

A Review: Short-Term Wind Power Forecasting Using Machine Learning

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ABSTRACT : Wind energy has become one of the most important renewable energy sources for sustainable power generation. However, the irregular and changing nature of wind creates challenges in maintaining stable electricity production. Accurate short-term wind power prediction helps power systems improve grid stability, energy management, and operational efficiency. Machine learning techniques have recently gained significant attention because of their ability to learn patterns from large datasets and improve prediction accuracy. This review paper presents an overview of short-term wind power prediction methods based on machine learning. The paper discusses different preprocessing methods, feature engineering techniques, and forecasting models used in recent studies. A review of ten research papers is also presented to understand the current progress in this field. Furthermore, the paper identifies major research gaps such as data uncertainty, model complexity, and lack of generalized frameworks. Finally, the study concludes that hybrid and deep learning models provide better forecasting performance, but further research is required to improve accuracy, scalability, and real-time implementation.

KEYWORDS: Wind Power Prediction, Machine Learning, Deep Learning, Renewable Energy, Short-Term Forecasting, Neural Networks, Hybrid Models

I INTRODUCTION

The increasing demand for clean and sustainable energy has encouraged many countries to adopt renewable energy technologies. Among different renewable energy sources, wind energy plays a major role due to its environmental benefits and large energy generation capacity. Wind power generation has expanded rapidly in recent years because it reduces dependence on fossil fuels and decreases carbon emissions.

Despite its advantages, wind energy faces one major challenge: wind speed changes continuously due to atmospheric conditions. Because of this uncertainty, wind power generation becomes highly variable and difficult to predict accurately. Inaccurate forecasting can affect power system stability, increase operational costs, and create difficulties in balancing electricity demand and supply.

Short-term wind power prediction generally refers to forecasting wind power from a few minutes to several hours ahead. Accurate short-term forecasting is important for grid scheduling, load balancing, energy trading, and battery storage management. Traditional statistical methods such as ARIMA and Kalman filters were initially used for forecasting, but these methods have limitations in handling nonlinear and complex wind patterns.

Machine learning techniques have become popular because they can analyze large datasets and identify hidden patterns in wind data. Models such as Support Vector Machine (SVM), Artificial Neural Networks (ANN), Random Forest (RF), Long Short-Term Memory (LSTM), and Convolutional Neural Networks (CNN) are widely used in modern forecasting systems. These methods improve prediction accuracy by learning relationships between meteorological variables and wind power generation.

This review paper focuses on machine learning approaches used for short-term wind power prediction. The paper also reviews important studies, identifies research gaps, and discusses future research directions.

II REASEARCH REVIEW

[1] Meng et al. (2022) proposed a hybrid short-term wind power forecasting model using Ensemble Empirical Mode Decomposition (EEMD), attention mechanisms, and Recurrent Gated Recurrent Units (RGRU). The model first decomposed wind power data into different components to reduce noise and improve data quality. Attention mechanisms were used to identify important features from the input data for better forecasting accuracy. The proposed approach effectively captured temporal dependencies and nonlinear patterns in wind speed variations. Experimental results showed that the hybrid model achieved lower forecasting errors compared to traditional machine learning methods. The study highlighted that combining decomposition techniques with deep learning can significantly improve short-term wind power prediction performance. However, the model required high computational resources and increased training complexity for large-scale datasets.

[2] Ouyang et al. (2017) proposed a short-term wind power prediction system using Support Vector Machine (SVM) and feature engineering techniques. The study applied preprocessing methods such as normalization, smoothing, and missing value handling to improve data quality before prediction. Granger causality testing and mutual information methods were used for selecting important meteorological variables. The proposed SVM model effectively handled nonlinear relationships between wind speed and power generation. Experimental results demonstrated improved forecasting accuracy and reduced prediction errors compared to conventional statistical methods. The authors emphasized the importance of preprocessing and feature selection in renewable energy forecasting systems. However, the model performance decreased when handling large-scale and highly dynamic wind datasets.

[3] Yan and Ouyang (2019) proposed a wind power forecasting framework using logistic regression, random forest, and boosted tree algorithms. The system included abnormal data detection and smoothing techniques to improve forecasting reliability. Pearson correlation coefficient analysis was used to identify highly relevant features affecting wind power generation. The hybrid ensemble model successfully improved forecasting stability and reduced prediction uncertainty under changing weather conditions. Experimental analysis showed that tree-based models performed better than individual prediction techniques. The study highlighted that ensemble learning approaches can effectively manage complex and nonlinear wind data. However, the proposed framework faced limitations in real-time forecasting applications due to increased computational complexity.

[4] Zhou et al. (2019) developed an LSTM-based short-term wind power prediction model integrated with DBSCAN clustering and Kernel Density Estimation (KDE). The model utilized clustering techniques to identify similar wind patterns from historical datasets. LSTM networks captured estimate probability distributions and improve prediction reliability. The proposed framework achieved better forecasting accuracy compared to traditional neural network approaches. The study demonstrated that combining clustering methods with deep learning improves wind forecasting performance under uncertain environmental conditions. However, the model required extensive training data and high processing time for practical implementation.

[5] Bokde et al. (2019) proposed a hybrid wind power forecasting model using Empirical Mode Decomposition (EMD), Variational Mode Decomposition (VMD), Convolutional Neural Networks (CNN), and Long Short-Term Memory (LSTM) networks. The decomposition methods separated wind signals into multiple frequency components for easier analysis. CNN extracted spatial features from the decomposed signals, while LSTM learned long-term temporal relationships. The hybrid framework effectively reduced noise and improved forecasting accuracy compared to standalone machine learning models. Experimental results showed significant improvements in RMSE and MAE values. The study concluded that decomposition-based deep learning models are highly suitable for renewable energy prediction systems. However, the integration of multiple algorithms increased model complexity and computational cost.

[6] Yang et al. (2024) introduced a CNN-LSTM hybrid forecasting model using Multivariate Variational Mode Decomposition (MVMD) and Elastic Net feature selection techniques. The MVMD method decomposed wind signals into stable subcomponents for efficient learning. Elastic Net feature selection identified the most relevant

meteorological variables influencing wind power generation. CNN layers extracted local patterns from wind datasets, while LSTM networks captured sequential information. Experimental results demonstrated improved forecasting stability during seasonal and environmental variations. The study emphasized that feature engineering techniques play a major role in improving prediction performance. However, the model required careful hyperparameter tuning to achieve optimal results.

[7] Liu et al. (2024) proposed a short-term wind power prediction model using wavelet decomposition, mutual information feature selection, and LSTM networks. Wavelet decomposition was used to remove noise and divide wind signals into different frequency bands. Mutual information techniques selected highly relevant input features for improving forecasting efficiency. The LSTM model effectively captured nonlinear and long-term dependencies in wind power data. Experimental findings showed reduced prediction errors and improved robustness under fluctuating wind conditions. The study highlighted the importance of decomposition and feature selection techniques in renewable energy forecasting systems. However, the framework faced challenges in handling sudden extreme weather changes.

[8] Hanifi et al. (2024) proposed a deep learning-based wind forecasting framework using ridgelet transformation, CNN, and LSTM models. The ridgelet transform extracted meaningful features from complex wind speed signals before prediction. CNN networks captured spatial characteristics, while LSTM handled temporal relationships in sequential data. Hyperparameter optimization using Tree-structured Parzen Estimator (TPE) improved model efficiency and forecasting accuracy. Experimental analysis showed lower forecasting errors compared to conventional deep learning methods. The study demonstrated that optimization techniques can enhance the performance of hybrid forecasting systems. However, the proposed framework required large training datasets and high computational power.

[9] Alkesaiberi et al. (2022) proposed a wind power forecasting approach using Gaussian Process Regression (GPR), Support Vector Regression (SVR), and Ensemble Learning methods. Bayesian optimization was applied to automatically tune model hyperparameters for improved performance. The study compared different machine learning models using multiple wind datasets collected from renewable energy systems. Results showed that ensemble learning methods achieved better generalization and prediction accuracy than individual algorithms. The proposed framework effectively handled nonlinear and uncertain wind behavior. The authors concluded that optimization algorithms significantly improve forecasting reliability and efficiency. However, the model performance was sensitive to parameter initialization and data quality issues.

[10] Li et al. (2020) proposed a hybrid short-term wind power prediction system using wavelet decomposition and Support Vector Machine (SVM). Wavelet decomposition reduced signal complexity and removed noise from historical wind datasets. The SVM model learned nonlinear relationships between meteorological variables and wind power generation. The proposed hybrid framework improved prediction stability during sudden wind fluctuations and changing weather conditions. Experimental results demonstrated higher forecasting accuracy compared to traditional SVM and statistical models. The study highlighted that decomposition-based hybrid techniques are effective for renewable energy forecasting applications. However, the system faced difficulties in handling very large datasets and real-time forecasting scenarios.

III REASEARCH GAP

Although many machine learning and deep learning models have been developed for short-term wind power prediction, several important challenges still remain in this research area. Most wind power datasets contain missing values, noise, and abnormal readings that reduce forecasting accuracy. Many researchers mainly focus on developing prediction models and give less attention to advanced preprocessing and data cleaning techniques. Deep learning models such as LSTM, GRU, and Transformer provide better forecasting performance, but these models require high computational power, long training time, and large datasets. Another major issue is the lack of model

generalization because most forecasting systems are tested only on specific wind farms and may not work effectively under different climatic and geographic conditions. In addition, many studies are based on offline simulations and do not support real-time wind power forecasting applications. Selecting important meteorological variables also remains difficult because wind behavior changes continuously due to environmental conditions. Hybrid forecasting models improve prediction accuracy, but combining multiple algorithms increases system complexity and implementation cost. Existing models also face problems during seasonal variations and sudden weather changes, which reduce prediction reliability. Therefore, future research should focus on lightweight and adaptive hybrid models, efficient feature selection methods, real-time forecasting systems, and generalized frameworks that can perform effectively under different environmental conditions.

IV CONCLUSION

Short-term wind power prediction is important for improving the stability and efficiency of renewable energy systems. Machine learning and deep learning techniques have significantly improved forecasting accuracy compared to traditional statistical methods. Different models such as SVM, Random Forest, CNN, and LSTM have shown strong performance in handling nonlinear wind data. Hybrid models that combine decomposition methods, optimization techniques, and deep learning algorithms provide the best forecasting results. However, challenges such as computational complexity, poor generalization, and real-time implementation still exist.

Future research should focus on lightweight, adaptive, and scalable forecasting models for practical industrial use.

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