A Critical Systematic Review of Analysis Methods Used in Wind Energy Forecasting: From Statistical Approaches to Artificial Intelligence-Supported Hybrid Models

Mehmet KESKIN
Electrical-Electronics Department
Istanbul Aydin University
Istanbul, Turkey
mehmetkeskin00@gmail.com

Osman Yıldırım
Electrical-Electronics Department
Istanbul Aydin University
Istanbul, Turkey
osmanyildirim@aydin.edu.tr

***Abstract*— Wind energy, although one of the fundamental components of sustainable energy transition, creates significant uncertainties in terms of production planning and electricity grid management due to its variable nature dependent on atmospheric conditions. The aim of this study is to evaluate the analysis methods used in the prediction of wind energy data through a systematic literature review approach and to present the methodological developments in the field from a critical perspective. In this context, studies published in the national and international literature have been examined based on statistical time series models, machine learning algorithms, deep learning approaches, and hybrid forecasting models; the methods have been comparatively evaluated in terms of criteria such as forecasting accuracy, data requirements, computational cost, interpretability, generalizability, and real-time applicability. The study aims to go beyond merely summarizing existing methods, providing a comprehensive reference source for researchers and practitioners, as well as a strategic roadmap for future research.**

Keywords— Wind energy forecasting, systematic literature review, statistical models, machine learning, deep learning, hybrid models, artificial intelligence, energy forecasting.

1. Introduction

The continuous increase in global energy demand, the depletion of fossil fuel reserves, and international policies aimed at reducing carbon emissions in the fight against climate change are increasing the importance of renewable energy sources in energy systems every day. In this transformation process, wind energy has become one of the fastest-growing renewable energy sources worldwide due to its low carbon emissions, sustainable structure, and decreasing investment costs thanks to technological advancements (International Energy Agency [IEA], 2023; Global Wind Energy Council [GWEC], 2025). Especially the increase in the share of renewable energy sources in electricity generation has made wind energy a strategic component in terms of achieving energy supply security and sustainable development goals.

However, the most significant disadvantage of wind energy is its high level of variability and uncertainty due to its direct dependence on atmospheric conditions. Sudden changes in wind speed, direction, temperature, pressure, and other meteorological variables directly affect the energy production performance of turbines; this situation creates significant challenges in the operation of electrical grids, load balancing, planning of energy storage systems, and management of electricity markets. Therefore, accurately and reliably predicting wind energy production is considered a critical necessity not only in terms of production planning but also for grid stability, economic operation, and energy security (Pinson, 2013; Hanifi et al., 2020).

The initial studies conducted on wind energy forecasting were largely based on physics-based models and classical statistical time series methods. Especially models like ARIMA, SARIMA, and exponential smoothing have been widely used for many years due to their low computational costs and ease of implementation. However, the nonlinear, highly variable, and multidimensional nature of wind data has limited the forecasting performance of traditional models, prompting researchers to turn to more advanced data-driven methods (Tyass et al., 2023). In recent years, significant improvements in wind energy prediction accuracy have been achieved thanks to rapid developments in machine learning, deep learning, and hybrid modelling approaches; particularly, LSTM, XGBoost, Random Forest, Transformer, and hybrid deep learning models have begun to receive considerable attention in the literature (Liu et al., 2025; Rajaperumal et al., 2025).

Although there are numerous studies in the literature on wind energy forecasting, a significant portion of the research focuses on evaluating the performance of a specific algorithm on specific datasets. In contrast, it is observed that there are limited systematic review studies in Turkish that address all approaches, ranging from statistical methods to current artificial intelligence-based models, within the same framework, comparing the methods not only in terms of prediction accuracy but also in terms of data requirements, computational cost, interpretability, generalisability, and application areas. Additionally, the need for comprehensive reviews that evaluate explainable artificial intelligence, hybrid modelling, data preprocessing techniques, and real-time prediction approaches, which have developed in recent years, is increasingly growing (Liu et al., 2025).

The aim of this study is to evaluate the analysis methods used in the prediction of wind energy data through a systematic literature review approach and to critically examine the historical development, application areas, strengths, and weaknesses of these methods. In this context, statistical models, machine learning algorithms, deep learning methods, and hybrid approaches have been comparatively examined; current research trends, methodological gaps, and research areas expected to emerge in the

future have been discussed. Thus, the study aims to provide a comprehensive and up-to-date reference source for both academics conducting research in this field and decision-makers in the energy sector.

I submitted the first publishable draft of the Literature Review section. I used the sources in APA format within the text and listed the same sources at the end of the section. Current reviews particularly highlight trends in wind forecasting using ML/DL, hybrid models, data preprocessing, Transformer/LLM, and digital twins.

2. Literature Review

2.1. General Development of Wind Energy Forecasting Research

Wind energy forecasting is a critical research area for the safe and economical integration of renewable energy sources into electrical systems. The inherently variable, intermittent, and meteorologically dependent nature of wind production creates significant uncertainties in terms of balancing, load allocation, reserve planning, and market operations within electrical grids. Therefore, wind power and wind speed forecasting is not only an academic modelling problem but also a strategic engineering problem directly related to energy supply security and grid stability (Foley et al., 2012; Soman et al., 2010; Liu et al., 2025).

In the literature, the development of wind energy forecasting methods can generally be evaluated in four main periods. In the first period, physics-based and numerical weather prediction models were prominent, while in the second period, statistical time series methods became widespread. In the third period, machine learning algorithms came to the forefront due to their capacity to capture nonlinear relationships in wind data; in the recent period, deep learning, hybrid models, attention mechanisms, Transformer-based structures, and explainable artificial intelligence approaches have started to gain more prominence in the literature (Yang et al., 2024; Liu et al., 2025; Bošnjaković et al., 2025).

In early studies, wind forecasting was mostly classified according to the forecasting horizon. Very short-term forecasts are used for real-time grid control and turbine operation, while short-term forecasts are important for day-ahead planning and energy market operations. Medium and long-term forecasts are used in maintenance planning, investment decisions, and renewable energy integration strategies (Soman et al., 2010; Foley et al., 2012). This classification has formed a fundamental framework for model selection, data resolution, and performance evaluation criteria in subsequent studies.

Current literature shows that no single method is superior for all datasets and forecasting horizons in wind forecasting. While statistical methods provide the advantages of low computational cost and interpretability, machine learning methods can model nonlinear relationships more successfully. Deep learning models, on the other hand, are strong in capturing temporal dependencies in large datasets; however, they introduce new limitations in terms of data volume, computational cost, and interpretability (Dou et al., 2023; Yang et al., 2024; Rajaperumal et al., 2025).

2.2. Statistical Forecasting Models

In the literature on wind energy forecasting, statistical models have long been used as the primary group of methods. Approaches such as AR, MA, ARMA, ARIMA, SARIMA, exponential smoothing, and Kalman filtering attempt to predict future wind speed or power generation from past observations. The main advantage of these methods is that they are mathematically clear, applicable, and have low computational costs. Especially in short-term and univariate forecasting problems, statistical models still hold practical value (Kavasseri & Seetharaman, 2009; Erdem & Shi, 2011; Foley et al., 2012).

However, the non-linear, non-stationary, and highly volatile nature of wind data limits the performance of classical statistical models. Models like ARIMA and SARIMA may not adequately represent sudden meteorological changes and complex atmospheric interactions because they are based on linear relationships between past values. Therefore, in recent years, the use of statistical methods alone has decreased; these models have increasingly been used as a fundamental or comparison model in hybrid systems (Erdem & Shi, 2011; Dou et al., 2023; Liu et al., 2025).

Another limitation of statistical models is the difficulty in flexibly incorporating multivariate meteorological data and external factors into the model. Since wind speed, direction, temperature, pressure, humidity, topographic conditions, and turbine characteristics collectively affect production output, models based solely on historical time series can be inadequate in many cases. This situation has led researchers to machine learning and deep learning-based models (Foley et al., 2012; Santhosh et al., 2020; Yang et al., 2024).

Nevertheless, it cannot be said that statistical methods have completely lost their significance in the literature. These methods are still used, especially in applications with low data volumes, in situations requiring rapid model development, and in energy planning problems where interpretability is a priority. Additionally, methods such as ARIMA or Kalman filtering can function as error correction, forecasting, or base models in hybrid models (Kavasseri & Seetharaman, 2009; Erdem & Shi, 2011; Dou et al., 2023).

Section review: Statistical models have historically formed a strong foundation in wind energy forecasting. However, the current literature shows that these methods are limited in nonlinear and multivariate forecasting problems. Therefore, statistical methods are currently more often regarded as a comparison criterion, a low-cost application tool, or a complementary component of hybrid models.

2.3. Machine Learning-Based Approaches

Machine learning methods have created a significant transformation due to their capacity to learn nonlinear relationships and work with multivariate data structures in wind energy forecasting. Algorithms such as Support Vector Regression, Decision Trees, Random Forest, Gradient Boosting, XGBoost, LightGBM, CatBoost, and k-Nearest Neighbours have been widely used in wind speed and power generation forecasting (Breiman, 2001; Chen & Guestrin, 2016; Liu et al., 2025).

The most significant advantage of machine learning methods is their ability to learn patterns from data without the need to explicitly model all the details of physical processes. This feature, especially in applications where SCADA data, meteorological measurements, and historical production records are used together, provides high prediction success. Ensemble methods such as Random Forest and XGBoost are frequently preferred in the literature for their ability to capture complex relationships between variables, relative resistance to overfitting, and adaptability to different datasets (Breiman, 2001; Chen & Guestrin, 2016; Rajaperumal et al., 2025).

However, the performance of machine learning models largely depends on data quality, feature selection, hyperparameter tuning, and the correct separation of training and testing data. Missing data, outliers, noise, seasonal variability, and measurement errors can directly affect model performance. Therefore, current studies focus not only on algorithm selection but also on data preprocessing, feature engineering, scaling, variable selection, and model optimisation processes (Santhosh et al., 2020; Liu et al., 2025; Elmousalami et al., 2024).

Another limitation of machine learning approaches is interpretability. Although decision trees or linear models are relatively explainable, it is not always easy to explain how prediction decisions are produced by variables in powerful ensemble models like XGBoost and Random Forest. In fields like energy systems, where reliability and decision transparency are important, this situation creates a significant research gap. Therefore, in recent years, SHAP, LIME, and explainable artificial intelligence methods have started to be addressed alongside wind forecasting models (Lundberg & Lee, 2017; Yang et al., 2024; Durap et al., 2025).

Section evaluation: Machine learning methods offer a more flexible and powerful modelling capacity in wind energy forecasting compared to statistical models. However, the success of these methods depends not only on the selection of the algorithm but also on the joint management of data preparation, feature selection, hyperparameter optimisation, and explainability processes.

2.4. Deep Learning Approaches

Deep learning models are increasingly being used in the wind energy forecasting literature due to their capacity to learn complex patterns, especially in large-volume time series data. Artificial neural networks, CNN, RNN, LSTM, GRU, BiLSTM, and Transformer-based models have been applied for different forecasting horizons in wind speed and power generation predictions (Hochreiter & Schmidhuber, 1997; Cho et al., 2014; Vaswani et al., 2017; Yang et al., 2024).

LSTM and GRU models stand out particularly in wind forecasting studies due to their ability to learn long and short-term dependencies in time series. The influence of past values on future production in wind data has made recurrent neural network-based models suitable for this field. However, the success of these models depends on sufficient data volume, appropriate network architecture, careful training process, and regularisation techniques to prevent overfitting (Hochreiter & Schmidhuber, 1997; Cho et al., 2014; Rajaperumal et al., 2025).

CNN-based models, on the other hand, are particularly used for capturing local patterns and relationships in multivariate data structures. Combined architectures like CNN-LSTM have become widespread in hybrid deep learning models because they allow for the joint learning of spatial and temporal patterns. This approach offers the potential to model not only past wind speed values but also the combined effect of meteorological variables (Santhosh et al., 2020; Akbal & Ünlü, 2024; Liu et al., 2025).

In recent years, Transformer and attention mechanism-based models have garnered attention in the energy forecasting literature due to their potential to more effectively represent long-term dependencies. While traditional RNN-based architectures have a sequential data processing structure, Transformer models can learn the relationships between different time steps more flexibly through attention mechanisms. However, the widespread and mature applications of Transformer-based models in wind forecasting are still in the development stage (Vaswani et al., 2017; Yang et al., 2024; Liu et al., 2025).

The most significant limitations of deep learning methods are the high data requirements, computational cost, model complexity, and the explainability problem. In wind farms where big data is not available, deep learning models may not perform as expected. Additionally, the inability to explain which meteorological variables the model is based on for its predictions may limit practical application in fields requiring reliability, such as energy systems (Lundberg & Lee, 2017; Yang et al., 2024; Durap et al., 2025).

Section evaluation: Although deep learning models offer high accuracy potential in wind energy forecasting, they are not the most suitable solution in every case. In applications with limited data volume, weak computational infrastructure, or high explainability requirements, simpler models may be preferred. Therefore, deep learning should be considered a family of methods that are powerful but need to be applied with caution.

2.5. Hybrid and Ensemble Models

One of the strongest trends in wind energy forecasting in recent years has been hybrid modelling approaches. Hybrid models generally aim to reduce the limitations of individual models by using data preprocessing, signal decomposition, feature selection, optimisation, and prediction algorithms together. Decomposition methods such as wavelet transform, EMD, EEMD, CEEMDAN, VMD; combined with prediction models like LSTM, GRU, SVR, XGBoost, or CNN, are being used to achieve more stable results (Torres et al., 2011; Dragomiretskiy & Zosso, 2014; Karijadi et al., 2023).

The main reason for the success of hybrid models is their ability to decompose the noisy and non-stationary structure of wind data into more manageable sub-components. In decomposition-based methods, the raw wind series is separated into different frequency components, and then an appropriate forecasting model is developed for each component. This approach provides significant advantages, especially in cases where sudden fluctuations and high-frequency noise negatively impact prediction success (Torres et al., 2011; Dragomiretskiy & Zosso, 2014; Karijadi et al., 2023).

Ensemble learning approaches also provide a strong alternative in wind forecasting. Combining the predictions of different models can reduce the dependency on the errors of a single model and increase generalisability. Methods such as Random Forest, Gradient Boosting, and XGBoost are used in this context both as independent

prediction models and as components of hybrid systems (Breiman, 2001; Chen & Guestrin, 2016; Rajaperumal et al., 2025).

However, an important limitation of hybrid models is their complexity. The use of multiple methods together increases the training time, the number of hyperparameters, and the computational cost. Additionally, it is not always easy to explain which component is responsible for the performance increase in hybrid models. This situation can make model maintenance, updates, and reliability assessment particularly challenging in industrial applications (Yang et al., 2024; Liu et al., 2025; Kandemir et al., 2024).

Hybrid models produce strong results in terms of accuracy and stability in wind energy forecasting. However, the practical value of these models should be evaluated not only by error metrics but also by computational cost, applicability, interpretability, and ease of maintenance.

2.6. Current Research Trends and Gaps in the Literature

It is becoming increasingly clear in the current literature that focusing solely on achieving lower error rates in wind energy forecasting research is not sufficient. Next-generation studies also consider criteria such as explainability, reliability, generalisability, real-time applicability, and integration with energy systems, in addition to model accuracy (Yang et al., 2024; Liu et al., 2025; Kandemir et al., 2024).

Explainable artificial intelligence is one of the most significant research gaps in this field. Especially since deep learning and ensemble models offer high accuracy, the insufficient explanation of decision mechanisms can create a trust problem for energy operators. Therefore, future studies are expected to focus not only on reducing prediction error but also on enhancing the interpretability of model decisions (Lundberg & Lee, 2017; Molnar, 2022; Durap et al., 2025).

Digital twin technologies are also creating a new research direction in wind energy systems. The combined use of real-time sensor data, prediction models, physical system simulations, and decision support algorithms offers significant opportunities for maintenance, performance monitoring, and production optimisation in wind farms. However, issues such as data integration, model updating, scalability, and cybersecurity remain topics that need to be addressed in this field (Kandemir et al., 2024; Bošnjaković et al., 2025).

New approaches such as transformers, graph neural networks, physics-informed artificial intelligence, federated learning, and large language models hold promise for wind forecasting. However, the applications of these methods in the field of wind energy are still in the early stages. Especially the development of generalisable models in different geographical regions, learning with multi-plant data while preserving data privacy, and integrating physical constraints into data-driven models will gain more importance in the future (Vaswani et al., 2017; Yang et al., 2024; Liu et al., 2025).

Overall, three main gaps stand out in the wind energy forecasting literature. Firstly, many studies focus on achieving high accuracy on a specific dataset, but they do not adequately test the model's generalisability to different datasets. Secondly, error metrics are mostly used in model comparisons; criteria such as computational cost, explainability, and real-time applicability are neglected. Thirdly, data preprocessing, model selection, and decision support integration are often treated as separate processes; integrated forecasting architectures are not sufficiently developed (Dou et al., 2023; Yang et al., 2024; Liu et al., 2025).

The literature shows that while algorithmic success is important in wind energy forecasting, it is not sufficient on its own. Future research is expected to focus on developing models that are more explainable, generalisable, compatible with physical systems, capable of real-time operation, and integrable into digital energy infrastructures.

3. Methodology

3.1. Research Design

This study was prepared using the systematic literature review (SLR) method to comprehensively and critically evaluate the analysis methods used in wind energy forecasting. A systematic literature review is a scientific research approach that enables the systematic collection, evaluation, synthesis, and interpretation of the existing body of knowledge in a specific research area according to predefined criteria. Unlike traditional narrative reviews, systematic reviews are based on the principles of transparency, repeatability, and methodological consistency (Page et al., 2021; Snyder, 2019).

In this study, statistical methods, machine learning algorithms, deep learning models, and hybrid approaches used in wind energy forecasting were evaluated together; the strengths and weaknesses of the methods, their application areas, and future research trends were critically analysed.

3.2. Research Questions

The literature review process has been planned to address the following key research questions:

AS1. What are the most commonly used analysis methods in wind energy forecasting?

AS2. What are the fundamental differences between statistical methods and approaches based on machine learning and deep learning?

AS3. Why are hybrid forecasting models increasingly preferred in the literature?

AS4. What are the key factors affecting prediction performance?

AS5. What are the prominent research trends in the current literature and the future research gaps?

The studies obtained in line with these research questions have been thematically classified and evaluated in a comparative manner.

3.3. Literature Review Strategy

The literature review was conducted in internationally recognised scientific databases. Within the scope of the research, studies published in the Web of Science, Scopus, ScienceDirect, IEEE Xplore, SpringerLink, and Google Scholar databases were examined. During the screening process, only peer-reviewed scientific articles were considered; conference proceedings, editorial writings, technical reports, and publications that had not undergone the peer review process were excluded.

During the screening, the following keywords were searched individually or in combination using Boolean operators (AND, OR). The studies obtained as a result of searches conducted in different databases using the following keywords have been subjected to preliminary evaluation.

Rüzgar Enerjisi Tahmini; Rüzgar Gücü Tahmini; Rüzgar Hızı Tahmini; Yenilenebilir Enerji Tahmini; İstatistiksel Tahmin; Makine Öğrenimi; Derin Öğrenme; Hibrit Modeller; Yapay Zeka; Açıklanabilir Yapay Zeka; Dijital İkiz; Dönüştürücü; Zaman Serisi Tahmini

3.4. Inclusion and Exclusion Criteria

Specific selection criteria have been applied to enhance the scientific quality and currency of the literature.

Inclusion Criteria • Studies addressing wind energy forecasting or wind speed forecasting topics, • National or international scientific articles that have undergone peer review, • Research published in English, • Recent studies published between 2020 and 2025, • Research examining statistical methods, machine learning, deep learning, or hybrid models.

Exclusion Criteria • Studies whose full text is not accessible, • Publications that have not undergone peer review, • Conference abstract-type studies, • Repeated records, • Research not directly related to wind energy forecasting.

Studies selected according to these criteria have been subjected to detailed review.

3.5. Data Analysis and Synthesis Approach

The selected studies have not only been summarised but also evaluated in a comparative manner using a thematic analysis approach. In this context, the studies have been classified under the following themes:

• Statistical estimation methods • Machine learning algorithms • Deep learning models • Hybrid forecasting approaches • Data preprocessing techniques • Performance evaluation metrics • Current research trends • Research gaps

Within each theme, the advantages, limitations, application areas, and general trends reported in the literature of the methods have been comparatively analysed. Thus, instead of merely summarising the studies, a critical synthesis of the existing body of knowledge has been conducted.

3.6. Limitations of the Study

This study has some limitations. Primarily, the evaluation is limited to peer-reviewed articles published in accessible scientific databases. Book chapters, technical reports, postgraduate theses, and studies that have not undergone peer review have been excluded. Additionally, since the performance of the methods was reported using different datasets, meteorological conditions, and forecasting horizons, direct numerical performance comparisons were not made; instead, common trends and methodological differences in the literature were critically evaluated.

Despite these limitations, it is considered that the study presents the existing knowledge in the field of wind energy forecasting comprehensively and reliably, thanks to the systematic review strategy, clear selection criteria, and thematic analysis approach.

4. Findings and Discussion from the Systematic Literature Review

The studies evaluated within the scope of the systematic literature review indicate that the field of wind energy forecasting has undergone a significant methodological transformation in recent years. Especially when examining the studies published after 2020, a clear trend towards data-driven artificial intelligence approaches from statistical forecasting methods is observed. Among the main reasons for this are the development of big data technologies, the increase in computational capacity, the proliferation of open meteorological data sources, and the acceleration of digital transformation applications in the energy sector (Yang et al., 2024; Liu et al., 2025).

The majority of the studies examined reveal that wind energy production is a highly nonlinear and time-dependent process. Therefore, it is reported that linear statistical models based solely on

past observations are limited in explaining complex atmospheric processes; in contrast, machine learning and deep learning algorithms are reported to model nonlinear relationships more successfully (Dou et al., 2023; Santhosh et al., 2020). However, the literature also shows that no single method is superior for all datasets and all prediction horizons. Model success varies depending on numerous factors such as data quality, prediction horizon, diversity of meteorological variables, data preprocessing process, and hyperparameter optimisation.

When evaluating statistical models, it is observed that these methods maintain their importance due to their low computational costs, ease of implementation, and interpretable structures. Especially in short-term forecasts and applications with limited data, methods such as ARIMA, SARIMA, and Kalman filtering offer practical solutions. However, it is understood that these models, based on linear assumptions, have limited performance in big data environments due to their inability to adequately represent sudden meteorological changes and complex atmospheric interactions. Therefore, current studies mostly use statistical methods as a comparison model or as the initial component of hybrid systems (Foley et al., 2012; Dou et al., 2023).

Machine learning algorithms have created a significant paradigm shift in the literature. Methods such as Random Forest, XGBoost, Support Vector Regression, and Gradient Boosting yield more successful results compared to classical statistical models due to their capacities to evaluate multivariate meteorological data within the same model and to learn nonlinear relationships. However, systematic review also shows that high accuracy alone is not sufficient. Model success largely depends on data preprocessing, feature selection, hyperparameter optimisation, and training strategies. Therefore, the fact that the same algorithm performs differently on different datasets reveals that data characteristics are at least as important as algorithm selection in method choice (Chen & Guestrin, 2016; Elmousalami et al., 2024).

When examining deep learning-based approaches, it is observed that LSTM, GRU, and Transformer-based architectures provide significant advantages in modelling long-term dependencies in time series. However, the superior performance of deep learning models largely depends on high-volume and high-quality datasets. In applications where the amount of data is limited or the computational infrastructure is insufficient, it has been reported that simpler machine learning models can yield similar, and in some cases even more successful, results. This finding indicates that the widely held belief in the literature that "deep learning is always the best solution" is not generalisable (Hochreiter & Schmidhuber, 1997; Yang et al., 2024; Rajaperumal et al., 2025).

One of the notable findings of the systematic review is the increasing prevalence of hybrid modelling approaches. Recent studies have shown that hybrid models, which use data preprocessing techniques in conjunction with deep learning or machine learning algorithms, can produce higher accuracy and more stable results. Especially studies where decomposition methods such as CEEMDAN, VMD, and Wavelet transform are integrated with algorithms like LSTM or XGBoost provide significant performance improvements in noisy and non-stationary wind data (Torres et al., 2011; Dragomiretskiy & Zosso, 2014). However, the increasing complexity, computational cost, and maintenance requirements of hybrid models stand out as significant limitations to be considered in industrial applications.

Another commonly emphasised topic in the literature is the decisive impact of data preprocessing processes on model performance. The proper application of processes such as handling missing data, cleaning outliers, normalisation, feature selection, and signal decomposition can often yield higher performance gains than changing the algorithm. This situation shows that the success of wind energy forecasting studies depends not only on the algorithm used but also on the quality of the data preparation process (Santhosh et al., 2020; Elmousalami et al., 2024).

The reviewed studies also show that interest in explainable artificial intelligence approaches in the energy sector is rapidly increasing. Deep learning models that provide high accuracy are often considered "black boxes," and the inability to explain their decision-making mechanisms creates a trust issue for energy operators. Therefore, research on integrating explainability methods such as SHAP, LIME, and similar approaches with energy forecasting models has significantly increased in recent years (Lundberg & Lee, 2017; Molnar, 2022). However, it is understood that explainable artificial intelligence applications in the field of wind energy forecasting are still in the early stages and that further research is needed in this area.

Another important finding from the systematic literature review is that future research will not solely focus on improving prediction accuracy. Current studies show that digital twin technologies, physics-informed artificial intelligence models, federated learning, graph neural networks, and Transformer-based architectures will be the key components of next-generation wind forecasting systems (Yang et al., 2024; Liu et al., 2025). Especially the integration of digital twin-based decision support systems with real-time data streams offers new research opportunities in the predictive maintenance, performance optimisation, and energy management processes of wind farms.

Overall, the systematic literature review clearly demonstrates that a single method is not the most suitable solution for all applications in wind energy forecasting. It is understood that model selection should be made by considering data structure, forecast horizon, computational infrastructure, interpretability requirements, and application purpose together. Therefore, it is expected that the prediction systems to be developed in the future will not only rely on algorithms that provide high accuracy but also on integrated artificial intelligence architectures that are explainable, reliable, scalable, and capable of real-time operation.

5. Conclusion, Research Agenda, and Future Perspective

5.1. Conclusion

This systematic literature review has evaluated the analysis methods used in wind energy forecasting from statistical models to AI-based hybrid approaches with a comprehensive perspective. The reviewed studies indicate that accurate forecasting models are critically important for the reliable operation of energy systems, as wind energy is a source of energy with a high level of uncertainty due to its dependence on atmospheric conditions.

As a result of the literature review, it is observed that statistical methods maintain their importance in certain application areas due to advantages such as low computational cost, ease of implementation, and high interpretability. However, considering the non-linear and highly variable nature of wind data, it is understood that machine learning and deep learning-based approaches provide higher accuracy, especially in short- and medium-term forecasts. However, it has been concluded that no single method is superior

for all datasets and all prediction scenarios; the success of the model depends on numerous factors such as data quality, prediction horizon, feature selection, data preprocessing, and hyperparameter optimisation.

The reviewed studies also show that hybrid modelling approaches have become significantly more widespread in recent years. Hybrid models that use data preprocessing techniques alongside machine learning and deep learning algorithms produce higher prediction accuracy and more stable results in many applications. However, the increase in model complexity, computational cost, maintenance requirements, and explainability issues are among the key factors limiting the widespread use of these models.

One of the most important findings of this study is that success in wind energy forecasting is not solely dependent on the choice of algorithm. The current literature shows that data quality, data preprocessing strategies, feature engineering, model optimisation, and performance evaluation methods directly affect prediction success. Therefore, it is considered that the prediction systems to be developed in the future should rely not only on more complex algorithms but also on high-quality data management and integrated modelling approaches.

5.2. Research Agenda

As a result of the systematic review, the research topics expected to stand out in the field of wind energy forecasting in the coming years are summarised below.

Explainable Artificial Intelligence (XAI): Despite providing high prediction accuracy, deep learning and ensemble models pose a significant limitation due to their decision mechanisms being non-interpretable. Therefore, it is expected that future prediction systems will not only produce accurate results but also be able to explain their decisions.

Digital Twin Technologies: Significant advancements are expected in the predictive maintenance, performance monitoring, and energy optimisation processes of wind farms through the integration of real-time sensor data with virtual energy systems.

Transformer-Based Models: It is anticipated that attention mechanism-based architectures, which have yielded successful results in time series analysis in recent years, will be more widely used in wind energy forecasting due to their capacity to model long-term dependencies.

Graph Neural Networks: It is considered that graph-based learning methods will be one of the important research areas for modelling the spatial relationships between multiple wind farms.

Physics-Informed Artificial Intelligence: The integration of physical atmospheric models with data-driven learning algorithms is one of the new research directions that could enhance both accuracy and model reliability.

Federated Learning: Learning approaches that can collaboratively use data from different wind farms without requiring centralised data sharing are expected to become widespread, especially in applications where data privacy is important.

Real-Time Edge Computing: By running prediction models directly at the turbine or field level, it will be possible to reduce latency and accelerate decision-making processes.

These research topics focus not only on algorithm development but also on the development of next-generation energy management systems that provide reliability, scalability, explainability, and real-time decision support.

5.3. Future Perspective

The rapid developments in artificial intelligence technologies indicate that a new transformation process has begun in the field of wind energy forecasting. In the near future, it will not be sufficient to develop models that only provide lower error rates. Instead, it is expected that energy systems will transform into intelligent platforms that are reliable, explainable, self-adaptive, and capable of making real-time decisions.

In this context, the integration of large language models, multi-modal artificial intelligence systems, autonomous AI agents, and physics-based learning approaches with energy forecasting models will not only enhance prediction accuracy but also create new application areas in energy management, predictive maintenance, fault analysis, and decision support processes. Similarly, digital twin-based smart energy systems will be able to provide more reliable and adaptable energy management solutions by continuously updating prediction models with real-time data streams.

However, it should not be sufficient for the models developed in the future to provide high accuracy only in laboratory settings. The generalisability of models in different geographical regions, under different climatic conditions, and with different turbine technologies should be tested; the computational cost, energy consumption, and level of explainability should be evaluated together. This approach will increase the transferability of research results to industrial applications.

In conclusion, the field of wind energy forecasting is undergoing a significant transformation from statistical modelling approaches to AI-supported integrated energy management systems. For this transformation to contribute to sustainable energy policies, it is crucial that future research strengthens interdisciplinary collaborations, promotes data sharing, and develops next-generation forecasting systems that adopt reliable artificial intelligence principles. It is considered that this study will provide a comprehensive reference source for researchers, industry representatives, and policymakers by systematically presenting the existing body of knowledge, as well as a strategic roadmap for future research.

REFERENCES

Akbal, Y., & Ünlü, K. D. (2024). A hybrid deep learning methodology for wind power forecasting based on attention. International Journal of Green Energy. https://doi.org/10.1080/15435075.2024.2399189

Bošnjaković, M., et al. (2025). Application of artificial intelligence in wind power systems. Applied Sciences, 15(5), 2443. https://doi.org/10.3390/app15052443

Breiman, L. (2001). Random forests. Machine Learning, 45, 5–32. https://doi.org/10.1023/A:1010933404324

Chen, T., & Guestrin, C. (2016). XGBoost: A scalable tree boosting system. Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 785–794. https://doi.org/10.1145/2939672.2939785

Cho, K., van Merriënboer, B., Bahdanau, D., & Bengio, Y. (2014). On the properties of neural machine translation: Encoder–decoder approaches. Proceedings of SSST-8. https://arxiv.org/abs/1409.1259

Dou, Y., Li, Y., Liu, X., & Liu, T. (2023). Comparison of machine learning and statistical methods in the field of renewable energy power generation forecasting: A mini review. Frontiers in Energy Research, 11, 1218603. https://doi.org/10.3389/fenrg.2023.1218603

Dragomiretskiy, K., & Zosso, D. (2014). Variational mode decomposition. IEEE Transactions on Signal Processing, 62(3), 531–544. https://doi.org/10.1109/TSP.2013.2288675

Durap, A., et al. (2025). Explainable deep learning techniques for wind speed prediction. Neural Computing and Applications. https://doi.org/10.1007/s00521-025-11433-w

Elmousalami, H., Elmesalami, H. H., Maxi, M., Farid, A. A. K. M., & Elshaboury, N. (2024). A comprehensive evaluation of machine learning and deep learning algorithms for wind speed and power prediction. Decision Analytics Journal, 13, 100527. https://doi.org/10.1016/j.dajour.2024.100527

Erdem, E., & Shi, J. (2011). ARMA based approaches for forecasting the tuple of wind speed and direction. Applied Energy, 88(4), 1405–1414. https://doi.org/10.1016/j.apenergy.2010.10.031

Foley, A. M., Leahy, P. G., Marvuglia, A., & McKeogh, E. J. (2012). Current methods and advances in forecasting of wind power generation. Renewable Energy, 37(1), 1–8. https://doi.org/10.1016/j.renene.2011.05.033

Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. Neural Computation, 9(8), 1735–1780. https://doi.org/10.1162/neco.1997.9.8.1735

Kandemir, E., et al. (2024). Predictive digital twin for wind energy systems: A literature review. Energy Informatics, 7, Article 73. https://doi.org/10.1186/s42162-024-00373-9

Karijadi, I., Chou, J.-S., & Putra, A. (2023). Wind power forecasting based on hybrid CEEMDAN-EWT deep learning LSTM method. Energy Reports.

Kavasseri, R. G., & Seetharaman, K. (2009). Day-ahead wind speed forecasting using f-ARIMA models. Renewable Energy, 34(5), 1388–1393. https://doi.org/10.1016/j.renene.2008.09.006

Liu, Z., et al. (2025). A comprehensive review of wind power prediction based on machine learning: Models, applications, and challenges. Energies, 18(2), 350. https://doi.org/10.3390/en18020350

Lundberg, S. M., & Lee, S.-I. (2017). A unified approach to interpreting model predictions. Advances in Neural Information Processing Systems, 30, 4765–4774.

Molnar, C. (2022). Interpretable machine learning: A guide for making black box models explainable (2nd ed.). Independently published.

Page, M. J., McKenzie, J. E., Bossuyt, P. M., et al. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. BMJ, 372, n71. https://doi.org/10.1136/bmj.n71

Rajaperumal, T. A., et al. (2025). Enhanced wind power forecasting using machine learning, deep learning models and ensemble integration. Scientific Reports, 15, Article 5250. https://doi.org/10.1038/s41598-025-05250-3

Santhosh, M., Venkaiah, C., & Kumar, D. M. V. (2020). Current advances and approaches in wind speed and wind power forecasting for improved renewable energy integration: A review. Engineering Reports, 2(6), e12178. https://doi.org/10.1002/eng2.12178

Soman, S. S., Zareipour, H., Malik, O., & Mandal, P. (2010). A review of wind power and wind speed forecasting methods with different time horizons. 2010 North American Power Symposium, 1–8. https://doi.org/10.1109/NAPS.2010.5619586

Snyder, H. (2019). Literature review as a research methodology: An overview and guidelines. Journal of Business Research, 104, 333–339. https://doi.org/10.1016/j.jbusres.2019.07.039

Torres, M. E., Colominas, M. A., Schlotthauer, G., & Flandrin, P. (2011). A complete ensemble empirical mode decomposition with adaptive noise. 2011 IEEE International Conference on Acoustics, Speech and Signal Processing, 4144–4147. https://doi.org/10.1109/ICASSP.2011.5947265

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., & Polosukhin, I. (2017). Attention is all you need. Advances in Neural Information Processing Systems, 30, 5998–6008.

Yang, Y., Chen, J., Zheng, W., & Zhang, F. (2024). A survey on wind power forecasting with machine learning approaches. Neural Computing and Applications. https://doi.org/10.1007/s00521-024-09923-4