An Integrated Stacked Sparse Autoencoder and CNN-BLSTM Model for Ultra-Short-Term Wind Power Forecasting with Advanced Feature Learning

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***Abstract*—With the increasing integration of renewable energy sources into the power grid, accurate and reliable ultra-short-term forecasting of wind power is critical for optimizing grid stability and energy efficiency, especially for a highly dynamic and variable environment. This paper combines Stacked Sparse Autoencoders (SSAE) with a Convolutional Neural Network-Bidirectional Long Short-Term Memory (CNN-BLSTM) architecture to address this challenge, which forms a novel deep learning framework, namely hybrid Stacked Sparse Autoencoder and Convolutional neural network-Bidirectional CNN-BLSTM with advanced Feature selection (SSACBF). The process starts with rigorous data preprocessing and key variable selection through a three-step approach based on expert and statistical methods. The framework employs a stacked sparse multi-layer CNN autoencoder to distil inputs into a robust feature set capturing complex temporal dependencies. These features are then processed by a CNN-BLSTM model, which leverages CNN layers for spatial-temporal nuances and BLSTM layers to simultaneously learn from past and future data. The approach significantly outperforms existing models in accuracy and efficiency, demonstrating potential for real-time applications in wind farm operational planning and energy management systems.**

***Index Terms*—Ultra-short-term wind power forecasting, neural networks, feature extraction, wind turbines, stacked sparse autoencoder**

I. Introduction

Wind power forecasting is a critical component in the integration of renewable energy sources into the power grid. Given the inherent variability and intermittency of wind energy, its accurate predictions are key to maintaining power system reliability and efficiency [1]. Furthermore, amidst global efforts to achieve carbon neutrality, enhancing wind power predictability is vital to reduce emissions in the electricity sector. It helps accurately predict wind power and subsequently optimize generation scheduling, contributing significantly to carbon reduction and sustainable energy transitions.

Ultra-short-term wind power forecasting, typically within a 30-minute horizon, is crucial for real-time grid management and market operations. Enhanced forecasting accuracy directly impacts the efficiency of wind power utilization, which is essential for meeting carbon neutrality targets and minimizing reliance on fossil fuels [2].

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A. State-of-the-Art of Wind Power Forecasting

Wind power forecasting has evolved significantly over the years, transitioning from basic statistical models to sophisticated machine learning and deep learning approaches [3], [4]:

(1) Traditional Statistical Models: Historically, wind power forecasting relied on traditional statistical methods such as the Autoregressive Integrated Moving Average (ARIMA) and exponential smoothing. These methods are favoured in scenarios where simplicity and interpretability are prioritized over capturing complex patterns. For example, [5] demonstrated the efficacy of ARIMA in stable wind conditions, highlighting its limitations in volatile environments. While these models form a baseline for accuracy, they often fail in scenarios with high variability, a common characteristic of wind data.

(2) Machine Learning Models: As the complexity and volume of data increased, machine learning models began to gain prominence. Techniques such as Support Vector Machines (SVM), Random Forests (RF), and k-Nearest Neighbors (kNN) were adopted due to their ability to handle non-linear data more effectively than traditional methods. SVM was utilized in [6] to forecast wind power with considerable success in forecasting scenarios. These models, however, typically lack the ability to inherently capture temporal dependencies, crucial for ultra-short-term forecasting.

(3) Advanced Deep Learning Models: To address the shortcomings of machine learning models in capturing temporal dynamics, deep learning models, especially Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks, have been increasingly used. These models excel in scenarios where data exhibits significant temporal dependencies. For instance, [7] demonstrated how LSTM models outperform traditional machine learning models in predicting ultra-short-term wind power.

(4) Hybrid and Ensemble Models: The latest research has shown a trend towards hybrid and ensemble methods that integrate multiple forecasting techniques to leverage their strengths. For example, a framework combining complete ensemble empirical mode decomposition with adaptive noise, monarch butterfly optimization and LSTM was proposed in [8] to make predictions based on better extracted complex hidden features. Hybrid models combining CNNs with LSTMs have also been explored, such as in the work by [9], which combined spatial and temporal feature extraction for enhanced accuracy.

B. Main Contribution: The SSACBF Model

Building upon these developments, this paper develops and validates a novel ultra-short-term wind power forecasting model that utilizes advanced deep learning techniques, specifically integrating a stacked sparse autoencoder (SSAE) with a CNN-BLSTM network to boost forecasting accuracy while maintaining computational efficiency. The main contributions are summarized as follows:

(1) Feature Extraction: The Convolutional SSAE model extracts the most relevant features, effectively reducing feature dimensionality.

(2) Relationship Learning and Prediction: The CNN-BLSTM model performs relationship learning and output prediction, adeptly capturing both spatial and temporal dependencies in the data.

(3) Data Preprocessing and Feature Selection: The 10-minute multivariate data of wind turbines collected from Supervisory Control and Data Acquisition (SCADA) systems [10] are acquired and analyzed. Rigorous data preprocessing cleans and corrects the SCADA data, addressing missing values and outliers. An improved three-step feature selection method identifies the most relevant variables for forecasting before fed into SSAE.

Results show that the proposed framework can realize higher forecasting accuracy while maintaining high prediction efficiency, which can help enhance the operational efficiency of wind farms and improve the reliability of power grid operations. Furthermore, by advancing wind power forecasting, this research contributes to global carbon neutrality efforts and aids in reducing carbon emissions, supporting a more sustainable energy future.

The paper is organized as follows: The methodology is introduced in Section II, the proposed models and data processing techniques are described in Sections III and IV respectively. The experimental setup and results are presented in Section V, and the paper concludes in Section VI with a summary of the contributions and discussion of potential future work.

II. Methodology Overview

A. Problem Formulation

The primary goal of this study is to develop an accurate ultra-short-term wind power forecasting model. The problem can be formulated as a time series prediction task where the objective is to forecast the future wind power output P_{t+1} given historical observations. Let $\mathbf{X}_t = [\mathbf{x}_{t-n}, \mathbf{x}_{t-n+1}, \ldots, \mathbf{x}_t]$ represent the input features at time t, where n is the number of previous time steps considered. The forecasting task can be expressed as finding a function f such that:

$$P_{t+1} = f(\mathbf{X}_t) \tag{1}$$

In this study, $\mathbf{x}_t$ includes various features extracted from the SCADA data at time t, such as wind speed, wind direction, temperature, and other relevant variables.

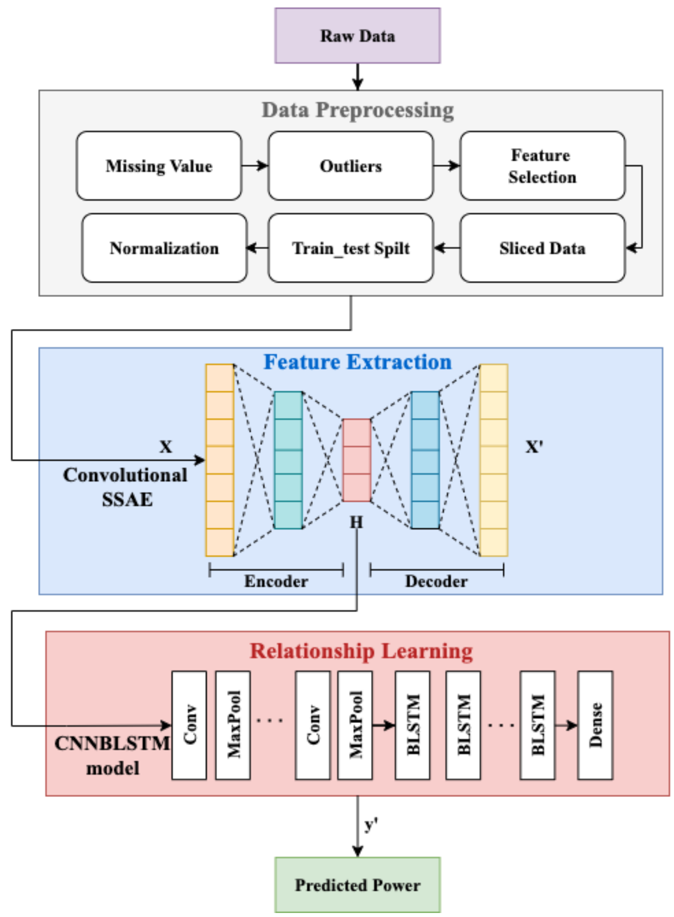


Fig. 1: SSACBF model

B. Overview

The wind power forecasting framework consists of three main steps: data preprocessing, feature extraction, and relationship learning, as shown in Fig. 1. The data preprocessing phase involves handling missing values, identifying and correcting outliers using a quantile-based method with mean imputation, performing three-stage feature selection, setting the appropriate time length for the sliding data, splitting data into a test set and train set, and normalizing data before training. Details about the dataset used and the preprocessing procedures will be discussed in Section IV. Feature extraction is executed using a Convolutional SSAE, which reduces the dimensionality of the input data while preserving essential patterns.

In the relationship learning phase, a CNN-BLSTM model is utilized to exploit both spatial and temporal dependencies in the data. These steps are crucial for enhancing the model's ability to forecast accurately and will be explored further in the subsequent section. By following these methodological steps, the study aims to improve the accuracy of ultra-short-term wind power forecasting, contributing to the effective management and integration of renewable energy sources into the power grid.

III. Proposed Models

A. Convolutional SSAE

Feature extraction is a crucial step in ensuring that the model captures the most relevant information for accurate predictions. In this study, feature extraction is accomplished using a convolutional SSAE consisting of three stacked sparse autoencoders (SAE). Each SAE includes both an encoder and a decoder, which work together to reduce the dimensionality of the input data while preserving essential patterns and temporal dependencies critical for forecasting.

Initially, the input data denoted as X, is processed by the encoder of the first SAE block. The encoder applies convolutional operations combined with max pooling and dropout to reduce noise and extract primary features. The features are then encoded into a compressed dimensional space, represented by H_1. The encoded features from H_1 are subsequently passed through the decoder of the first SAE block, which begins the process of reconstructing the original data dimensions. The decoder section of the SAE reverses the encoder's configuration. It starts with upsampling followed by convolutional layers that incrementally reconstruct the original dimensions of the input data. This symmetric architecture, with both encoding and decoding components, is pivotal for learning a compact representation of the input data, ensuring that essential information is preserved while minimizing noise. The specific structures can be found in Fig. 2

This pattern of encoding to reduce dimensionality and decoding to reconstruct data is repeated in the second and third SAE blocks. The encoded features H of the last SAE will be directly fed into the encoder of the next SAE block. Each subsequent block further compresses and then reconstructs the data, producing progressively refined feature representations, H_2 and H_3, respectively. This stepwise refinement is crucial for effectively capturing more abstract features of the data. After processing through the final SAE block, the output H_3 is fed into a CNN-BLSTM network, which is described in the next subsection.

Unlike standard autoencoders, which simply aim to replicate the input at the output layer, the SAEs used in the model incorporate a sparsity penalty on the hidden layers. The sparsity penalty in SAEs is implemented using the Kullback-Leibler (KL) divergence, as shown in (2). The KL divergence is used to enforce sparsity by penalizing the deviation of the actual activation of hidden neurons from a specified sparsity parameter, ρ. Typically, ρ is a small value close to zero, indicating the desired average activation for the hidden neurons.

$$D_{KL}(\rho||\hat{\rho}_j) = \rho \log \frac{\rho}{\hat{\rho}_j} + (1-\rho) \log \frac{1-\rho}{1-\hat{\rho}_j} \tag{2}$$

where $\hat{\rho}_j$ is the average activation of the j-th neuron in the hidden layer. This penalty is summed over all neurons in the hidden layer and added to the overall loss function of the autoencoder. By minimizing this loss, the SAE learns to activate only the most essential neurons, thus achieving a sparse representation. The inclusion of this sparsity penalty helps to prevent overfitting by reducing the number of active neurons, which in turn enhances the generalization ability of the model. It also helps in identifying the most significant features from the input data, which are crucial for effective feature extraction in tasks such as ultra-short-term wind power forecasting. The definition and details of SAE and SSAE can be found in [11] and [12].

B. CNN-BLSTM Forecasting Model

The relationship learning model combines CNN and BLSTM networks to predict wind power output, as illustrated in Fig. 1. This model leverages the spatial-temporal features extracted and refined by the SSAE models, enhancing the model's predictive accuracy through sophisticated relationship learning. The CNN-BLSTM model first employs five CNN layers with MaxPooling to extract spatial features from the input sequences. These layers are adept at identifying patterns that are spatially localized, such as those arising from geographical variations in wind patterns or environmental influences specific to certain locations.

Following the spatial feature extraction by the CNN layers, three BLSTM layers process these features to capture temporal dependencies. The bidirectional structure of the BLSTM allows the model to learn from both past and future contexts, significantly enhancing its ability to understand sequence data over time. This capability is crucial for wind power forecasting, where it is essential to balance past data and future expectations to make accurate predictions.

The hybrid CNN-BLSTM model leverages the strengths of both architectures, providing a comprehensive understanding of the spatial and temporal patterns in the data. By integrating these two approaches, the model captures a more detailed and nuanced picture of how wind power can be expected to change, considering both the immediate and broader temporal context. The final output layer of the model is a fully connected layer that produces the predicted wind power output. This layer integrates all learned features from the CNN and BLSTM layers and transforms them into the final forecast.

IV. Dataset and Preprocessing

A. Dataset Description

The dataset for this study is sourced from the Penmanshiel Wind Farm in the UK, covering 10-minute intervals of SCADA and events data from 2016 to mid-2021 [10]. It includes data for 14 Senvion MM82 wind turbines, with

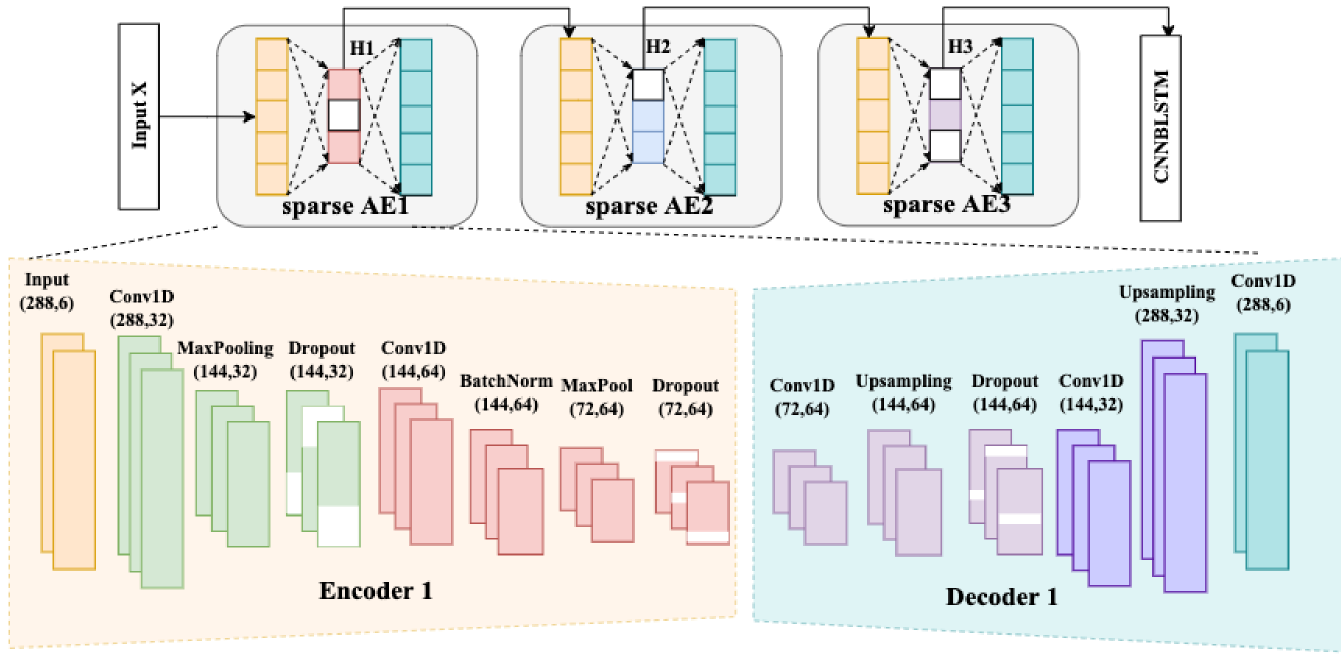


Fig. 2: Architecture of the Convolutional SSAE for feature extraction.

over 300 variables each. For this analysis, the study focuses exclusively on data from Turbine 1, spanning from 01/01/2017 to 06/30/2021, with the 'Power(kW)' variable selected as the primary target for forecasting.

B. Data Cleaning and Normalization

Data preprocessing is critical for ensuring the quality and reliability of the forecasting model. The preprocessing steps implemented are as follows:

(1) **Missing Values Imputation**

Columns with over 10% missing values are removed, eliminating 135 columns, including 9 columns that contained only NaN values. The remaining missing values are imputed using the backward fill (BFILL) method. This method replaces missing entries with the subsequent valid observation, ensuring temporal consistency in the dataset.

(2) **Outlier Detection and Correction**

Outliers are initially identified using a piecewise quantile-based method that compares actual power output against potential power derived from the power curve provided by manufacturers [13]. These outliers are then corrected by substituting them with the mean values from similar wind speeds. The result of identifying and correcting outliers is illustrated in Fig. 3.

(3) **Feature Selection**

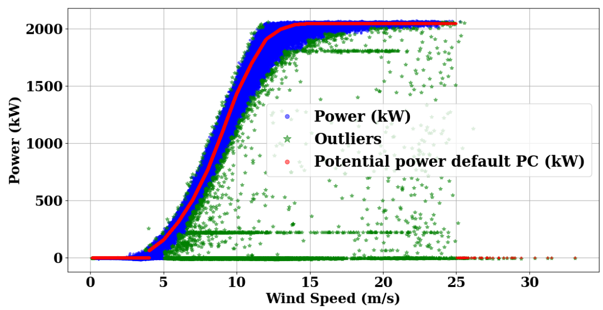
Feature selection in this study is the variable filter process before extracting info using SSAE. It is executed through a systematic three-step process, designed to filter the most significant variables from the high-dimensional SCADA dataset for accurate wind power forecasting. Initially, expert insights and an extensive literature review guide the identification of a preliminary set of 68 features pertinent to wind power output. Subsequently, these features undergo ranking via an RF algorithm, which evaluates their importance in influencing wind power output. In the final stage, features demonstrating high correlation are methodically eliminated to minimize redundancy. This step enhances the model's clarity by concentrating on unique contributors to variability in power output. Six key variables are kept including 'Wind speed (m/s)', 'Wind direction (°)', 'Rotor speed (RPM)', 'Generator RPM (RPM)', 'Density adjusted wind speed (m/s)', and 'Nacelle ambient temperature (°C)'.

C. Data Slicing and Splitting

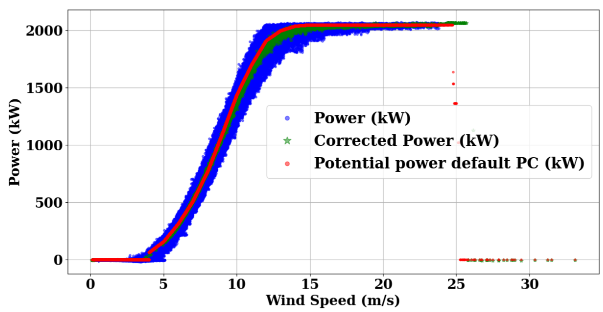
In this study, a sliding window approach is employed to create training sequences from time series data, which is crucial for capturing temporal dependencies in wind power output. Fixed-length sequences are generated using this method, enabling the model to learn from temporal patterns within these windows.

To determine the optimal window size for the model's performance, various lengths are tested. A window size of 288 time steps—corresponding to two full days, with data recorded at 10-minute intervals—is identified as the most accurate and time-efficient. This length allows the model to capture daily patterns and fluctuations in wind power, essential for accurate forecasting.

The dataset is subsequently divided into training, testing, and validation subsets, allocated at 75%, 20%, and 5% respectively. This distribution ensures a robust training dataset for model development, a comprehensive test set for performance evaluation, and a smaller validation set for final adjustments of model parameters and hyperparameters.



(a) Outliers Identification and Removal



(b) Outliers Correction

Fig. 3: Outliers Removal and Data Correction

Normalization is applied before training to improve model training efficiency and accuracy. The data is normalized using standard normalization, which involves standardizing features to have a mean of zero and a standard deviation of one. The standardization formula is expressed as:

$$z = \frac{x - \mu}{\sigma} \tag{3}$$

where x is the original value, μ is the mean of the feature, and σ is the standard deviation of the feature. This scaling shrinks the data such that the distribution of the transformed feature has a mean of 0 and a standard deviation of 1.

V. Experiment

A. Evaluation Metrics

To evaluate the performance of the forecasting model, Normalized Mean Absolute Error (NMAE), Normalized Root Mean Square Error (NRMSE), and Coefficient of Determination (R^2) are chosen for the accuracy evaluation, defined as follows.

$$\text{NMAE} = \frac{1}{N}\sum_{i=1}^{N}\frac{|P_i - \hat{P}_i|}{P_{\text{cap}}} \times 100\% \tag{4}$$

$$\text{NRMSE} = \frac{1}{P_{\text{cap}}}\sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_i - \hat{P}_i)^2} \times 100\% \tag{5}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(P_i - \hat{P}_i)^2}{\sum_{i=1}^{N}(P_i - \bar{P})^2} \tag{6}$$

where P_i and $\hat{P}_i$ are the actual and predicted power values for the i-th sample, N is the number of samples, and P_{cap} is the rated capacity of the wind turbine, $\bar{P}$ represents the mean value of the actual power across all samples.

Besides, Training Time (TT) and Prediction Time(PT) are used for measuring time efficiency. Training Time refers to the total time required to train the model, whereas Prediction Time is the time needed to generate predictions per time.

B. Experiment Setup

The experiments are conducted on a GPU-enabled server to meet the computational demands of training sophisticated deep learning models. Specifically, an NVIDIA 4090 GPU server is utilized, providing the necessary computational power. The models are implemented using TensorFlow, with training parameters set to a batch size of 32 and a total of 100 epochs. The loss function, Mean Squared Error (MSE), is optimized using the Adam optimizer at a learning rate of 0.001.

To evaluate the effectiveness of the proposed model, comparative analyses are conducted against a range of baseline models. These include traditional machine learning algorithms including SVM, RF, kNN, and Gradient Boosting (GBR). Additionally, comparisons are made with other deep learning architectures, including CNN and LSTM [14]. This diverse set of benchmarks enables a thorough validation of the model's performance across different computational approaches.

C. Result Analysis

The experimental results demonstrate the SSACBF model's superior accuracy and efficiency, as shown in Table I. In summary, the model not only outperforms traditional and other machine learning models across key metrics such as NMAE, NRMSE, R^2, and MAPE, but also excels in prediction time efficiency. This makes it particularly suitable for real-time forecasting applications where speed is critical. For accuracy, the SSACBF model achieves the lowest NMAE and NRMSE values at 2.47 and 4.15, respectively, demonstrating superior accuracy in forecasting wind power. This is a substantial improvement compared to the next best model, LSTM, which records NMAE and NRMSE of 3.48 and 5.24, respectively. With an R^2 of 0.98, the SSACBF model shows exceptional predictive strength, outperforming all other models reviewed, including CNN and LSTM, which exhibit values of 0.96 and 0.97 respectively. This indicates a nearly perfect fit for the actual wind power generation data.

Despite its high accuracy, the SSACBF model also achieves a short prediction time. Traditional models like SVM are hindered by long training times due to the curse of dimensionality and the computational demands of large datasets. In contrast, ensemble methods such as RF and GBR offer faster prediction times. RF utilizes multiple decision trees to enhance prediction speed and robustness, while GBR employs a sequential tree-building methodology that quickly corrects past errors, improving prediction speed after training.

The SSACBF model strikes a balance between accuracy and rapid prediction capabilities, ideal for dynamic operational environments demanding both speed and accuracy. Fig. 4 from the last day of data collection (06/30/2021) showcases the model's exceptional ability to capture complex temporal patterns in wind power data, significantly enhancing forecasting precision. The prediction curve closely aligns with actual power generation data, capturing peaks and troughs with remarkable accuracy. While neural network-based models like LSTM and CNN perform well, they slightly underperform in predicting peak values compared to the SSACBF model. Meanwhile, GBR, RF, and SVM manage to capture the general trend but struggle with peak accuracy and rapid changes. The KNN model, in particular, shows difficulty in handling fluctuations, indicating potential areas for model tuning or feature selection reevaluation.

TABLE I: Results of Different Models

Models	***NMAE***	***NRMSE***	R^2	***TT***	***PT***
kNN	7.69	11.47	0.86	Short	Very Long
RF	4.50	7.40	0.91	**Short**	**Very Short**
SVM	7.26	11.68	0.81	Super Long	Very long
GBR	4.40	7.35	0.95	Very Long	Short
CNN	3.90	5.81	0.96	Long	Medium
LSTM	3.48	5.24	0.97	Very Long	Medium
SSACBF	**2.47**	**4.15**	**0.98**	Medium	Short

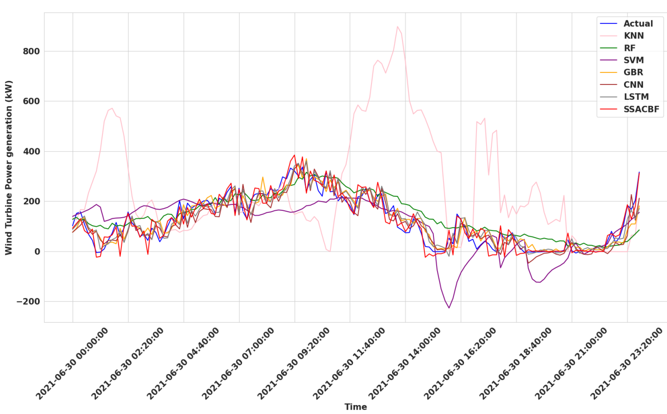


Fig. 4: Wind Turbine Power Forecasting Comparison based on Different Models

VI. Conclusion

This paper has introduced the SSACBF model, which integrates a Stacked Sparse Autoencoder (SSAE) with a CNN-BLSTM network for ultra-short-term wind power forecasting. This innovative hybrid model significantly enhances forecasting accuracy and operational efficiency by exploiting both the spatial and temporal complexities inherent in wind power historical data. Our experimental results validate the superior performance of the SSACBF model, which achieves the lowest NMAE of 2.47 and NRMSE of 4.15, demonstrating a marked improvement over both traditional machine learning models and other advanced deep learning approaches.

Despite its intricate architecture, the SSACBF model maintains short prediction times, aligning well with the demands of real-time applications essential for effective grid management and operational planning in wind farms. These attributes make it a highly suitable choice for integrating wind energy into the power grid, where rapid and accurate decision-making is critical to accommodate fluctuations in wind power generation.

Looking ahead, further research will focus on enhancing the model's robustness under varying weather conditions to ensure reliability across different scenarios. Additionally, exploring transfer learning strategies could enable the model to generalize across different turbines and sites within wind farms without extensive retraining. Advanced optimization techniques for hyperparameter tuning are also anticipated to yield further improvements in accuracy and efficiency. The potential incorporation of attention mechanisms may provide new avenues for model enhancement by prioritizing salient features over time and space. Finally, integrating a broader range of data sources, including high-resolution weather forecasts and real-time turbine data, is expected to refine the model's forecasting capabilities even further.

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