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Regional Wind Power Forecasting Using Bayesian Feature Selection and Machine Learning Techniques

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Abstract- The rapid growth of renewable energy sources has increased the importance of accurate wind power forecasting for reliable power system operation. Wind power generation is inherently variable due to changing weather conditions, making prediction a challenging task. This paper presents an intelligent wind power forecasting framework based on Bayesian Feature Selection combined with machine learning models. The proposed approach processes numerical weather prediction data and removes irrelevant spatial features to improve prediction accuracy. A dimensionality reduction technique is applied to select the most informative sub-areas of weather data, thereby reducing computational complexity while maintaining important predictive information. Various machine learning algorithms such as Support Vector Machines, Artificial Neural Networks, and Convolutional Neural Networks are employed for forecasting regional wind power output. The proposed model enhances prediction performance by optimizing feature selection and improving model efficiency. Experimental evaluation demonstrates that the system significantly improves forecasting accuracy while reducing the dimensionality of input data. The framework can assist energy providers and power grid operators in planning and managing renewable energy resources more effectively.

Keywords – Autonomous DevOps, SAP S/4HANA, AIOps, Continuous Integration and Delivery (CI/CD), Machine Learning, Quality Assurance, Self-Healing Systems, Anomaly Detection, Business Technology Platform.

I. INTRODUCTION

The increasing demand for clean and sustainable energy has led to the rapid development of renewable energy technologies worldwide. Among various renewable energy sources, wind energy has become one of the most important contributors to modern power systems due to its environmental benefits, cost efficiency, and wide availability. Wind power generation helps reduce greenhouse gas emissions and dependence on fossil fuels, making it a key component in the global transition toward sustainable energy systems [1], [2]. However, the inherent variability and uncertainty of wind conditions make accurate wind power forecasting a challenging task for power system operators and energy market participants.

Wind power forecasting plays a crucial role in ensuring the stability and reliability of electrical grids. Since wind speed and direction fluctuate continuously due to atmospheric conditions, the amount of electricity generated by wind turbines can vary significantly over time. Accurate forecasting enables grid operators to balance electricity supply and demand, optimize energy scheduling, and ensure efficient integration of renewable energy sources into power systems. Without reliable predictions, unexpected variations in wind power output may cause operational challenges and increase system management costs [3], [4].

Traditional forecasting methods such as statistical time-series models have been widely used for wind power prediction. Techniques including Auto-Regressive Integrated Moving Average (ARIMA) and exponential smoothing provide basic forecasting capabilities and are relatively easy to implement. However, these methods often fail to capture the complex nonlinear relationships between meteorological variables and wind power generation, resulting in limited forecasting accuracy when dealing with large datasets and dynamic environmental conditions [5], [6].

Recent advancements in machine learning and artificial intelligence have significantly improved wind power forecasting performance. Machine learning algorithms such as Support Vector Machines (SVM), Artificial Neural Networks (ANN), and deep learning models are capable of learning complex patterns from historical wind data and numerical weather prediction datasets. These models analyze meteorological variables such as wind speed, temperature, and atmospheric pressure to identify hidden relationships affecting power generation. As a result, machine learning techniques have become widely adopted for improving wind power forecasting accuracy [7], [8].

Despite these improvements, one major challenge in wind power forecasting is the high dimensionality of input data obtained from numerical weather prediction systems. These datasets often include large numbers of variables across multiple spatial regions, some of which may not significantly contribute to forecasting performance. Including unnecessary features increases computational complexity and may degrade model performance. Therefore, efficient feature selection techniques are essential for identifying the most relevant input variables and improving the efficiency of forecasting models [9], [10].

Several studies have explored advanced feature selection and spatial analysis techniques to improve forecasting performance. Methods such as neural kriging, spatial interpolation, and hybrid statistical–machine learning models have been applied to estimate wind power generation across different geographical regions. These techniques help capture spatial dependencies in meteorological data and enhance prediction accuracy for regional wind power forecasting [11]–[13].

To address these challenges, this study proposes a wind power forecasting framework that incorporates Bayesian Feature Selection to identify the most informative spatial regions from numerical weather prediction data. By dividing weather datasets into sub-regions and eliminating less relevant spatial inputs, the proposed approach reduces the dimensionality of the dataset while preserving critical predictive information. This preprocessing strategy improves the efficiency and accuracy of machine learning models used for forecasting.

The proposed framework integrates Bayesian feature selection with machine learning algorithms to enhance regional wind power forecasting performance. The system is designed to handle large-scale weather datasets and automatically identify optimal input variables for forecasting models. Experimental results demonstrate that the proposed method improves prediction accuracy while reducing computational complexity. This approach can support power system operators in managing renewable energy resources more effectively and ensuring the stable operation of modern power systems [14]–[17].

II. LITERATURE SURVEY

Wind power forecasting has attracted significant research attention due to its importance in ensuring the reliability and stability of modern power systems. Accurate prediction of wind power generation helps grid operators manage energy resources efficiently and maintain system balance. Various statistical, machine learning, and deep learning techniques have been proposed to improve forecasting accuracy. Earlier studies primarily relied on statistical approaches, while recent research focuses on intelligent data-driven techniques capable of modeling complex nonlinear relationships between meteorological variables and wind energy production [1]–[3].

Traditional time-series forecasting methods such as Auto-Regressive Integrated Moving Average (ARIMA) and exponential smoothing have been widely used for wind power prediction. These techniques analyze historical wind power data to identify patterns and trends over time. Although such models are relatively simple and computationally efficient, they typically assume linear relationships and stationary datasets. Consequently, these methods may fail to capture the highly dynamic and nonlinear characteristics associated with wind power generation [4], [5].

To overcome the limitations of statistical models, researchers have increasingly applied machine learning techniques to wind power forecasting problems. Algorithms such as Support Vector Machines (SVM), Decision Trees, Random Forests, and Artificial Neural Networks (ANN) have demonstrated improved performance in predicting wind power output. These models can learn complex relationships between weather conditions and wind power generation by analyzing large volumes of meteorological and historical power data [6], [7]. In particular, neural network-based models have been widely used due to their capability to capture nonlinear relationships between input variables and forecasting outputs.

With advancements in computational capabilities and data availability, deep learning approaches have been introduced into wind power forecasting systems. Models such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) can extract spatial and temporal patterns from large-scale meteorological datasets. These models are capable of processing multidimensional weather data and automatically learning features that influence wind power production, leading to improved forecasting performance compared with conventional machine learning methods [8], [9].

Another important research direction in wind power forecasting focuses on regional forecasting methods. Two commonly used techniques are the aggregation method and the upscaling method. The aggregation approach combines forecasts from individual wind farms to generate a regional forecast. Although this method is simple and widely adopted in operational systems, it may not fully capture spatial weather dependencies across large geographical areas [12], [13].

In contrast, the upscaling method models the relationship between meteorological variables and regional wind power generation using machine learning techniques. This method utilizes numerical weather prediction (NWP) data and advanced learning algorithms to estimate power output across broader regions. By analyzing meteorological variables such as wind speed, wind direction, and atmospheric pressure, upscaling models can provide more accurate regional wind power forecasts [14], [15].

Despite the progress achieved in wind power forecasting research, one major challenge remains the high dimensionality of numerical weather prediction datasets. Weather data often contain a large number of spatial and meteorological features, many of which may not significantly contribute to prediction accuracy. Including unnecessary input variables increases model complexity, training time, and the risk of overfitting [16], [17].

To address this issue, researchers have investigated various feature selection techniques, including filter-based, wrapper-based, and embedded feature selection approaches. Feature selection methods aim to identify the most informative input variables while removing redundant or irrelevant features. Efficient feature selection improves forecasting performance, reduces computational cost, and enhances model generalization ability [18], [19].

More recently, Bayesian-based feature selection methods have gained attention due to their probabilistic learning capabilities. Bayesian approaches evaluate feature relevance by estimating the probability distribution of input variables, enabling the selection of the most informative spatial and meteorological features. By reducing dataset dimensionality and eliminating irrelevant data, Bayesian feature selection techniques can significantly improve forecasting performance and computational efficiency [20].

In this study, a Bayesian feature selection framework is integrated with machine learning models to improve regional wind power forecasting accuracy. The proposed approach processes numerical weather prediction data by dividing the dataset into spatial sub-areas and eliminating non-informative regions. This method reduces the number of input variables and enhances the predictive performance of machine learning models used for wind power forecasting.

III. SYSTEM ANALYSIS

Existing System

Traditional wind power forecasting systems mainly rely on statistical models and conventional machine learning techniques to estimate the amount of electricity generated by wind turbines. These systems typically analyze historical wind data together with meteorological variables such as wind speed, wind direction, temperature, and atmospheric pressure to predict future wind power output. Common forecasting models include Support Vector Machines (SVM), Artificial Neural Networks (ANN), Decision Trees, Random Forests, and linear regression models, which are trained using historical weather and power generation datasets [1]–[3].

In many existing forecasting frameworks, numerical weather prediction (NWP) data is directly used as input for machine learning models without performing effective feature selection. Weather datasets often contain a large number of spatial and meteorological variables, which increases the dimensionality of the input data. Processing high-dimensional datasets introduces redundant or irrelevant information that may negatively affect the performance of forecasting models and increase computational complexity [6], [9].

Furthermore, several traditional forecasting approaches utilize the entire weather dataset during the training phase without identifying which spatial regions contribute most significantly to wind power generation. This results in inefficient model training because some spatial regions may contain meteorological information that is not directly related to the target forecasting location. Consequently, forecasting models may require greater computational resources and longer training times while producing less accurate predictions.

Researchers have attempted to improve forecasting accuracy by applying ensemble learning techniques and hybrid forecasting models that combine multiple machine learning algorithms. Although these approaches may enhance prediction performance, they still face challenges related to high-dimensional input datasets, model complexity, and computational cost. Without an effective mechanism for selecting the most relevant features, forecasting systems may struggle to generalize well when applied to new datasets and varying weather conditions [7], [8].

Disadvantages Of The Existing System

- **High-Dimensional Data**

Numerical weather prediction datasets contain a large number of spatial and meteorological variables. Processing all these inputs increases computational complexity and reduces forecasting efficiency.

- **Redundant and Irrelevant Features**

Many meteorological variables may not significantly influence wind power generation. Including such features introduces noise and reduces forecasting accuracy.

- **Overfitting and Underfitting**

Machine learning models trained on large datasets may either memorize training data or fail to capture complex patterns, resulting in inaccurate predictions.

- **Computational Complexity**

Handling large-scale weather datasets requires significant computational resources and longer training times.

- **Poor Feature Selection**

Existing forecasting systems often lack an effective mechanism to identify the most relevant spatial regions and meteorological variables.

- **Scalability Issues**

As the size of weather datasets and forecasting regions increases, maintaining model efficiency and accuracy becomes more challenging.

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Proposed System

To overcome the limitations of traditional forecasting methods, this study proposes an intelligent wind power forecasting framework based on Bayesian Feature Selection and machine learning techniques. The objective of the proposed system is to improve forecasting accuracy while reducing computational complexity by selecting the most informative spatial regions from numerical weather prediction data.

In the proposed framework, meteorological data are collected from numerical weather prediction systems and historical wind power generation datasets. These datasets contain multiple weather variables and spatial regions associated with wind power production. The collected data are first processed through data preprocessing techniques such as noise removal, missing value handling, and normalization to improve data quality and consistency.

`After preprocessing, the weather dataset is divided into multiple spatial sub-areas to capture regional weather characteristics. A Bayesian feature selection method is then applied to evaluate the importance of each spatial region. This method determines which sub-areas contribute the most useful information for wind power forecasting and eliminates non-informative regions from the dataset.

By removing irrelevant spatial features, the proposed system significantly reduces the dimensionality of the input data and improves computational efficiency. The selected features are then used to train machine learning forecasting models, including Support Vector Machines, Artificial Neural Networks, and Convolutional Neural Networks. These models learn complex relationships between meteorological variables and wind power generation patterns.

The performance of the forecasting models is evaluated using cross-validation techniques and standard forecasting metrics such as Mean Absolute Error (MAE) and Mean Squared Error (MSE). The experimental results demonstrate that integrating Bayesian feature selection with machine learning algorithms improves prediction accuracy and reduces computational complexity.

Overall, the proposed framework provides a scalable and efficient solution for regional wind power forecasting, supporting improved decision-making for power system operators and facilitating the integration of renewable energy into modern power systems [14]–[17].

IV.SYSTEM DESIGN

System Architecture

Below diagram depicts the whole system architecture.

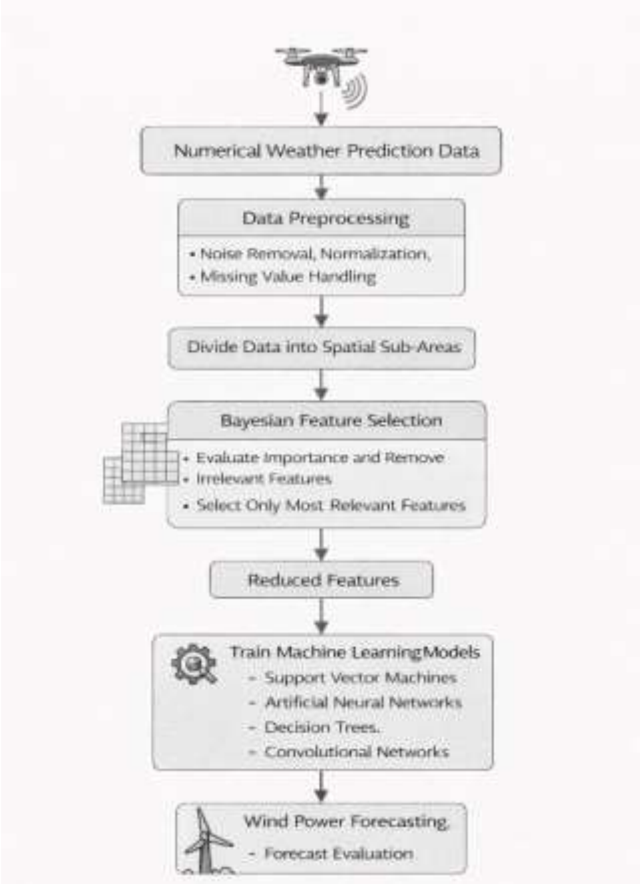

Fig 1. Methodology followed for proposed model

V. SYSTEM IMPLEMENTATION

Modules

This section describes the core implementation modules of the proposed wind power forecasting framework based on Bayesian Feature Selection and machine learning techniques. The system follows a structured pipeline consisting of data collection, preprocessing, spatial feature selection, machine learning model training, forecasting, and performance evaluation.

This modular architecture improves system scalability, forecasting accuracy, and computational efficiency when processing large numerical weather prediction datasets[1], [3].

Data Collection and Preprocessing Module

The Data Collection Module gathers meteorological data and historical wind power generation records from numerical weather prediction (NWP) systems and wind energy databases. The dataset contains several important meteorological parameters such as wind speed, wind direction, atmospheric pressure, temperature, and humidity, which significantly influence wind power generation [1], [2]..

Since raw meteorological datasets may contain noise, missing values, and inconsistencies, a preprocessing stage is applied before model training. The preprocessing process includes the following steps:

- **Missing Value Handling**

Missing meteorological measurements are handled using interpolation and statistical imputation techniques to maintain data completeness.

- **Noise Removal:**

Outliers and abnormal weather values are removed using statistical filtering methods.

- **Data Normalization:**

Feature scaling and normalization are applied to ensure consistent ranges across different meteorological variables.
These preprocessing steps improve dataset quality and prepare the data for efficient machine learning analysis.

Spatial Division and Bayesian Feature Selection Module

Numerical weather prediction datasets typically contain information from multiple spatial regions, many of which may not significantly influence wind power generation for the target forecasting location. Processing all spatial variables increases model complexity and computational cost.To address this issue, the dataset is divided into multiple spatial sub-areas, allowing the system to analyze regional meteorological patterns more effectively.

After spatial division, a Bayesian Feature Selection technique is applied to evaluate the importance of each spatial region [12], [18], [19]. The Bayesian method estimates the probability that each spatial region contributes useful information for forecasting wind power output. Regions with low predictive importance are removed from the dataset. This process:

- Reduces dataset dimensionality
- Eliminates redundant or irrelevant spatial features
- Improves computational efficiency
- Enhances model generalization capability

By selecting only the most informative spatial regions, the system improves the performance of machine learning forecasting models.

Machine Learning Training Module

After feature selection, the processed dataset is used to train multiple machine learning forecasting models. These models learn the relationship between meteorological variables and wind power generation patterns.

The following machine learning algorithms are implemented and evaluated:

1. Support Vector Machines (SVM)
2. Artificial Neural Networks (ANN)
3. Decision Trees
4. Convolutional Neural Networks (CNN)

Each model is trained using historical weather and wind power data. During the training phase, the algorithms learn nonlinear relationships between meteorological conditions and electricity generation output.To ensure reliable model performance, cross-validation techniques are used to evaluate each model during training. This helps prevent overfitting and ensures that the model generalizes well to unseen data [6], [7], [15].

Wind Power Forecasting Module

The Wind Power Forecasting Module uses the trained machine learning models to predict future wind power generation. When new meteorological data becomes available, the system processes the selected features and generates forecasts of wind energy output for a specific geographic region.
This module plays a critical role in energy management and grid operation, as accurate forecasting allows power system operators to:

- Balance electricity supply and demand
- Schedule power generation efficiently
- Integrate renewable energy sources into the grid

By providing accurate forecasts, the system helps reduce uncertainty associated with wind power variability.

Model Evaluation and Performance Monitoring Module

The final module evaluates the performance of the forecasting models using standard forecasting evaluation metrics. The main performance metrics include:

- Mean Absolute Error (MAE)
- Mean Squared Error (MSE)
- Root Mean Squared Error (RMSE)
- Prediction Accuracy

These metrics measure how closely the predicted wind power values match the actual observed power generation.Continuous performance monitoring is also implemented to track model accuracy over time. If forecasting performance decreases due to changing weather patterns, the model can be retrained using updated datasets to maintain high prediction accuracy [1], [14].

VI. RESULTS AND DISCUSSION

This section presents the experimental results and performance evaluation of the proposed wind power forecasting framework based on Bayesian Feature Selection and machine learning models. Multiple forecasting algorithms were trained and tested using the processed numerical weather prediction dataset. The evaluation focuses on comparing model performance, analyzing forecasting accuracy, and examining the impact of feature selection on prediction performance[6], [15].

Accuracy Comparison of Machine Learning Models

Several machine learning algorithms were evaluated to determine the most suitable model for wind power forecasting. The models include Support Vector Machines (SVM), Artificial Neural Networks (ANN), Decision Trees, and Convolutional

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Neural Networks (CNN). Model performance was evaluated using forecasting metrics such as Mean Absolute Error (MAE) and Mean Squared Error (MSE) [6], [7].

Table 1. Performance Comparison of Machine Learning Models

Model	MAE	MSE	Forecast Accuracy (%)
Decision Tree	0.142	0.036	86.8
Support Vector Machine	0.128	0.031	89.2
Artificial Neural Network	0.114	0.027	91.5
Convolutional Neural Network	0.101	0.022	93.7

From the comparison results, the Convolutional Neural Network model achieved the highest forecasting accuracy of 93.7%, outperforming the other models. This improved performance is mainly due to the model's ability to capture complex nonlinear relationships between meteorological variables and wind power generation patterns.

The results also demonstrate that integrating Bayesian Feature Selection helps reduce irrelevant input variables, allowing machine learning models to focus on the most informative weather features

Forecasting Performance Analysis

1. The forecasting performance of the proposed framework was further analyzed by comparing predicted wind power values with actual generation values obtained from the dataset.

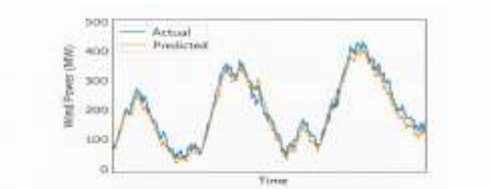

Fig. 2. Predicted vs Actual Wind Power Generation

The graph illustrates the comparison between predicted and actual wind power generation values. The predicted curve closely follows the actual power generation pattern, indicating that the forecasting model effectively captures variations in wind energy production.The results demonstrate that the proposed forecasting system can accurately model wind power trends and reduce prediction errors[14], [16].

Feature Importance Analysis

To better understand which meteorological variables influence wind power forecasting, a feature importance analysis was conducted after applying Bayesian Feature Selection.

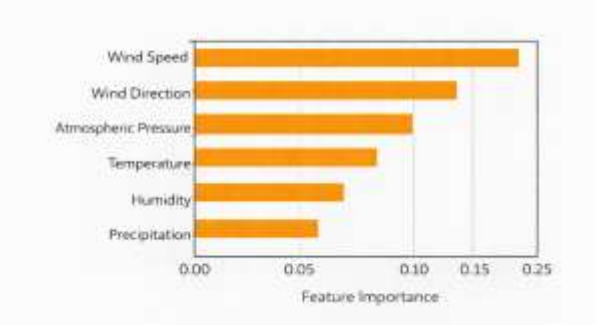

Fig. 3. Feature Importance for Wind Power Forecasting

The feature importance analysis indicates that wind speed, wind direction, and atmospheric pressure are the most influential variables affecting wind power generation. Features with higher importance scores contribute more significantly to the forecasting model's predictions.The results also show that removing less relevant spatial regions through Bayesian Feature Selection reduces dataset dimensionality without degrading prediction accuracy. This improves computational efficiency and enables faster model training.

Overall, the experimental evaluation demonstrates that the proposed framework improves forecasting performance by combining feature selection techniques with advanced machine learning models, making it suitable for large-scale regional wind power forecasting applications[1], [6].

VII. CONCLUSION AND FUTURE WORK

This study presented a wind power forecasting framework based on Bayesian Feature Selection and machine learning techniques. The proposed system processes numerical weather prediction data and identifies the most informative spatial regions that significantly influence wind power generation. By eliminating non-informative spatial features before model training, the framework reduces dataset dimensionality and improves computational efficiency.

Several machine learning models, including Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Convolutional Neural Networks (CNN), were implemented to forecast wind power generation based on meteorological variables. Experimental evaluation demonstrated that the proposed framework improves forecasting accuracy while reducing prediction errors and computational complexity. The integration of Bayesian feature selection enables the forecasting models to focus on the most relevant weather features, resulting in more reliable and efficient prediction performance.

Accurate wind power forecasting plays an important role in renewable energy management and power grid stability, as it assists energy operators in balancing electricity supply and demand and improving energy scheduling strategies [1]–[3]. The results obtained in this study highlight the effectiveness of combining feature selection techniques with machine learning models for large-scale renewable energy forecasting applications.

Future work may focus on integrating advanced deep learning architectures, real-time meteorological data streams, and hybrid ensemble learning techniques to further improve forecasting performance. In addition, the proposed framework can be extended to support other renewable energy forecasting applications such as solar power generation and regional energy demand prediction, enabling more intelligent and sustainable energy management systems [14]–[17].

REFERENCES

1. R. Tawn and J. Browell, "A review of very short-term wind and solar power forecasting," Renewable and Sustainable Energy Reviews, vol. 153, Art. no. 111758, 2022.
2. X. Wang, P. Guo, and X. Huang, "A review of wind power forecasting models," Energy Procedia, vol. 12, pp. 770–778, 2011.
3. G. Giebel and G. Kariniotakis, "Wind power forecasting—A review of the state of the art," in Renewable Energy Forecasting, pp. 59–109, 2017.
4. G. Sideratos and N. D. Hatziargyriou, "A distributed memory RBF-based model for variable generation forecasting," International Journal of Electrical Power & Energy Systems, vol. 120, Art. no. 106041, 2020.
5. J. Henze, M. Siefert, S. Bremicker-Trübelhorn, N. Asanalieva, and B. Sick, "Probabilistic upscaling and aggregation of wind power forecasts," Energy, Sustainability and Society, vol. 10, pp. 1–19, 2020.
6. W. Dong, H. Sun, J. Tan, Z. Li, J. Zhang, and H. Yang, "Regional wind power probabilistic forecasting based on an improved kernel density estimation, regular vine copulas, and ensemble learning," Energy, vol. 238, Art. no. 122045, 2022.
7. H. Zhang, Y. Liu, J. Yan, S. Han, L. Li, and Q. Long, "Improved deep mixture density network for regional wind power probabilistic forecasting," IEEE Transactions on Power Systems, vol. 35, no. 4, pp. 2549–2560, Jul. 2020.
8. X. Dong, Y. Sun, Y. Li, X. Wang, and T. Pu, "Spatio-temporal convolutional network based power forecasting of multiple wind farms," Journal of Modern Power Systems and Clean Energy, vol. 10, no. 2, pp. 388–398, 2022.
9. Z. Wang, W. Wang, C. Liu, B. Wang, and S. Feng, "Short-term probabilistic forecasting for regional wind power using distance-weighted kernel density estimation," IET Renewable Power Generation, vol. 12, no. 15, pp. 1725–1732, 2018.
10. H. Apaydin, F. K. Sonmez, and Y. E. Yildirim, "Spatial interpolation techniques for climate data in the GAP region in Türkiye," Climate Research, vol. 28, no. 1, pp. 31–40, 2004.
11. M. Cellura, G. Cirrincione, A. Marvuglia, and A. Miraoui, "Wind speed spatial estimation for energy planning in Sicily: A neural kriging application," Renewable Energy, vol. 33, no. 6, pp. 1251–1266, 2008.
12. M. B. Ozkan and P. Karagoz, "Data mining-based upscaling approach for regional wind power forecasting: Regional statistical hybrid wind power forecast technique (RegionalSHWIP)," IEEE Access, vol. 7, pp. 171790–171800, 2019.
13. P. Pinson, N. Siebert, and G. Kariniotakis, "Forecasting of regional wind generation by a dynamic fuzzy-neural networks based upscaling approach," in Proc. European Wind Energy Conference, 2003, p. 5.
14. S. Basu, S. Watson, E. Lacoa-Arends, and B. Cheneka, "Day-ahead wind power predictions at regional scales: Post-processing operational weather forecasts with a hybrid neural network," in Proc. 7th International Conference on the European Energy Market, 2020, pp. 1–6.
15. W. Dong, H. Sun, J. Tan, Z. Li, J. Zhang, and Y. Y. Zhao, "Short-term regional wind power forecasting for small datasets with input data correction, hybrid neural network, and error analysis," Energy Reports, vol. 7, pp. 7675–7692, 2021.
16. D. A. Wood, "Trend decomposition aids short-term countrywide wind capacity factor forecasting with machine and deep learning methods," Energy Conversion and Management, vol. 253, Art. no. 115189, 2022.
17. Y. Yu, M. Yang, X. Han, Y. Zhang, and P. Ye, "A regional wind power probabilistic forecast method based on deep quantile regression," IEEE Transactions on Industry Applications, vol. 57, no. 5, pp. 4420–4427, Sep.–Oct. 2021.
18. R. Archibald and G. Fann, "Feature selection and classification of hyperspectral images with support vector machines," IEEE Geoscience and Remote Sensing Letters, vol. 4, no. 4, pp. 674–677, Oct. 2007.
19. S. B. Serpico and L. Bruzzone, "A new search algorithm for feature selection in hyperspectral remote sensing images," IEEE Transactions on Geoscience and Remote Sensing, vol. 39, no. 7, pp. 1360–1367, Jul. 2001.
20. E.-S. M. El-Kenawy, A. Ibrahim, S. Mirjalili, M. M. Eid, and S. E. Hussein, "Novel feature selection and voting classifier algorithms for COVID-19 classification in CT images," IEEE Access, vol. 8, pp. 179317–179335, 2020.