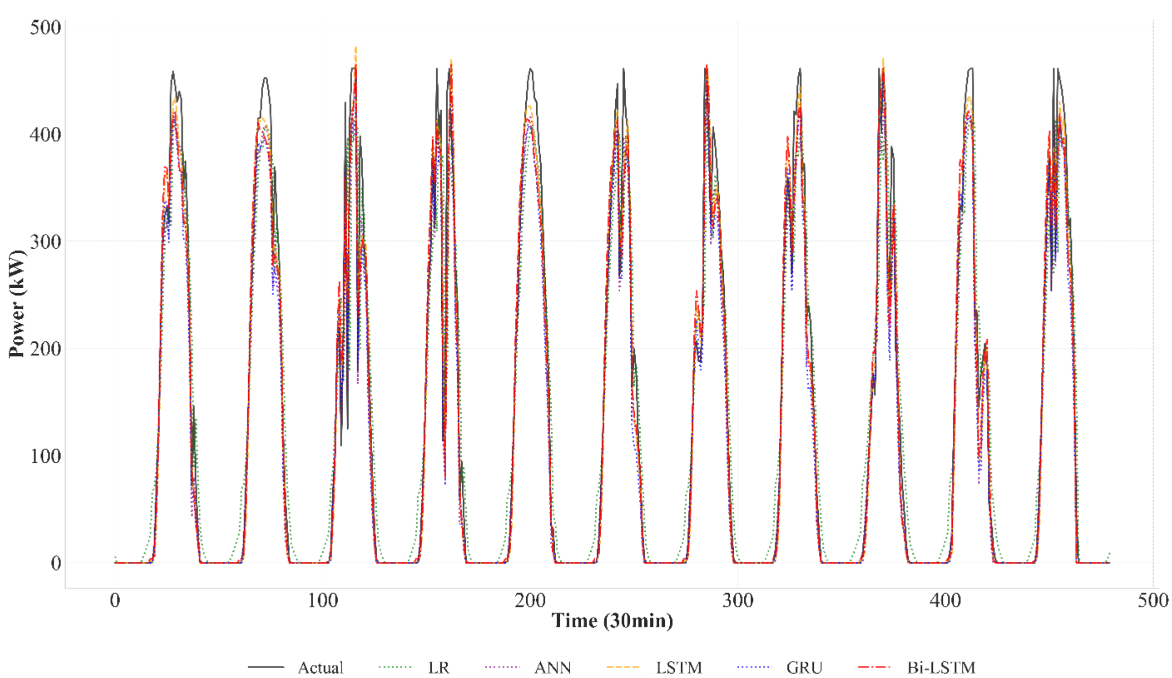


Fig. 9. The forecasted results for the entire test set.

Among the models examined, the LR model exhibited relatively high errors, with MAE, RMSE, and n-RMSE values of 34.04, 63.88, and 13.86%, respectively. In contrast, the ANN and CNN models demonstrated improved performance with MAE values of 32.04 and 32.7, RMSE values of 63.42 and 63.44, and n-RMSE values of 13.76% for both.The GRU model, while slightly less effective than ANN and CNN, still displayed respectable performance with MAE, RMSE, and n-RMSE values of 33.75, 63.36, and 13.75%, respectively. The LSTM model showcased good accuracy, outperforming LR, GRU, ANN, and CNN, with MAE, RMSE, and n-RMSE values of 30.09, 60.61, and 13.15%. However, the Bi-LSTM model emerged as the standout performer, achieving the lowest error metrics. It demonstrated superior accuracy with an MAE of 32.29, RMSE of 56.20, and n-RMSE of 12.19%. In conclusion, for precise forecasting of rooftop solar power, the Bi-LSTM model is deemed the most favorable choice among all the experimented models.

Table 2. Accuracy results for comparative models across inverter 157

Forecasting Model	MAE (kW)	RMSE (kW)	n-RMSE (%)
LR	34.04	63.88	13.86
ANN	32.04	63.42	13.76
CNN	32.7	63.44	13.76
GRU	33.75	63.36	13.75
LSTM	30.09	60.61	13.15
Bi-LSTM	32.29	56.20	12.19

4. CONCLUSIONS

In our research, both deep learning and statistical models were used to forecast rooftop solar power generation on residential buildings in Tây Ninh province. A rigorous data preprocessing procedure, employing the IQR method, was employed, followed by splitting the dataset into training and testing sets for input into the LR, ANN, CNN, GRU, LSTM, and Bi-LSTM models. The analysis results demonstrated the remarkable superiority of the Bi-LSTM model compared to others, with the lowest MAE, RMSE, and n-RMSE values of 32.29, 56.2, and 12.19%, respectively. On the contrary, the statistical LR model exhibited the poorest performance, yielding MAE, RMSE, and n-RMSE values of 34.04, 63.88, and 13.86%, respectively. The remaining models showed relatively similar error rates, highlighting the application of foracting methods using deep learning models in comparision with traditional statistical ways.. Among the compared models, Bi-LSTM showcased the best forecasting ability. These findings emphasize the significance of accurate solar power generation predictions and underscore the effectiveness of deep learning models over traditional statistical approaches.

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