The Short-Term Wind Power Forecasting by Utilizing Machine Learning and Hybrid Deep Learning Frameworks

Sunku V.S., Namboodiri V., Mukkamala R.
School of Energy & Clean Technology, NICMAR University of Construction Studies, Hyderabad, India.

Abstract. Wind power has become more popular due to an increase in energy demand and the rapid decline in conventional fossil fuels. This paper addresses the rising demand for accurate short-term wind power forecasting, which is critical for minimizing the impacts on grid operations and reducing associated costs. The objective is to develop an innovative deep learning (DL) model that integrates a convolutional neural network (CNN) with a gated recurrent unit (GRU) to enhance forecasting precision for day-ahead applications. In pursuit of these objectives, the CNN GRU model was rigorously tested and compared against three additional models: CNN with bidirectional long short-term memory (BiLSTM), extreme gradient boosting (XGBoost), and random forest (RF). Key performance metrics—namely, mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), and the coefficient of determination (R^2)—were employed to assess the efficacy of each model. Statistical validation was also performed using the Diebold-Mariano test to establish significant differences in performance. The most important results reveal that the CNN GRU model outperformed the other models, achieving a MAE of 0.2104 MW, an MSE of 0.1028 MW, an RMSE of 0.3206 MW, and an R^2 of 0.9768. These findings underscore the model's superior accuracy and reliability in the realm of short-term wind power forecasting. The significance of this research resides in its demonstration of the CNN GRU model as an effective and practical instrument for renewable energy forecasting.
***Keywords*:** wind power, forecasting, deep learning, renewable energy, performance metrics.

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O prognoză pe termen scurt a puterii energiei eoliene prin utilizarea învățării automate și a sistemelor hibride de Deep Learning

Sunku V.S., Namboodiri V., Mukkamala R.B.
Școala de Energie și Tehnologie Curată, Institutul Național de Management și Cercetare în Construcții, Hyderabad, India.
Rezumat. Energia eoliană a devenit mai populară datorită creșterii cererii de energie și scăderii rapide a combustibililor fosili convenționali. Această lucrare abordează cererea în creștere pentru prognoza precisă a energiei eoliene pe termen scurt, care este esențială pentru minimizarea impactului asupra operațiunilor rețelei și reducerea costurilor asociate. Obiectivul este de a dezvolta un model inovator de învățare profundă (DL) care să integreze o rețea neuronală convoluțională (CNN) cu o unitate recurentă convoluțională (GRU) pentru a îmbunătăți precizia prognozei pentru aplicațiile de zi înainte. În urmărirea acestor obiective, modelul CNN GRU a fost testat riguros și comparat cu trei modele suplimentare: CNN cu memorie bidirecțională de lungă durată (BiLSTM), intensificare a gradientului extrem (XGBoost) și pădure aleatoare (RF). Valorile cheie de performanță - și anume eroarea medie absolută (MAE), eroarea medie pătratică (MSE), eroarea medie pătratică (RMSE) și coeficientul de determinare (R^2) - au fost folosite pentru a evalua eficacitatea fiecărui model. Validarea statistică a fost efectuată și folosind testul Diebold-Mariano pentru a stabili diferențe semnificative de performanță. Cele mai importante rezultate arată că modelul CNN GRU a depășit celelalte modele, realizând un MAE de 0,2104 MW, un MSE de 0,1028 MW, un RMSE de 0,3206 MW și un R^2 de 0,9768. Aceste constatări subliniază acuratețea și fiabilitatea superioară a modelului în domeniul prognozării energiei eoliene pe termen scurt. Semnificația acestei cercetări rezidă în demonstrarea modelului CNN GRU ca instrument eficient și practic pentru prognoza energiei regenerabile.
Cuvinte-cheie: energie eoliană, prognoză, deep learning, energie regenerabilă, metrici de performanță.

Краткосрочное прогнозирование ветровой энергии с использованием машинного обучения и гибридных систем глубокого обучения

Сунку В.П., Намбоодири В., Муккамала Р.Б.
Факультет энергетики и чистых технологий, Национальный институт управления строительством и исследованиями, Хайдарабад, Индия
Аннотация. Ветроэнергетика стала более популярной из-за роста спроса на энергию и быстрого снижения традиционных ископаемых видов топлива. В этой статье рассматривается растущий спрос на точное

краткосрочное прогнозирование ветроэнергетики, что имеет решающее значение для минимизации воздействия на работу сети и снижения связанных с этим затрат. Цель состоит в разработке инновационной модели глубокого обучения (DL), которая интегрирует сверточную нейронную сеть (CNN) с управляемым рекуррентным блоком (GRU) для повышения точности прогнозирования для приложений на день вперед. Для достижения этих целей модель CNN GRU была тщательно протестирована и сравнена с тремя дополнительными моделями: CNN с двунаправленной долговременной краткосрочной памятью (BiLSTM), экстремальным градиентным бустингом (XGBoost) и случайным лесом (RF). Ключевые показатели производительности, а именно средняя абсолютная ошибка (MAE), средняя квадратичная ошибка (MSE), среднеквадратическая ошибка (RMSE) и коэффициент детерминации (R^2), использовались для оценки эффективности каждой модели. Статистическая проверка также была выполнена с использованием теста Диболда-Мариано для установления существенных различий в производительности. Наиболее важные результаты показывают, что модель CNN GRU превзошла другие модели, достигнув MAE 0,2104 МВт, MSE 0,1028 МВт, RMSE 0,3206 МВт и R^2 0,9768. Эти результаты подчеркивают превосходную точность и надежность модели в области краткосрочного прогнозирования ветроэнергетики. Значимость этого исследования заключается в демонстрации модели CNN GRU как эффективного и практичного инструмента для прогнозирования возобновляемой энергии.
Ключевые слова: wind power, forecasting, deep learning, renewable energy, performance metrics.

INTRODUCTION

The use of renewable energy sources offers numerous advantages, not only in terms of energy generation but also in ecological preservation, ensuring a sustainable future for generations to come. Among the various renewable energy sources, wind and solar power have attracted significant attention and are expected to dominate the energy landscape soon. Renewable energy has a crucial advantage in its ability to minimize the release of greenhouse gases. By mitigating these emissions, the adverse effects of rising temperatures can be avoided, which poses a serious threat to the planet. Therefore, the widespread adoption of wind and solar energy as renewable sources will undoubtedly help alleviate these consequences. There has been a significant increase in the use of renewable energy, particularly wind energy, over the past few years. This sector has now become a crucial component of the global energy supply. This growth has been driven by rising energy demands, increasing fossil fuel prices, and the urgent need to reduce carbon dioxide emissions. When considering the various renewable energy sources available globally, wind and solar energy are significantly more abundant compared to other options [1].

Wind energy is considered one of the primary forms of renewable energy and is experiencing a significant increase in its utilization. In comparison to traditional power sources, India has a vast amount of wind energy reserves. Still, its generation is subject to the weather and geographical conditions, resulting in unpredictable patterns that are highly variable. Various factors such as wind speed, direction, ambient temperature, humidity, and altitude will affect wind power production. The significance of wind power as a prominent energy source in India is gradually increasing. With wind energy prediction, it is imperative to conduct thorough research to explore the possibilities of leveraging this valuable resource [2]. Accurately predicting wind power generation is crucial for successful integration into the electrical grid. The main impediment to the growth of wind power integration in the power grid is the unpredictable and variable nature of wind speeds. Achieving a delicate balance between power supply and demand is a significant challenge for distribution networks due to the constant fluctuations in wind power generation. As a result, accurately predicting wind power presents a significant challenge that can have a major impact on the efficient operation of power systems. Wind power generation is characterized by its stochastic nature, stemming from the unpredictable and variable behavior of wind. To minimize the uncertainty in the system caused by the variability of wind energy, it is crucial to develop more accurate and reliable forecasting models. These models can significantly enhance the profitability of power plants by providing more precise output projections [3]. Furthermore, wind power prediction, using cutting–edge algorithms, optimizes the integration of power generation with the electricity grid [4]. Reliable short-term wind power forecasting is crucial for integrating wind power into the grid seamlessly and reducing the load on peak regulation and frequency control within the power system. [5]. The primary objective of wind power forecasting is to mitigate the inherent uncertainty associated with wind patterns, thereby enabling a greater degree of wind energy integration. It is also important for optimizing dispatch operations, planning maintenance activities, and determining the necessary operating equipment, among other critical factors [6]. The varying weather patterns, particularly wind speed and direction, emphasize the need to address these obstacles. In the ongoing energy transition, wind power generation is emerging as a frontrunner. This is primarily due to its environmentally friendly nature and abundance [7].

Wind power forecasting can be categorized based on time horizons or the methodology used. Depending on different time frames, wind power forecasting can be classified as short-term and long-term. Improved results are achievable due to the advancement of state-of-the-art algorithms and the introduction of more sophisticated computational methods. To overcome the intermittent characteristics of wind power and enhance the reliability of the power supply system, it is essential to secure reserve capacity. This reserve ensures a continuous power supply, even during periods when wind power is insufficient [8]. Nevertheless, the reserve capacity indirectly influences the overall expenditure, emphasizing the importance of employing an efficient forecasting strategy [9]. The accurate prediction of power output is crucial for developing a well-structured strategy that considers the varying levels of power generation. This helps minimize the need for standby capacity in the power grid, resulting in lower operational costs for the power system [10]. Understanding the wind energy forecast is essential to meet the increasing demand for a reliable power supply for industries. Hence, accurate prediction of wind power generation has become a prominent focus of research in literature. To promote ecological development and meet the increasing demand for electricity, it is crucial to conduct research on predicting wind power generation.

Previous research has shown that traditional statistical methods have been effectively used to forecast time series data in various applications. However, the existence of nonlinearity and irregularity in time series data, as well as the possibility of additional errors, can sometimes affect their suitability for predicting wind power output. The complexity of wind power generation is due to the influence of multiple variables, making it challenging to forecast accurately using any single model or approach [11]. Machine learning (ML) and deep learning (DL) frameworks can independently adapt and learn, making them ideal for efficiently managing the dynamic, non-linear, and complex attributes associated with wind power [12]. Achieving precise results with minimal errors in predicting wind power generation requires the use of various models and statistical tools. The feed-forward neural networks (FANN) were used to forecast daily average wind energy generation. The results demonstrate that neural networks are a viable solution for identifying patterns of energy estimation evolution [13]. The performance of regression trees in predicting wind power in distribution networks in Cyprus has been evaluated, resulting in a root mean square error of 0.0242 [14]. The short-term wind power generation of a wind power plant in Pakistan was predicted using GRU and Autoregressive Integrated Moving Average models. The results indicated that the GRU model was the most effective among the others, showing high accuracy and minimal errors [1]. The comparison of Autoregressive Moving Average with multilayer perceptron feed-forward architecture and Adaptive Neuro-fuzzy Inference Systems (ANFIS) shows that artificial neural networks (ANNs) and ANFIS are effective for short-term wind power forecasting [15]. LSTM has been effectively used to enhance the reliability and accuracy of wind power generation forecasting through a multi-step predictive model [16]. Harrou et al. [17] proposed a variational autoencoder (VAE) with a self-attention model. The results show that the proposed model outperforms other models. Recently, ensemble-based models also exhibited better prediction capabilities [18]. The LSTM and BiLSTM models have found extensive application in various domains, such as wind speed/power, solar power, solar irradiance, and electrical load forecasting. These models utilize historical data to make accurate predictions in these areas. The literature did not mention the use of hybrid models, particularly CNN GRU, in forecasting various parameters in the power sector. Thus need of performance improve models are essential and this motivates to conduct the present study. The present study aims to improve short-term wind power generation forecasting by improving the current cutting-edge prediction models. Deep learning models have been considered to achieve accurate short-term wind power forecasting. The present study proposes two DL frameworks for predicting the short-term day-ahead wind power generation in megawatts (MW) of an Indian wind power plant. These models are the CNN and Bi-directional LSTM (Bi-LSTM) models, collectively referred to as the CNN BiLSTM model. Additionally, the CNN GRU architecture, referred to as CNN GRU, is also used to forecast the short-term day-ahead wind power generation

(MW). These frameworks aim to enhance efficiency and facilitate accurate data forecasting from a real-time environment. The proposed study is capable to implement in the wind farms for the wind power prediction applications.

I. METHODOLOGY

DATA COLLECTION

The importance of renewable energy cannot be overemphasized. One of the strategies employed by the Indian Government to promote this cause is the implementation of power exchange through the interstate transmission system. To gather information on short-term wind power generation, secondary data was collected from an integrated paper mill in India participating in this scheme. This paper mill is equipped with sixteen wind turbines, each capable of generating 2 MW of power, resulting in a total installed capacity of 32 MW. The power generated by these wind turbines is then supplied to the distribution companies of the respective state. The dataset consists of day-ahead wind power generation data in MW, recorded at 15-minute intervals, spanning from 10/1/2016 to 10/20/2016. In total, there are 1920 data points available for analysis [19]. The data was used for further analysis and integration with deep learning models.

LSTM MODEL

LSTM networks, which are part of the recurrent neural networks (RNNs) category, enhance memory retrieval by preserving previous information [20]. Using backpropagation for training improves the model's accuracy in predicting time series data with varying time delays. The LSTM model is specifically designed to address long-term dependency problems and effectively overcome the vanishing gradient problem. It is divided into three distinct sections. The opening section emphasizes the significance of data gathered in the previous period, establishing its relevance or potential for dismissal. In the following two sections, the focus is on integrating new data from the input and transferring the updated information from the current time step to the next time step. This is done while considering the LSTM cycle as a single time step.

These three sections of the LSTM unit are referred to as the forget gate, input gate, and output gate.

An LSTM network consists of memory cells that resemble individual layers of neurons in a conventional feedforward neural network. In this comparison, each neuron in the LSTM network contains both a hidden layer and an ongoing state. These gates effectively address the issue of vanishing gradient commonly encountered in RNNs, making LSTM networks widely utilized in various time series prediction applications [21**].**

CNN BILSTM MODEL

The BiLSTM architecture consists of two LSTM layers, with one processing data in a forward direction and the other in a backward direction. Unlike traditional LSTM models that operate in only one direction, BiLSTM considers both preceding and succeeding data points. This enables a more comprehensive approach to decision-making by leveraging historical and prospective information [22]. The model performs both forward and backward computations, enabling a bidirectional exchange of time series data. This approach contrasts with conventional models, where data moves linearly from the input layer to the hidden layer and then to the output layer [23]. Using the LSTM twice helps the model learn long-term dependencies and improve accuracy [24].

The CNN BiLSTM hybrid model combines the CNN, BiLSTM, and a connection layer; the model has been proposed to forecast the day ahead power generation (MW) of a wind power plant located in India. In this particular model, the input first goes through the CNN layer, where convolution operations and max-pooling are executed, ultimately producing a newly generated feature matrix. The BiLSTM is fed with input from the feature matrix extracted from the CNN. The BiLSTM then produces its hidden output, which is directed through the connection layer consisting of a linear layer. Finally, the connection layer returns the ultimate results [25]. The hybrid model architecture is illustrated in Figure 1 [23].

The interaction between input and output is explained by the hybrid model. A univariate time series forecasting model is constructed using a recursive multi-step forecasting technique. To accommodate the CNN input and output BiLSTMs, the univariate time series needs to be adjusted since the hybrid model employs supervised learning. When considering a univariate time series sample p(1), p(2), ..., p(n) with a lag, the projected value of $p(\epsilon+1)$ can be obtained by following the previously outlined steps. Subsequently, the one-dimensional vector is reconstructed into a matrix with dimensions of (ϵ+1), as demonstrated in Equation 1, which outlines the process of generating the reconstructed sample matrix, Θ.

where

$$\theta = [P^{(1)}, P^{(2)}, ..P^{(\epsilon)}, P^{(\epsilon+1)}] \quad (1)$$

$$P^{(1)} = [P^{(1)}, P^{(2)}, ..P^{(\epsilon)}, P^{(\epsilon+1)})]$$

The hybrid model uses a matrix R as its input, formed by the preceding τ column vectors $\left[P(1), P(2), \ldots, P(\epsilon)\right]$.The output, as depicted in Equation (1), is the (ϵ + 1) value. Once the forecasting reaches step ϵ + 1, the input vector encompasses all the anticipated values, indicating the successful completion of extrapolation [26]. The training process of the hybrid model for forecasting the day ahead power generation (MW) is outlined as follows:

- Start by removing any unnecessary elements, converting time data into a serialized format, and splitting the data into separate training and testing sets.
- To begin the training process, the preprocessed time series data must be input into the hybrid model.
- Use the trained model to make predictions by feeding it with the training data.
- Apply the provided formulas to restore the predicted data.
- A visual comparison should be created between the observed and forecasted values, using both datasets to evaluate the model's predictive accuracy.

CNN GRU MODEL

Developed for complex data analysis, the CNN GRU architecture combines CNNs and GRUs to deliver powerful performance. This model stands out for its innovative approach of combining the spatial feature extraction capabilities of CNNs with the temporal dependency modeling abilities of GRUs, resulting in a powerful and effective solution. The extraction of essential spatial features from input data sources is a crucial task in predicting wind power generation, and CNNs play a vital role in achieving this. These attributes are seamlessly integrated into the GRU layer, which is well-known for its ability to capture temporal relationships and historical capacity data. The overall architecture of the CNN GRU model proposed in this study consists of four key layers: the input layer, CNN layer, GRU layer, and output layer. The CNN layer begins by extracting information on day-ahead wind power generation. The pooling layer uses convolution kernels to compute additional feature data and expand the scope of the convolution results. Next, the preprocessed wind power generation data is inputted into the GRU network for optimization training through a fully connected layer. Within the GRU layer, the model effectively learns the underlying patterns and internal variability, which are essential for ensuring accurate predictions. The output layer ultimately produces important forecasts, providing valuable information on wind power generation. [27]. This architecture allows for precise predictions of wind power generation, which is advantageous for the power sector. Figure 2 depicts the structure of the hybrid prediction model using CNN GRU architecture.

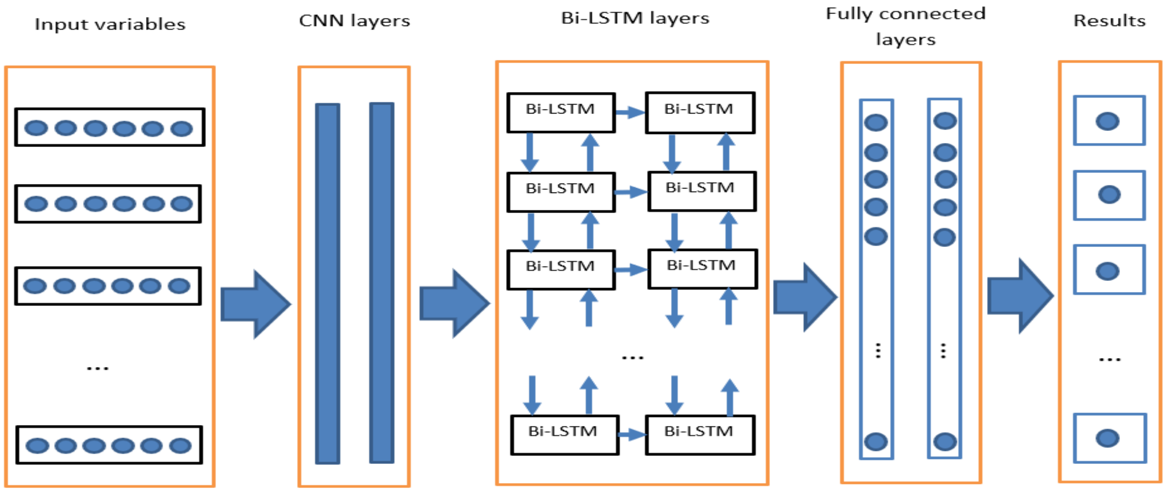

Fig. 1. CNN BiLSTM hybrid model architecture [25].

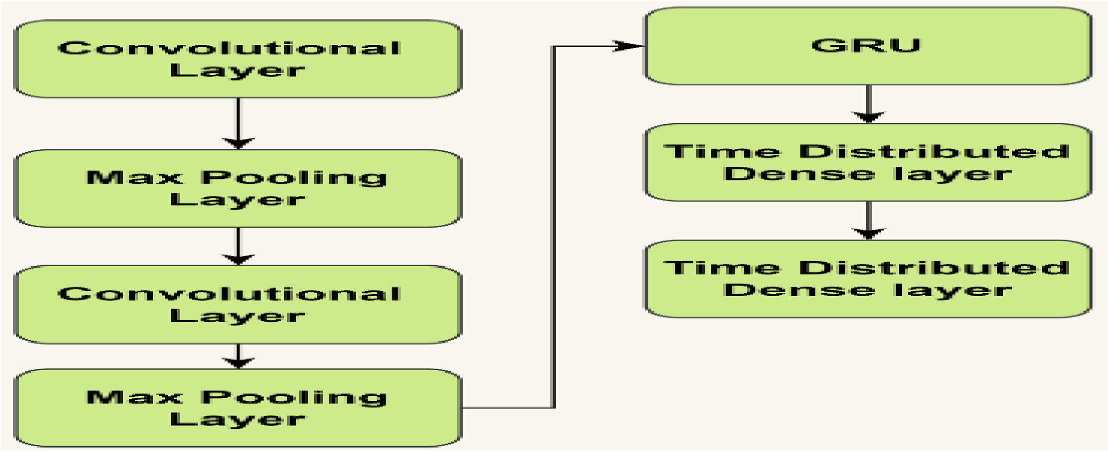

Fig. 2. CNN GRU hybrid model architecture.

II. PERFORMANCE METRICS

The models' performance was evaluated using four main statistical metrics: mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE), and coefficient of determination (R^2), as outlined in Equations (2) to (5).

$$MAE = 1/n\sum_{k=1}^{n}|O-F| \tag{2}$$

$$MSE = 1/n\sum_{k=1}^{n}|O-F|^2 \tag{3}$$

$$RMSE = \frac{1}{n}\sqrt{\sum_{k=1}^{n}|O-F|} \tag{4}$$

$$R^2 = 1-\frac{\sum_{k=1}^{n}|O-F|}{\sum_{k=1}^{n}|\bar{O}-\bar{F}|} \tag{5}$$

In power generation forecasting, the formula for calculating the error between the predicted and observed power generation values is as follows: F represents the expected power generation for a specific time interval (15 minutes), and O represents the observed power generation for the same interval. To further analyze the accuracy of the predictions, the average predicted power generation ($\bar{F}$) and the average observed power generation ($\bar{O}$) are calculated. The number of observations (n) is also taken into consideration.

III. RESULTS AND DISCUSSION

DATA PREPROCESSING

The preprocessing of data is a crucial step in developing short-term wind power predictions. Table 1 shows the statistical information of the dataset. This stage involves using important approaches to improve the quality of input data, which will have a direct influence on prediction accuracy. To ensure the continuity of data, the missing values are to be removed. Additionally, removing outliers, which are extreme data variations, enhances model performance by reducing undesirable noise during training. Normalization involves standardizing the variables to a common range between zero and one**.** The process of normalization is essential for preventing any single variable from dominating the model's learning process. This ultimately leads to more efficient model convergence and improved accuracy [28**]**. After preprocessing, it was determined that the dataset had no missing values. The data was then normalized using MinMax Scaler to a range of 0 to 1. After this, the preprocessed dataset was divided into training and testing sets. Out of the 1920 input points, 1527 (79.5%) were used for training, while the remaining 393 (20.5%) were allocated for testing to evaluate the model's predictive performance.

EXPERIMENTAL RESULTS OF CNN BILSTM AND CNN GRU MODELS

The pre-processed data was used to analyse with the CNN BiLSTM model. The proposed model is a deep neural network and consists of two CNN layers in the first stage. The output from the CNN layers is then passed to the two Bi-LSTM layers in the second stage. These Bi-LSTM layers are responsible for analyzing information and predicting time series data. The final stage consists of two fully connected layers, which are used to generate the predicted wind power output. Number of hidden neurons are 31 and the total weight coefficients including biases are 5101.

Performance metrics are employed to evaluate the accuracy of the predicted values produced by the proposed model. To ensure a fair comparison, both the CNN BiLSTM and CNN GRU models are set up with identical model and training parameters.

Table 1

Details of the dataset.

Count	Minimum	Maximum	Mean	Standard deviation
1920	0.00	31.48	8.356	8.435

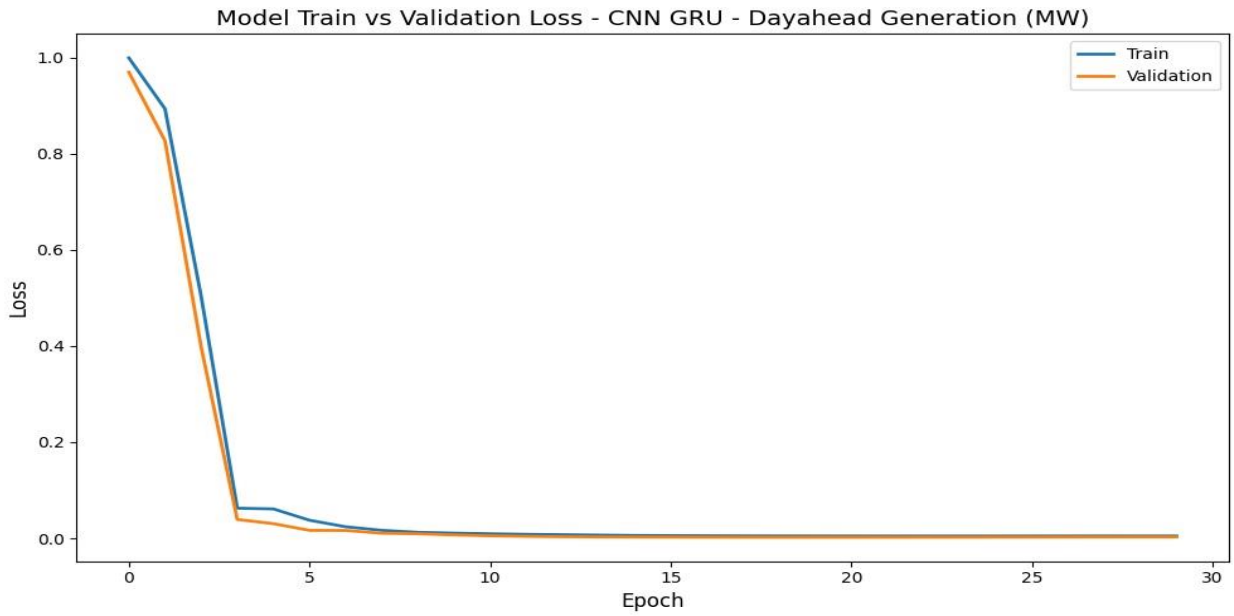

Fig.3. Learning curve of CNN GRU model.

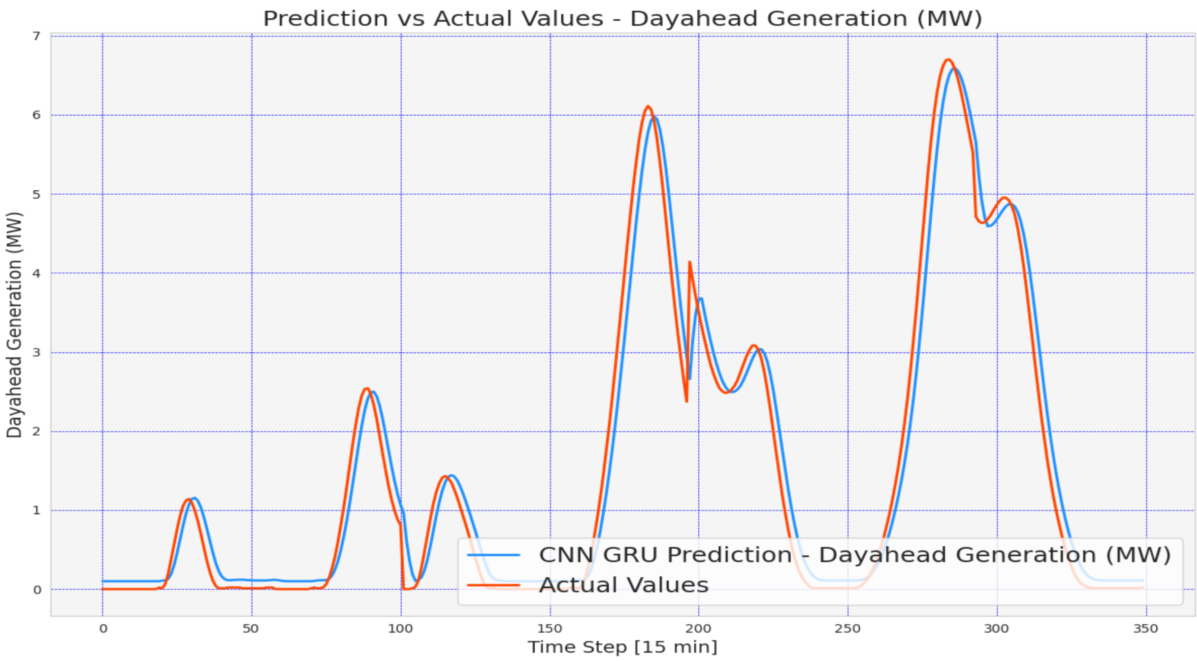

Fig. 4. Actual and predicted values of CNN GRU model.

Table 2

Performance metrics of various models.

Model	MAE[MW]	MSE[MW]	RMSE[MW]	R^2 [-]
Random forest	1.1907	1.9499	1.3964	0.7687
XG Boost	0.7694	0.6759	0.8221	0.9156
CNN GRU	0.2104	0.1028	0.3206	0.9768
CNN BiLSTM	0.2725	0.1473	0.3838	0.9667

To calculate the adaptive learning rate for parameters, the Adam optimizer considers the first and second moments of the gradient. A learning rate of 0.0001 is specified, and the MAE is chosen as the loss function. The MAE focuses only on the average absolute error of the predicted values, without taking direction into account, thus improving robustness against outliers. A batch size of 32 and a total of 50 epochs are selected for the experiment.

The test dataset is employed for forecasting once the training process is completed. Figures 3 exhibit the learning curve of the CNN GRU models, in predicting short-term wind power generation. The learning curve is constructed to assess the adequacy of the train and validation datasets in representing the domain area. The learning curves for both models indicate a satisfactory model fit, as the training and validation losses converge to a stable point with minimal disparity between their final loss values. Figure 4 illustrate the plot of the CNN GRU model, showing the relationship between the actual and predicted values over the last 350 data points. To analyze and compare the results of these models, several fundamental evaluation indicators, namely MAE, MSE, RMSE, and R^2, are employed. The proposed model (CNN GRU) is compared with CNN BiLSTM, extreme gradient boosting (XGBoost), and random forest (RF). These indicators serve the purpose of determining the disparity between the predicted and actual values of short-term wind power generation. The values of these indicators can be found in Table 2. Notably, the R^2 score of the CNN GRU model surpasses that of the CNN BiLSTM model, indicating a higher level of accuracy in predicting wind power generation. Furthermore, the CNN GRU model exhibits significantly lower scores in terms of MAE, MSE, and RMSE, further affirming the model's precise predictive capabilities. It is worth mentioning that the CNN GRU model demonstrated superior performance across all metrics when compared to CNN BiLSTM model. Moreover, the research presented a cutting-edge forecasting model utilizing the CNN GRU framework. This innovative model demonstrated a remarkable enhancement in the accuracy of short-term wind power generation prediction, surpassing the performance of the CNN BiLSTM model. The proposed CNN GRU model, with its exceptional predictive power, signifies fair progress in the domain of renewable energy.

CNN GRU model surpasses in capturing prolonged dependencies in sequential data, adeptly adjusts to diverse operational scenarios, and consistently exceptional in evaluating the performance criteria [27]. These attributes collectively establish it as the better option for the renewable energy sector, which seeks reliable and precise planning as well as grid management. When compared to alternative machine learning models, the CNN GRU unified framework excelled in short-term residential load forecasting by achieving the lowest error rate, with MSE, RMSE, and MAE values of 0.09, 0.31, and 0.24, respectively [29]. The CNN GRU model's learning curve demonstrates a satisfactory model fit, indicating the absence of both overfitting and underfitting. The performance of the CNN GRU model was then compared with five other DL models. In both scenarios, the CNN GRU model demonstrated superior performance, achieving the lowest values for the performance criteria [30].

The CNN GRU model has the ability to undergo training and application in conjunction with various other factors that affect the production of wind energy. The Diebold-Mariano test is performed for CNN GRU and CNN BiLSTM. The p-value is 0.0025 and indicates that the performance of CNN GRU is significant as compared to CNN BiLSTM.

CONCLUSION

The current investigation outlines the primary viewpoints and significant numerical findings derived from the study into forecasting short-term wind power generation. The significance of the study is implementing a novel DL that effectively combines CNN and GRU framework. Moreover, the CNN GRU model surpasses the CNN BiLSTM model in terms of performance. The model's efficacy was substantiated through rigorous experiments, resulting in a significant decline in key performance metrics. In the current study, the proposed methodology exhibited exceptional precision in forecasting and surpassed the performance of the CNN BiLSTM model. This was substantiated by the values of MAE, MSE, RMSE, and R^2, which were recorded as 0.2104 MW, 0.1028 MW, 0.3206 MW, and 0.9768 respectively, highlighting its outstanding performance. To enhance the efficiency of the model in predicting short-term wind power generation, it is advisable to integrate various factors such as wind speed, direction, altitude, and other operational dimensions. Additionally, comparing the outcomes of power output prediction using both multi and univariate data would be beneficial. Furthermore, training the model on a larger and more varied database would enhance its reliability. The CNN GRU model demonstrates superior performance when compared to other models, thus affirming its viability for practical implementation in the renewable energy sector.

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About authors.

Sunku Venkata Siva Raja Prasad , Associate Professor, NICMAR University of Construction Studies, Hyderabad, Telangana.
Research interests: AI/ML Safety, Risk Management
E-mail: rajaprasad@nicmar.ac.in

Mukkamala Ram Babu , Assistant Professor, NICMAR University of Construction Studies, Hyderabad, Telangana.
Place of work: NUCS,Hyderabad,Telangana. Research interests:Semantic Web,AI/ML
E-mail: rmukkamala@nicmar.ac.in

Namboodiri Vishnu, Assistant Professor, NICMAR University of Construction Studies, Hyderabad, Telangana.
Research interests Energy
E-mail: nvishnu@nicmar.ac.in