

SCADA-based early detection of wind turbine yaw motor current failures using Gaussian process surrogate models and Fisher's combined probabilistic alarm thresholding

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ABSTRACT

The reliable operation of wind turbines is critical for generating low-carbon electricity in renewable energy systems. To maximize turbine uptime and minimize maintenance disruptions, smart condition monitoring and early fault detection strategies are essential. Yaw pitch failures, a common cause of performance degradation in wind turbines, are challenging to detect due to the complex relationship between wind speed, yaw pitch current, and grid current. This study proposes a Gaussian Process (GP) regression framework with square exponential covariance functions for early detection of yaw pitch failures in wind turbines. By analysing Supervisory Control and Data Acquisition (SCADA) data from a 2.5 MW wind turbine over a six-month operational wind farm, we establish predictive models for three critical performance relationships: power curve ($R^2 = 0.951$, RMSE = 68.5 kW), yaw pitch current versus wind speed ($R^2 = 0.893$, RMSE = 0.82 A), and yaw pitch current versus grid current ($R^2 = 0.908$, RMSE = 0.74 A). The yaw pitch current versus grid current reference curve demonstrates superior fault detection performance, identifying faults 80 min after threshold exceedance with minimal false alarms, significantly outperforming power curve-based detection and wind speed-based detection. Fisher's combined probability test with an optimized threshold ($p = 0.581$) effectively balances detection sensitivity and false alarm minimization. The results demonstrate the model's ability to detect yaw pitch faults (>6 A) effectively with minimal false alarms, offering a cost-effective SCADA-based solution for wind turbine condition monitoring that leverages the strong correlation ($r = 0.79$) between grid current and yaw pitch current.

1. Introduction

As the deployment of wind energy generation has rapidly increased, the reliability of wind turbines has become a significant focus for commercial competitiveness among manufacturers and operators. In offshore environments, turbines with low reliability can present a more serious impact on electricity generation efficiency, as upon the occurrence of a fault, a longer downtime for maintenance is required, compared with on-shore turbines [1–3]. Owing to situational access restrictions, the occurrence of faults can lead to extended downtime for maintenance, and a resulting increase in operational and maintenance (O&M) cost of wind turbines. It has been widely recognised that for wind turbines, O&M may account for ~25–35% of total electricity generation costs [4], hence reliability is one of the leading considerations for operators and manufacturers of wind turbines.

The Condition Monitoring System (CMS) was an add-on system

dedicated to capture and track key parameters of wind turbines. However, due to the cost and added technical complexity, often over €11,000 per turbine, this meant that, despite proven economic advantages of early fault detection provided by CMS, this system has not seen widescale deployment [5,6]. More recently, an alternative solution has been proposed, through use of the Supervisory Control and Data Acquisition (SCADA) data, for use in condition monitoring in wind turbines. This approach introduces a low-cost method for condition monitoring, without the requirement of additional sensors. The SCADA system can track over 200 parameters once every 10 min. Over the life of the turbine, this accumulates as a large volume of data, which can then be data processed, and used for early fault detection.

Data captured by a SCADA system is influenced by both the operating condition of the wind turbine, and by the different surrounding environments, experienced by different turbines [7]. Changes in SCADA data, changes are not necessarily due to a fault in the turbine, which makes it essential to seek trends in the data and eliminate noise and

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Nomenclature

O&M	Operation and maintenance
CM	Condition monitoring
HMI	Human-machine interface
CMS	Condition Monitoring System
SCADA	Supervisory Control and Data Acquisition
NSET	Nonlinear State Estimation Technique
NN	Neural Network
MAE	Mean absolute error
MAPE	Mean absolute percentage error
WT	Wind Turbine
GP	Gaussian Process
RVM	Relevance Vector Machine
CDF	Cumulative distribution function
IGA	Interactive genetic algorithm
ELM	Extreme learning machine
ANN	Artificial neural network

other signals introduced by the turbine's environment and operational variability in SCADA data. As such, the relevant data analytics methods need to be identified and applied.

1.1. Relevant literature

The application of condition monitoring for fault detection is a relatively recent technique for tracking system performance, where a large volume of sensor data is collected to verify design specifications, and to optimise system performance. In order to target maintenance and repair activities, an early detection of imminent faults, including cracks, wear, rotor mass imbalance, etc., can increase the reliability of the system. Specific parameters are selected for training algorithms, in order to provide detection of faults. At the final stage, the resulting alarms are interpreted by an intelligent alarm system, which then recommends the necessary corrective actions [8]. This is the case with use of a traditional condition monitoring system (CMS); meanwhile, condition monitoring using SCADA data has also been demonstrated as a cost-effective method for performance of condition monitoring.

The SCADA (Supervisory Control and Data Acquisition) system is a prevalent industrial control architecture, which in the wind energy industry, plays a pivotal role in real-time responsive turbine control, data collection and interpretation, and is used for optimizing asset performance. In the context of fault analysis for wind turbines, two techniques using SCADA data are dominant: in one method, data captured by the SCADA system including wind speed, rotor speed, vibration, among health indicators such as bearing / gearbox temperature, or oil debris, as the basis for fault monitoring. In the other method, characteristics of wind turbines such as the raw output power curve, turbine yaw and blade pitch, can be monitored to detect and raise attention to potential faults [9]. By following these strategies, SCADA data can be exploited to provide pro-active fault assessment, and improve efficiency of operation of the wind turbines, increasing their asset reliability and maintainability, while optimizing the maintenance process to minimize associated down-time. A key indicator for wind turbine condition lies in vibration data and is often a focal point for finding fault indicators, for example, Zhang et. al. proposed a fault monitoring system that utilized vibration data from the turbine transmission system [10]. In a SCADA system, vibration is characterized as acceleration measured by the system. In this research, an improved k-means clustering model is applied to vibration data of wind turbines. Since time is not a factor that the clustering accounts for, it is not possible to observe the relationship between acceleration and time; as such, a model that can follow trends in acceleration is needed, in order to ascertain the turbine's future

condition.

In their research, Kusiak et al. [11] analyzed vibration data in this context, in both the time and the frequency domains. The time domain was approached in three aspects: significance analysis of a predictor variable, overall sensitivity analysis, and an assessment of correlation coefficient, to identify parameters that hold a strong relation with the vibration dynamics. Where models factor for energy and climate, the effects of temperature and generated energy are utilized; where a change in temperature should be expected to lead to a change in power generation by the turbine, which should be accounted for, by the adopted model [12]. However, other mechanisms, including overloading, reduction of lubricant, or reduction in cooling processes, could also be indicated by a change in temperature. In 2012, Guo et al. [13] implemented trend analysis for temperature data, using Nonlinear State Estimation Technique (NSET) to model temperature profile of the turbine, under normal operating conditions. This approach uses an averaging sliding window to smooth the time-series temperature data, forming a prediction of generator temperature based on current operational parameters, which they demonstrated could filter for changes that are statistically significant, while still providing effective sensitivity. On the occurrence of a fault in the SCADA data, the residual difference of the measured data from the predicted value increases, raising the prediction of a potential fault.

Similarly, in their research, Astolfi, Castellani & Terzi demonstrated the use of generator bearing temperature trends to predict the upcoming onset of faults, prior to them being registered by the control system [14]. Hou et al. proposed a wind condition clustering (WCC) method, using k-means clustering, to train temperature models for differing wind conditions, and an enhanced Interactive Genetic Algorithm to fine-tune the model [15]. With this approach, the applied method counters optimization from converging on local minima, which may be introduced by fluctuating wind conditions.

Among the leading causes of failures in wind turbines include gearbox failures, where they can encompass approximately 50% of service downtime for that year [16]. The most common gearbox failures in wind turbines has been summarized in a study by Feng et. al., which evaluated the use of data models applied to vibration data, output power, lubricant particle count, and lubricant temperature to identify onset of faults. Their approach enabled exploration of relationships between rotor speed, efficiency, temperature, and generated power, enabling detection of long-term faults with low frequency data from a SCADA system.

Selecting from the most popular data mining algorithms, Wang et al. [17] found that Deep Neural Networks (DNN) was best suited to provide accurate prediction of gearbox lubricant pressure under normal operating conditions. In addition to gearbox faults, the wear of bearings presents a leading source of failure and associated maintenance costs. Kusiak et al. demonstrated the training of neural network algorithms with wind turbine data, in order to generate fault prediction models for bearings, whereas Weighted Best First Search Wrapper method (WBFS) was applied, and the key parameters to achieve prediction of bearing temperature identified [18].

An artificial neural network (ANN) was developed by Santolmazza et al. [19], training a model for gearbox and generator failures, using statistical process control (SPC) on data consisting of wind speed, direction, and ambient temperature, in order to form prediction of developing faults. The wind power curve opens up the critical relationship between wind speed and generated power output, where modelling of which is essential for forming predictions of power output from wind turbines [20]. Mehrjoo et al. [21], introduced a more advanced approach for prediction of power output, using monotonic regression, which would not exhibit the same issues of overfitting and non-linearity, that other modelling approaches can encounter; the researchers found that incorporating air density as a factor when using wind speed, this approach reduced the root mean squared error when compared with a similar approach using wind speed alone [22].

Looking further from the choice of sensing, and more closely at the methodology itself, Butler *et al.* [23], proposed the use of a healthy wind turbine model, as the basis for providing detection of faults. Similarly, Guo *et al.* [24], implemented a multivariate power curve model, using a Gaussian process, and the resulting residuals from the predictive model were used to provide indication of faults; referring to their approach as the Sequential Probability Ratio Test (SPRT) method. Meanwhile, blade pitch control plays a key role in turbine performance adapting blade angles in response to changes in wind speed, in order to optimise output power performance, and provide protection from damaging high wind speeds. Traditional approaches to fault-finding in turbine pitch systems have been found to have limitations; relying either on using physical models, which may not capture the complexity and non-linear behaviour of the wind turbines; or on data-based models such as Artificial Neural Networks (ANNs), or Support Vector Machines (SVMs), which often carry considerable training data and computational cost for even a subset of the numerous of possible given scenarios, making the approach less practical. In answer to this, an approach by Wei *et al.* implementing Relevance Vector Machine regression (RVM) provided a novel Normal Behaviour Modelling (NBM) method, which is capable of detecting multiple variable-pitch system failures at an early stage, including: encoder failure, slip ring failure, and motor failure [25].

1.2. Research gap and contribution to knowledge

Much of the attention in failure detection has been focused on gears and bearings, but failure prediction dedicated to yaw systems remains at an early stage [26]. Few studies utilize SCADA data to monitor yaw motor operational state, with most efforts concentrating on signal processing-based diagnostics. The contribution of yaw motor health to energy conversion efficiency has been greatly neglected, as affected wind turbines may operate for years without significant disruption. However, once faults progress untreated, resulting in yaw misalignment, annual power generation can be reduced by 2–3% [27]. Early detection is therefore critical to avoid production losses and maximize turbine lifetime [28,29].

The key to identifying yaw system underperformance lies in understanding relationships between operational parameters and environmental conditions [30]. While complex data-driven techniques have been applied to yaw fault diagnosis, variations in state parameters characterize multiple operational modes, making root cause identification challenging [31]. Existing approaches incorporating operating parameters into multivariate power curve models have not adequately addressed which specific parameters provide the most sensitive fault indicators for yaw pitch systems.

This research fills these gaps through three contributions. First, we establish that yaw pitch current exhibits strong correlations with grid current ($r = 0.79$) and wind speed ($r = 0.78$), enabling GP-based probabilistic modelling for fault detection. Second, we demonstrate through comparative analysis that the yaw pitch current versus grid current relationship provides superior fault sensitivity, achieving 80-minute detection time compared to 120 min (power curve) and 200 min (wind speed)—representing 40% and 60% improvements respectively. Third, we introduce an adaptive detection framework using Fisher's method with GP confidence intervals that maintains consistent performance across varying operational conditions while minimizing false alarms through dynamic thresholding. These contributions provide wind farm operators with a cost-effective SCADA-based solution for yaw pitch monitoring with quantified uncertainty, addressing the industrial need for early fault detection without additional sensors.

The remainder of this paper is organized as follows. Section 2 describes the case study wind farm, SCADA data acquisition system, and dataset description and pre-processing. Section 3 introduces the wind turbine power curve and air density corrections. Section 4 outline the proposed methodology. Section 5 presents comparative analysis and

discussion. Section 6 concludes with key findings, contributions summary, and future research directions including extensions to other sub-systems and predictive maintenance integration.

2. Data description and pre-processing

The collected SCADA data can typically provide a wealth of useful information for analysing the current operational status of wind turbines. This data is often freely available, eliminating the need for additional expenditure on condition monitoring systems. This makes the use of SCADA data for condition monitoring a highly cost-effective approach. Analysing SCADA data not only allows for an effective understanding of the overall health of the wind turbine but also enables early detection of failures and performance issues through data mining.

The SCADA dataset used in this paper comes from the Kelmars wind farm located in Northamptonshire, England, UK [32]. The data includes over 100 different signals, including timestamps, wind speed, power output, current, voltage, rotational speed, temperature measurements, wind direction, and related calculated values, among others. The data within the SCADA dataset consists of 10-minute measurement averages, and also records the maximum, minimum, and standard deviation values for that time period.

Due to malfunctions in the measuring sensors and data transmission systems, missing data and invalid data may occur. These issues need to be addressed before the data is analysed; otherwise, they will impact the performance of power curve fitting. Additionally, problems like data exceeding the range, negative power values, and turbine power curtailment should also be addressed as early as possible to minimize their impact on subsequent analyses.

The data used in this paper are for the 2.05 MW Senvion turbine at the Kelmars wind farm in England, UK. The dataset contains 16,398 unprocessed data points as shown in Fig. 1, starting with the timestamp “1/19/2021 07:30 AM” and ending at the timestamp “21/05/2021 17:30 PM”. After pre-processing (of [28]), it is reduced to 10,515 data points, as shown in Table 1, which are used for developing data-driven models in the subsequent sections.

3. Wind turbine power curve and air density correction

The power curve of a wind turbine serves as a crucial metric in evaluating its performance. This curve elucidates the intricate nonlinear correlation between the wind velocity at the turbine's hub and its ensuing power generation. Analysing the power curve is instrumental in detecting anomalies in wind turbine operation and provides insights into its performance. The curve is represented by the subsequent mathematical expression:

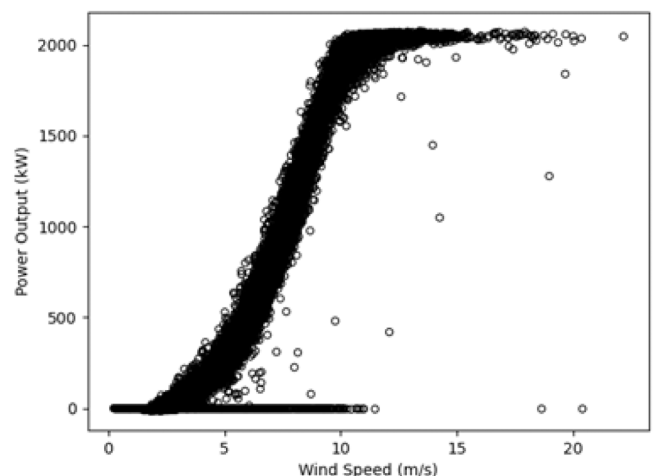


Fig. 1. Measured power curve.

Table 1
SCADA dataset description.

Start Timestamp	End Timestamp	Measured data	Filtered data
1/19/2021 07:30	21/05/2021 17:30	16,398	10,515

$$P = 0.5\rho AC_p(\lambda, \beta)v^3 \quad (1)$$

where ρ denotes the air density (kg/m^3), A represent the swept area (m^2), C_p be the power coefficient of the wind turbine, and v characterize the hub wind speed (m/s). The power coefficient C_p is a function of the tip speed ratio, symbolized as λ , and the pitch angle, denoted by β .

Due to the various factors affecting the power curve, its description by the formula is only a simplified representation with limited accuracy [33]. Establishing a more precise power curve model will be beneficial for analysing the operational status of wind turbines. To analyse the performance of variable pitch wind turbines, it is essential to consider the impact of environmental factors on air density. Air density varies with weather conditions and the altitude at which the wind turbine is located, and it undergoes significant changes due to ambient temperature. Therefore, it is necessary to correct the air density according to the IEC standard 61400-12-1 [34], and the calculation formula is as follows:

$$\rho = 1.225 \left[\frac{288.15}{T} \right] \left[\frac{B}{1013.3} \right] \quad (2)$$

and,

$$V_c = V_m \left[\frac{\rho}{1.225} \right]^{\frac{1}{3}} \quad (3)$$

where V_c and V_m represent the corrected and measured wind speeds, respectively, both in m/sec . The corrected air density is deduced using Eqs. (2) and (3). Furthermore, B signifies the atmospheric pressure (in mbar), and T denotes the temperature (in Kelvin). B and T are environmental data recorded by the SCADA system and are used to calculate the corrected air density. The adjusted air density is then used to correct the wind speed, and this corrected wind speed is utilized in the subsequent development of the non-parametric model. After the air density correction and the removal of misleading data, the power curve as shown in Fig. 2 is obtained.

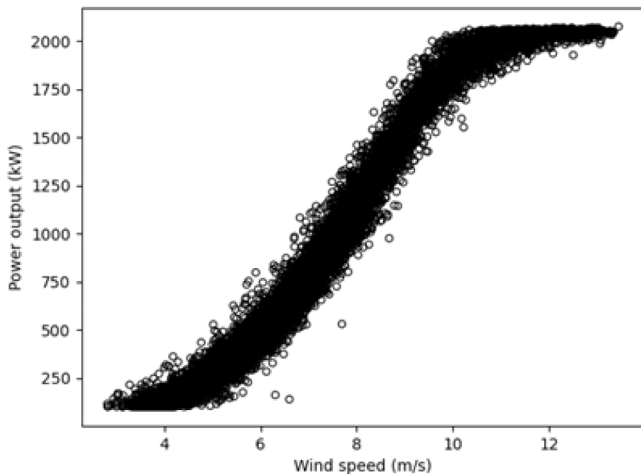


Fig. 2. Pre-processed power curve.

4. Methodology

4.1. Features analysis to identify failures trend

During operation, the performance of wind turbines can be influenced by the functioning of specific components, such as the yaw system responsible for aligning the turbine blades with the wind direction to optimize energy capture. Consequently, operational parameters related to the yawing process become crucial for assessing wind turbine performance. These parameters typically encompass yaw current, yaw angle, yaw motor power, yaw braking pressure, and more [35]. In the dataset utilized, there were 25 instances of "high yaw pitch current" faults observed over a span of 5 months, making this fault the primary focus of research and technology development for fault identification.

This study utilizes the Pearson correlation coefficient to identify parameters associated with yaw pitch faults for subsequent analysis. The Pearson correlation coefficient quantifies the degree and orientation of linear association between two continuous variables, with values spanning -1 to 1 , where 1 indicates perfect positive correlation and -1 indicates perfect negative correlation. The mathematical formulation is:

$$r = \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^n (X_i - \bar{X})^2} \sqrt{\sum_{i=1}^n (Y_i - \bar{Y})^2}} \quad (4)$$

where X_i and Y_i are data values for variables X and Y respectively. $\bar{X}$ and $\bar{Y}$ are mean values of X and Y respectively. We calculated the correlation between the Yaw pitch current and other important wind turbine parameters using the Pearson correlation coefficient. This study focuses specifically on yaw pitch current analysis, distinct from the pitch current system. The yaw system aligns the turbine with wind direction for optimal energy capture, differentiating its operational characteristics from the pitch system. Tables 4–1 presents correlation coefficients between yaw pitch current and key wind turbine parameters and Fig. 3 also show pre-processed yaw pitch current and grid current curve. The correlation analysis reveals significant relationships between yaw pitch current and operational parameters. Notably, yaw pitch current shows strong correlation with grid current ($r = 0.79$) and wind speed ($r = 0.74$), indicating the yaw system's sensitivity to directional changes requiring motor engagement. Unlike the pitch system, which adjusts to wind speed for power regulation, yaw system current variations are primarily driven by directional alignment needs.

The pre-processed yaw motor current curves (Fig. 4) underscore distinct yaw system operational dynamics. The yaw motor current exhibits similar trends with wind speed and grid current beyond certain thresholds (8 m/s for wind speed and 1000 A for grid current), suggesting potential fault conditions specific to the yaw system. These strong correlations justify selecting yaw pitch current versus wind speed and yaw pitch current versus grid current as the primary relationships for GP modelling and fault detection in subsequent sections.

4.2. Gaussian process

The Gaussian process, rooted in Bayesian principles, is a non-parametric and intrinsically nonlinear regression methodology. Within

Table 4–1
Correlation score with yaw motor current.

Parameters	Yaw Motor current
Power	0.78
Grid current	0.79
Rotor speed	0.48
Wind speed	0.74
Ambient temperature	0.21
Gearbox speed	0.48
Nacelle ambient temperature	0.09

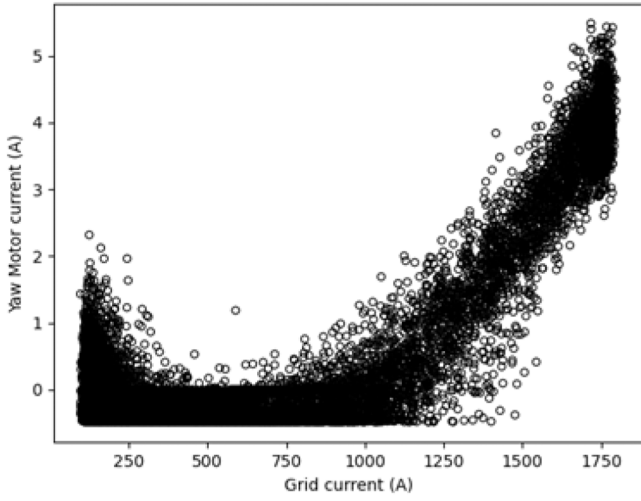


Fig. 3. Pre-processed yaw pitch current and grid current curve.

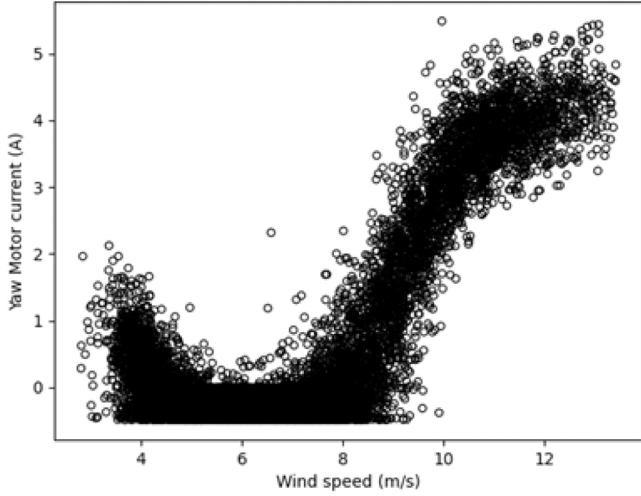


Fig. 4. Pre-processed yaw pitch current and wind speed curve.

a Gaussian process model, each position within a continuous input domain correlates with a random variable that adheres to a normal (Gaussian) distribution. It leverages a similarity measure between two data points as the kernel function to predict the value of unknown points based on the provided training data. Mathematically, it is defined by its mean function and covariance function as:

$$\mathbf{Y} \sim \mathcal{GP}(\boldsymbol{\mu}, \boldsymbol{\Sigma}) \quad (5)$$

where $\boldsymbol{\mu}$ is the mean function and $\boldsymbol{\Sigma}$ is the covariance function that has an associated probability density function.

$$P(\mathbf{x}; \boldsymbol{\mu}, \boldsymbol{\Sigma}) = \frac{1}{(2\pi)^{n/2} |\boldsymbol{\Sigma}|^{1/2}} \exp\left\{-\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu})^T \boldsymbol{\Sigma}^{-1}(\mathbf{x} - \boldsymbol{\mu})\right\} \quad (6)$$

where $|\boldsymbol{\Sigma}|$ be the determinant of matrix $\boldsymbol{\Sigma}$, n denotes the dimensionality of the random input vector $\mathbf{x}$, and $\boldsymbol{\mu}$ represents the mean vector of vector $\mathbf{x}$. The expression found beneath the exponential, $\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu})^T \boldsymbol{\Sigma}^{-1}(\mathbf{x} - \boldsymbol{\mu})$, exemplifies a quadratic form.

The covariance function illustrates the degree of interrelation between two distinct variables. The selection of covariance function is pivotal for enhancing the model's precision. This choice is intimately tied to the specific use-case or application of the model. For the purposes of our study, we employ the squared exponential covariance function,

articulated as follows:

$$k_{SE}(\mathbf{x}, \mathbf{x}') = \sigma_f^2 \exp\left(-\frac{(\mathbf{x} - \mathbf{x}')^2}{2l^2}\right) \quad (7)$$

Given that SCADA data inherently encompasses measurement inaccuracies, there's an imperative to incorporate a noise component into the covariance function. This adjustment addresses and offsets the implications of this introduced variability. Consequently, the amended covariance function is expressed as:

$$k_{SE}(\mathbf{x}, \mathbf{x}') = \sigma_f^2 \exp\left(-\frac{(\mathbf{x} - \mathbf{x}')^2}{2l^2}\right) + \sigma_n^2 \delta(\mathbf{x}, \mathbf{x}') \quad (8)$$

where σ_f^2 and l are known hyper-parameters. σ_f^2 represents the signal variance, while l serves as a characteristic length scale, elucidating the rate at which covariance diminishes as the spatial separation between points increases. σ_n denotes the standard deviation associated with noise fluctuations and offers insights into the model's uncertainty level. Meanwhile, δ corresponds to the Kronecker delta [36].

Using the GP model, the power curve and the yaw motor current curve as shown in Figs. 5–7 are obtained by fitting. A comparison between the curves drawn based on measured values and those obtained through GP fitting suggests that the GP provides effective estimations.

The confidence of the model can be estimated by calculating the confidence interval of the curve. In GP model, confidence interval represents the model's uncertainty about the distribution parameters of the predicted outcome, such as the mean and standard deviation. Therefore, the properties of the normal distribution can be exploited to calculate confidence intervals. By selecting a confidence level, the corresponding critical value is determined. For example, for a 95% confidence level, the critical value is about 1.96. Therefore, the upper and lower bounds of the 95% confidence interval are $\mu \pm 1.96\sigma$, which is the blue area of the above figures.

The confidence interval of the power curve estimated using the GP model is relatively narrow, and the data points outside the region are very concentrated, indicating that the model has relatively low predictive uncertainty for the data. Additionally, the curve is very smooth, indicating good model performance. On the other hand, the confidence interval of the yaw motor current curve estimated using the GP model is relatively wide, which may be because the parameters are not strongly correlated, and the data points are more dispersed. However, since the main focus for fault analysis is on the portion of the curve that shows an increasing trend, and the confidence interval for this portion of the curve is relatively narrow and the curve is relatively smooth, it also shows good model performance.

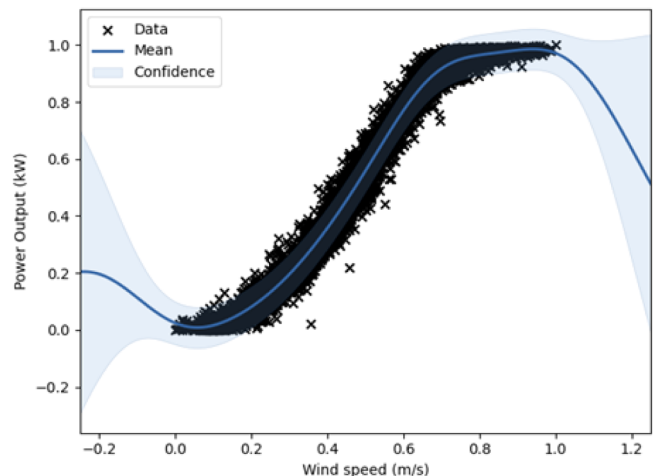


Fig. 5. Measured and GP estimated mean power curve comparison.

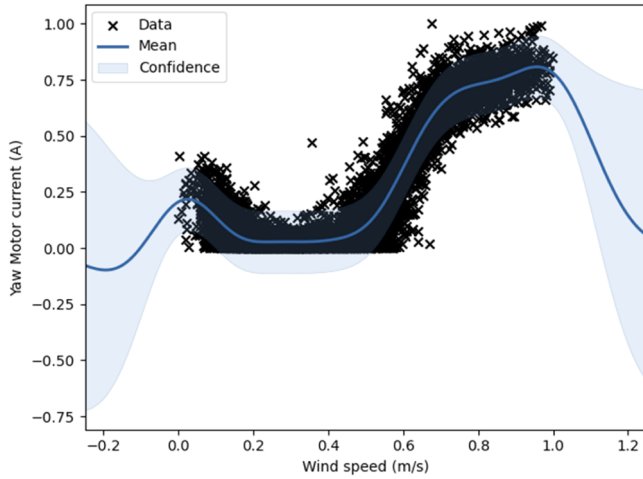


Fig. 6. Measured and GP estimated mean yaw pitch current and wind speed curve comparison.

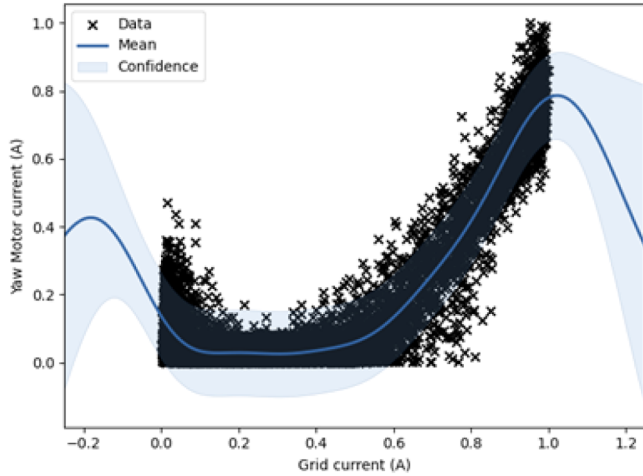


Fig. 7. Measured and GP estimated mean yaw pitch current and grid current curve comparison.

To quantify model performance, we employed three well-established statistical metrics commonly used for evaluating machine learning model accuracy: coefficient of determination (R^2), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) [37–40]. For the power curve model, we achieved $R^2 = 0.951$, $RMSE = 68.5$ kW, and $MAE = 45.2$ kW. The yaw pitch current versus wind speed model yielded $R^2 = 0.893$, $RMSE = 0.82$ A, and $MAE = 0.61$ A. The yaw pitch current versus grid current model—our primary fault detection indicator—demonstrated $R^2 = 0.908$, $RMSE = 0.74$ A, and $MAE = 0.53$ A. These results indicate strong predictive performance across all three models. The power curve R^2 of 0.951 demonstrates excellent fit, with error metrics representing only 3.3% of the 2.05 MW rated power. For yaw pitch current predictions, both models achieved R^2 values exceeding 0.89, indicating robust capture of nonlinear dynamics. Notably, the yaw pitch current versus grid current model showed slightly superior performance (lower RMSE and MAE) compared to the wind speed model, consistent with the stronger observed correlation ($r = 0.79$) between grid current and yaw pitch current. The low error values ($MAE < 0.7$ A, $RMSE < 0.9$ A) relative to the 6 A fault threshold provide sufficient sensitivity for reliable fault detection while maintaining model precision across normal operating conditions.

Analysing the residuals of the GP model is crucial for understanding its performance. The residual is defined as the difference between the

measured and estimated values. The residual plots, depicted in Figs. 8–10 as a function of time series, suggest that the estimated values from the GP model are close to the measured ones.

Theoretically, the residuals of the GP model should follow a Gaussian distribution. Figs. 11–13 show the frequency distribution of the residuals and the fitted Gaussian distribution. For the power curve obtained by GP fitting, the mean of the residuals is close to 0, and the distribution of the residuals presents an approximately symmetric bell-shaped curve, with relatively uniform heights of the bars, indicating that the distribution

of GP residuals is close to a Gaussian distribution. For the yaw motor current curve obtained by GP fitting, the mean of the residuals is also close to 0, but the heights of the bars are not uniform, indicating the presence of non-random characteristics, although the distribution of the residuals is still approximately symmetric.

4.3. Probability Fisher test to trigger fault alarm in point-by-point basis

The combined p-value is a statistical method used to merge multiple individual p-values into a single overall p-value, allowing for the evaluation of the overall statistical evidence. Applications of the combined p-value are diverse, encompassing the amalgamation of results from independent studies as well as the integration of results from individual component questions as part of a holistic test [40,41]. In this paper, the Fisher's combined test is employed for the subsequent development of the GP algorithm. The Fisher's combined test is grounded on the idea that, should all null hypotheses be true, individual p-values should uniformly distribute across the [0,1] interval. Hence, a combined p-value that falls below a specified significance threshold may suggest that the null hypothesis does not hold. The equation utilized for the Fisher combined probability test is:

$$X_{2k}^2 \sim -2 \sum_{i=1}^k \ln p_i \quad (9)$$

where p_i denotes the probability that the i th variable exceeds the observed value under the null hypothesis. Under this hypothesis, X_{2k}^2 conforms to a chi-squared distribution with $2k$ degrees of freedom. In this setting, k indicates the number of independent tests conducted.

If the combined p-value obtained exceeds a predefined threshold, then it means that the null hypothesis is rejected and that there is a significant difference between the actual measured value and the expected health value. It can be assumed that this discrepancy may be due to a fault, and an alert is generated at the point in time corresponding to this data. Due to the high costs of unscheduled maintenance and potential economic benefits reduction, the alert system needs to avoid false alarms. The fault alert system designed in this paper adjusts the alert

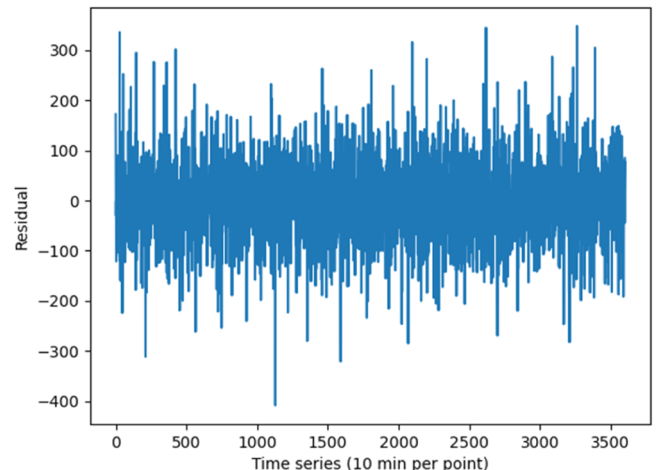


Fig. 8. GP residuals of power curve.

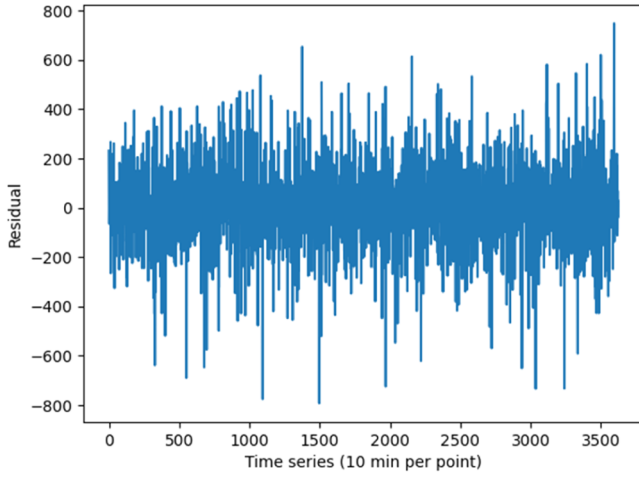


Fig. 9. GP residuals of yaw motor current and wind speed curve.

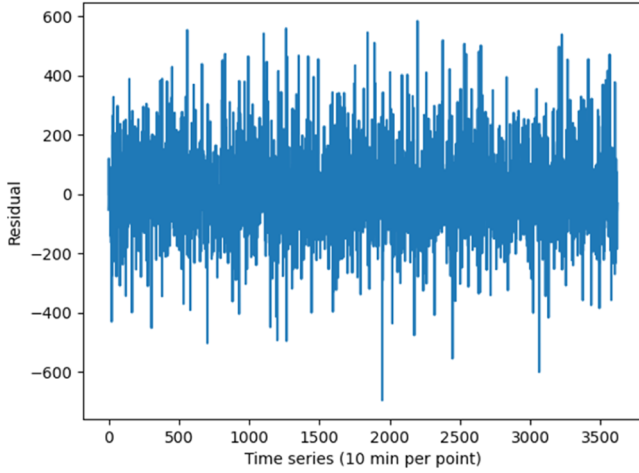


Fig. 10. GP residuals of yaw pitch current and grid current curve.

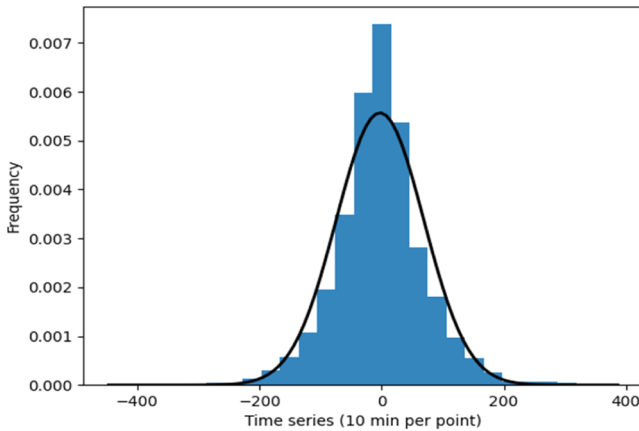


Fig. 11. GP residuals histogram fitting of power curve.

intensity based on the duration of consecutive alerts. The specific process is shown in Fig. 14, and is conducted as follows:

- Calculate the error between the GP model estimate and the fault data. The error value is obtained by finding the closest GP model estimate to the current fault data and calculating its difference. If the

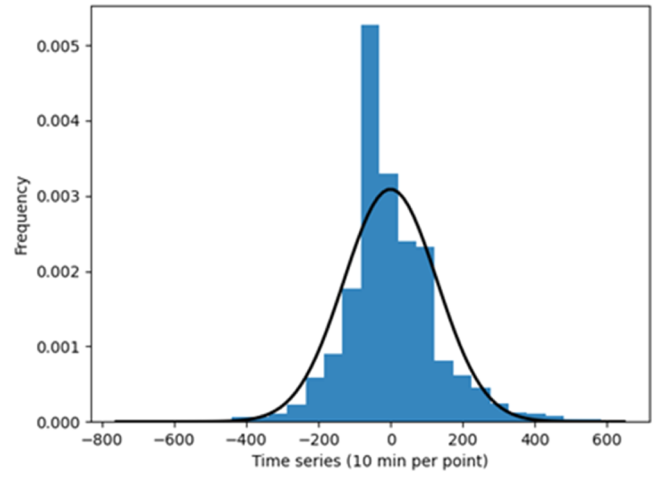


Fig. 12. GP residuals histogram fitting of yaw pitch current and wind speed curve.

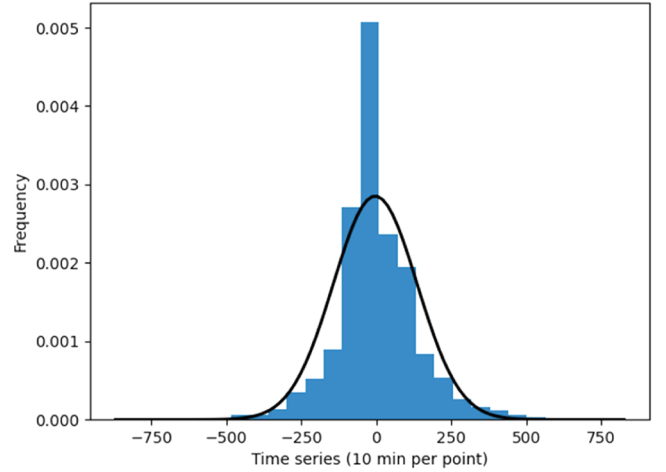


Fig. 13. GP residuals histogram fitting of yaw pitch current and grid current curve.

corresponding estimated value is exceeded, this will be recorded, and the relevant data will be saved.

- For each failure data, the p-value associated with that data point is calculated using the cumulative distribution function (CDF) of the normal distribution. For each calculated p-value, it is corrected if it is greater than the given confidence interval threshold.
- Combine pairwise adjacent p-values using Fisher's combined probability test to obtain an overall significance estimate.
- Determine whether to trigger an alarm based on a given threshold. If a combined p-value exceeds a threshold, it is flagged as triggering an alert. Calculate the number of consecutive alarm triggers, record the continuous trigger period, and generate an alarm log.

5. Comparative analysis and discussion

The curve fitted by the GP model intrinsically represents the fitting error, so the curve can be evaluated using confidence intervals. The confidence interval of the curve provides information about the estimation uncertainty based on the model. Points outside the confidence interval can be considered anomalous, that is, the corresponding data when the wind turbine fails. The data during the fault period are evaluated sequentially according to the reference curve. Here, the above-mentioned Fisher combined probability test will be used to judge the

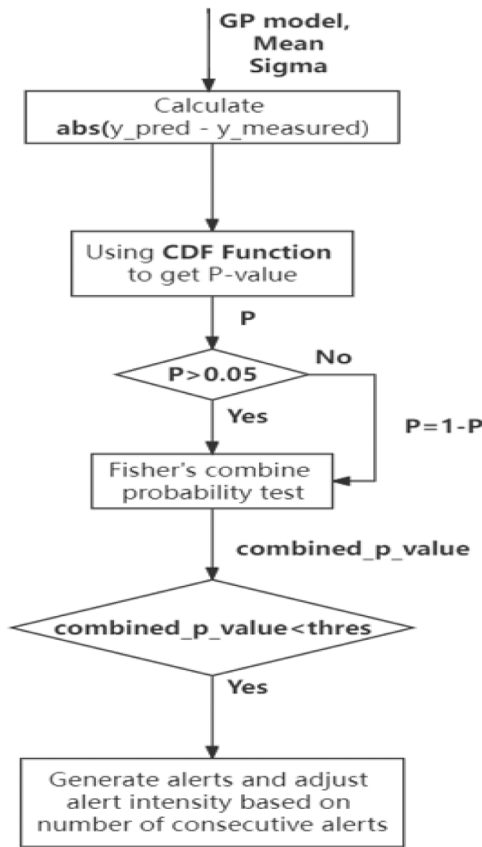


Fig. 14. Flowchart of fault detection alert.

degree of deviation between the data points and the reference curve. To avoid false alarms, the probability threshold used for filtering is adjusted until no false alarms occur. In this paper, the probability threshold is ultimately set at 0.581. Fig. 15 plots the fault alert and yaw motor current as a time series together, demonstrating the effectiveness of the fault detection algorithm.

It is considered that a Yaw pitch current exceeding 6 A means that a fault has occurred. On January 19, 2021, at 10:30, the Yaw pitch current reached 6.7 A, and the SCADA system issued a "High Yaw pitch current" alarm. An alert generated by a GP model using the Power curve as reference was issued at 12:30 on January 19, 2021, 120 min after the fault occurred as shown in Fig. 15. An alert generated by a GP model using the yaw pitch current and wind speed curve as reference was issued at 13:50 on January 19, 2021, 200 min after the fault occurred. An alert generated by a GP model using the yaw pitch current and grid current curve as reference was issued at 11:50 on January 19, 2021, 80 min after the fault occurred, see Fig. 15. It can be found that taking the yaw pitch current and the grid current curve as a reference can identify the occurrence of faults faster and produce the least false alarms. This may be due to the strong correlation between the grid current and the yaw pitch current. Using the power curve as a reference can also quickly identify the occurrence of faults, but the performance is not as good as the above one, and there are more false alarms, which affects the efficiency of fault detection. It is worth noting that no model is perfect. Even when there are no glitches, the graph will occasionally show anomalies. This discrepancy could be due to suboptimal fit of the GP model or other interrelated variables in the wind turbine ecosystem. Therefore, choosing an evaluation index that is more related to the fault itself as a reference can monitor the occurrence of the fault more intuitively. The challenge lies in the refinement of the model and the selection of reference indicators that are closely related to the relevant faults. This should be the key task of follow-up research.

Overall, the GP model shows reliable performance in fitting the given data. However, it can be found from the analysis that the accuracy of the GP power curve model may be reduced due to a large number of data points, and due to the inverse cubic problem [42], the size of the data will affect the time of model establishment, so it is necessary to calculate the cost and model performance, as a reasonable trade-off between accuracy.

6. Conclusion

This research advance's fault detection in wind turbines by leveraging Gaussian Process Modelling and correlation analysis to dissect the relationship between yaw and pitch currents, wind speed,

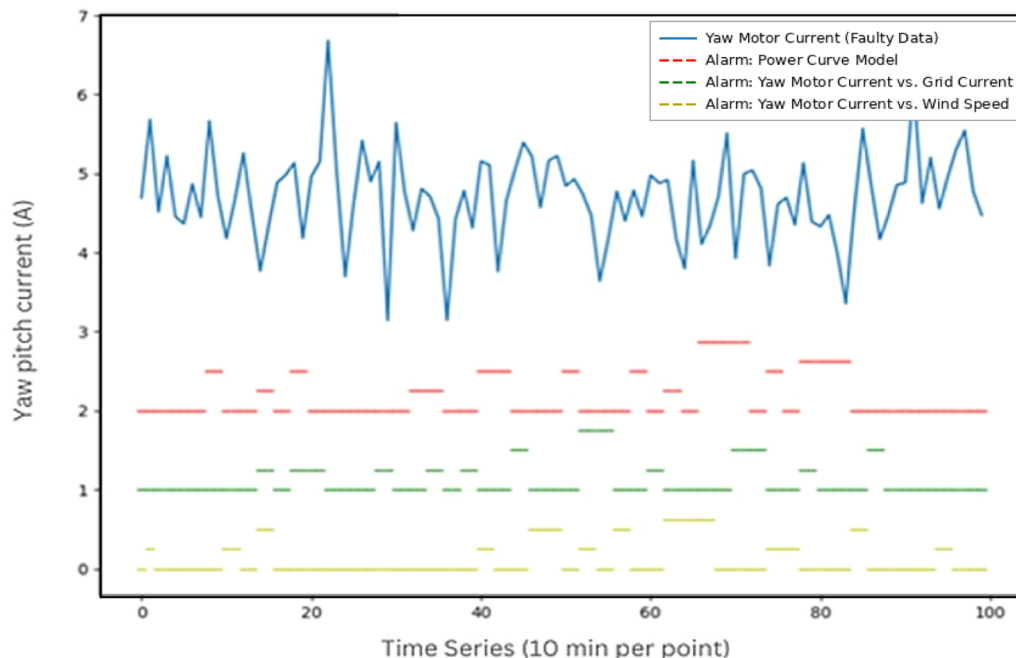


Fig. 15. Yaw pitch current failure detection using GP model.

and grid current. By employing the Pearson correlation coefficient, we analysed relationships within wind turbine SCADA data, establishing a robust statistical connection between yaw pitch current, wind speed, and grid current. This analysis provided valuable insights for fault detection, using GP to model the intricate relationship between these parameters.

A significant finding of our research is the observed trend in yaw pitch current, which exhibits similarities to wind speed and grid current under specific operational conditions. Particularly, when wind speeds exceed 8 m/s or grid current surpasses 1000 A, the yaw pitch current tends to increase, indicating potential fault conditions. This trend, while sometimes aligning with high wind speeds, is inherently related to the yaw system's operational dynamics rather than the pitch system, which is primarily responsible for power regulation.

The utilization of a GP model, with a square exponential covariance function, proved successful for modelling the curves, validated through comparisons with measured data. The GP model's confidence intervals revealed prediction uncertainties, with relatively narrow intervals and smoothness in critical regions of the power curve and yaw pitch current curve, signifying the model's reliability. Additionally, residual analysis supported the GP model's performance, showing Gaussian distributions in power curve residuals and a near-Gaussian pattern in yaw pitch current curve residuals.

Our comparison of three reference curves confirmed the GP model's efficacy in detecting anomalies in wind turbine yaw pitch current. The yaw pitch current and grid current curves, in particular, showed the highest efficiency in promptly identifying faults while minimizing false alarms. This highlights the importance of selecting appropriate evaluation indicators for GP model-based fault detection.

Comparative analysis of the proposed GP approach against alternative machine learning techniques such as neural networks, support vector machines, ensemble methods kept for the future work.

CRedit authorship contribution statement

Pandit Ravi: Writing – review & editing, Writing – original draft, Supervision, Project administration, Funding acquisition. **Jianlin Wang:** Visualization, Validation, Software, Resources, Methodology, Formal analysis, Data curation, Conceptualization. **Lawrence Tinsley:** Writing – review & editing, Project administration.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

The data that has been used is confidential.

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SCADA-based early detection of wind turbine yaw motor current failures using Gaussian process surrogate models and Fisher's combined probabilistic alarm thresholding

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