Literature Review

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# Introduction

<< This section should outline the context of the work. What is the real-world problem you are trying to address? What are the quantifiable issues which need to be overcome?>>

<<The section should state the major categories within which the literature review will be scoped>>

<<The section should provide high level reference into which the subsections interrelate>>

# AI approaches

<< For core technical area 1 this section should outline the relevance of the technical area to the overall research agenda. Why is this technical area being discussed? How can this area be sub-categorised? How can these technologies address the overall challenge discussed in section 1?>>

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.

# Deep Learning approaches

In [1] propose a Long Short-Term Memory (LSTM) model based on three 4 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.

[2] uses Gradient Boosted(GB) tress to do short-term and long-term forecasting. They expanded on the variables my collecting meteorological data from MERRA-2 and GEOS forecasts. The resulted 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.

[3] 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.

# Statistical Approaches

[4] presents a short-term forecasting model based on the data collected from wind a 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. This decomposing helps the ARIMAX model to better understand the relationship between variables. The X in ARIMAX is for the exogenous variables that ere combined with the ARIMA model.

[5] tries to solve the error carried forward by decomposition of high frequency wind speed data in WT-ARIMA models [6]. They proposed a Repeated WT based ARIMA model (RWT-ARIMA). In this method they further decompose the high frequency time series data into further wavelets. This further decomposition helps captures the time variations caused by wind turbulences. The model is evaluated using multiple metrics and shows good short-time prediction for varying window sizes.

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. Following this [8] proposes a SRIMA model to predict short-term wind speeds from data collected from a hub at different heights. The SRIMA is proposed to capture the seasonality in wind speeds prominent in offshore scenarios. The SRIMA was compared with the performance LSTM and GRU trained on the same data and showed comparable results to them.

# 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 [7] 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.

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 model has been evaluated properly on both short-term and long-term prediction. The work done by [9] 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.

[10] 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.

# Physical Variables for Energy Production

<< For core technical area 2 this section should outline the relevance of the technical area to the overall research agenda. Why is this technical area being discussed? How can this area be sub-categorised? How can these technologies address the overall challenge discussed in section 1?>>

# Terrain and Topology

Gao and associates carried out a study on three different wind farm areas in Northern China, comparing flat, moderate, and complex terrains. (Gao et al., 2022).

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).

# 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).

# 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 honed 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

<< For core technical area 3 this section should outline the relevance of the technical area to the overall research agenda. Why is this technical area being discussed? How can this area be sub-categorised? How can these technologies address the overall challenge discussed in section 1?>>

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.

# 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.

# 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.

# 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.

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# **Conclusion**

<< This is a critical part of the literature review. Briefly state again the overall context of the work. Briefly state the literature review process including technical core areas and subcategories. Compare and contrast the relevance of the technologies under discussion. Compare and contrast the potential for existing technologies to address the overall research challenge. Identify limitations in existing approaches. Discuss future work which can enhance the existing state of the art in order to address the overall research challenge>>

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