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Research Article

A Predictive Framework for Hourly Wind Speed Forecasting Using Stacked Recurrent Neural Networks

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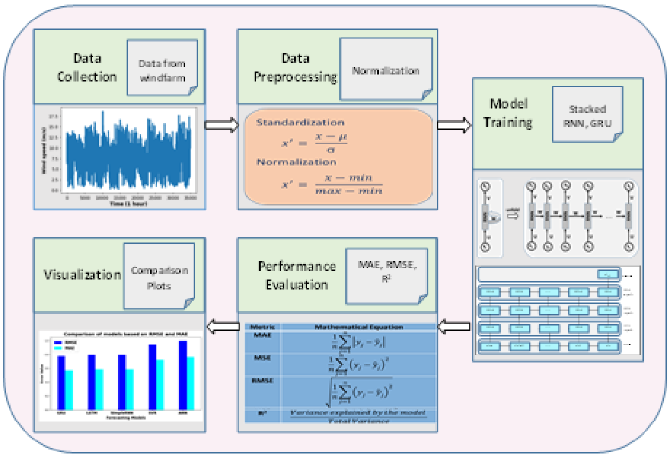
Abstract: The growing demand for low-cost, eco-friendly energy has established wind power as a pivotal renewable source, making accurate wind speed forecasting critical. The study introduces a deep learning framework that integrates stacked Gated Recurrent Unit (GRU) and Long Short-Term Memory (LSTM) networks to predict hourly wind speed. The model's performance is assessed using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the Coefficient of Determination (R^2), and benchmarked against Support Vector Regression (SVR) and Artificial Neural Network (ANN) models. Experimental findings reveal that the proposed stacked GRU and LSTM models consistently surpass the comparative methods, highlighting its robustness and effectiveness in wind speed forecasting.

Keywords: Wind speed forecasting, Deep learning, recurrent neural networks, Gated Recurrent Unit, Long Short-Term Memory Networks, Mean Absolute error

Graphical Abstract-



1. Introduction

Wind energy stands out as one of the most efficient renewable sources. The primary driver of global warming is the emission of greenhouse gases during the combustion of conventional energy sources like fossil fuels. In contrast, renewable energy sources offer a pollution-free, cost-effective, abundant, and environmentally responsible alternative. The escalating demand for renewable energy is propelled by factors such as urbanization, population growth, and industrial activities. Notably, after 2001, there was a significant surge in wind power production. Optimizing wind power output involves ensuring that the available wind speed surpasses the turbine's cut-in speed. Continuous monitoring of wind speed is essential for the effective management of wind farms. Precise wind speed forecasting is vital for optimizing turbine performance and maximizing wind power generation efficiency.

Several studies have investigated wind speed forecasting through the use of intelligent predictors, deep learning architectures, and hybrid modeling techniques. Intelligent predictors include models such as fuzzy logic, Support Vector Machines (SVMs), Extreme Learning Machines (ELMs), and Artificial Neural Networks (ANNs). Deep learning predictors, including autoencoders, convolutional neural networks (CNNs), radial bias functions (RBF), and recurrent neural networks (RNNs), are instrumental in wind speed and energy forecasting. Time series forecasting models relying on deep learning include RNN, LSTM, and GRU. Overcoming the challenge of learning long-term dependencies is a central concern in deep learning. A subset of neural networks designed for sequential data analysis comprises RNNs.

The wind speed forecasting systems are classified into various categories based on multiple factors as given in Figure 1. Forecasting models can be classified along two primary dimensions: the nature of their inputs and the scope of their outputs. In terms of inputs, a model is either relying on a single variable or incorporating multiple parameters. Regarding outputs, a model is either single-step (predicting one immediate future point) or multistep (projecting a series of future time steps)Based on methodology employed, forecasting models can be statistical, AI and hybrid models.

Statistical models are linear and are typically used for very short-term forecasts, such as wind speed. Common examples include ARMA, ARIMA, multiple regression, and VAR. These techniques, with regression at their core, function by establishing the linear relationship between a dependent variable and one or more independent variables.

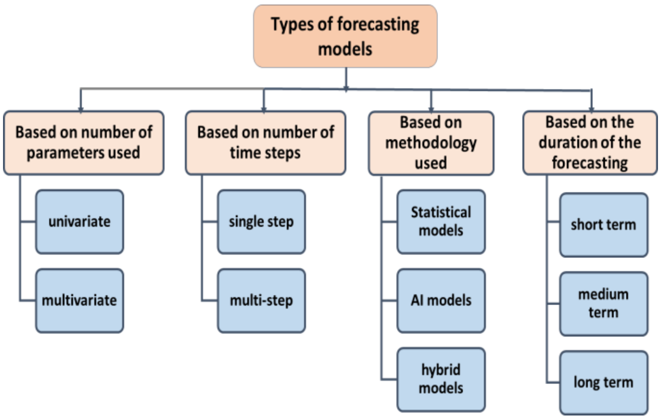


Figure 1. Classification of wind speed forecasting models

Artificial Intelligence (AI) models, on the other hand, are adept at managing non-linear datasets. Their ability to learn complex patterns often grants them superior forecasting performance compared to traditional statistical methods for more intricate forecasting tasks.These models demonstrate robustness and efficacy in comparison to statistical models. They are further categorized into two groups: machine learning predictors and deep learning predictors. Machine learning and deep learning techniques prove to be more adept at managing datasets with nonlinear characteristics. Support Vector Machines (SVM), Artificial Neural Networks (ANN), Extreme Learning Machines (ELM), and Random Forests stand out as well-known machine learning predictors extensively applied in the prediction of wind speeds.

Deep learning, a branch of machine learning, utilizes artificial neural networks to derive meaningful insights from large and complex datasets. It predominantly utilizes supervised or unsupervised techniques within intricate structures to autonomously acquire layered representations. Among these, recurrent neural networks are widely utilized deep learning frameworks for analysing time series information. Hybrid models are created by integrating two or more models, allowing for the combination of linear or nonlinear approaches. These cutting-edge models have demonstrated enhanced performance outcomes. Wind speed prediction methods are categorized into four distinct time scales: short term, medium term and long term. Among these, the accuracy of predictions tends to be higher for short-term and very short-term time models compared to medium and long-term predictions.

1.1 Objective of the Study

The main objective of this research is to propose an advanced forecasting framework to enhance the accuracy of hourly wind speed predictions. This involves the construction of a stacked recurrent neural network model integrating GRU and LSTM layers. A further objective is to conduct a comparative performance analysis against benchmark models like SVR and ANN to substantiate the efficacy of the proposed approach.

1.2 Organization

The paper is organized as follows: Section 2 elucidates the related works, while section 3 gives the proposed methodology and Section 4 details the results attained by the system. Finally, Section 5 presents the conclusions drawn from the study and lastly the references.

2. Related Work

The recent studies on wind speed forecasting focus on improving predictive accuracy and quantifying forecast uncertainty. Key strategies include leveraging deep learning architectures, hybrid models, ensemble frameworks, and optimization algorithms to handle spatio-temporal dependencies. Some of the papers reviewed are outlined below. A novel wind speed forecasting method combining HMD and OSORELM and optimizing it with CSO is introduced in [1]. The VMD algorithm decomposes wind speed, and the OSORELM-C model predicts sub-series, demonstrating the effectiveness of online models in various scenarios. An extensive analysis of intelligent predictors for wind energy forecasting, exploring deep learning, ensemble learning, and metaheuristic optimization is provided in [2]. The study categorizes techniques and emphasizes the underutilization of deep learning and multi-objective metaheuristic optimization in existing literature. A hybrid wind forecasting model using deep LSTM and SAE is presented in [3]. The study identifies the optimal SAE architecture and deep LSTM model, demonstrating that hybrid models based on deep learning outperform individual models in predicting wind speed.

An integrated model using data processing technology and optimization algorithms, enhancing short-term wind speed prediction accuracy and stability compared to traditional separate models is proposed in [4]. Hybrid models combining intelligent methods (ANN) and statistical methods (ARIMA) for wind energy forecasting is focused in [5]. While the Wavelet Packet-ARIMA-BFGS model is accurate, the paper suggests more attention to emerging technologies like deep learning. A novel wind speed forecasting model utilizing clustering, deep feature extraction, and LSTM is introduced in [6]. The proposed DBSCAN-SDAE-LSTM model outperforms other models, indicating its promising potential for wind speed forecasting.

A wind speed forecasting model using ELM is presented in [7]. The proposed hybrid algorithm outperforms standard ELM algorithms in wind speed prediction, demonstrating superior performance compared to other hybrid algorithms. f-ARIMA models for accurate wind speed forecasts, reducing mean square error compared to the persistence method is investigated in [8]. The proposed method proves advantageous, especially during unpredictable wind speed regimes. Various forecasting algorithms for wind speed, with the Jaya-SVM model showing the lowest MSE, MAE, and MAPE values, highlighting its efficiency and reliability is evaluated in [9]. A hybrid deep learning-based evolutionary technique for accurate and stationary short-term wind speed forecasts is proposed in [10]. The evolutionary-based decomposition approach and parallel bi-directional long-term memory model show improved prediction accuracy compared to recurrent models.

A dynamic non-constraint ensemble model for probabilistic forecasting of wind power and wind speed is proposed in [11]. The model combines diverse predictors to produce predictive distributions, enhancing robustness across different wind regimes. A multi-objective, model-selection-based ensemble for interval-valued wind speed forecasting is introduced in [12]. The approach optimizes forecast intervals for accuracy, reliability, and width, addressing explicit interval prediction challenges. An interpretable combined learning model that balances forecast performance with model transparency is developed in [13]. This approach addresses operational requirements for explainable predictions.

An interpretable wind speed forecasting model that integrates meteorological feature exploration with a two-stage decomposition approach is introduced in [14]. This model aims to enhance forecasting accuracy and interpretability, providing valuable insights for decision-making in wind energy applications. VMD-SCINet, combining Variational Mode Decomposition (VMD) with SCINet is presented in [15]. Deep learning is integrated with an improved dung-beetle optimization algorithm for hyperparameter tuning, enhancing predictive performance while managing nonconvex optimization challenges in [16].

Research findings indicate that deep learning architectures, particularly RNN, LSTM, and GRU exhibit robust self-learning capabilities, making them advanced models for time series prediction. LSTM-based structures are validated as dependable models adept at capturing long-term dependencies within datasets. Therefore, this paper introduces a forecasting model based on deep learning, utilizing stacked LSTM and GRU to predict wind speed in a wind farm located in Dhanushkodi, Tamil Nadu, India. The model's efficiency is subsequently compared with other standard machine learning models such as SVR and ANN. The experimental results underscore the significance of LSTM and RRU networks in wind speed forecasting.

3. Proposed Methodology

3.1. Dataset

Hourly wind speed data obtained from the wind farm located in Dhanushkodi, Tamil Nadu, India, covering the period from October 2013, to September 2017, has been utilized in this study to predict the wind speed for the next hour. Table 1 presents the statistical overview of the data gathered from the Dhanushkodi wind farm. The distribution of wind speed data is depicted in Figure 2.

Table 1. Statistical information of data collected from Dhanushkodi

Attribute	Unit	Count	Mean	std	min	max
Wind speed	m/s	35013	7.808225	3.011609	0.228	18.628

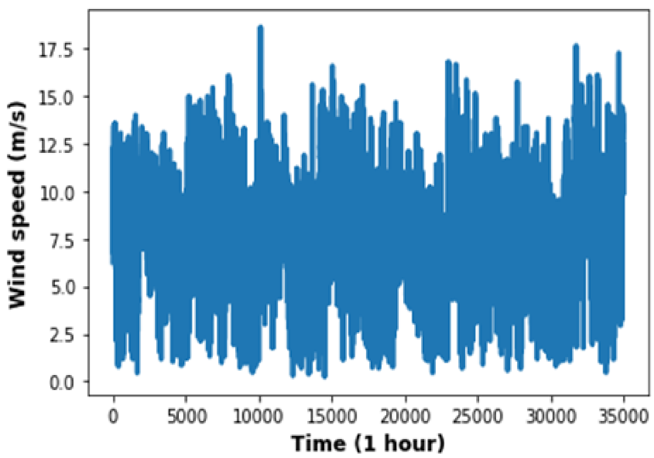


Figure 2. Distribution of wind speed

3.2 Methods Employed

The prediction of wind speed problems frequently makes use of recurrent neural networks (RNNs). They are proficient in identifying sequential dependencies within data. In order to train a model that recognizes patterns and trends to produce precise wind speed forecasts, recurrent neural network architectures can be utilized. The recurrent neural networks employed in the study are GRU, LSTM, and SimpleRNN. The performance of the model is compared using ANN and SVM.

3.2.1 Simple Recurrent Neural Network (SimpleRNN)

Deep learning is a branch of machine learning that is distinguished by the use of neural networks composed of multiple layers, enabling the extraction of abstract features from extensive datasets. Deep neural networks exhibit a hierarchical structure, accommodating structured or unstructured and labeled or unlabeled data. Architectures in deep learning, such as RNN, LSTM, and GRU are widely acknowledged for their efficacy in time series prediction. Time-series data involves interdependent inputs across successive time steps, with the output at any given moment contingent on both current and past inputs.

Recurrent Neural Networks (RNNs) function by retaining the output from a previous layer and feeding it back as input to forecast the output of the next layer. The development of

RNNs stemmed from the recognition of limitations in feed-forward neural networks, including their incapacity to handle sequential data, exclusive focus on present input, and inability to retain past inputs.

RNNs serve as a solution to these challenges. By incorporating both current and preceding inputs, RNNs adeptly handle sequential data. The internal memory of RNNs facilitates the retention of earlier inputs, effectively overcoming the identified limitations. Figure 3 illustrates the architecture of a single-layer Simple Recurrent Neural Network (RNN).

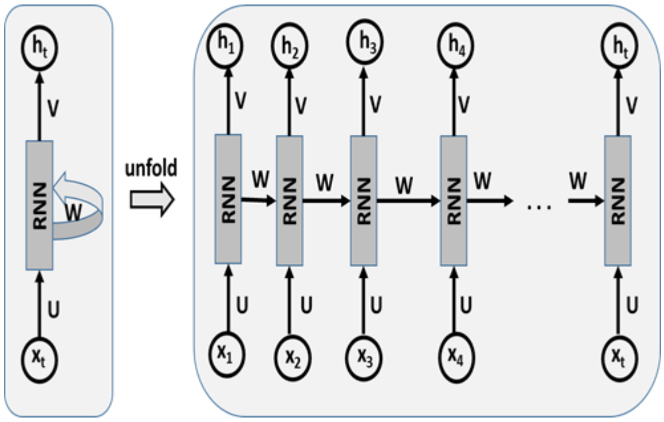


Figure 3 Simple Recurrent Neural Network

Traditional Recurrent Neural Networks (RNNs) struggle to learn long-term dependencies in time series data due to the vanishing and exploding gradient problem [17]. This issue, where gradients become unstable during training, limits their effectiveness. Long Short-Term Memory (LSTM) networks, a specialized RNN variant, overcome this limitation with an architecture explicitly designed to capture long-term temporal dependencies.

3.2.2 Long Short- Term Memory (LSTM)

The Long Short-Term Memory network (LSTM) belongs to the Recurrent Neural Networks (RNNs) category. Unlike the conventional approach of solely transmitting signals to the next layer, each neuron in an LSTM communicates signals laterally within its own layer. Recurrent connections in the network introduce a memory aspect or state. The distinctive advantage of the LSTM lies in its ability to effectively capture and retain long sequences of information.

LSTM networks were introduced to address the challenge of learning long-term dependencies in [18]. In addition to the input and output layers, these networks may include one or more hidden layers. Each LSTM cell within a hidden layer contains three gates: the input gate, output gate, and forget gate. The structure of an LSTM cell is depicted in Figure 4. The forget gate improves network efficiency by removing less relevant information from the cell state, the input gate incorporates new information into the cell state, and the output gate conveys significant information from the memory cell to the output. The mathematical formulation of an LSTM network is presented in Equations (1) to (6) [19, 21].

$$o_t = \sigma(W_o\, h_{t-1} + U_o\, x_t + b_o\ ) \tag{1}$$

$$i_t = \sigma(W_i\, h_{t-1}) + U_i\, x_t + b_i\ ) \tag{2}$$

$$f_t = \sigma(W_f\, h_{t-1} + U_f\, x_t + b_f\ ) \tag{3}$$

$$\tilde{s_t} = \tanh(Wh_{t-1} + Uxt + b\ ) \tag{4}$$

$$s_t = f_t \odot s_{(t-1)} + i_t \odot \tilde{s_t} \tag{5}$$

$$h_t = o_t \odot \tanh(s_t\ ) \tag{6}$$

At time step t, s_t denotes the state of the network, x_t represents the input, and h_t indicates the corresponding output. The variables o_t, i_t and f_t correspond to the output

gate, input gate, and forget gate, respectively. The term s_t denotes a temporary or candidate state. U, V, and W represent the weight matrices, while b denotes the bias vector. Element-wise multiplication is denoted by the symbol ʘ [19].

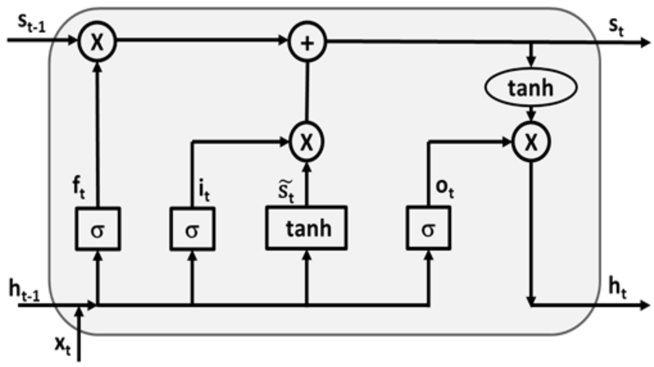


Figure 4. Layout of LSTM cell

3.2.3 Gated Recurrent Unit Network (GRU)

A significant variant of Recurrent Neural Networks (RNNs) is the Gated Recurrent Unit (GRU), which consists of three gates and does not possess the internal cell state characteristic of LSTM (Long Short-Term Memory) units. Unlike LSTMs, GRUs merge the information typically stored in the LSTM's internal cell state into the hidden state, which is then passed to the next GRU. The Update Gate controls the extent to which previous information influences future predictions, analogous to the Output Gate in LSTM units. The Reset Gate regulates how much past information is discarded before processing new input, serving a role similar to the combined function of the Input Gate and Forget Gate in LSTM units.

A stacked (or deep) RNN, LSTM, or GRU architecture consists of multiple recurrent layers, where each layer's output becomes the input for the next. The configuration of a stacked GRU network with three hidden layers is depicted in Figure 5. Stacked GRU cells are capable of retaining greater amounts of information across multiple hidden layers. Each GRU layer handles a specific part of the computation and passes its output to the next layer, with the final predictions obtained from the output layer. The incorporation of hidden layers in a stacked manner enhances the depth of the recurrent model, allowing for more accurate feature learning [20].

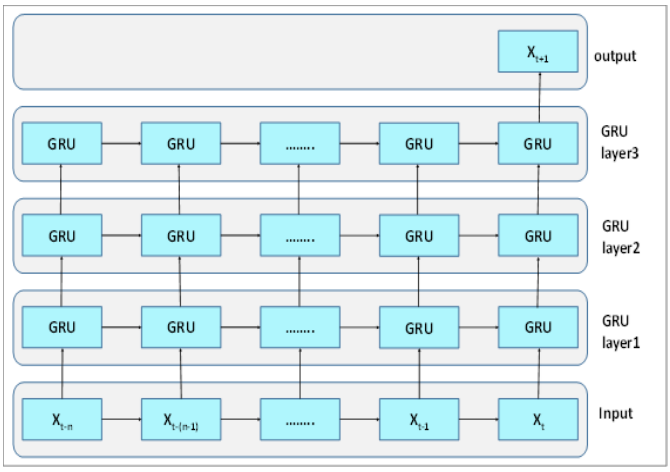


Figure 5. Architecture of stacked GRU network

3.3 Proposed Framework

Figure 6 illustrates the distinct steps within the proposed method. The framework is comprised of four sequential steps, namely, data collection, data pre-processing, model training, and performance evaluation. Each step is elucidated below:

Figure 6. Proposed framework

3.3.1 Data Collection

The quality and quantity of data play a pivotal role in enhancing forecast accuracy. Data collection is performed from wind farms, and subsequent datasets are partitioned into train and test sets. The model undergoes training using the train datasets, and its effectiveness is subsequently evaluated using the test datasets.

The study utilizes wind speed data recorded at ten-minute intervals from a wind farm located in Dhanushkodi, Tamil Nadu, India, spanning the period from 01.10.2013 to 30.09.2017. These datasets were provided by the National Institute of Wind Energy (NIWE), an organization under the Government of India. Since the main objective of this research is to forecast wind speed for the upcoming hour, the data is transformed into a one-hour interval by computing the average of six entries with ten-minute intervals.

3.3.2 Data Preprocessing:

Enormous amounts of both valuable and irrelevant data, often in unstructured form, have been amassed during the data collection phase. The performance of a machine learning model is directly dependent on data quality, making data pre-processing an essential first step. This primarily involves three key procedures: data cleaning, transformation, and reduction. The purpose of preprocessing is to enhance the integrity of the collected data. Data is refined and optimized for training during this stage. Data cleaning methods are employed to eliminate errors, missing values, and disturbances from the dataset. Following this, the data undergoes normalization or standardization techniques, shaping it into a format conducive for subsequent processing during data transformation procedures.

This study employs z-score normalization to standardize the data, rescaling it to a mean of 0 and a standard deviation of 1. The formula for z-score normalization is expressed in Equation (7), where x represents the original data, x' denotes the normalized data, σ is the standard deviation, and μ is the mean value.

3.3.3 Model Selection and Training

For wind speed forecasting, we designed and trained stacked RNN, LSTM, and GRU models. Each model has three hidden layers with 100 neurons. Given the importance of historical data for time series prediction, the selection of an optimal lag value is critical. For these experiments, a lag of 24 is selected, indicating that data from the previous 24 time steps (one day) is used to forecast wind speed for the next hour. The dataset is divided into training and testing sets in a 70:30 ratio. The model is trained using the training set, and its performance is evaluated on the test set. Weight updates in the proposed model are performed using the Backpropagation Through Time (BPTT) algorithm.

3.3.4 Performance Evaluation:

The forecasting model's accuracy can be effectively evaluated through the use of metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the Coefficient of Determination (R^2). MAE measures the absolute difference between the predicted value ($\hat{y}$) and the actual value (y), as shown in Equation (8). RMSE represents the square root of the mean of the squared differences between the predicted ($\hat{y}$) and actual (y) values, as described in Equation (9). The Coefficient of Determination quantifies the goodness of fit of the model and is calculated using Equation (10), with higher values indicating closer agreement between predicted and actual values. The performance of the proposed model is further compared against machine learning models such as Support Vector Machines (SVM) and Artificial Neural Networks (ANN).

$$\text{MAE} = \frac{1}{n}\sum_{j=1}^{n}|y_j-\hat{y}_j| \tag{8}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{j=1}^{n}(y_j-\hat{y}_j)^2} \tag{9}$$

$$\text{Coefficient of Determination} = 1 - \frac{\sum_{j=1}^{n}(y_j-\hat{y}_j)^2}{\sum_{j=1}^{n}(y_j-\bar{y}_j)^2} \tag{10}$$

3.4 Parameter Settings of the models

The proposed model features a three-layer stacked architecture of RNN, LSTM, and GRU networks, each with 100-neuron hidden layers, using the ReLU activation function and the Adam optimizer. The effectiveness of these models are compared with SVM and ANN models. The ANN model is constructed with three hidden layers, featuring 50, 25, and 10 neurons in the first, second, and third hidden layers, respectively. The SVR model, used for comparison, is configured with the RBF (radial basis function) kernel. The parameter settings for these models are outlined in Table 2.

Table 2 Parameter settings of the models

Forecasting Models	Parameters	Number or Type
RNN, LSTM, GRU	Hidden layer count	3
	Neuron count in the hidden layers	100
	Output layer activation function	Relu
	Optimizer	Adam
SVR	Kernel function	Radial basis function
ANN	Hidden layer count	3
	Neuron count in the hidden layers	(50, 25, 10)
	Learning rate	0.001

4. Result Analysis

The wind speed is predicted using LSTM, GRU, and RNN methods. The efficacy of the proposed deep learning-based wind speed prediction model is assessed by comparing it with conventional machine learning models such as ANN and SVR. The comparison is conducted by analyzing the predicted and actual values, employing statistical error indices. Table 3 details the prediction accuracy of the various models based on RMSE, MAE, and Coefficient of Determination. Smaller MAE and RMSE values indicate higher forecast accuracy, while larger Coefficient of Determination values indicate a stronger linear relationship between predicted and actual values.

The presented results in the table highlight the efficiency of the proposed model in predicting hourly wind speed, showcasing minimal errors with MAE at 0.5723 and RMSE at 0.7763. The higher Coefficient of Determination value for GRU further validates the effectiveness of the developed model in comparison to other models. From the table, it can be inferred that while the GRU model demonstrated superior prediction accuracy compared to other models, deep learning-based Simple RNN and LSTM also achieved comparable performance. In contrast, the SVM and ANN models exhibited lower performance when compared to the deep learning-based models. Therefore, from the analysis, it can be deduced that deep learning-based models outperform other approaches in time series prediction, particularly in the context of wind speed forecasting. Comparison of results of various model is given in Table 3.

Table 3. Comparison of results of various forecasting models

Algorithm	MAE (m/s)	RMSE(m/s)	Coeff of Determination
GRU	0.5723	0.7763	92.97
LSTM	0.5847	0.7918	92.47
Simple RNN	0.5868	0.7937	92.35
SVR	0.7255	0.9432	89.34
ANN	0.7624	0.9976	88.05

Fig. 7 illustrate the accuracy of the proposed models based on RMSE and MAE, clearly indicating that the proposed GRU model produces lower MAE and RMSE values compared to other models. Comparison of model performance using the Coefficient of Determination is depicted in Figure 8. The results indicate that RNN, LSTM, and GRU models are highly effective for predicting hourly wind speed, demonstrating higher prediction accuracy when compared to SVM and ANN models. should be editable and be written below the figures.

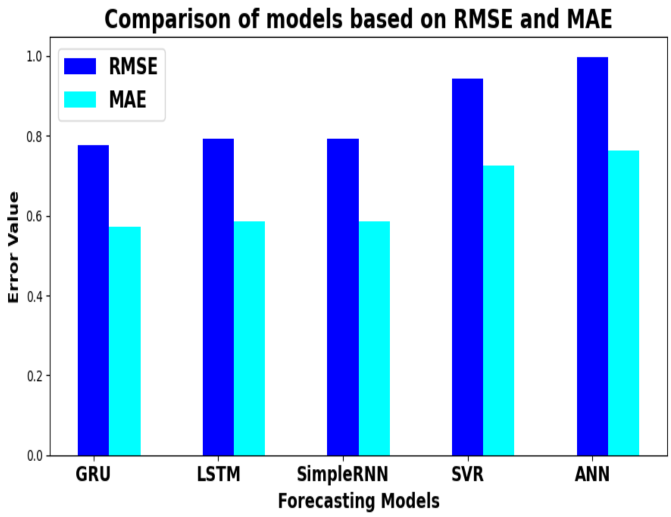


Figure 7 Comparison of model performance based on RMSE and MAE

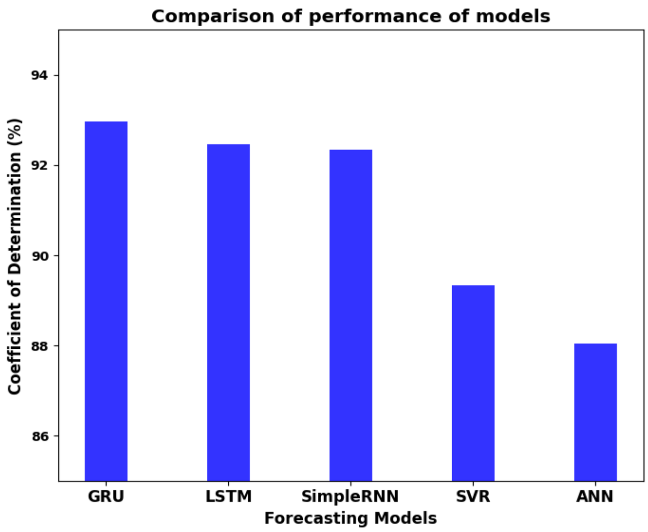


Figure 8 Comparison of model performance based on Coefficient of Determination

5. Conclusion

This study presents a wind speed forecasting model using deep learning architectures, specifically stacked LSTM, GRU, and RNN models. The proposed model's efficiency is evaluated against traditional machine learning models including SVM and ANN. The developed model demonstrates superior performance, achieving a minimum MAE of 0.5723, RMSE of 0.7763, and a maximum Coefficient of Determination value of 92.97%. These findings underscore the model’s capability to accurately capture the temporal dependencies and nonlinear patterns inherent in hourly wind speed data. Further enhancements in predictive accuracy can be explored through the utilization of deep learning-based hybrid models.

While the proposed model shows promising results, several avenues can be explored to further enhance forecasting performance:
1. Integrating decomposition techniques, attention mechanisms, or ensemble frameworks with stacked LSTM and GRU architectures could improve robustness and predictive accuracy.
2. Incorporating additional meteorological variables, satellite imagery, or numerical weather prediction (NWP) outputs may enhance the model's ability to predict extreme or rapidly changing wind conditions.
3. Incorporating interpretability techniques can provide insights into model predictions, facilitating operational decision-making and stakeholder trust.

The proposed deep learning-based wind speed forecasting model provides a highly effective framework for hourly predictions. Future research focusing on hybridization, multimodal data integration, and interpretability can further strengthen its practical applicability and operational relevance in wind energy management.

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Authors' Contributions-
Jaseena K U: Conceptualization, methodology design and model evaluation.
Sreddha Sajeev: Data analysis, Model development.
Leena C Sekhar: Manuscript drafting, visualization and reviewing.

Conflict of Interest- The authors have no conflict of interest.

Data Availability- The data supporting the findings of this study are provided by the National Institute of Wind Energy (NIWE) and are subject to access restrictions. These data can be obtained from the corresponding author upon reasonable request, subject to approval from NIWE.

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