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REVIEW

A comprehensive review on enhancing wind turbine applications with advanced SCADA data analytics and practical insights

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Abstract

The aim of this study is to explore the potential and economic benefits of utilising Supervisory Control and Data Acquisition (SCADA) data to improve wind turbine operation and maintenance activities. The review identifies a gap in the current understanding of how to effectively use SCADA data in wind turbine applications. It emphasises the need for pre-processing SCADA data to ensure data integrity by addressing outliers and employing interpolation techniques. Additionally, it highlights the challenges associated with early fault detection methods using SCADA data, including the development of physical models, data-driven machine learning models, and statistical regression models. The review also recognises the limitations caused by the lack of public data from wind turbine developers and the imbalance between normal operation data samples and abnormal data samples, negatively impacting model accuracy. The key findings of the review demonstrate that SCADA data-driven techniques can lead to significant improvements in wind turbine operations and maintenance. The application of data-driven technologies based on SCADA data has proven effective in reducing operation and maintenance costs and enhancing wind power generation. Moreover, the development of robust decision support systems using SCADA data minimises the need for frequent maintenance interventions in offshore wind farms. To bridge the gap and further enhance wind turbine applications using SCADA data, several recommendations are provided. These include encouraging greater openness in sharing SCADA data to improve the robustness and accuracy of AI models, adopting transfer learning techniques to overcome the scarcity of quality datasets, establishing unified standards and taxonomies, and providing specialised resources such as software applications with interactive graphical user interfaces for easier storage, annotation, and analysis of SCADA data.

The authors' review paper identifies a gap in the current understanding of how to effectively utilise SCADA data in wind turbine applications. It emphasises the importance of pre-processing SCADA data to ensure data integrity by addressing outliers and employing interpolation techniques. Furthermore, the authors highlight the challenges associated with early fault detection methods using SCADA data, including the development of physical models, data-driven machine learning models, and statistical regression models.

1 | INTRODUCTION

Wind power, as a renewable energy source, has witnessed a remarkable surge, growing at an average annual rate of 30% over the past two decades, positioning itself as a key player in the global energy landscape [1]. Since offshore wind speeds are more consistent and powerful, more power is produced when wind turbines are built there. As a result, wind turbines frequently operate in hot and humid climates as well as in remote locations [2]. The maintenance and operation of wind turbines are severely hampered by this. The dependability of wind turbines is a top priority for manufacturers and operators.

Low-reliability wind turbines in an offshore setting may have a more negative effect on the effectiveness of energy production because they need more time to repair faults once they occur [3]. Low-reliability wind turbines can significantly reduce the efficiency of power generation in offshore conditions. This is due to the possibility of prolonged maintenance downtime due to access constraints if a wind turbine malfunctions. As a result, the costs associated with wind turbine operation and maintenance (O&M) are high. It is widely accepted that between 25% and 35% of the overall costs of producing power come from the operation and maintenance (O&M) of wind turbines [4]. As a result, manufacturers and operators are quite concerned about the dependability of wind turbines. A sizable sample of operational wind farms' annual average availability is represented in [5], showing a sizable disparity between the highest availabilities (which are 50% higher than 97.5%) and lowest availabilities (which are 10% lower than 92.5%) [5]. This suggests that there may be room to raise wind turbine dependability. Developing acceptable maintenance procedures and conducting appropriate condition monitoring (CM) are efficient ways to increase reliability. Although the economic benefits of early fault detection by the Condition Monitoring System (CMS) have been demonstrated, it has not yet been widely adopted [6] due to cost and technical complexity restrictions (typically more than 11,000 Euros per turbine). Recently, a low-cost monitoring technique that does not need extra sensors has been suggested: employing Supervisory Control and Data Acquisition (SCADA) data as CM for wind turbines. At 10-min intervals, this system records more than 200 wind turbine-related variables, creating a significant amount of data that, after suitable data processing, is used for early failure identification. SCADA data is influenced by a variety of operational circumstances and environmental factors in addition to how well the wind turbine is performing [7]. It is critical to track data trends and remove negative impacts caused by environmental and operational variability from SCADA data since changes in SCADA data do not always indicate a problem with the wind turbine. To locate problems in wind turbines, suitable data analysis technologies must be proposed.

This review aims to make substantial contributions to the field by pursuing three key objectives. First, it conducts a comprehensive literature study to provide an in-depth overview of the causes of wind turbine failures, analyzing trends in failure rates, and assessing the broader financial implications on the overall cost of wind energy. This exploration is vital for advancing our understanding of the underlying factors contributing to wind turbine failures and their sector-wide effects. Second, the review critically evaluates various SCADA data analysis techniques, shedding light on their benefits and drawbacks. As SCADA data analysis plays a pivotal role in identifying potential issues and anomalies in wind turbines, the review aims to offer nuanced insights into the most effective strategies for leveraging SCADA data. The examination encompasses a diverse range of approaches, including both physical models and data-driven methodologies. Lastly, this review endeavours to introduce innovative technologies for the early identification and diagnosis of wind turbine failures. By delving into current research and advancements in the field, the paper seeks to uncover novel approaches and technologies that hold the potential to significantly enhance the reliability and efficiency of wind energy systems. In essence, this review aims to deepen our understanding of wind turbine failures, provide a balanced assessment of various SCADA data analysis methods, and propose cutting-edge technologies to advance the early identification of failures in wind turbines.

2 | OVERVIEW OF SCADA SYSTEMS

2.1 | Introduction to SCADA systems

A typical automation system used to manage industrial operations is the SCADA system. It gathers data in real time for control or monitoring purposes from sensors at distant places and collects it at a central location. SCADA gives businesses the resources they need to make data-driven choices about their industrial operations. Both hardware and software components make up SCADA systems. The field controller system receives data from the hardware and processes it. Additionally, the data is prepared and shown on the user interface. SCADA systems also capture and document all occurrences in order to report on the status and problems of the process. The SCADA system provides notifications when errors happen [8]. SCADA systems comprise hardware for on-site real-time data collection as well as data support and automation software. SCADA's components include the following (Figure 1):

1. Instruments or sensors used in the field: Sensors gather information from the environment, such as temperature, pressure, liquid level, etc.
2. SCADA field controllers: SCADA field controllers are often separated into two types and are directly connected to sensors. RTUs, or remote terminal units, take data from sensors and send it to the system. Industrial equipment is controlled by Programmable Logic Controllers (PLCs), which are linked to actuators.
3. SCADA monitoring computers: Manage all SCADA functions and issue instructions to industrial equipment controllers based on information gathered on-site.
4. Human–Machine Interface (HMI) software: Integrates and displays data within the SCADA system, allowing operators to intuitively comprehend the state of industrial processes.
5. The SCADA monitoring system's communication infrastructure links field equipment with it, enabling remote data gathering and equipment control.

SCADA systems operate at five of the six levels for enterprise integration [8], which is shown in Figure 2:

- Level 0: Process-controlling actuators and sensors that transmit data on field processes.
- Level 1: Local controllers receive sensor data and communicate commands to field equipment.
- Level 2: Local monitoring systems provide commands and summarise data from level controllers.

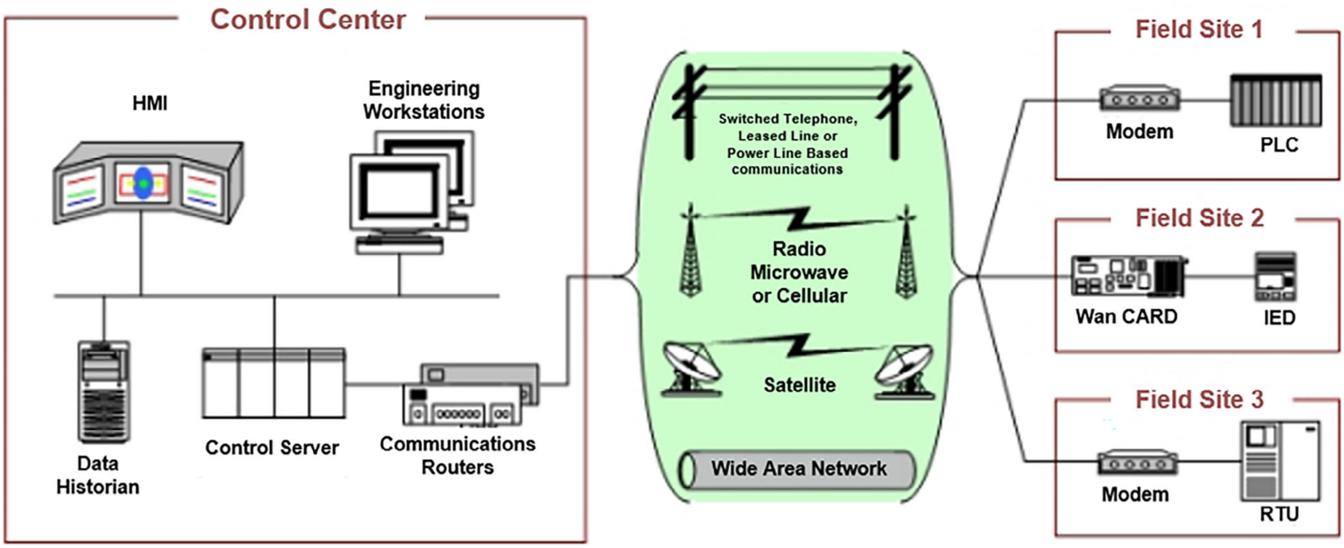

FIGURE 1 Component of SCADA system [9].

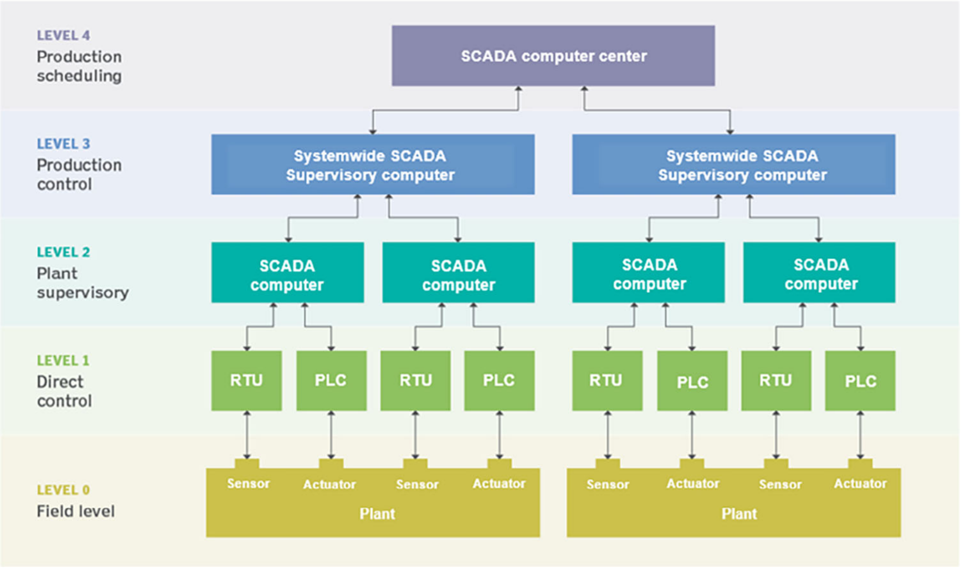

FIGURE 2 Layers of SCADA system architecture [8].

- Level 3: Regionally functional system monitoring devices produce data reports for usage at the production scheduling level.
- Level 4: Systems used by businesses to handle ongoing activities are at Level 4.

2.2 | Data acquisition and communication protocols

Data from the wind turbine, such as wind speed, wind direction, rotor speed, power output, etc., are collected and interpreted by a SCADA system for the wind turbine. This information is gathered by sensors placed all around the turbine and then transmitted to a central control system for monitoring and analysis. The guidelines that specify how information is sent and received between devices in a SCADA system are known as communication protocols. These protocols make guarantee that the data being communicated is dependable and safe and that all components of the system can properly communicate with one another.

The most widely used protocols in wind turbines are IEC 61400-25, DNP3, and Modbus. Because of its widespread acceptance and ease of implementation, the Modbus protocol is straightforward and reliable. In contrast, DNP3 offers more sophisticated functionality including event recording and timestamping. For applications involving wind power, the IEC 61400-25 protocol was created expressly. It offers a standard model for data exchange between wind power plants and control centres, simplifying the integration of various systems and parts.

3 | SCADA DATA COLLECTION IN WIND TURBINES

Wind turbines rely on SCADA systems to gather real-time operational and historical data. This comprehensive dataset enables operators and engineers to assess turbine efficiency, detect potential faults, and optimise overall performance. SCADA data, often collected at frequent intervals, is transmitted from the turbines, typically located in remote areas, to centralised processing centres. SCADA data collection is briefly described as follows.

3.1 | Integration of SCADA systems in wind turbine operations

Wind turbine operation efficiency depends on SCADA systems. They make it possible for the equipment to be controlled and monitored centrally, improving performance, foreseeing any problems, and even providing remote access and control. There are numerous ways to incorporate SCADA systems into wind turbine operations:

- Remote Monitoring and Control: With the help of the SCADA system, operators can keep an eye on things like wind speed, rotor speed, power output, and temperature on wind turbines that are in operation. The turbines may also be started, stopped, and their blade angles and rotation speeds can be changed remotely.
- Predictive Maintenance: Machine learning algorithms can be used in conjunction with the data gathered by SCADA systems to forecast equipment breakdown. By preventing unanticipated breakdowns and prolonging the lifespan of wind turbine components, this preventative maintenance can result in significant cost savings.
- Alarm Management: The SCADA system can set off alarms to alert the operators if it detects any abnormal conditions, such as high temperature, low oil level, or high vibration. This makes it easier to find and fix problems fast.
- Grid Integration: SCADA systems are also useful for controlling how wind turbines are integrated into the grid. They can keep an eye on and control the power output to match the demand on the grid, assisting in grid stabilisation and averting blackouts.

The wind turbine SCADA system's parameters are listed in Table 1. The data is recorded by the SCADA system as 10-min averages of 1-Hz sampling values. Additionally, the system records the greatest and lowest variances of specific parameters [6]. A part of the CM also includes the start-stop count and alert logs that the SCADA system has logged. Different groups of wind turbines have various equipment and collection standards. More sensors are being added to contemporary turbines is already a general tendency.

TABLE 1 Parameters collected from SCADA system [6, 10].

Environmental	Electrical characteristics	Part temperatures	Control variables
Wind speed	Active power output	Gearbox bearing	Pitch angle
Wind direction	Power factor	Gearbox lubricant oil	Yaw angle
Ambient temperature	Reactive power	Generator winding	Rotor shaft speed
Nacelle temperature	Generator voltages	Generator bearing	Generator speed
	Generator phase current	Main bearing	Fan speed/status
	Voltage frequency	Rotor shaft	Cooling pump status
		Generator shaft	Number of yaw movements
		Generator slip ring	Set pitch angle/deviation
		Inverter phase	Number of starts/stops

3.2 | Data acquisition process and frequency

SCADA systems enable remote operation of machinery and processes, as well as data collection to track and evaluate wind turbine performance. The following steps are commonly involved in the data acquisition process in an SCADA system for wind turbines:

- Data Collection: This is the main stage of the SCADA system's data collection process for information from sensors installed in wind turbines. The sensors can keep an eye on a number of variables, including wind direction and speed.
- Data Communication: The collection and transmission of data to a data concentrator or centralised control system. Typically, several communication methods, such as wireless networks, fibre optic cables, or internet connections, are used for this. It is also possible to time-stamp the data to ensure correct capture and analysis.
- Data processing and control: The central control system controls and processes data once it has been gathered and sent. This system, which is frequently a computer running SCADA software, allows human operators to remotely manage wind turbines while also interpreting data, generating alerts or instructions based on predetermined criteria, and interpreting data.
- Data Analysis and Storage: Data is kept in databases for further reporting and analysis. This enables operators

to see patterns, anticipate breakdowns, plan maintenance, and enhance the wind turbines' general productivity and efficiency.

4 | APPLICATIONS OF SCADA DATA IN WIND TURBINES

4.1 | Condition monitoring and fault detection

Condition monitoring and fault detection is a developing method used for observing system performance. It collects data to verify design values and make decisions to help enhance system performance. Early detection of imminent faults such as cracks, wear, rotor mass imbalance, etc., can improve system reliability. This method selects specific parameters for monitoring and uses algorithms to determine the occurrence of faults. Finally, an intelligent alarm system interprets the alarms and takes corrective actions [11].

4.1.1 | Vibration analysis

Vibration is a crucial indicator of the health of wind turbines and a study topic for spotting irregularities in their functioning. The creation of a defect monitoring system employing vibration data gathered from the tower and wind turbine transmission system has been suggested by Zhang et al. [12]. Acceleration detected by the SCADA system serves to define vibration. Despite being connected, the accelerations of the gearbox system and the tower are examined independently in this study because there is no statistically significant correlation between them.

An enhanced k-means clustering technique is used in this study to track wind turbine vibration. This algorithm for unsupervised learning evaluates data similarity and groups data into groups. Turbine maintenance choices are made using the clustering model. A warning message will be generated and the proper steps for maintaining wind turbines will be conducted if the data is a part of a cluster that represents an incorrect state. A few occurrences will be randomly chosen for diagnostic analysis if the data is part of a cluster representing an unknown state of the wind turbine. No action is required if the data are part of a cluster that represents a regular state.

The relationship between acceleration and time cannot be observed because clustering does not account for the passage of time. The state of the wind turbine in the future must therefore be predicted using a model that can track acceleration trends. The study suggests using control charts to track acceleration trends and spot unusual wind turbine incidents. The control chart's centreline, the NEE baseline model, is used to track outliers that deviate from the norm.

The models provided by Kusiak et al. [13] for tracking wind farm power output are numerous. To track the performance of the wind farm, a non-linear parametric model was constructed using an evolutionary computation approach. For the wind farm running under typical circumstances, the k-NN model provided good performance. In a later investigation, they suggested applying anticipatory control to WTs. A non-linear restricted optimisation problem was resolved using a modified evolutionary strategy approach. In a later study, Kusiak et al. suggested a strategy for improving the power that WTs produce. The pitch and yaw angles of the blades were optimised using the control strategy they suggested.

TABLE 2 Performance of five classifiers for predicting drive train acceleration.

Classifier	MAE	MAPE
NN	1.17	0.07
SVM	8.64	0.27
Standard C&RT	4.23	0.16
Boosted tree	3.20	0.20
Random forest	2.06	0.09

From two separate approaches, time domain and frequency domain, Kusiak et al. [14] proposed evaluating vibration data of wind turbine units. To identify the wind turbine parameters that can reduce turbine vibration, three data-driven methodologies were used in the time domain analysis: predictive variable importance analysis, global sensitivity analysis, and correlation coefficient analysis. Fourier analysis was utilised to transform time-domain data into the frequency domain for the frequency domain analysis. The association between parameters and wind turbine vibrations was determined using five data mining algorithms, and the best one was selected for modelling and in-depth computer investigation.

Table 2 illustrates the performance of the five classifiers for predicting the drive train acceleration. The NN model provides the lowest MAE and MAPE. Thus, the NN model is selected as the most accurate model to predict wind turbine vibrations.

4.1.2 | Temperature monitoring

Unexpected temperature increases in wind turbines could be a sign of overloading, insufficient lubrication, or ineffective passive or active cooling. Potential breakdowns can be predicted by using neural networks to create normal operating temperature models for the gearbox and generator based on SCADA data. However, increasing the accuracy of neural network methods in predicting wind turbine failures is challenging due to the lengthy model training time and the issue of local minima. Guo et al. proposed a temperature trend analysis technique based on the Non-linear State Estimation Technique (NSET) [15]. The sensitivity of this method to isolated model errors can be decreased by utilising NSET to build a normal operating model of wind turbine temperature and a moving average window to smooth the time series residuals between the actual observed temperature and the estimated value. The residual distribution of a wind turbine's temperature over time will be different from normal operation when it has a possible malfunction.

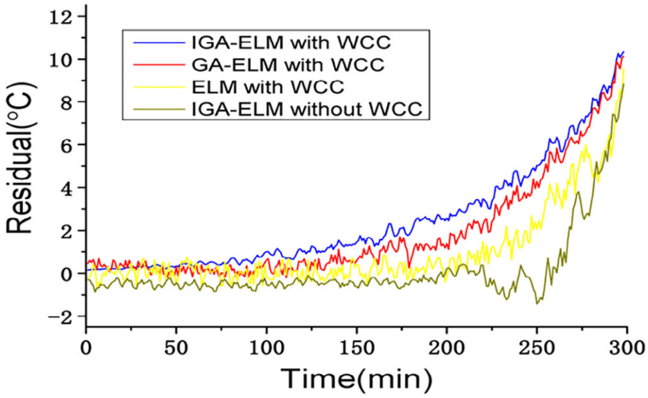

FIGURE 3 Residual results of different solutions in main bearing offset failure [18].

The mechanical performance of wind turbines may be impacted by considerable wake effects caused by the separation between turbines. In order to prevent the deterioration of the wind turbines, it is important to pay attention to the impact of temperature changes. Astolfi et al.'s method [16] displays a graph depicting the correlation between observations from wind turbine temperature sensors and the percentage of power relative to rated values to anticipate impending serious damage to wind turbines. This technique is used on historical data and in real time on a test wind turbine, and it is demonstrated that it can identify temperature patterns that are developing into traumatic machine stoppage.

The fluctuating load circumstances that wind turbines run under make it difficult for typical bearing monitoring techniques to produce reliable findings. Cambron et al. suggested an approach for monitoring the condition of a wind turbine's main bearing by constructing an empirical physical model based on the discrepancy between the actual temperature and the expected temperature [17]. They employed least-squares fitting to establish the model's parameters after choosing data from typical operational scenarios. Additionally, they developed an EWMA control chart based on this physical model to keep track of potential bearing problems. The system will sound an alarm if the monitoring signal based on bearing temperature exceeds the control limit.

Hou et al. proposed a WCC scheme using the k-means algorithm, which can build models under different wind conditions, thereby improving the reliability and accuracy of fault detection [18]. An Improved Genetic Algorithm (IGA) is used to optimise the Extreme Learning Machine (ELM) to avoid local minima caused by the irregularity of wind condition changes and the randomness of initial weights and biases. Figure 3 shows the two IGA-ELM solutions. On average, the solution without WCC lags the solution with WCC by more than 60 min, reaching roughly 90 min at a residual result of 2°C. The solution with WCC also displays consistent performance with changes in wind conditions, and the residual results are often less than 0.5°C, according to the findings of the WCC performance test. However, with the solution without WCC, the residual results under normal working state might be greater than 1°C, occasionally even reaching 4°C, due to the change in wind condition. These findings show that monitoring can produce early failure alarms using WCC.

4.1.3 | Gearbox and bearing health

The gearbox has the longest downtime per failure of all the parts of a wind turbine. When a failure occurs, the downtime can reach a maximum of 55.2% of the annual downtime and the energy loss can reach a maximum of 52.0% of the annual output. A physical model for gearbox problem identification based on the correlations between temperature, efficiency, rotational speed, and power production was proposed by Feng et al. [19] after summarising the typical failure types of wind turbine gearboxes. Using low-speed SCADA data, this technique is appropriate for long-term gearbox fault identification.

In order to precisely replicate the lubrication pressure of a healthy gearbox, Wang et al. [20] created a data-driven model utilising Deep Neural Networks (DNN). The DNN model was found to be the best accurate for simulating gearbox lubricant pressure after comparisons were made between six of the most popular data mining algorithms. Before a defect manifests, the Absolute Percentage Error (APE) of the DNN will vary. The guidelines for monitoring lubricant pressure were developed using an Exponentially Weighted Moving Average (EWMA) chart in order to detect changes in the APE.

Turbine bearings are essential parts, and dynamic and unpredictable pressures can cause early bearing wear, increasing turbine maintenance costs and raising the possibility of unexpected turbine failures. By analysing historical data from wind turbines, Kusiak et al. [21] suggested employing neural network techniques to create bearing failure prediction models. In the study, supervised learning was done using the Weighted Best First Search Wrapper (WBFS) approach, which used 10-fold cross-validation to identify the parameters that were most important for predicting generator bearing temperature. The association between input parameters and generator bearing temperature during typical behaviour was captured by the neural network technique through optimisation. To examine model error residuals and foretell overheating episodes, a moving average window was used. 1.5 h prior to a failure occurring, overheating events were expected.

In order to characterise the behaviour of wind turbine gearboxes and generators and to predict operational anomalies using statistical process control (SPC), Santolamazza et al. [22] created a model employing artificial neural networks (ANN). Italian wind turbines were used to assess the effectiveness and applicability of the suggested strategy. In addition to wind speed, ambient temperature, and standard deviation of wind speed, which, albeit to a lesser extent, contribute to the performance of the model, are also employed as inputs in the FFNN model used to monitor output power. A control chart of Power Output deviations is presented in Figure 4 as an illustration of how this model might be used.

Figure 5 presents a control chart of power output deviations using this other reference model. By the comparison between

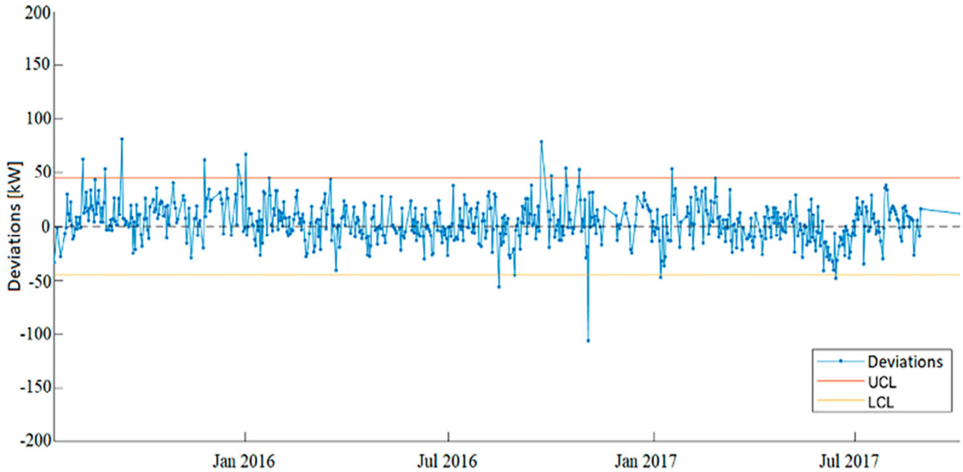

FIGURE 4 Control chart of power output deviations using the ANN model.

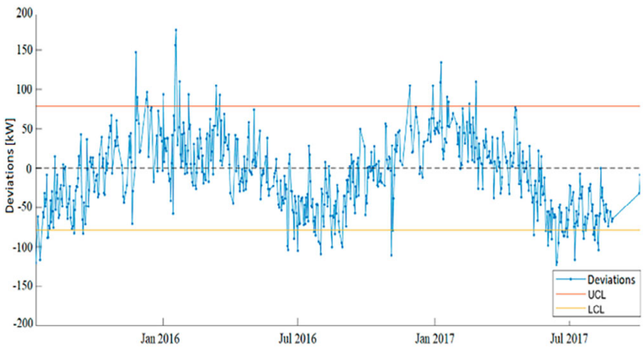

FIGURE 5 Control chart of power output deviations using the non-linear regression model.

the two models, it is clear that the first one, the ANN model, is able to overcome the issue of seasonality, assuring a better representation of the behaviour of the wind turbine.

4.2 | Performance analysis and optimisation

Analysing performance data across multiple turbines or wind farms allows for performance benchmarking. This can help identify best practices and standardise operations across the fleet, leading to more consistent and reliable performance. Besides, continuous monitoring of turbine performance can help identify issues early on before they become major problems. This not only prevents equipment failures but can also extend the useful life of the turbines, resulting in significant cost savings.

4.2.1 | Power output and efficiency analysis

In the field of wind energy, the power curve of a wind turbine represents a key characteristic, linking the wind speed at hub height to the power output of the turbine. Accurate modelling of this power curve is crucial for accurately predicting the power generation of wind turbines. Pandit et al. [23] introduced the application of Quantile–Quantile (QQ) plots in assessing the Gaussian process-based error distribution function of wind turbine power curves. The study verified that using QQ plots as an assessment tool can help understand the accuracy and reliability of the prediction models applied to the wind turbine power curves. In statistical models, identifying the correct distribution function is key to its performance. Therefore, accurate assessment of the distribution function plays a crucial role in state monitoring using Gaussian Process (GP). The 'goodness of fit' between a collection of observed data and a theoretically postulated distribution may be intuitively assessed using QQ plots, which lends them practicality. In order to determine if the anticipated GP power curve adhered to the assumed Gaussian error distribution, the study presented the QQ plot. The study shows how QQ plots can be used to identify specific sources of non-normality, such as skewness, heavy tails, or multimodality, which may indicate problems with the underlying model or how well the results conform to the assumed Gaussian error distribution. The study emphasises how these insights can be applied to enhance the GP model, resulting in estimates of wind turbine power that are more precise and effective [23].

An advanced technique for forecasting wind turbine power output is presented by Mehrjoo et al. [24] using a model based on the principles of monotonic regression. Traditional power curve modelling techniques frequently run into issues with overfitting and non-linearity. The research suggests utilising monotonic regression to address these issues because it preserves trend direction and is thus appropriate for the wind turbine power curve's intrinsic monotonicity. By doing this, the training model's data set is not reduced as a result of deleting data that leads to non-monotonicity from the training data, which can have unintended consequences. In the study, the power curve fitting method's inherent need for monotonicity lessens the influence of outliers on the predicted curve. This approach is a useful way to describe the power curve of wind turbines and can increase the predicted accuracy of the fitting

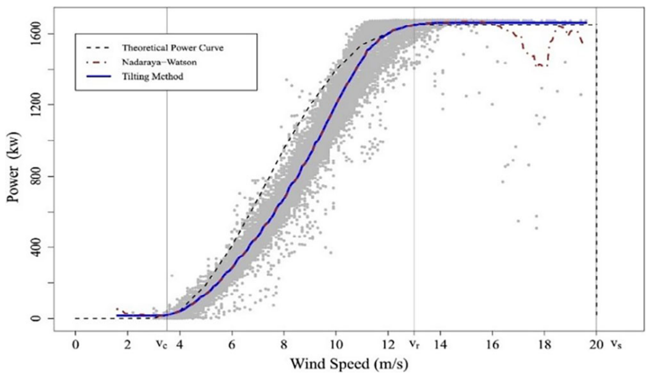

FIGURE 6 Effect of tilting method on the Nadaraya–Watson kernel estimator [24].

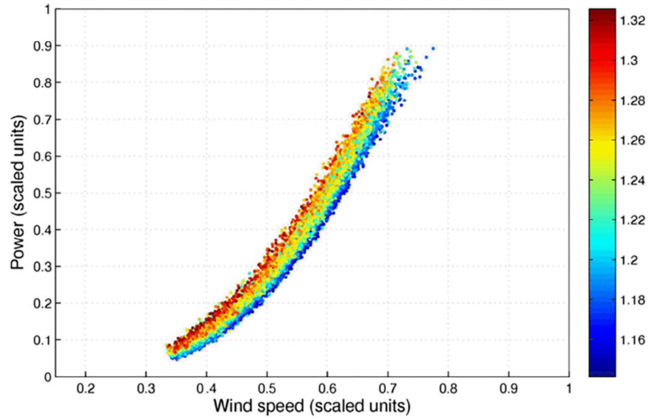

FIGURE 7 Scatter plot of filtered 10-min average wind speed and power measurements [25].

curve. By applying the monotonic regression model to real wind power generator data, the paper discusses the iterative process of determining the optimal power curve and presents the output in a visual way to show improved fitting compared to traditional methods. Cross-validation and sensitivity analysis are carried out to test the model under different wind conditions and turbine types. The results of this validation process show that the monotonic regression model provides better fitting and more accurate power predictions than traditional power curve models [24]. Figure 6 shows the Nadaraya–Watson kernel estimator and its corresponding monotonised curve. One can notice that in monotone regions both fitted curves are essentially the same; however, in non-monotone regions there exist some differences between fitted curves.

An approach for early failure identification of wind turbines using a no-fault behaviour model of the turbine was proposed by Butler et al. [25]. The relationship between weather observations, turbine sensor observations, and the average power produced by the turbine is included in the model. The trained model is then used to track the performance of the associated turbine after modelling using the no-fault behaviour. The properties of the residual signal, which is the difference between the turbine's predicted and actual power output at each time step, are used to identify faults. The authors found a 16% decrease in the root mean squared error when predicting turbine power output using both wind speed and air density, as opposed to using simply wind speed as a model input. This led them to recommend utilising air density as an input. The output power generated for a given wind speed climbs as the air density value rises, as shown in Figure 7, clearly demonstrating.

A multivariable input power curve model with an enhanced Gaussian process method was introduced by Guo et al. [26]. The power curve model prediction residuals were analysed using the Sequential Probability Ratio Test (SPRT) approach, which also produced wind turbine operation alerts. The usefulness of the suggested power curve modelling and monitoring method was demonstrated by the presentation of two wind turbine case studies, one including an anemometer failure and the other involving a pitch control failure. Using penalty factors and slack variables in the computation, Yang et al. [10] proposed a model based on Support Vector Regression (SVR) for rebuilding models to forecast early failures in components. The study also showed that the SVR algorithm can, to a certain extent, filter out noise in the training data and recognise outliers during model formation.

4.2.2 | Turbine control and pitch optimisation

The pitch control system plays a vital role in this process, adjusting the angle of the turbine blades according to wind speed variations. These adjustments optimise power generation, protect the turbine from damaging wind speeds, and ensure system stability.

The effectiveness and performance of wind turbines can be considerably improved by using optimisation approaches, according to Biegel et al. [27]. Pitch control optimisation's main objective is to increase power output in light to moderate winds and safeguard the mechanical structure of the turbine in strong gusts. In order to do this, modern turbines use sophisticated control techniques like Model Predictive Control (MPC) and adaptive control. To forecast future behaviours and optimise control inputs, MPC uses a mathematical model. Contrarily, adaptive control modifies control parameters in response to changes in the system. These techniques have successfully improved turbine power output and decreased mechanical stress. Use Sequential Convex Programming (SCP) to locate local solutions to the non-convex multi-objective optimisation issue of maximising average output torque while maintaining uniformity and minimising fatigue load [27]. Physical models and data-driven models are examples of conventional methods for fault detection in wind turbine pitch systems that have limitations. Due to the intricacy and non-linearity of wind turbines, physical models frequently have trouble. Contrarily, data-driven models like Artificial Neural Networks (ANNs) or Support Vector Machines (SVMs) would need a lot of training data and computer capacity, which is sometimes not feasible.

The Relevance Vector Machine (RVM) regression approach was suggested by Wei et al. [28] as a novel Normal Behaviour

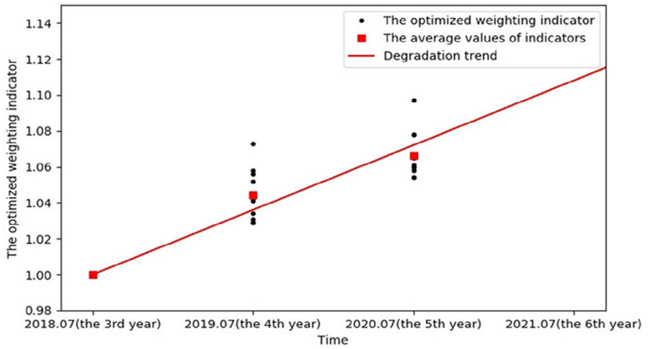

FIGURE 8 The degradation trend of pitch systems [29].

Modelling (NBM) technique. With fewer basis functions, it can attain accuracy comparable to SVM, resulting in a sparser and more understandable model. The Artificial Bee Colony algorithm's kernel function is used to modify the RVM model's parameters. The encoder, slip ring, and motor failures that commonly occur in variable-pitch systems can all be quickly identified using the suggested method.

For monitoring SCADA data and evaluating fault data, Wei et al. [29] established four independent ageing indicators, namely functional, energy consumption, temperature, and reliability indicators. They also proposed an ageing evaluation approach for the wind turbine electric pitch system. The suggested method can gauge how much the pitch systems degrade each year. The degradation trend of the pitch systems during their life cycle can be determined with enough degradation-degree data. The line is fitted using the annual average values of ageing markers, as seen in Figure 8. The ageing indicator in this instance will rise by 0.036 each year.

4.3 | Predictive maintenance and reliability analysis

4.3.1 | Failure prediction and preventive maintenance

By performing timely maintenance, anticipating downtime, spotting anomalies, and aiding in the diagnosis of different failure types, predictive maintenance can assist managers in bridging the gap between reactive maintenance and planned maintenance. Extreme Gradient Boosting (XGBoost) and Long Short-Term Memory (LSTM) were utilised by Udo et al. [30] to create a model that represents the typical behaviour of wind turbines. The discrepancy between the healthy wind turbine model and the gathered data is compared using SCADA data in this model. The Statistical Process Control (SPC) control chart is used to track these variations; data points that are above the permitted failure threshold are regarded as anomalies. The model is trained using fresh data from several wind turbines with failure statistics, and following validation, it is deemed ready for real-time monitoring.

Using clustering and box plot approaches, Rodriguez et al. [31] established a method for spotting abnormalities in SCADA data and identifying incorrect behaviours of wind turbines. This data-driven strategy attempts to enhance predictive maintenance and successfully identify anomalous behaviours. The K-means algorithm is used in the study to determine the ideal number of clusters. The silhouette criteria is the parameter used in the MATLAB function 'evalclusters' for this purpose. In order to determine the mean, quartiles, maximum and minimum values, and outliers, the box plots of the variables are utilised. Points that fall outside these boundaries are referred to as anomalies and can help identify potential flaws.

Full Signal Reconstruction (FSRC) and AutoRegressive model with eXogenous inputs (ARX) are two Normal Behaviour Modelling (NBM) strategies that were compared by McKinnon et al. in their article [32]. To examine the effect of the training time on each model's capacity to detect anomalies, the models trained using 12 months and 6 months of data were compared. A moving window and a sliding window were both used to compare the models in order to better examine the absolute inaccuracy. The NARX and NN models were compared in Figure 9 using training data from 12 months of 10-min averaged SCADA data. The daily sliding window is shown in Figures 9a and 9b, and the daily moving window is shown in Figures 9c and 9d. The RMSE for the training period is represented by the light-yellow lines, while the RMSE for the testing period is represented by the dark-brown lines. It is clear that the RMSE of the NARX models is lower than that of the NN models. Overall, their peaks seem to occur at the same times, but the NN's peaks seem higher [32].

Unsupervised clustering was utilised by Zhao et al. [33] to predict the Remaining Useful Life (RUL) of wind turbines. In order to more clearly see the fault development trajectory of wind turbines, the Abnormal Operation Index (AOI) idea was put forth. Before a problem developed, the wind turbines' performance degraded for roughly 44 days. Other wind turbines also experience this phenomenon. The forecast accuracy of RUL for the five turbines experiencing generator fault is shown in Figure 10a. Figure 10a illustrates the overall pattern that the average prediction accuracy rises as the lead time needed for repairs and maintenance reduces. The graph has a small random variation due to the functioning of wind turbines, but the general trend is still evident. The average accuracy is displayed in Figure 10b. The accuracy increases as the number of days employed to anticipate in advance decreases, as illustrated in Figure 10b. More specifically, if the necessary repair and maintenance lead-time is 18 days out, the average prediction accuracy is roughly 80% [33].

The diagnostic performance of four classifiers on the basic behaviour of wind turbines was compared, and whether these classifiers are applicable to generator fault diagnosis was discussed.

Table 3 shows the accuracy of different classifiers. The best performance of different classifiers is indicated in bold print. As Table 3 demonstrates, overall, there is no best classifier for maximising $\boldsymbol{TPR}$, $\boldsymbol{TNR}$, and $\boldsymbol{ACC}$ simultaneously. The main reason is that the different classifiers are suitable for various scenarios.

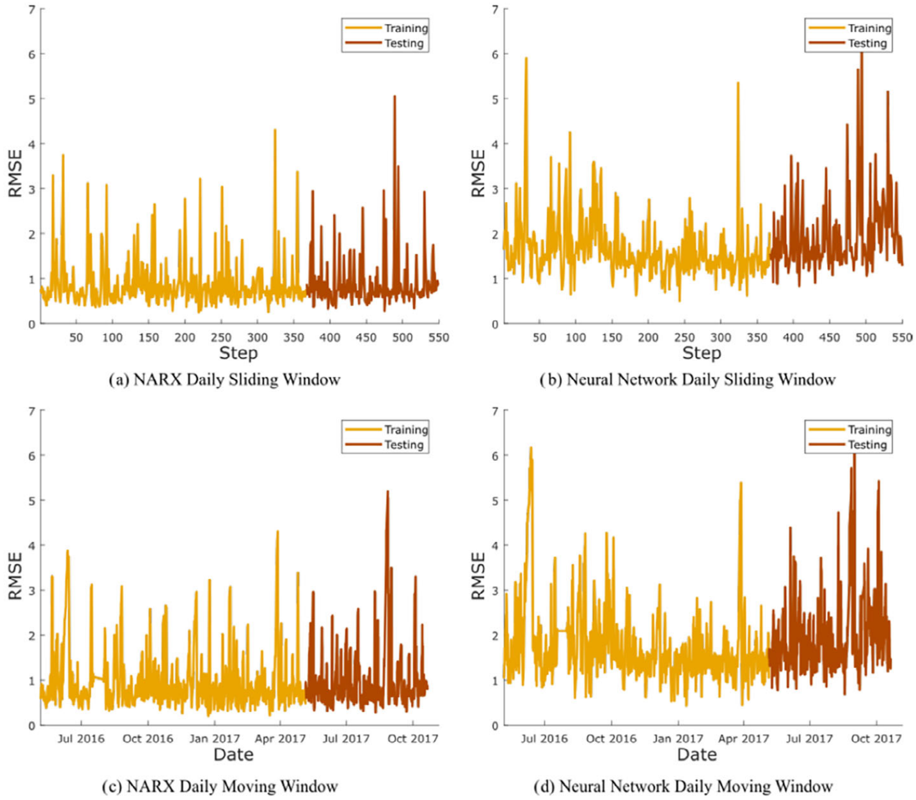

FIGURE 9 Comparison of RMSE for NARX vs. neural network considering 12 months training period and 10-min mean data resolution [32].

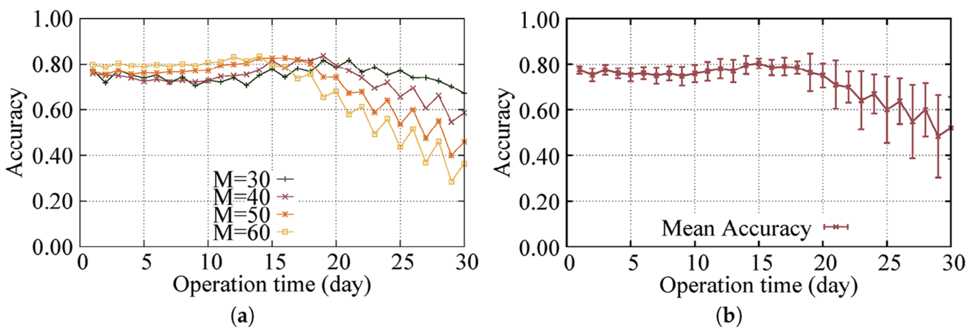

FIGURE 10 Prediction accuracy of RUL with different days ahead (a), mean prediction accuracy of RUL (b) [33].

TABLE 3 Classification accuracy for different algorithms [33].

	ANN	KNN	SVM	Naive Bayes
TPR	0.7115	0.2741	0.4025	0.4198
TNR	0.9859	0.9975	0.9936	0.9827
ACC	0.9821	0.9759	0.9796	0.9642

TABLE 4 Comparative analysis of machine learning models for gear bearing [36].

	ANN	SVM	LR
Correct prediction	72.5%	60%	59%
Missed failure	20%	36%	31%
False positive	7.5%	4%	10%

The ANN classifier performs best in identifying ***TPR*** and ***ACC***, as it is based on the data characteristics of finding the non-linear relationship between the feature and the corresponding status (Table 4).

4.3.2 | Remaining useful life estimation

To determine how long a wind turbine will operate, Dimitrov et al. [34] suggested a regression model based on an ANN with three hidden layers, trained with a lot of load data. By combining SCADA data, correcting for wind observations, and applying an alternative model based on simulation to take into consideration the impacts of wake flow, it is possible to accurately anticipate power production and load time series. A regression model that has been trained and estimated wind-free conditions are used to predict load. By contrasting the expected power output with the SCADA records that are readily available, the model's performance is confirmed. The findings indicate that, both at the wind farm and individual turbine levels, there is a strong correlation between anticipated and measured power output. When providing measured load time series of rotor speed, power generation, wind speed, pitch angle, and tower top acceleration, the alternative model successfully reproduced the load time series of the leaf root and tower base components [34]. Additionally, Dai et al. [35] created four ageing evaluation criteria by optimising the weighting factors based on professional opinions, in order to characterise the ageing problem of wind turbine units from various angles. They created an ageing evaluation approach using a blend of traditional and informational methods on the basis of this. Finally, using actual SCADA data gathered from wind farms, the effectiveness of the suggested method in evaluating ageing was tested.

A novel approach for estimating the usable life left in wind turbine gearboxes using machine learning techniques is presented by Carroll et al. in [36]. This study uses substantial tagged SCADA and vibration data from wind turbines to anticipate the failure and remaining usable life (RUL) of gearboxes in contemporary multi-megawatt wind turbines. The study finds that in terms of failure and RUL prediction, artificial neural networks perform better than conventional tried-and-true machine learning techniques. The investigation shows that SCADA data can reliably foresee failure 1 month in advance, and high-frequency vibration data can increase this capability to 5 to 6 months. Depending on the failure scenario, two-class neural networks trained using SCADA data may accurately forecast gearbox breakdowns 72.5 to 75% of the time. When trained using vibration data, this accuracy rises to 100%. Also mentioned are data patterns that precede failure and the weighting of SCADA data inputs [36].

5 | DATA ANALYTICS TECHNIQUES FOR SCADA DATA

5.1 | Data pre-processing and cleaning

Due to measurement, transmission, control, and wind curtailment, many anomalous data arise throughout the gathering of WT data. This has no practical application value for the expected state, or it influences the WT's power prediction. For WT power forecast and health management, it is crucial to properly evaluate wind turbine data and identify problematic circumstances.

The power characteristic in Figure 11, which is depicted by the curve of wind turbine output power changing with wind speed, is a significant indicator of the fundamental performance

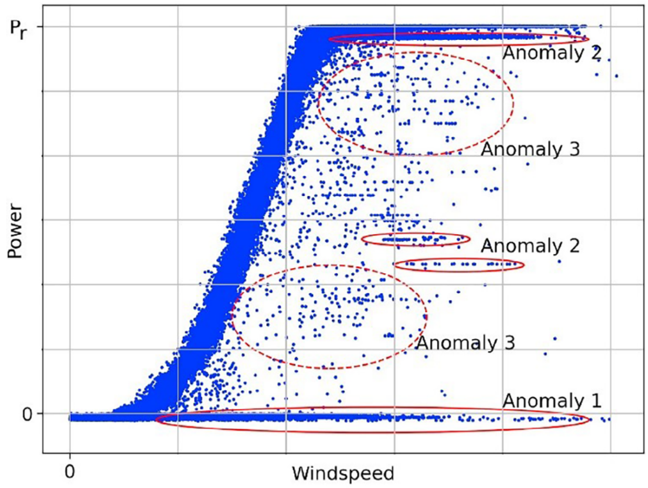

FIGURE 11 Anomalies in SCADA [37].

of a wind turbine. According to the operation status of the wind turbine unit, data anomalies are split into three categories, and their typical characteristics are as follows:

- The horizontal accumulation data at the bottom or middle (Anomaly 1 and Anomaly 2) are referred to as accumulation points. Anomaly 1 data is typically produced when a wind turbine stops operating for maintenance or when the wind speed is below the cut-in speed, which prevents the wind turbine from producing energy. Over a particular time period, the output power of these locations is negligibly low or zero. Anomaly 2 data is frequently brought on by man-made power outages, communication breakdowns, etc., with output power being lower than usual and not varying much (or at all) with wind speed over time. Although they do not immediately show whether there is an anomaly in the wind turbine unit, these points will have an impact on the predictions. Based on human experience [37], these two forms of aberrant data can be deleted.
- In anomalies, the abnormal data is spread at certain spots (Anomaly 3). Sensor anomalies, random noise, and changes in operational circumstances are the main culprits. The outlier data fluctuate at random rates. The performance forecast accuracy of wind turbines will be impacted when the percentage of outlier data is high and the dispersion is significant, even though it somewhat mirrors the real working conditions. Additionally, there are continuous outliers in the timing sequence that result from frequent control switching caused by the extreme volatility of the operating conditions, although the major parameter changes with wind speed defy physical principles. Thus, in addition to wind power, the corresponding characteristic factors should be taken into account when cleaning the data. Use correlation analysis tools to find important variables and spot outliers [37].

An SCADA data pre-processing technique based on the Thompson tau-local outlier factor (TTLOF), which eliminates outliers by parameter correlation, was proposed by Yao et al.

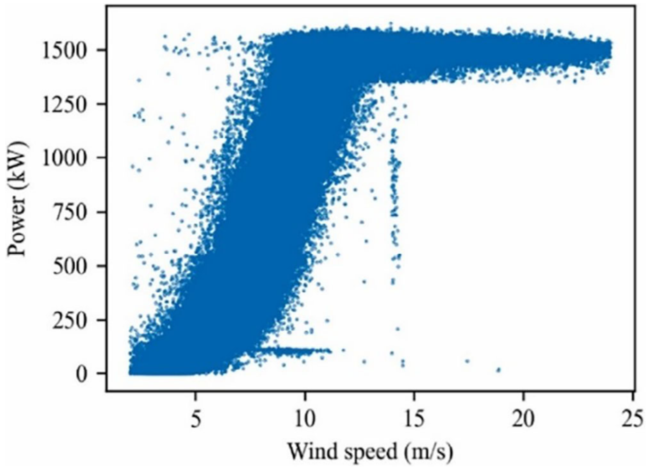

FIGURE 12 Wind turbine power curve scatter plot after filtration [38].

[38]. First, data from manually curtailed power is removed using the correlation between wind power and pitch angle based on the workings of wind turbines. The ECMI approach is then utilised to choose pertinent parameters for the evaluation of aberrant feature using the wind power as the observation point. In order to filter away outlier data, these factors are paired with wind power and integrated into a high-dimensional space, from which the local density is determined. The data of the wind turbine SCADA system can be processed with data such as wind speed, active power, generator speed, and pitch angle. Firstly, outliers whose speed is less than or equal to 0 and whose wind speed is outside the cut-in wind speed or cut-out wind speed need to be deleted. Secondly, the data is processed by selecting threshold of pitch angle in the allowed power range at the rated power (Figure 12). Those points which exceed the pitch angle threshold and the allowed power range are discarded. Thirdly, the scatters whose powers are less than 10% of the maximum power and whose pitch angles are greater than 2° are removed. The pre-processed wind speed and active power scatter points are shown in Figure 3. However, it is found that some anomalies still remain, and further data processing is required [38].

In order to eliminate outliers based on parameter correlations, the data were further cleaned using the TTLOF approach [38]. Below is written the TTLOF method's defined process.

- Using ECMI, relevant parameters were chosen and prioritised.
- Equal intervals are created within the wind speed. Each parameter's mean value, standard deviation, and absolute deviation are calculated. And in order to find anomalous points, the anomaly coefficient is obtained. Until the outliers could not be filtered out, the step is repeated.
- Additional processing is done on the previously unfiltered points. All points are subjected to the outlier quantisation in accordance with the local outlier factor. The outlier threshold identifies the outliers.

Binning has been used by Astolfi et al. [39] to analyse measurement channels associated with the rotor and blade pitch control in the polynomial regression of the power curve of wind turbines. The fundamental conclusion of this study is that rotor imbalance and the observed much lower performance of hydraulic pitch turbines compared to wind turbines are both thought to be connected to the gradual decline in pitch pressure. According to the data gathered for this study, wind turbines' hydraulic pitches are delicate parts that need to be closely regulated. The average generator speed-power curves of the two wind turbines with the biggest performance discrepancies are shown in Figure 13 in terms of differences from 2017 for the years 2019 and 2021. In both T2 and T4, the power output for a certain generator speed declined over time in 2019, although it at least somewhat increased in 2021 (Figure 14).

In 2017, 2019, and 2021, wind turbines T2 and T4's average pitch manifold pressure and generator speed were compared using the function shown in Figure 15. In contrast to wind turbine T4, which has an increasing pressure over time for a particular generator speed, wind turbine T2's pressure gradually lowers over time. This research suggests that hydraulic pitch control may be to blame for the performance reduction of wind turbines.

The most recent improvements in data-driven models for condition monitoring and preventive maintenance of important wind turbine components were examined by Pandit et al. [40]. They noted that while generators, which are more crucial for wind turbine failures, are understudied, the health status research on hydraulic blade pitch is still in its infancy. The literature on gear and bearing condition monitoring predominates, they said, but there is less on these components. To get beyond the vibration data's complexity and boost prediction accuracy and specificity, multi-time-scale data is used. The types of wind turbine failures (bearing failures, gearbox failures, generator failures, pitch system failures, and yaw failures) were evaluated along with research methodology.

5.2 | Statistical analysis and anomaly detection

Generally, fault detection approaches can be divided into model-based methods and data-driven methods. The data-driven model methods use data mining techniques, such as artificial intelligence algorithms to capture discrepancies between observed data and that predicted by a model.

Zhao et al. [41] propose using Denoising Autoencoders (DAEs) for fault analysis and anomaly detection in wind turbine components. The DAE model captures the turbine's dynamic behaviour and is trained with WT data. The reconstruction error of the model determines component health. Abnormal detection and fault location are achieved using a condition index, adaptive threshold, and input–output residual. The DAE leverages reconstruction errors from SCADA data, even during normal operation with variable wind speed. An adaptive threshold prevents false alarms, and tracking the reconstruction error enables early flaw detection. Extreme value theory designs a threshold for abnormal detection and condition evaluation. The DAE outperforms a neural network model, detecting faults over

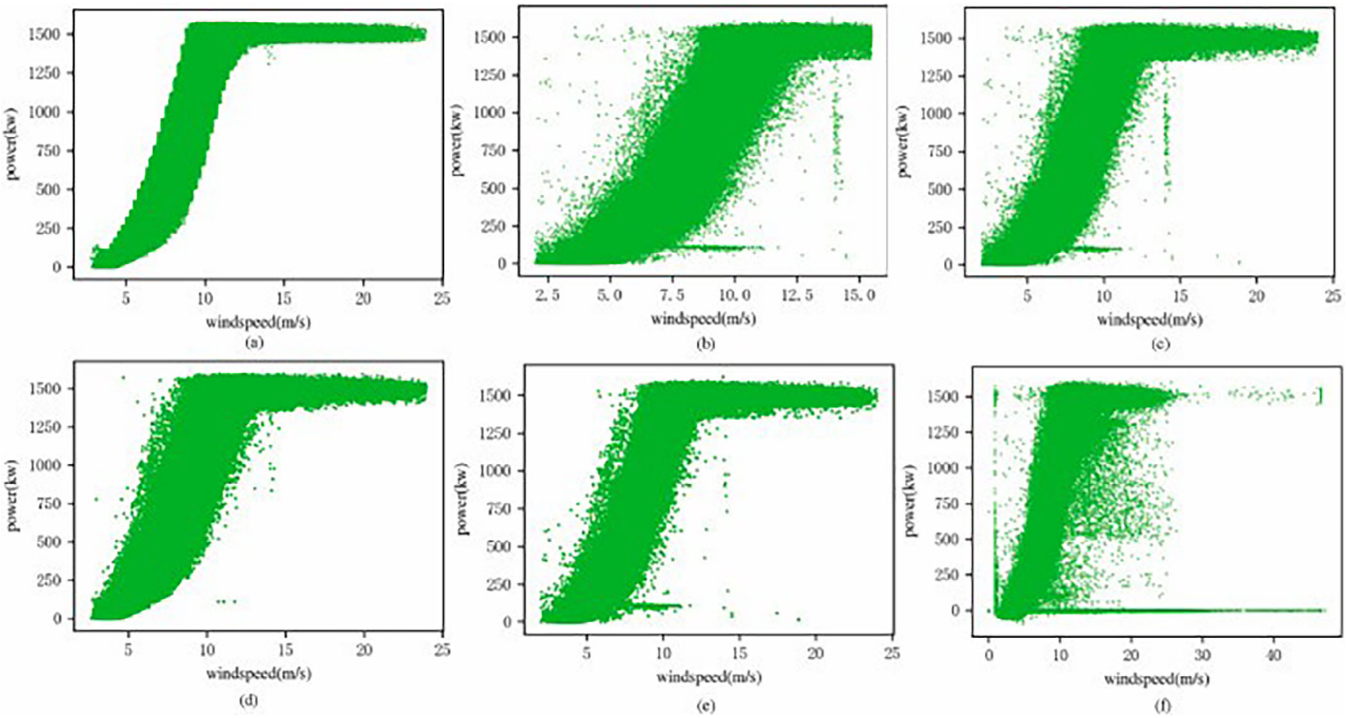

FIGURE 13 The scatters of the wind speed and the power using different cleaned methods. (a) The proposed method; (b) the quarterback method; (c) cleaning method based on pitch angle; (d) TTLOF algorithm; (e) LOF algorithm; (f) the raw data [38].

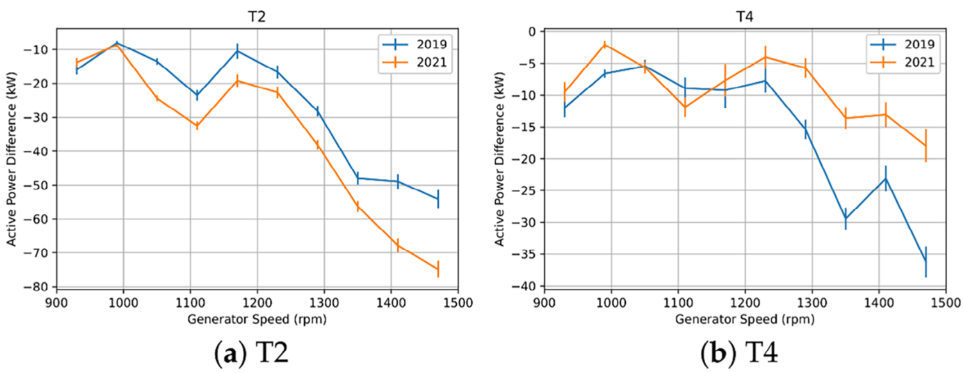

FIGURE 14 The average yearly generator speed–power curve: years 2019 and 2021 in the form of difference with respect to the year 2017 [39].

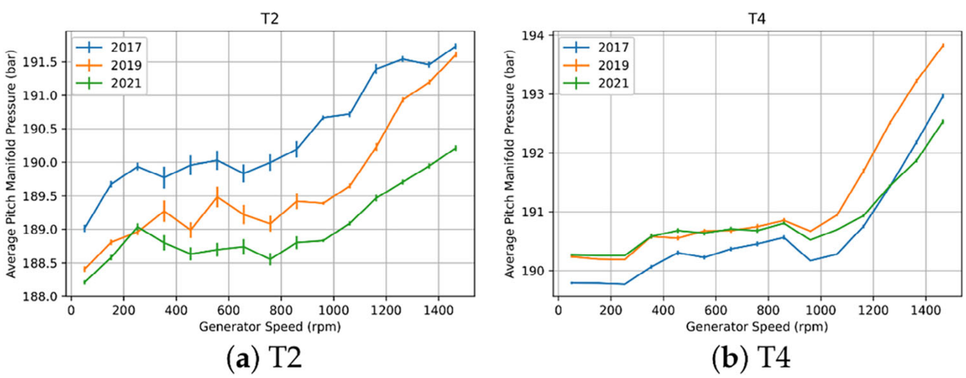

FIGURE 15 The average yearly generator speed–average pitch curve [39].

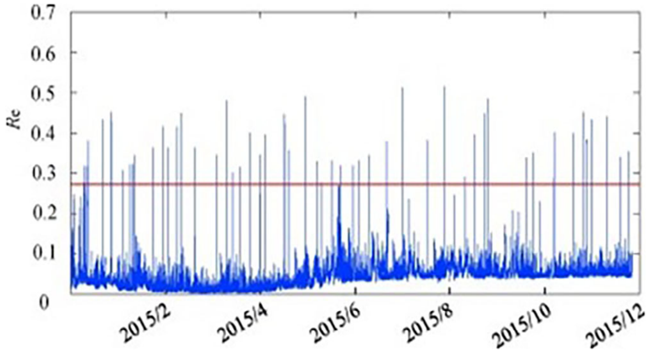

FIGURE 16 Reconstruction error of wind turbine generator under normal condition [41].

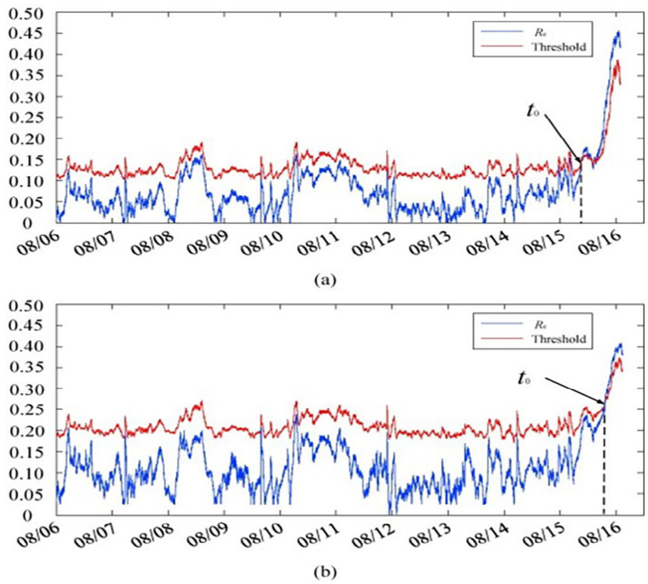

FIGURE 17 Control chart of wind turbine gearbox (a) by DAE network, (b) by NN [41].

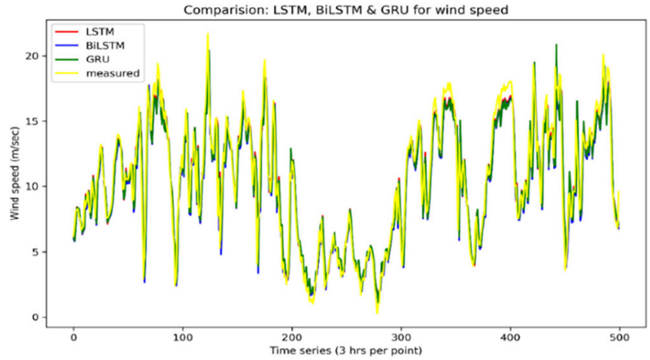

FIGURE 18 Performance comparison: wind speed [43].

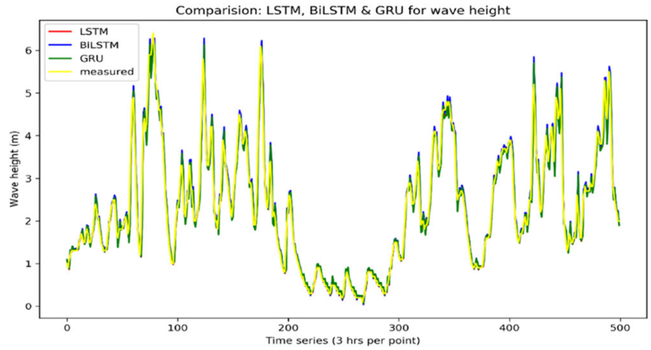

FIGURE 19 Performance comparison: wave height [43].

14 h ahead of downtime and nearly 10 h earlier than the NN (see Figures 16 and 17). This highlights the DAE's superior accuracy in describing wind turbine component behaviour.

Wind turbines plagued by yaw problems could continue to run for many years without producing distressing disruptions, according to Astolfi et al. [42]. The remaining life of the machine may be impacted by these faults, which have a certain non-negligible impact on wind energy conversion efficiency total working times. The accuracy of yaw error inspections can be increased by adding more downwind sensors, but the expense is prohibitive. Furthermore, it is impossible to tell from SCADA data whether the rotor is correctly oriented in relation to the incoming wind. As a result, it is difficult and worthwhile to do research to detect yaw problems in wind turbine systems using data-driven models based on SCADA data.

A recent study [43] indicates that underperformance reliably signals the impact of yaw error on wind turbines. Data-driven analysis of power curves can detect yaw faults, but ruling out machine-specific processes can be challenging. Multivariate power curve models address this issue but pose interpretation challenges. Causality tests can determine the relationship between power output and yaw error, with future research focusing on operational factors and structural responses linked to yaw errors. Additionally, distinguishing system yaw errors from deviations can be done using measurements from the nacelle anemometer. Pandit et al. [43] propose using sequence data-driven models (LSTM, BiLSTM, GRU) to enhance offshore O&M through weather forecasting. These models exhibit similar accuracy in predicting wind speed and wave height, with GRU being faster but less accurate compared to LSTM and BiLSTM, making them suitable for larger datasets as shown in Figures 18 and 19.

Pandit et al. [44] present a Gaussian Process (GP) technique for wind turbine condition monitoring, using rotor speed to derive a rotor curve. The developed GP model is compared with the binning technique to identify operational anomalies, and a comparative analysis highlights the strengths and weaknesses of each approach. Optimising the hyperparameter values of the squared exponential covariance function is necessary to reflect correlations in the processed rotor curve data. The GP model closely follows the binned and measured rotor power curve, with low uncertainty within the cut-in and rated wind speed range. However, above rated wind speed, limited SCADA data result in a less well-determined GP curve, showing some mismatch with the binned rotor power curve. This emphasises the importance of an optimal dataset size for accurate

GP modelling, considering the trade-off between data volume, complexity, and processing costs.

5.3 | Big data analytics and cloud-based solutions

According to Abdallah et al. [45], they developed bagged decision tree classifiers that can better tolerate noise and forecast the likelihood of excessive vibration. Ignore routine activities first, then locate every leaf node that has the relevant fault categories. Once the nodes have been sorted and filtered based on relevance, pathways including target fault leaf nodes are retrieved in order to pinpoint the underlying issue. To handle the continually changing system and system feedback behaviour, the framework additionally employs an object-oriented decision tree learning technique. Wind turbines are regarded as a multi-layer object system built on super-abstract classes. In order to assess conditional probabilities and produce an updated risk indicator for potential component failures, the decision tree classifier is further translated to a Bayesian network.

When used to monitor tiny wind turbines, IoT and cloud computing technologies performed best in real time, according to Akyuz et al. [46]. The software transfers data to the Microsoft Azure cloud computing system using data loggers and Raspberry Pi gateways. Thus, visualisation is made possible with the aid of the cloud system, providing real-time data monitoring and performance evaluation across many platforms. Data from the user interface, including wind speed, current, voltage, turbine rotation speed, and input torque, were measured. These statistics were used to compute the power coefficient, alternator efficiency, and wind turbine output. The entire information was displayed on a single GUI platform. Different users can easily make instantaneous data interpretation and visualisation via platforms such as mobile device and can analyse historical data from the SQL database.

Roy et al. [47] introduce a Cloud-Based Real-Time Monitoring System (CRMS) that employs a wireless sensor network for early fault detection in wind turbines. The CRMS incorporates vibration and temperature sensors to identify faulty motors, issue timely fault warnings, and enable intelligent maintenance for motor longevity and prevention of equipment damage. Result suggests that accelerometer and gyroscope data clearly demonstrate the amplitude disparity between a healthy generator and one with bearing faults. Vibrations increase noticeably at a frequency of 50 Hz during bearing faults.

IoT-based technologies offer opportunities to improve efficiency and reliability in wind energy microgrids. Real-time monitoring and control enable downtime reduction, resource optimisation, cost savings, and lower maintenance needs. Li et al. [48] summarise research on IoT-based wind energy microgrid management and control techniques. They emphasise the use of historical and real-time data for energy production prediction, facilitating microgrid operation adjustments to maximise renewable energy utilisation and reduce dependence on traditional sources. Additionally, they propose blockchain technology as a means to enhance security and transparency in microgrid transactions, promoting the adoption of renewable energy and facilitating the transition to a sustainable energy system.

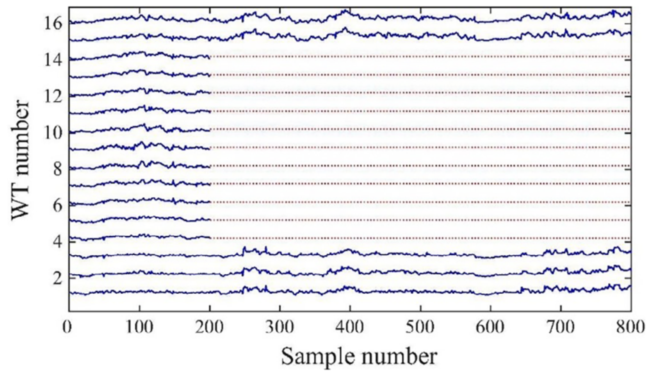

FIGURE 20 An example of wind speed data missing case in large-scale WTs [49].

6 | CHALLENGES AND LIMITATIONS

6.1 | Data quality and integrity issues

Data integrity and quality problems can come in a variety of forms [46]:

- *Sensor Defects*: To assess vital operational factors including wind speed, direction, temperature, and vibration levels, wind turbines rely on sensors. Inaccurate system performance brought on by malfunctioning sensors might result in unneeded system shutdowns or even catastrophic failure.
- *Errors in data transmission*: Since wind turbines are frequently positioned in remote areas, data from these turbines must be sent to a centralised place for processing. Data loss or corruption can be caused by problems with communication networks.
- *Inaccurate data logging*: Data logging errors are inevitable because of noise. Signals in real-world applications are invariably tainted by measurement noise in addition to other sources of variability and uncertainty, such as transmission problems, calibration concerns, or misalignment between recorded and actual timestamps. As a result, features that have been retrieved from tainted data may be quite tainted, making it difficult to interpret the features.

Data imputation techniques are required to address the SCADA data in wind turbines' incompleteness. These techniques can be divided into two groups: data mining- and statistics-based [49]. The efficiency of these technologies, however, declines because of the challenging data collection environment present at wind turbines. The estimation of missing data in wind turbines presents unique difficulties. WT data are strongly impacted by the environment's fluctuation, which makes it difficult to forecast missing data accurately. As seen in Figure 20, where multiple turbines have missing wind speed data, it is common to encounter data missing in wind farms with large-scale turbines. This limits the amount of data that can be used for imputation. The wake flow in wind turbines introduces a strong non-linear relationship among the data from different turbines. As a result, simple models fail to achieve satisfactory imputation results in such cases [49].

6.2 | Data security and privacy concerns

Wind-based energy units were once considered immune to cyber-attacks, but in March 2019, a wind power facility in Salt Lake City, USA, fell victim to an attack that disrupted control over 500 megawatts of wind turbines. This incident highlighted the need for robust cyber security measures in the wind energy sector, leading the U.S. Department of Energy to prioritise strategies for protecting wind units against cyber threats [50].

Denial of service (DoS) and deception attacks, such as false data injection, are common types of adversarial actions targeting power and networked control systems. In a DoS attack, the attacker aims to obstruct or interrupt communication channels within the power system. Deception attacks involve manipulating and injecting manipulated signals into the system.

When DFIG-based wind power plants are connected to series compensated transmission systems, a phenomenon known as sub-synchronous interaction (SSI) can occur, posing security risks to wind turbines. However, there are several challenges related to SSI damping [50]:

- The existing SSI damping methods rely on continuous-time measurement and control updates, which impose restrictive assumptions.
- The current SSI damping schemes assume a secure, attack-free environment, which may not hold true in the presence of DoS and deception threats.
- The feasibility of using fuzzy controllers for SSI damping in DFIG-based wind power plants has not been extensively studied.

6.3 | Scalability and computational requirements

The management of data streams gathered by sophisticated condition monitoring devices is a particularly difficult problem. When transferring to big Operation and Maintenance (O&M) platforms, these data suffer from poor scalability due to their high complexity and typical need for specialised knowledge to read them appropriately. Engineers and technicians might not prioritise manually annotating (or creating appropriate automation techniques) to build a corpus for alarm messages that summarise contextual information for low-priority faults, which results in a significant variation in the quality of the available messages across different sub-components. Additionally, because the authors typically apply models to very specific SCADA datasets (which differ greatly in terms of features and specifications), it is extremely difficult to produce meaningful new results and comparisons with baselines [51]. Furthermore, the data used in the papers is typically not shared with the published research.

TABLE 5 Proposal's predictive models vs. based work's ones [52].

Global measure types	Accuracy	Sensitivity	Specificity
Base work	76.50%	77.60%	75.70%
Proposed method	82.04%	92.34%	60.58%

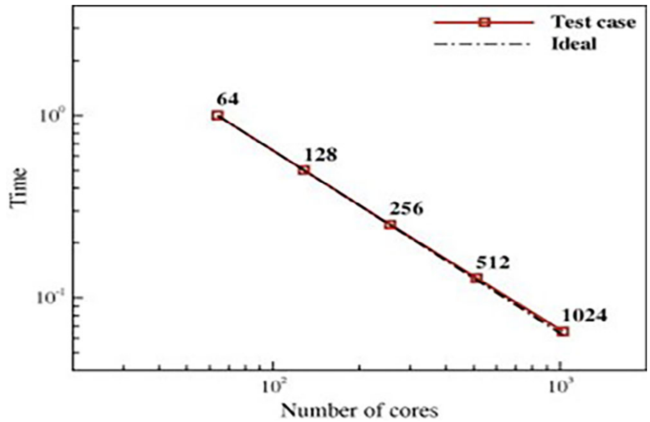

FIGURE 21 Scalability study for turbulent Taylor–Couette flow simulation. The computation time is normalised by the result of 64-processor case [53].

Canizo et al. [52] propose a cloud-based data-driven solution for predicting wind turbine failures. The solution is designed to operate in a scalable cloud computing environment, allowing it to handle increasing data volumes efficiently. The study demonstrates the solution's advantages in terms of speed, scalability, automation, and reliability. Instead of relying on vertical scalability with more powerful hardware, the solution leverages cloud computing and big data frameworks to horizontally scale and process data from numerous wind turbines. The study utilises Hadoop Data File System (HDFS) for offline processing to generate predictive models and Spark Core and Spark Streaming for real-time predictions. Additionally, Spark SQL and Spark's machine learning library (MLlib) are employed for data querying and mining purposes, respectively.

Monitoring agents receive data from wind turbines and provide geographic location visualisation, prediction, and status information notifications. ETL processes are used to eliminate unnecessary data and format it appropriately. The identified status patterns and operational data are combined to create training sets. Six training sets were prepared using the original method, and the random forest algorithm was applied to generate six prediction models. Experiments were conducted to optimise the algorithm's parameters for this specific use case, and each model was saved in HDFS. This approach shows significant improvements, with nearly a 6% increase in global accuracy and a higher sensitivity of 15% for precise failure prediction as shown in Table 5. However, it has a lower specificity of approximately 15%, resulting in more false positives.

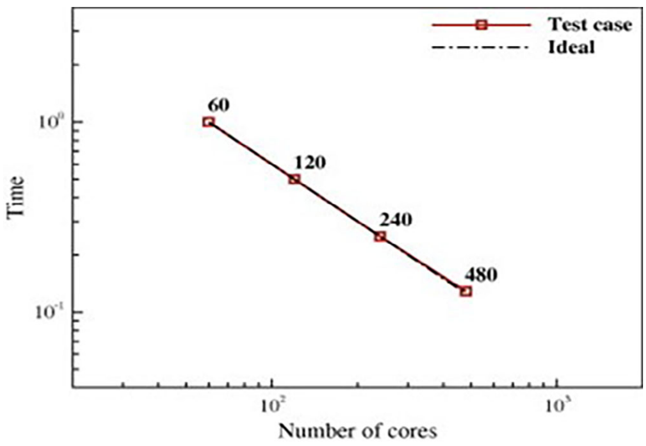

FIGURE 22 Scalability study for wind turbine rotor simulation. The computation time is normalised by the result of 60-processor case [53].

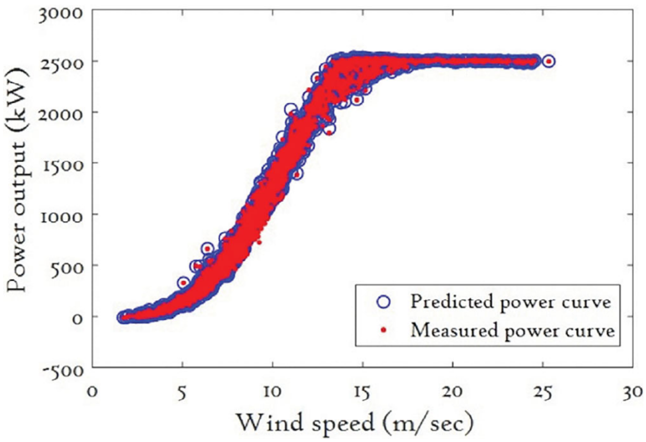

FIGURE 23 GP power curve incorporating rotor speed [49].

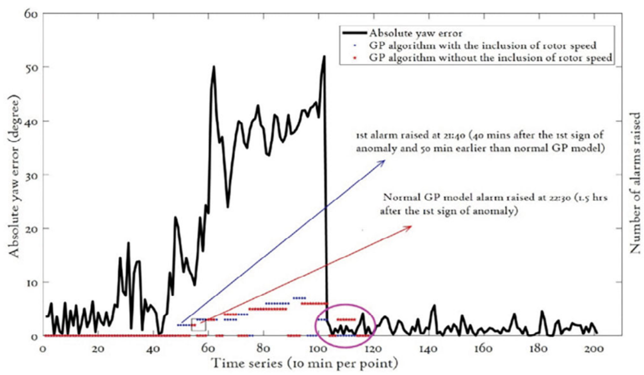

FIGURE 24 Impact of rotor speed on GP fault detection algorithm [49].

TABLE 6 Alarm record and detection by each approach [49].

Model	Time taken to identify the fault
Online power curve model	6 h
Probabilistic assessment using binning	~4 h
Probabilistic assessment using GP	1.5 h

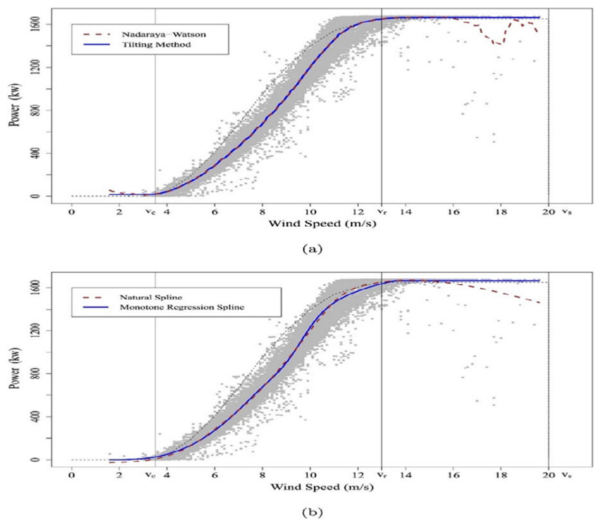

FIGURE 25 Four power curve fitting methods on real data from wind turbines in a wind farm located in Canada: (a) Nadaraya-Watson Kernel Estimator (NWKE) and Tilting Method (TM) applied to NWKE, (b) Natural Cubic Spline (NCS) and Monotone Regression Spline method (MRS) [56].

Hsu et al. [53] propose a high-performance computational framework for advanced flow simulations, based on Residual-Based Variational Multiscale (RBVMS) methods and isogeometric analysis. They have showcased the simulation and parallel scalability results of turbulent Taylor-Couette flow and NREL 5 MW offshore baseline wind turbine rotor, achieving near-perfect linear parallel scaling, as shown in Figures 21 and 22.

7 | CASE STUDIES AND SUCCESS STORIES

7.1 | Real-world applications of SCADA data in wind turbines

As wind-power data are often noisy, even after polishing data using proper methods, fitted wind turbine power curves could be very different from the theoretical ones that are provided by manufacturers. Mehrjoo et al. [24] introduce two nonparametric methods, the tilting method and monotonic spline regression, for constructing wind turbine power curves that maintain monotonicity. They evaluate and compare these techniques with the commonly used power curve fitting methods using historical data from a wind farm in Manitoba, Canada.

In a separate study, Pandit et al. [54] propose a data-driven machine learning approach based on GP for monitoring wind turbine failures. They demonstrate that incorporating rotor speed into the GP model enhances accuracy, as depicted in Figure 23. Additionally, the combined GP model and rotor speed enable automatic detection of yaw errors without false positives. Figure 24 illustrates that signs of yaw errors can be detected within 40 min, significantly improving the early fault detection capability compared to the GP model without rotor speed.

The binned power curve was utilised by Pandit et al. [55] to identify yaw defects and suggest a monitoring system based on the Gaussian Process. By using Fisher's combined probability test, evaluate potentially harmful incoming data point by point against the relevant bin and its uncertainty. To assess the speed and accuracy of anomaly detection, a real-time power curve form is constructed using a modified IEC approach, and both methods are compared using the Gaussian Process model, as shown in Table 6.

A system yaw error detection algorithm is proposed by Astolfi et al. [56] based on the examination of nacelle anemometer signals. Less than 10° of yaw error correction is thought to yield an order of 15% performance gain based on a study of the power curves with and without the systematic yaw error. This study suggests a power–power method based on the relative performance in comparison to the other wind turbines in the farm because the presence of the yaw error affects the nacelle wind speed data.

7.2 | Benefits and outcomes achieved

The modelling of power curves in wind turbines frequently uses non-parametric kernel approaches. The Nadaraya–Watson (NW) kernel regression estimator is a well-known non-parametric kernel estimator of the regression function; however, it does not always maintain the monotonicity of the curve. In order to enforce the monotonicity property, the kernel estimator must be modified. As a result, they have suggested an all-encompassing technique for monotonicity correction that can be used with any curve estimation technique and is also appropriate for other generic kernel estimator techniques. This method can be used to enforce shape requirements in addition to monotonicity. This technique can be used, for instance, to force a wind turbine's theoretical power curve to decline in specified places where the wind speed is specific.

7.3 | Lessons learned and best practices

Models are applied to proprietary wind data from North American wind farms. Figure 25 shows that the tilting method and the monotone regression method result in curves that are more similar to manufacturer power curve as both are monotone in all regions. Consequently, since these two power curve estimators are similar to the manufacturer one, it makes more sense to use these methods in practice.

8 | FUTURE DIRECTIONS AND RESEARCH OPPORTUNITIES

8.1 | Advancements in SCADA systems and data collection techniques

To avoid the studied models being unlearnable due to the usage of specialised datasets, more wind farm owners need to be encouraged to give accessible SCADA data. For the successful development and implementation of extremely complex artificial intelligence models, quality control of the datasets used by the wind energy industry, specifically through data standardisation and the establishment of uniform standards and taxonomies by turbine operators and manufacturers, is in fact essential. To enable informed decision-making even in situations with sparse and unbalanced data, the wind energy sector should concentrate on adopting oversampling techniques more broadly.

8.2 | Integration of SCADA with other emerging technologies

In the wind industry, the application of AI techniques, specifically transfer learning, is crucial for achieving more detailed analysis and accurate prediction of turbine failures. By leveraging knowledge from various sources such as historical alarm message records, operator manuals, and work orders, transfer learning enables the development of high-performance learners even with limited training data. Furthermore, the wind industry can greatly benefit from the use of advanced language models like OpenAI's GPT-2/GPT-3, which have been pre-trained on massive amounts of data. These models can be fine-tuned with custom data, addressing the challenges posed by limited availability and quality of alarm messages [57]. By utilising these models, a more comprehensive understanding of faults and effective O&M strategies can be obtained, surpassing the limitations of brief alarm messages currently prevalent in the industry.

8.3 | Standardisation and interoperability considerations

Wind farm operators could train engineers and technicians in the fundamentals of annotating, analysing, and interpreting information on turbine operational conditions in accordance with a common framework or industry standards that could be created for O&M based on the global agreement of many turbine operators. By giving engineers and technicians specialised resources in this field (such as software applications with interactive graphical user interfaces (GUIs) to simplify the storage, annotation, and analysis of SCADA data, failure logs, and alarm messages) and supporting them with advice and insights from data scientists, it would probably be beneficial to encourage the adoption of data science and analytics techniques in the wind industry [58].

8.4 | Recommendations for future SCADA data utilisation

Enhancing the robustness and accuracy of AI models can be achieved through greater openness in sharing SCADA data, while preserving confidentiality through data anonymisation and non-disclosure agreements [59]. Wider adoption of transfer learning techniques is recommended to overcome the scarcity of quality datasets in the wind energy sector. Developing unified standards, taxonomies, and training personnel to follow them will improve dataset quality. Specialised resources such as software applications with user-friendly interfaces can simplify SCADA data storage, annotation, and analysis.

8.5 | Challenges in consistent SCADA data analysis for wind turbines

The variability in SCADA data from turbine to turbine introduces a significant challenge in accurately discerning between genuine operational irregularities and potential false errors [60]. Operational circumstances, including environmental factors and turbine specifications, contribute to the divergence in the data collected. This diversity complicates the identification of patterns that signify actual issues, making it crucial to develop robust analytical techniques that account for the inherent differences in SCADA datasets [51]. The challenge lies not only in detecting anomalies but also in distinguishing between normal variations and anomalies induced by factors such as sensor malfunctions, calibration issues, or communication errors. Addressing this challenge requires the implementation of advanced statistical methods, machine learning algorithms, and anomaly detection techniques tailored to the unique characteristics of each turbine's SCADA data [61]. By enhancing the accuracy of error identification and minimising false positives, these approaches contribute to more reliable condition monitoring and predictive maintenance strategies in wind turbine operations.

9 | CONCLUSION

Condition monitoring (CM) based on SCADA data holds significant potential for improving wind turbine operations and maintenance. However, pre-processing of SCADA data is necessary, including outlier removal and ensuring data integrity. Early fault detection methods for wind turbines can be implemented through physical models, data-driven machine learning models, and statistical regression models. While data-driven machine learning algorithms offer closer alignment with actual wind turbine operation, accuracy is limited due to the lack of public data and imbalanced datasets.

SCADA data-driven technologies have reduced O&M costs and improved wind power generation, enabling the development of robust decision support systems. This has resulted in fewer maintenance interventions for offshore wind farms. In conclusion, this review paper emphasises the importance of harnessing SCADA data, identifies existing gaps, and presents key findings on its potential benefits for wind turbine applications. The provided recommendations aim to guide the future utilisation of SCADA data, optimising wind turbine operations and maintenance in the wind energy sector.

AUTHOR CONTRIBUTIONS

Ravi Pandit: Writing—review and editing. **Jianlin Wang**: Formal analysis; investigation.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

Data available on request from the authors

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