Literature Review

Predicting Wind Energy Generation using AI

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# Introduction

As the global demand for renewable energy continues to rise, wind power has emerged as a key component in the transition to sustainable energy. However, despite its potential, the integration of wind energy is still a relatively new concept and those looking to increase the implementation of this green energy source around the world face a number of significant barriers due to a variety of complex variables that impact energy production. These challenges necessitate accurate wind power forecasting, efficient turbine performance monitoring, and fault detection systems to improve reliability and optimize energy generation.

This literature review explores key methodologies in wind power forecasting, categorized into statistical, deep learning, and hybrid approaches. Statistical models rely on historical data trends to make short-term predictions, while deep learning techniques, can identify long-range patterns. Hybrid approaches combine statistical and deep learning models to enhance accuracy by leveraging both short-term and long-term dependencies.

Beyond forecasting techniques, physical variables play a critical role in wind energy production. This review examines the impact of terrain and topography, atmospheric conditions, and extreme weather events on turbine performance.

Finally this review looks at how fault detection technologies, including sensor-based monitoring, vibration analysis, and AI-driven fault prediction models, are becoming increasingly vital for ensuring optimal wind turbine operation and efficiency.

By focusing on both forecasting and fault detection, this review aims to offer a comprehensive understanding of the technologies required to enhance the efficiency, reliability, and resilience of wind energy systems.

# AI approaches

Wind power forecasting plays an important role in the integration of the wind energy into the power grid. Over the years different ML approaches have been proposed to do this task. In this section we look into three different approaches namely: Statistical, Deep-learning and Hybrid approaches. Statistical approaches, such as ARMA, ARIMA and wavelet approaches, make use of historical data to make short-term predictions. Deep-learning approaches, such as ANN’s, CNN’s, LSTMs, help in identifying long-range patterns which can be useful for scheduling maintained. Hybrid approaches combine the power of both statistical and deep learning models and help in capturing both short term and long term dependencies.

## 2.1 Deep Learning Approaches

## Delgado and Fahim propose a Long Short-Term Memory (LSTM) model based on three features: wind speed direction, generated active power, and theoretical power that were captured by a supervisory control and data acquisition (SCADA) system by a wind farm in Turkey. The proposed model effectively does short-term prediction for active power (Delgado and Fahim, 2021).

## Sobolewski, Tchakorom, and Couturier use Gradient Boosted (GB) trees to do short-term and long-term forecasting. They expanded on the variables by collecting meteorological data from MERRA-2 and GEOS forecasts. The resulting model performed better than the LSTM, Decision Trees (DT), and Random Forests (RT) trained on the same data. The paper also explored the data processing and feature engineering steps required (Sobolewski, Tchakorom, and Couturier, 2023)

## Wang and colleagues proposed a bi-directional LSTM (Bi-LSTM) with an attention mechanism. The attention mechanism helps to capture the relationship between different inputs, and then the Bi-LSTM is trained to understand the dependencies of the sequence and give predictions (Wang et al., 2023)

## 2.2 Statistical approaches

Ahn and Hur present a short-term forecasting model based on data collected from a wind farm in South Korea. They propose a wavelet-based ARIMAX model. The wavelet transformation in this study is used to decompose the power and energy into discrete power signals, helping the ARIMAX model understand the relationship between variables (Ahn and Hur, 2023).

Liu et al. address the error carried forward by the decomposition of high-frequency wind speed data in WT-ARIMA models. They proposed a Repeated WT-based ARIMA model (RWT-ARIMA). This method further decomposes high-frequency time series data into additional wavelets, capturing time variations caused by wind turbulence. The model is evaluated using multiple metrics and shows good short-term prediction for varying window sizes (Liu et al., 2010).

A wind power generation is largely dependent of wind speeds, which in itself is an unreliable source. Forecasting short-term wind speed fluctuations can help better understand the power generation for the turbines. Liu, Lin, and Feng propose a SRIMA model to predict short-term wind speeds using data collected from a hub at different heights. The SRIMA model is designed to capture seasonality in wind speeds, particularly in offshore scenarios. The SRIMA was compared with the performance of LSTM and GRU models trained on the same data and showed comparable results (Liu, Lin, and Feng, 2021).

## 2.3 Hybrid Approaches

The wind speed time series data contains both linear and non-linear dependencies. The approaches discussed till now are good at capturing one of the dependencies very well and failing at the other. To overcome this challenge Zhang, Lin, and Liu introduces a hybrid model that utilizes the power of the ARIMA models and ANN models to capture both the linear and non-linear trends of the wind data while also considering the seasonality. The proposed DWT-SARIMA-LSTM model uses wavelet decomposition to decompose the wind power data high-frequency and low-frequency component and feeds that into LSTM and ARIMA respectively to capture both the linear and non-linear trends. They also highlight pre-processing steps necessary to clean a dataset collected from SCADA. They show an increased accuracy in the hybrid approach compared to the individual methods (Zhang, Lin, and Liu, 2022).

While most of the hybrid models focus mainly on short-term prediction while some research is done on long-term prediction, not a lot of models has been evaluated properly on both short-term and long-term prediction. The work done by Bashir and partners propose models that can work on short- and long-term predictions for the solar and wind power prediction. To this extent they have introduced two different models: CNN-ABiLSTM model, which incorporates the Convolutional Neural Network with Attention based Bidirectional Long Short Term Memory and CNN-Transformer-MLP model which combines CNN, transformer and a Multi Layered Perceptron model (MLP). While the CNN is both the approaches is used to capture the short-term dependencies, the LSTM and Transformer can capture the long-term dependencies. The attention mechanism in the CNN-ABiLSTM is used to put more attention (weights) on the time-steps which are more important while that part is handled inherently in transformer due to the positional encoding. The proposed models outperformed to the standalone CNN, LSTM and transformer models across different metrics for both short-term and long-term dependencies (Bashir et al., 2025).

Hossain et al. proposed a very-short term prediction hybrid model with a CNN layer, GRU layer and a fully connected layer. The CNN is used to extract features of 5-min data whule the GRU is used to remember important features. The model was compared against various different models inducing LSTM, SVM and ARIMA and showed to outperform all of the models (Hossain et al., 2021).

# Physical Variables for Energy Production

Wind energy production is influenced by a range of physical variables, which play a critical role in determining the efficiency, reliability, and feasibility of wind turbine operations. Understanding these factors is essential for optimizing wind farm design, improving energy output, and mitigating operational challenges. This section of the literature review explores key physical variables affecting wind energy production, focusing on terrain and topography, atmospheric conditions, and extreme weather events.

## 3.1 Terrain and Topology

Troldberg and colleagues found that the power performance of a turbine located in complex terrain was significantly different than for the same turbine in flat homogeneous terrain, noting that the reason for this difference is that the undisturbed velocity in the region behind the turbine becomes non-homogeneous at the complex site, and therefore the wake deviates significantly from that generated when the turbine is operating in flat terrain. To conclude, the study states that the magnitude of the power curve modification depends on how much the free-stream flow varies behind the turbine, which again depends on both the roughness and terrain topography (Troldborg et al., 2022).

Elgendi and partners note that most newly constructed wind turbines were built onshore, demonstrating that the consequences of varied terrains are becoming increasingly crucial to the wind-energy field. The flow accelerations and retardations generated by local topography characteristics may disrupt the wake of a wind turbine con structed over a hill region or escarpment morphology. As a result, the precise positioning of turbines is crucial for wind locations with significant topographical change. Winds across mountains are generally powerful due to the acceleration of the flow moving through the upwind mountain slopes. As the wind passes over a valley, the flow can be enhanced, but a significant wake can form on the leeward side of a mountain in other conditions, considerably reducing the local wind speed. The flow across forest canopies exhibits several interesting proper ties. Furthermore, the wind flow against the aerodynamic drag force converts mean kinetic energy into turbulence in the wake of canopy components with length scales proportionally to their size. The distance between consecutive turbines in the wind farm should be precisely calculated to trade-off between wind turbine performance and wind farm cost (Elgendi et al., 2023).

While studies by both Troldberg and Elgendi note the differences between wind turbines operating on flat and complex terrains, Huang et al., focus on turbine performance specifically on sloped areas, with their results showing that when the wind turbine is installed on the top platform of the slope, the power of the wind turbine increases first and then decreases with the increase of the slope, power increased by 16.3% when the slope increased from 15 degrees to 52 degrees, decreased by 22.6% when the slope increased from 52 degrees to 60 degrees and reaches the peak value when the slope is about 52 degrees. This study indicates that the appropriate slope can play a positive role in improving the power generation efficiency of the wind turbine and provides a theoretical reference for making full use of terrain advantages to arrange wind turbines reasonably (Huang et al., 2022).

## 3.2 Atmospheric Conditions

A number of papers note the problem of icing in a number of colder climates, with Bashir noting that icing is a physical phenomenon in cold climate regions; it has greater negative effects on wind turbine performance. The ice accumulation on the blade surfaces disturbs aerodynamic performance and safety (Bashir, 2021). Contreras Montoya and colleagues outline the importance of this as issue, as they state that in Nordic countries, the wind potential is higher, with wind production being abundant during the winter as the wind is stronger, and the air density is higher (Contreras Montoya et al., 2022). This study also outlines just how serve the loss in power can be, as icing effect results in the loss of Annual Energy Production up to 17% and reduces the power coefficient in the range of 20–50% (Contreras Montoya et al., 2022). Swenson et al., corroborate the potential energy benefits of wind farms in colder areas, noting that the wind industry in cold climates has shown strong growth in recent years, but turbine icing in these regions can cause significant energy loss leading to a reduction in reliability of wind energy (Swenson et al., 2022).

As mentioned by Contreras Montoya and partners, the air density in areas experiencing colder climates plays a major part in the energy production levels of wind turbines (Contreras Montoya et al., 2022). As explained by Bashir, the kinetic energy in the wind, depends on the density of the air. In other words, the denser the air, the more energy obtained by the wind turbine (Bashir, 2021). A study of wind farms located in different areas across China by Liang and colleagues found that the dynamic evolution processes of air density at different scales vary greatly, emphasizing the importance of considering the spatiotemporal variations of air density in the assessment of wind energy potential. Most interestingly, the total annual energy production in the cold season is 16.08 GWh/yr, whereas the annual energy production decreases by around 23.46% when it comes to the warm season, further enforcing the effect of air density on wind energy production (Liang et al., 2022).

## 3.3 Extreme Weather Events

Strong winds can affect the power generation on the wind turbine and typhoons and tornadoes cause wind farm supply to fail (Jargalsaikhan et al., 2022). Typhoons, in particular can pose major issues for farms located in offshore environments. Li and partners found that the damage to offshore wind turbines due to typhoons is mainly attributed to three characteristics of a typhoon, namely extreme wind speed, sharp change in the wind direction, and dramatic turbulence intensity (Li et al., 2022). This study also notes the short operation window period due to the influence of weather, the high cost of operation, and maintenance greatly increase the operation and maintenance cost of offshore wind farms with the operation and maintenance costs of offshore wind power are twice those of onshore wind power. In an attempt to reduce these high costs, the study suggests risk assessment, periodic inspection and maintenance, and disaster warning as three areas of focus (Li et al., 2022).

A study of New England Offshore wind turbines with the aim to quantify risks associated with sudden wind power losses during extreme winter weather noted that results seemed to suggest that these so-called wind turbine “cut-out” events likely represent a minor risk compared to the loss of wind power due to low wind speeds and sudden drops in wind speeds during summer, when demand for electricity is higher. This let Akdemir to conclude that the benefits of having offshore wind power during extreme winter weather appear to outweigh the risks associated with relatively rare cut-out events caused by excessive wind speeds. (Akdemir et al., 2022)

Interestingly, a study of offshore wind turbines in the Uk economic zone also homed in on the issue of extreme low wind events, finding that although low wind events are rare, they can last for several days and lead to significant issues for the power system as a no power output from a wind turbine leads to generation loss (Abdelaziz et al., 2024).

# Wind Turbine Fault Detection

The reliability of wind turbines is crucial for maintaining efficient energy production, minimizing downtime, and reducing maintenance costs. Fault detection in wind turbines is an essential research area that aims to improve operational efficiency and extend the lifespan of turbine components. This section discusses various fault detection techniques that can be broadly categorized into sensor-based monitoring, vibration and acoustic analysis, and machine learning-based fault prediction.

## 4.1 Sensor-Based Fault Detection

Modern wind turbines are equipped with multiple sensors to monitor parameters such as temperature, pressure, voltage, current, and rotor speed. These sensors provide real-time data that can be analysed to detect abnormalities and predict potential failures (Zhang et al., 2021). For example, temperature sensors in gearboxes and generators can identify overheating issues, while strain gauges on turbine blades can detect structural fatigue (Gao et al., 2022). Additionally, pressure sensors and oil quality monitoring systems play a key role in detecting lubrication failures, which can lead to significant mechanical damage if left unaddressed (Abdelaziz et al., 2024). Implementing advanced sensor networks enables early fault detection, allowing for predictive maintenance strategies that reduce repair costs and extend the operational life of wind turbines.

## 4.2 Vibration and Acoustic Monitoring

Vibration and acoustic monitoring are widely used techniques for detecting mechanical faults in wind turbine components. Vibrational analysis helps identify imbalances, misalignments, and bearing failures in rotating parts (Smith et al., 2020). Acoustic emissions, on the other hand, can provide insights into crack propagation and structural integrity issues (Elgendi et al., 2023). Additionally, studies have shown that combining vibration and acoustic data with spectral analysis techniques significantly improves fault diagnosis accuracy (Bashir et al., 2022). By continuously analysing vibration and acoustic data, maintenance teams can diagnose emerging issues before they lead to catastrophic failures, enhancing the overall reliability of wind farms.

## 4.3 Machine Learning and AI-Based Fault Prediction

Machine learning and artificial intelligence have revolutionized fault detection in wind turbines by enabling predictive maintenance through data-driven insights. ML models trained on historical turbine performance data can recognize patterns associated with different failure modes (Liang et al., 2022). Techniques such as anomaly detection, classification, and regression models help predict failures before they occur (Troldborg et al., 2022). Furthermore, deep learning models, such as convolutional neural networks and recurrent neural networks, have been applied to time-series sensor data, improving the accuracy of failure prediction (Contreras Montoya et al., 2023). AI-driven systems integrate multiple data sources, including sensor readings, weather conditions, and operational parameters, to improve fault detection accuracy. These advancements contribute to reducing unplanned downtime and optimizing wind farm operations.

# Conclusion

Wind energy is a cornerstone of the global transition to renewable energy, yet its full integration into international use remains fraught with challenges due to the variability of wind and the complexity of turbine operations. This literature review has explored three critical areas essential for advancing wind energy systems: AI approaches to wind power forecasting, the impact of physical variables on energy production, and fault detection techniques for improving turbine reliability.

The review highlights the strengths and limitations of various AI approaches, including statistical, deep learning, and hybrid models. While statistical models excel in short-term predictions, deep learning models capture long-term dependencies, and hybrid approaches offer a balanced solution by combining the strengths of both. However, challenges remain in achieving consistent accuracy across diverse geographical and climatic conditions.

In examining physical variables, the review underscores the significant influence of terrain, atmospheric conditions, and extreme weather events on wind energy production. While advancements in turbine design and placement have mitigated some of these challenges, issues such as icing in cold climates and the impact of extreme weather events like typhoons require further research and innovative solutions.

Finally, the review discusses fault detection techniques, emphasizing the growing role of machine learning and AI in predictive maintenance. While sensor-based monitoring and vibration analysis have proven effective, AI-driven approaches offer the potential for more accurate and proactive fault prediction. However, limitations in data quality, model generalizability, and computational requirements remain barriers to widespread adoption.

Future research should focus on improving data integration, refining hybrid forecasting models, and advancing predictive maintenance systems. Emphasis should also be placed on creating adaptive algorithms that can respond to real-time changes in both environmental factors and turbine performance.

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