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Research Article

A SYSTEM OF MONITORING AND EVALUATION FOR PERFORMANCE AND MAINTENANCE MANAGEMENT IN THE WIND TURBINES

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Abstract

Wind turbines are a great source of energy that holds much potential to deliver clean, reliable, and low-cost power to many homes and businesses. While they can reduce carbon emissions and produce clean power on a regular basis, they have a few major drawbacks, some of which may require a certain level of maintenance to the blades, bearings, and gears. This dissertation proposed a new performance evaluation system and algorithms for wind turbines to detect and predict faults that may happen in the system. This work is contrary to the currently available wind turbine monitoring and assessment systems focused on some aspects of the turbine operation, such as power output or even cost management for performance measurement. This study, however, was able to move a step further by considering other main features in the processes for evaluation, including weather conditions, wind speed, turbine loads, system vibration levels, and other factors, which gave a complete picture of the health status and performance of a wind turbine. The results implemented by the model are presented through a four-dimensional array showing how the various factors were influencing the evaluation of the performance of a wind turbine. The models were validated against two prediction accuracy metrics: The Mean Absolute Error and the Root Mean Square Error. The implementations of MAE and RMSE result in 0%, thus proving the model is accurate. The support vector regression modeling approach has already been successfully applied to fault identification in a wind turbine system. The overall accuracy in all simulations performed using the model was 99.8%, and it exhibited behavioral patterns that predicted faults and their propagation within the wind turbine system.

Keywords: Turbine, Mean Absolute Error, Root Mean Square Error, Performance management, Maintenance management

1. INTRODUCTION

An easily navigable and instinctive wind turbine monitoring system is a critical part of the energy producing process. Wind turbine performance is monitored, systems efficiency is evaluated, and the safety and reliability of the turbines are maintained utilizing them. Wind turbines are an environmentally friendly and renewable energy source, and their efficient operation is crucial for the sustained continuity of energy production. However, a substantial amount of research has shown several problems with the wind turbine monitoring systems now in use (Knopper *et al.,* 2011). These concerns are known to diminish the efficiency and effectiveness of the wind turbine system. One of the challenges faced by academics and practitioners is the lack of a standardised nomenclature for wind turbine assessment and management. This hinders the ability to compare upshots from various research (Charabi & Abdul-Wahab, 2020). Various organisations sometimes choose distinct terms to depict the same event in wind turbine management or the deployment of wind monitoring systems, therefore complicating the comparison of data and the attainment of consensus on optimal procedures. The use of a standardised nomenclature would help reduce ambiguity and enhance the comprehensibility of comparisons across research studies. A substantial constraint in the advancement of precise turbine models is the insufficiency of long-term turbine performance data (Sun *et al.,* 2021). Most of the available information on turbine performance is limited to the first years of operation. However, subsequent to this first.

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This period is generally followed by a sharp deterioration of the turbines, loss of efficiency, and related increase in maintenance costs. Models of reliable performance and life time forecasting of a turbine are created based on huge data accrued on the performance of the turbines over a long period.

The fluctuating and unpredictable nature of wind poses several challenges for integrating wind power into the electric grid, since it necessitates substantial investments in wind farm construction and ongoing assessment studies. According to Fernández-González *et al.* (2018), wind energy is producible with fluctuations in wind speed, varying both between regions and time. The production of wind power is influenced by several meteorological factors, comprising wind direction, temperature, pressure, humidity, and others (Sharifian *et al.,* 2018). Therefore, the incorporation of wind power into the electrical grid requires, at the very least, forecasts of future wind speed values. The advancement of novel methodologies, i.e. simulation, forecasting, distribution curve fitting, filtering, and modelling, facilitates more accurate assessments of wind sector growth and enhances energy system administration. Furthermore, obtaining an accurate estimation of wind speed may enhance the safety, reliability, and financial viability of wind farm operations (Staid *et al.,* 2015). Comprehending the wind patterns in a certain area enables more precise predictions of future events by analysing past occurrences. An extensive monitoring and assessment system would provide a more complete perspective on turbine performance. Presently, the majority of monitoring systems focus on certain aspects of turbine operation, i.e. power generation or financial management (Charabi *et al.,* 2020; Stetco *et al.,* 2019). Nevertheless, these metrics fail to provide a complete overview of turbine condition and sometimes provide misleading information. Accordingly, the objective of the study is to develop a system of monitoring and evaluation for performance and maintenance management in the wind turbines by incorporating some variables that have hitherto been neglected by previous studies. These includes meteorological conditions, loads on the turbine, and levels of system vibration. In this way, problems could be picked up and resolved before there was any chance of serious damage or risk.

2. METHODOLOGY

2.1. Underlying theories

The proposed power model presented here differs from existing models in the literature by taking into account not only the power and turbine speed, but also the weather conditions, turbine loading, and vibration levels when evaluating wind turbine performance. The mathematical representation of the model is provided in Equation (3.1).

$$P = a * V + b * W + c * T + d * S \tag{2.1}$$

Where:
P = Power Output is the measured power output of the turbine in kilowatt (kW)
V = Vibration Levels is a measurement of the amount of vibration produced by the turbine.
W = Weather Conditions is measure of the current weather conditions i.e. humidity, measured in kg/m^3
T = Turbine Loading which is the measure of the amount of load on the turbine at any time.
S = Turbine is the measure of the current turbine speed, measured in m/s
a, b, c, d = These parameters or coefficients are determined through an optimization process.

With the power output model, the performance of the wind turbine is evaluate utilising the ensuing equation: Performance Evaluation = (Power Output x Efficiency) + (Constant).

If the efficiency of the wind turbine system is unknown, the performance of the turbine can be determine or equivalent to the overall power output, measured in Kilowatts KW.

Theorem 2.1. Let's assume that the power output of a wind turbine can be expressed as a function of V, W, T and S, if the function is expressed as,

$$P = f(V, W, T, S) \tag{2.2}$$

The parameters a, b, c, and d in Equation (3.1) can thus be viewed as the coefficients of the power function's linear terms. The wind turbine power model is claimed to be valid and accurate only when the parametric performance evaluation technique is utilised and the linearity principle is followed. In congruent with the linearity principle, when two linear functions are joined together, the result is another linear function. As a result, combining the functions $f(V, W, T, S)$ and P should yield another linear function.If the product of these two linear functions is given as $g(V, W, T, S)$. The result will then be stated as,

$$g(V, W, T, S) = f(V, W, T, S) + P = a * V + b * W + c * T + d * S \tag{2.3}$$

Considering that the concept of linearity states that the product of two linear functions is another linear function, the research may infer that $g(V, W, T, S)$ is a linear function of V, W, T, and S. As a result, the power model for the wind turbine is true and accurate when a parametric performance evaluation technique is utilised since it is a linear function of V, W, T, and S.

Theorem 2.2. Let the power model equation utilised to evaluate the wind turbine performance be expressed as

$$P = a * V + b * W + c * T + d * S$$

Where the parameters or the coefficients a, b, c, and d are a reflection of the contribution of each variable (V, W, T, and S) to the overall power output of the turbine and may be estimated by an optimization process. The least squares approach or a genetic algorithm can be utilised in the formation and expression of the power model equation. The least squares approach along with the genetic algorithm is utilised to determine the values of a, b, c, and d that minimalize the sum of the squared discrepancies between the observed $(P)$and forecast values of power output$(\hat{P})$.

The equation for the sum of the squared differences is as follows:

$$S = 2 * (P + \hat{P}) \tag{2.4}$$

To minimize S, the partial derivatives of S with respect to a, b, c, and d should be set to 0.

$$\frac{\partial S}{\partial a} = 2 * (P + \hat{P}) * (-V) = 0$$

$$\frac{\partial S}{\partial b} = 2 * (P + \hat{P}) * (-W) = 0$$

$$\frac{\partial S}{\partial c} = 2 * (P + \hat{P}) * (-T) = 0$$

$$\frac{\partial S}{\partial d} = 2 * (P + \hat{P}) * (-S) = 0$$

Solving for a, b, c, and d yields:

$$a = \frac{((V*\hat{P}-V*P)+(W*P-W*\hat{P})+(T*P-T*\hat{P})+(S*P-S*\hat{P}))}{(2V+2W+2T+2S)} \tag{2.5}$$

$$b = \frac{((V*P-V*\hat{P})+(W*\hat{P}*-W*P)+(T*P-T*\hat{P})+(S*P-S*\hat{P}))}{(2V+2W+2T+2S)} \tag{2.6}$$

$$c = \frac{((V*P-V*\hat{P})+(W*P-W*\hat{P})+(T*\hat{P}-T*P)+(S*P-S*\hat{P}))}{(2V+2W+2T+2S)} \tag{2.7}$$

$$d = \frac{((V*P-V*\hat{P})+(W*P-W*\hat{P})+(T*P-T*\hat{P})+(S*\hat{P}-S*P))}{(2V+2W+2T+2S)} \tag{2.8}$$

As a result, the collected data may be employed in the power model equation for evaluating wind turbine performance. These values can also be computed by an optimization procedure that seeks to minimize the sum of the squared discrepancies between the observed (P) and anticipated power output values $(\hat{P}')$.

Theorem 2.3. Let $P_1, P_2, P_3, \dots P_n$ be a set of n observations of the Power output of the wind turbine, and let $V_1, V_2, V_3, \dots V_n$, $W_1, W_2, W_3, \dots W_n$, $T_1, T_2, T_3, \dots T_n$ and $S_1, S_2, S_3, \dots S_n$ be the corresponding sets of vibration levels, Weather conditions, Turbine loading, and Turbine speed of the system, respectively. The study therefore can then define a function for the coefficients a, b, c and d as follows,

$$F(a,b,c,d) = \left(P_1 - (aV_1 + bW_1 + cT_1 + dS_1)\right)^2 + \left(P_2 - (aV_2 + bW_2 + cT_2 + dS_2)\right)^2 + \cdots + \left(P_n - (aV_n + bW_n + cT_n + dS_n)\right)^2 \quad (2.9)$$

The function F(a,b,c,d) may be minimised by utilising either the least squares technique or an optimisation method to find the values of the parameters a, b, c, and d. This provides the optimal values for the variables a, b, c, and d that are most suitable for the given data, together with the power model equation. The parameters a, b, c, and d of the model were computed utilising a Genetic Algorithm methodology in this paper.

A genetic algorithm, referred to as a search algorithm, utilises a series of stages to discover the most superior and efficient solution to a specified issue. Given a set of input parameters (V, W, T, and S), the algorithm would create a population of possible solutions (the coefficients a, b, c, and d). Each solution's performance would then be evaluated utilising a fitness function. The programme employs genetic operators i.e. crossover and mutation to repeatedly choose and refine the optimal solutions. After several iterations, the approach reaches a state where it finds the coefficients that maximise the model's performance owing to the provided input parameters. The genetic algorithm programme utilised in this research was created and utilised to assess the efficacy of the wind turbine system. The code was written and executed utilising MATLAB R2022a. Algorithms 1 and 2 correspond to the M-program files utilised for the genetic algorithm and the performance assessment of the wind turbine system, respectively.

2.2 Development of the Intelligent Model for Detecting and Predicting Faults

An intelligent model may be developed utilising supervised or unsupervised learning approaches, i.e. regression analysis, to discover and anticipate problems before they result in system downtime and damage. A supervised learning technique is a method utilised when there is labelled data available. In this approach, the model learns from the training data to make predictions about the target variable owing to the input qualities. Regression analysis may be utilised to identify and forecast faults before to their occurrence, hence preventing system downtime and minimising potential harm. Regression analysis is a supervised learning method utilised to identify relationships between a dependent variable (the variable being predicted) and one or more independent variables (the elements utilised to make predictions). Regression analysis may be utilised to identify and forecast faults before to their occurrence, hence preventing system downtime and minimising potential harm. The model that may use system data to identify patterns in the data may also indicate a possible system problem. Subsequently, the model may use this data to forecast an impending malfunction. The mathematical formulation of the model may be derived from the ensuing equation:

$$\hat{y}_i = \sum_{i=1}^{n} f(x_i, \beta) + \varepsilon_i \quad (2.10)$$

If $f(x_i, \beta) = y$, the corresponding regression expression will be given as,

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \cdots + \beta_n X_n + \varepsilon \quad (2.11)$$

where $\hat{y}_i$ is the observed dependent variable, $f(x_i, \beta)$ is the predicted value of the fault, β_0 is the intercept term, β_1, β_2, …, β_n are the regression coefficients or model parameters, X_1, X_2, …, X_n are the input variables, and ε is the residual error.

The coefficients β_1 to β_n are determined during the fitting procedure and quantify the magnitude of the link between the independent variables and the dependent variable. After the model has been trained, it may be utilised to forecast forthcoming problems. The mean square error difference may be determined by subtracting equation (2.7) from equation (2.6). The model's performance may be assessed by utilising measures i.e. accuracy, precision, recall, and F1-score.

This research use regression analysis, a predictive analytical method also known as Machine Learning Regression (MLR), to forecast the continuous output variable. The regression line is fitted utilising parameters i.e. slope and intercept to get the best match. However, the features must not be categorical, except for the target variable, when utilising a regression-based approach. Supervised regression approaches comprise linear regression, logistic regression, and support vector regression. Figure 1 displays a schematic representation of the MLR framework.

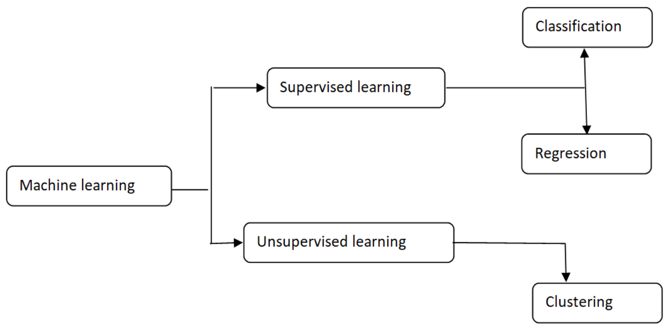

Figure 1. A schematic diagram of the regression in the Machine Learning framework

Support Vector Regression, an effective machine learning method for addressing regression-related problems, is an area of supervised learning useful for predicting continuous variables like expenses and other quantified types of information. Support Vector Regression works with the principles of support vector machines. This system first converts the input data to some higher dimension of space using a linear function and thereafter uses a linear equation, which shall make the prediction of output values. The equation for the Support Vector Regression is:

$$y = wx + b \quad (2.12)$$

Here, y is the variable to be estimated, w is the weight vector, x is the input vector, and b is the bias term. Using a labelled dataset, the weights and bias of the SVR model can be estimated by training. In the same equation, the weights and bias are chosen such that the cost function is minimized. Here is the cost function:

$$C(w,b) = \left(\frac{1}{N}\right) * \sum_{i} \left(y(i) - (wx(i) + b)\right)^2 \quad (2.13)$$

Let N be the number of examples used for training.

Here, $y(i)$ denotes the target value of the N sample, and $x(i)$is the input vector of the N sample. The weights and bias are denoted by the variables w and b respectively. The cost function is minimized by modifying the weights and bias.

The support vector regression method is a very powerful machine learning technique to solve regression problems. It is good at predicting continuous values with high accuracy and is immune to outliers. Also, in terms of computational efficiency, only a few training samples are needed to find the optimal weights and bias. This can be used with all types of kernel functions, including linear, polynomial, and Gaussian kernels. At the core, the support vector regression equation is actually an extremely effective way of machine learning to solve regression problems. Continuous valued output can, therefore, be predicted accurately, and the same is not easily affected by outliers. Further, it has computational efficiency since it requires only a few training samples to find the optimum weights and bias. It can also be used with any type of kernel function. The following three algorithms show the M-program files for a Support Vector Regression model used to classify failures in the wind turbine system. In this research, the failure data was generated in the algorithm due to the availability of less genuine data.

2.3 Data Source and Collection -Simulated and Real Data

Data collection is the process of gathering information or data from different sources and subsequently analyzing it. The process may either be done manually or automatically with the aid of software or specialized hardware. The types of data collected vary according to the purpose of collection but may range from quantitative data in the form of numerical measurements to qualitative data in the form of written questionnaires. Data collection forms an integral part of all research and analytical efforts, and very often, it involves mapping trends and patterns in the data that is gathered.

2.3.1 Simulated and Real Data

Such data is created by the algorithms of a computer in imitating real-world data and can be used for testing, validation, and R&D of very diverse sectors including engineering, science, and economics. Simulated data can be generated utilizing a variety of methodologies and techniques, such as Monte Carlo simulations, sampling, and machine learning algorithms. It is a method generally used to understand systems that are too difficult to measure or are too complex to be aptly represented. In the assessment of wind turbine performance and fault detection, simulated data can be used. Due to the aerodynamic behaviours of the turbine, computational methods can be used to generate data. Data of this nature can be used to project the energy production by the turbine, efficiency, and other performance measures. Here, simulated data are used to extract the fault information on the historical fault data, wind speed data, weather conditions, vibration level, and speed of the turbine for the fault detection and prediction in the wind turbine system. Similarly, real data is information that has actually been collected from real-life sources. Such information can be sourced from a number of sources, i.e. through surveys, experiments, and censuses. Real data may be used for a number of reasons, including trend analysis, behavior analysis, and prediction. Real-world data may also be used to test the accuracy of simulations or models. The quality of the data collection techniques used ensures the accuracy and reliability of real data. Real-time data can be used in assessing wind turbine performance to detect faults within the system. The data is normally obtained from sensors mounted on the turbine. The sensor detects wind speed, weather condition, level of vibration, speed of the turbine, and other features that relate to performance. This data may be utilised to calculate the turbine's energy production, efficiency, and other performance measures. This data may also be utilized to detect possible turbine faults i.e. blade fractures, misalignment, and other structural difficulties.

3. RESULTS

3.1 Results of the Implemented Model for Wind Turbine Performance Evaluation

In the implementation of the power model for the evaluation of the wind turbine performance, the two-model algorithm developed and presented in Chapter 3 was implemented. First for the determination of the coefficients of the models a, b, c, and d utilising the Genetic Algorithm, which is an optimization model, and secondly, for the actual evaluation of the wind turbine performance utilising the model Algorithm 2.

The results of the evaluation show that the coefficients a, b, c, and d have the ensuing optimal values: 0.8147, 0.9058, 0.1270, and 0.9134, respectively, after the implementation of the genetic algorithm, which uses a 10-generation best fitness simulation.The values of the vibration levels, weather conditions, likewise the turbine loadings and turbine speeds utilised for the evaluations of the wind turbine performance are given as follows:

V = [1, 2, 3, 4,5]; percent Vibration Levels in Hz
W = [20, 40, 60, 80, 100]; percent Weather Conditions/Humidity in kg/m^3
T = [5,10,15,20,25]; percent Turbine Loading
S = [2.6,3.0,4.6,5.8,8.9]; percent Turbine Speed in m/s

After implementing Algorithm 2, we received a four-dimensional array index result for the output of power. The simulation results of the four-dimensional array index provide the wind turbine performance owing to the developed power model in MATLAB. These results show the output of power of the wind turbine under various vibration levels, turbine loadings, turbine speeds, and weather conditions.

The performance simulation assessed the weather conditions by assessing the air density around the wind turbine system, which is influenced by the air humidity. The initial performance or power generation of the wind turbine was evaluated under varying vibration levels and weather conditions, likewise varied turbine loadings and turbine speed matrices.

The first performance data displays the output of power in the first column (21.9405kW, 22.7552 kW, 23.5699 kW, 24.3846 kW, and 25.1993 kW). These values are obtained from a vibration level of 1 Hz, a weather condition of 20 kg/m3, and a turbine loading of 5, while the turbine speed is 2.6 m/s. The second column (40.0565, 40.8712, 41.6859, 42.5006, and 43.3153) kW represents the power production and performance of the wind turbine under certain conditions. These conditions comprise a vibration level of 2 Hz, a weather condition of 40 kg/m3, a turbine loading of 5, and a turbine speed of 2.6 m/s. The third column displays the output of power and wind turbine performance at a vibration frequency of 3 Hz, a weather condition with a density of 60 kg/m3, a turbine loading of 5, and a turbine speed of 2.6 m/s. The values in this column are 58.1725 kW, 58.9872 kW, 59.8019 kW, 60.6166 kW, and 61.4313 kW. The fourth column (76.2885, 77.1032, 77.9179, 78.7326, and 79.5473) kW represents the power production and performance of the wind turbine under certain conditions.

The boundary conditions included a vibration frequency of 4 Hz, a weather condition with a density of 80 kg/m3, a factor of 5 in turbine loading, a speed of 2.6 m/s in turbine velocity, and an angle of attack ranging from 0° to 360°.

The fifth column, 94.4045, 95.2192, 96.0339, 96.8486, and 97.6633 in kW, indicates the power production and performance of the wind turbine under the following conditions: vibration level of 5 Hz, weather condition of 100 kg/m3, turbine loading of 5, and turbine speed of 2.6 m/s.

Here, the power production exhibits a positive correlation with the rise in parameter values. The wind turbine's output of power, as determined by the power model, ranges from 21.9405 to 94.4045 kilo Watts. This range is achieved when the wind turbine's vibration levels are between 1 and 5 Hz, the weather conditions range from 20 to 100 kg/m3, and the turbine is loaded at a fixed value of 5 with a speed of 2.6 m/s. The output of power of the wind turbine system ranges from 25.1993 to 97.6633 kiloWatts, with a vibration level of 5 Hz and a humidity of 100 kg/m3. The initial performance or output of power of the wind turbine varied across various vibration levels and weather conditions, likewise across the first parts of the turbine loadings and turbine speed matrices. Observe the correlation between the rise in output of power and the increase in parameter values. The wind turbine's second performance or output of power will vary owing to variable vibration levels, weather conditions, and the second parts of the turbine loadings and turbine speed matrices. Observe the correlation between the output of power and the growth in parameter values. The wind turbine's third performance or output of power will vary owing to variable vibration levels, weather conditions, and the third components of the turbine loadings and turbine speed matrices. Observe the correlation between the output of power and the growth in parameter values. The wind turbine's fourth performance or output of power will vary across varied vibration levels, weather conditions, and the fourth components of the turbine loadings and turbine speed matrices. Observe the correlation between the output of power and the growth in parameter values. The wind turbine's fifth performance or output of power will vary owing to varied vibration levels, weather conditions, and the fifth components of the turbine loadings and turbine speed matrices. Observe the correlation between the output of power and the growth in parameter values. Table 2displays the calculated output of power in kiloWatts (kW) for the first performance simulation.

Table 1. Computed results for output of power across the first element of the turbine loadings and the first element of the turbine speeds matrix in KiloWatt, kW

	P_1	P_2	P_3	P_4	P_5
:, :, 1, 1	21.9405	40.0565	58.1725	76.2885	94.4045
	22.7552	40.8712	58.9872	77.1032	95.2192
	23.5699	41.6859	59.8019	77.9179	96.0339
	24.3846	42.5006	60.6166	78.7326	96.8486
	25.1993	43.3153	61.4313	79.5473	97.6633

The second simulation result from the wind turbine power model represents the performance of the wind turbine as a four-dimensional array index. The values in the array index (:, 2,1) indicate the performance or output of power of the wind turbine across the different vibration levels and weather conditions, likewise across the second element of the turbine loadings and the first element in the turbine speeds matrix. The first column, which is (22.5755, 23.3902, 24.2049, 25.0196 and 25.8343) Kw shows the second performance evaluation and simulation, which results from a vibration level of 1 Hz, a weather condition of 20 kg/m3, a turbine loading of 10, and a turbine speed of 2.6 m/s. Similarly, the second column, which is (40.6915, 41.5062, 42.3209, 43.1356 and 43.9503) Kw shows the performance and output of power results at a vibration level of 2 Hz with a weather condition of 40 kg/m3, a turbine loading of 10, a turbine speed of 2.6 m/s. The third column, which is (58.8075, 59.6222, 60.4369, 61.2516 and 62.0663) kW, shows the performance and output of power results at a vibration level of 3 Hz with a weather condition of 60 kg/m3, a turbine loading of 10, a turbine speed of 2.6 m/s. The fourth column, which is (76.9235, 77.7382, 78.5529, 79.3676 and 80.1823) kW, shows the performance and output of power results at a vibration level of 4 Hz with a weather condition of 80 kg/m3, a turbine loading of 10, a turbine speed of 2.6 m/s. And the fifth column, which is (95.0395, 95.8542, 96.6689, 97.4836 and 98.2983) kW, shows the performance and output of power results at a vibration level of 5 Hz with a weather condition of 100 kg/m3, a turbine loading of 10, a turbine speed of 2.6 m/s. The values in each column represent the output of power of the wind turbine at the respective vibration levels and weather conditions. The first performance or output of power of the wind turbine was across the different vibration levels and weather conditions, likewise across the first elements of the turbine loadings and turbine speed matrixes. Take note as the output of power increases as the parameters increase in value. The second performance or output of power of the wind turbine is across the different vibration levels and weather conditions, likewise across the second elements of the turbine loadings and turbine speed matrixes. Take note as the output of power increases as the parameters increase in value. The third performance or output of power of the wind turbine will be across the different vibration levels and weather conditions, likewise across the third elements of the turbine loadings and turbine speed matrixes. Take note as the output of power increases as the parameters increase in value. The fourth performance or output of power of the wind turbine will be across the different vibration levels and weather conditions, likewise across the fourth elements of the turbine loadings and turbine speed matrixes. Take note as the output of power increases as the parameters increase in value. The fifth performance or output of power of the wind turbine will be across the different vibration levels and weather conditions, likewise across the fifth elements of the turbine loadings and turbine speed matrixes. Take note as the output of power increases as the parameters increase in value. The set of computed results for the wind turbine performance is shown in Table 2.

From the result in Table 2, it is not hard to see that the wind turbine performance result obtained from the power model implementation shows that the turbine produces between 22.5755 and 95.0395 kilowatts of power when the vibration levels of the wind turbine are between 1 and 5 Hz and the weather condition is between 20 and 100 kg/m3 and at a turbine loading of 10 and a turbine speed of 2.6 m/s, respectively. At 5 Hz and 100 kg/m3 for the vibration level and humidity of the wind turbine system, respectively, the turbine produces between 25.8343and 98.2983 kilowatts of output of power.

Table2: Computed results for output of power across the second element of the turbine loadings and the first element of the turbine speeds matrix in KiloWatt, kW

	P_1	P_2	P_3	P_4	P_5
2, 1	22.5755	40.6915	58.8075	76.9235	95.0395
	23.3902	41.5062	59.6222	77.7382	95.8542
	24.2049	42.3209	60.4369	78.5529	96.6689
	25.0196	43.1356	61.2516	79.3676	97.4836
	25.8343	43.9503	62.0663	80.1823	98.2983

Similarly, in the third simulation result from the wind turbine power model, which is presented in a four-dimensional array index (:,:,3,1), the wind turbine performance results show that the output of power across the different vibration levels and weather conditions, likewise across the third element of the turbine loadings and the first element in the turbine speeds matrix, produces a output of power that is (23.2105, 24.0252, 24.8399, 25.6546 and 26.4693) kW when the vibration level is 1 Hz, the weather condition is 20 kg/m3, the turbine loading is 15 and turbine speed is 2.6 m/s. Similarly, for the second performance simulation, a output of power of (41.3265, 42.1412, 42.9559, 43.7706 and 44.5853) kW was produced when the vibration level was 2 Hz, the weather condition was 40 kg/m3, the turbine loading was 15, the turbine speed was 2.6 m/s. The third column, which is (59.4425, 60.2572, 61.0719, 61.8866 and 62.7013) kW, shows the performance and output of power results at a vibration level of 3 Hz with a weather condition of 60 kg/m3, a turbine loading of 15, a turbine speed of 2.6 m/s.

The fourth column, which is (77.5585, 78.3732, 79.1879, 80.0026 and 80.8173) kW, shows the performance and output of power results at a vibration level of 4 Hz with a weather condition of 80 kg/m3, a turbine loading of 10, a turbine speed of 2.6 m/s. And the fifth column, which is (95.6745, 96.4892, 97.3039, 98.1186 and 98.9333) kW, shows the performance and output of power results at a vibration level of 5 Hz with a weather condition of 100 kg/m3, a turbine loading of 15, a turbine speed of 2.6 m/s. The first performance or output of power of the wind turbine was across the different vibration levels and weather conditions, likewise across the first elements of the turbine loadings and turbine speed matrixes. Take note as the output of power increases as the parameters increase in value. The second performance or output of power of the wind turbine was across the different vibration levels and weather conditions, likewise across the second elements of the turbine loadings and turbine speed matrixes. Take note as the output of power increases as the parameters increase in value. The third performance or output of power of the wind turbine will be across the different vibration levels and weather conditions, likewise across the third elements of the turbine loadings and turbine speed matrixes. Take note as the output of power increases as the parameters increase in value. The fourth performance or output of power of the wind turbine will be across the different vibration levels and weather conditions, likewise across the fourth elements of the turbine loadings and turbine speed matrixes. Take note as the output of power increases as the parameters increase in value. The fifth performance or output of power of the wind turbine will be across the different vibration levels and weather conditions, likewise across the fifth elements of the turbine loadings and turbine speed matrixes. Take note as the output of power increases as the parameters increase in value. The values in each column represent the output of power of the wind turbine at the respective vibration levels and weather conditions.

Table 3. Computed results for output of power across the third element of the turbine loadings and the first element of the turbine speeds matrix in KiloWatt, kW

	P_1	P_2	P_3	P_4	P_5
:, :, 3, 1	23.2105	41.3265	59.4425	77.5585	95.6745
	24.0252	42.1412	60.2572	78.3732	96.4892
	24.8399	42.9559	61.0719	79.1879	97.3039
	25.6546	43.7706	61.8866	80.0026	98.1186
	26.4693	44.5853	62.7013	80.8173	98.9333

Similarly, in the fourth simulation result from the wind turbine power model, which is presented in a four-dimensional array index (:,:,4,1), the wind turbine performance results show that the output of power across the different vibration levels and weather conditions, likewise across the fourth element of the turbine loadings and the first element in the turbine speeds matrix, produces a output of power that is (23.8455, 24.6602, 25.4749, 26.2896, 27.1043 and 24.4845) Kw when the vibration level is 1 Hz, the weather condition is 20 kg/m3, the turbine loading is 80 and turbine speed is 2.6 m/s. Similarly, for the second performance, a output of power of (41.9615, 42.7762, 43.5909, 44.4056 and 45.2203) Kw was produced when the vibration level was 2 Hz, the weather condition was 40 kg/m3, the turbine loading was 80, the turbine speed was 2.6 m/s. The third column, which is (59.4425, 60.2572, 61.0719, 61.8866 and 62.7013) Kw, shows the performance and output of power results at a vibration level of 3 Hz with a weather condition of 60 kg/m3, a turbine loading of 80, a turbine speed of 2.6 m/s.

The fourth column, which is (77.5585, 78.3732, 79.1879, 80.0026 and 80.8173) Kw, shows the performance and output of power results at a vibration level of 4 Hz with a weather condition of 80 kg/m3, a turbine loading of 80, a turbine speed of 2.6 m/s. And the fifth column, which is (95.6745, 96.4892, 97.3039, 98.1186 and 98.9333) Kw, shows the performance and output of power results at a vibration level of 5 Hz with a weather condition of 100 kg/m3, a turbine loading of 80, a turbine speed of 2.6 m/s. The first performance or output of power of the wind turbine was across the different vibration levels and weather conditions, likewise across the first elements of the turbine loadings and turbine speed matrixes. Take note as the output of power increases as the parameters increase in value. The second performance or output of power of the wind turbine was across the different vibration levels and weather conditions, likewise across the second elements of the turbine loadings and turbine speed matrixes. Take note as the output of power increases as the parameters increase in value. The third performance or output of power of the wind turbine was across the different vibration levels and weather conditions, likewise across the third elements of the turbine loadings and turbine speed matrixes. Take note as the output of power increases as the parameters increase in value. The fourth performance or output of power of the wind turbine is across the different vibration levels and weather conditions, likewise across the fourth elements of the turbine loadings and turbine speed matrixes. Take note as the output of power increases as the parameters increase in value. The fifth performance or output of power of the wind turbine will be across the different vibration levels and weather conditions, likewise across the fifth elements of the turbine loadings and turbine speed matrixes. Take note as the output of power increases as the parameters increase in value. The fifth performance or output of power of the wind turbine will be across the different vibration levels and weather conditions, likewise across the fifth elements of the turbine loadings and turbine speed matrixes. Take note as the output of power increases as the parameters increase in value.

Table 4. Computed results for output of power across the fourth element of the turbine loadings and the first element in the turbine speeds matrix in KiloWatt, kW

	P_1	P_2	P_3	P_4	P_5
:, :, 4, 1	23.2105	41.3265	59.4425	77.5585	95.6745
	24.0252	42.1412	60.2572	78.3732	96.4892
	24.8399	42.9559	61.0719	79.1879	97.3039
	25.6546	43.7706	61.8866	80.0026	98.1186
	26.4693	44.5853	62.7013	80.8173	98.9333

Similarly, in the fifth simulation result from the wind turbine power model, which is presented in a four-dimensional array index (:,:,5,1), the wind turbine performance results show that the output of power across the different vibration levels and weather conditions, likewise across the fifth element of the turbine loadings and the first element in the turbine speeds matrix, produces a output of power that is (24.4805, 25.2952, 26.1099, 26.9242 and 27.7393) Kw when the vibration level is 1 Hz, the weather condition is 20 kg/m3, the turbine loading is 100 and turbine speed is 2.6 m/s. Similarly, for the second performance, a output of power of (42.5965, 43.4112, 44.2259, 45.0406 and 458553) Kw was produced when the vibration level was 2 Hz, the weather condition was 40 kg/m3, the turbine loading was 100, the turbine speed was 2.6 m/s. The third column, which is (60.7125, 61.5272, 62.3419, 63.1566 and 63.9713) Kw, shows the performance and output of power results at a vibration level of 3 Hz with a weather condition of 60 kg/m3, a turbine loading of 100, a turbine speed of 2.6 m/s. The fourth column, which is (78.8285, 79.6432, 80.4579, 81.2726 and 82.0873) Kw, shows the performance and output of power results at a vibration level of 4 Hz with a weather condition of 80 kg/m3, a turbine loading of 100, a turbine speed of 2.6 m/s. And the fifth column, which is (96.9445, 97.7592, 98.5739, 99.3886 and 100.2033) Kw, shows the performance and output of power results at a vibration level of 5 Hz with a weather condition of 100 kg/m3, a turbine loading of 100, a turbine speed of 2.6 m/s. The first performance or output of power of the wind turbine was across the different vibration levels and weather conditions, likewise across the first elements of the turbine loadings and turbine speed matrixes. Take note as the output of power increases as the parameters increase in value. The second performance or output of power of the wind turbine was across the different vibration levels and weather conditions, likewise across the second elements of the turbine loadings and turbine speed matrixes. Take note as the output of power increases as the parameters increase in value. The third performance or output of power of the wind turbine was across the different vibration levels and weather conditions, likewise across the third elements of the turbine loadings and turbine speed matrixes. Take note as the output of power increases as the parameters increase in value. The fourth performance or output of power of the wind turbine was across the different vibration levels and weather conditions, likewise across the fourth elements of the turbine loadings and turbine speed matrixes. Take note as the output of power increases as the parameters increase in value. The fifth performance or output of power of the wind turbine is across the different vibration levels and weather conditions, likewise across the fifth elements of the turbine loadings and turbine speed matrixes. Take note as the output of power increases as the parameters increase in value.

Table 5. Computed results for output of power across the fifth element of the turbine loadings and the first element of the turbine speeds matrix in KiloWatt, kW

	P_1	P_2	P_3	P_4	P_5
:, :, 5, 1	24.4805	42.5965	60.7125	78.8285	96.9445
	25.2952	43.4112	61.5272	79.6432	97.7592
	26.1099	44.2259	62.3419	80.4579	98.5739
	26.9246	45.0406	63.1566	81.2726	99.3886
	27.7393	45.8553	63.9713	82.0873	100.2033

The values in each column represent the output of power of the wind turbine at the respective vibration levels and weather conditions etc. The set of computed results for the wind turbine performance is shown in Table 6.

From the result in Table 4.6, the wind turbine performance result shows that the power model for the wind turbine produces between 23.2105 and 95.6745 kilowatts of power when the vibration levels of the wind turbine are between 1 and 5 Hz and the weather condition is between 20 and 100 kg/m3 and at a turbine loading of 15 and a turbine speed of 2.6 m/s, respectively. At 5 Hz and 100 kg/m3 for the vibration level and humidity of the wind turbine system, respectively, the turbine produces between 26.4693 and 98.9333 kilowatts of output of power. The other performance results utilising the different input parameters for the wind turbine system when the turbine speed is 2.6 m/s and the turbine loading is 20 and 25, respectively, are also presented in Table 4.6. Other results comprised in the table are the performance results when the turbine loading is 5 and the turbine speed is 3.0 m/s (:,:,1,2), when the turbine loading is 10 and the turbine speed is 3.0 m/s (:,:,2,2), when the turbine loading is 15 and the turbine speed is 8.9 m/s (:,:,3,5), when the turbine loading is 20 and the turbine speed is 8.9 m/s (:,:,4,5), and when the turbine loading is 25 and the turbine speed is 8.9 m/s (:,:,5,5).

The purpose is to verify and confirm the effectiveness of the sophisticated model algorithm created for the purpose of monitoring and assessing the efficiency of wind turbine systems. The model's prediction accuracy was evaluated utilising two widely utilised metrics: the mean absolute error (MAE) and the root mean squared error (RMSE). The MAE gives the average magnitude of the errors in a set of predictions, considering the magnitude only and ignoring the direction.

Table 6. Four-dimensional array index computed results of output of power across different element of the turbine loadings and turbine speeds matrix for the wind turbine performance, measured in KiloWatt, kW

	P_1	P_2	P_3	P_4	P_5
:, :, 3, 1	23.2105	41.3265	59.4425	77.5585	95.6745
	24.0252	42.1412	60.2572	78.3732	96.4892
	24.8399	42.9559	61.0719	79.1879	97.3039
	25.6546	43.7706	61.8866	80.0026	98.1186
	26.4693	44.5853	62.7013	80.8173	98.9333
:, :, 4, 1	23.8455	41.9615	60.0775	78.1935	96.3095
	24.6602	42.7762	60.8922	79.0082	97.1242
	25.4749	43.5909	61.7069	79.8229	97.9389
	26.2896	44.4056	62.5216	80.6376	98.7536
	27.1043	45.2203	63.3363	81.4523	99.5683
:, :, 5, 1	24.4805	42.5965	60.7125	78.8285	96.9445
	25.2952	43.4112	61.5272	79.6432	97.7592
	26.1099	44.2259	62.3419	80.4579	98.5739
	26.9246	45.0406	63.1566	81.2726	99.3886
	27.7393	45.8553	63.9713	82.0873	100.2033
:, :, 1, 2	22.3059	40.4219	58.5379	76.6539	94.7699
	23.1206	41.2366	59.3526	77.4686	95.5846
	23.9353	42.0513	60.1673	78.2833	96.3993
	24.7500	42.8660	60.9820	79.0980	97.2140
	25.5647	43.6807	61.7967	79.9127	98.0287
:, :, 2, 2	22.9409	41.0569	59.1729	77.2889	95.4049
	23.7556	41.8716	59.9876	78.1036	96.2196
	24.5703	42.6863	60.8023	78.9183	97.0343
	25.3850	43.5010	61.6170	79.7330	97.8490
	26.1997	44.3157	62.4317	80.5477	98.6637
:, :, 3, 5	28.9650	47.0810	65.1970	83.3130	101.4290
	29.7797	47.8957	66.0117	84.1277	102.2437
	30.5944	48.7104	66.8264	84.9424	103.0584
	31.4091	49.5251	67.6411	85.7571	103.8731
	32.2238	50.3398	68.4558	86.5718	104.6878
:, :, 4, 5	29.6000	47.7160	65.8320	83.9480	102.0640
	30.4147	48.5307	66.6467	84.7627	102.8787
	31.2294	49.3454	67.4614	85.5774	103.6934
	32.0441	50.1601	68.2761	86.3921	104.5081
	32.8588	50.9748	69.0908	87.2068	105.3228
:, :, 5, 5	30.2350	48.3510	66.4670	84.5830	102.6990
	31.0497	49.1657	67.2817	85.3977	103.5137
	31.8644	49.9804	68.0964	86.2124	104.3284
	32.6791	50.7951	68.9111	87.0271	105.1431
	33.4938	51.6098	69.7258	87.8418	105.9578

On the other hand, RMSE refers to a method of quadratic scoring that also works by averaging the magnitude of the error. According to Jierula *et al.* (2021), the best fit would be achieved when the values of MAE and RMSE of a prediction model are low, which automatically gives higher accuracy. An MAE or RMSE of 0 percent would imply a perfect prediction, and higher values of MAE indicate less accurate predictions. The MATLAB output report provides the model correctness for Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE).

The Mean Absolute Error is 0
The Mean Absolute Error is 0
The Mean Absolute Error is 0
The Mean Absolute Error is 0
The Mean Absolute Error is 0
The Mean Absolute Error is 0

The Root Mean Square Error is 0
The Root Mean Square Error is 0
The Root Mean Square Error is 0
The Root Mean Square Error is 0
The Root Mean Square Error is 0
The Root Mean Square Error is 0

3.2 Simulation Result

The simulation results from the wind turbine power model presented in Table 4.1 – 4.6, which represents the performance of the wind turbine system were presented utilising a four-dimensional array index. The index which is a matrix with rows and columns, presents the different aspect of the output of power result, i.e. the output when a corresponding value for each of the four dimensions (turbine speed, vibration levels, weather condition and turbine loadings) were considered.

The four-dimensional array gives an in-depth analysis of the wind turbine performance. It allows for the assessment of the turbine's performance in a variety of variables. This gives a more accurate picture of how the turbine will work in real life. With the result presented in the Tables, it is not hard to see that, the study have been able to evaluate the impact of the different wind conditions and parameters on the turbine's performance evaluation. The index which is a matrix with rows and columns, presents the different aspect of the output of power result, i.e. the output when a corresponding value for each of the four dimensions (turbine speed, vibration levels, weather condition and turbine loadings) were considered.

3.2.1 Result of the Implemented the Support Vector Regression Model for Fault Prediction

In the implementation of the support vector regression, the support vector regression model was trained utilising a set of Nigeria wind speed data obtained mainly to evaluate the impact of wind and how it can also cause or result in faults in the wind turbine system. The data set were split into two parts, some for training and the others was utilised for testing. The support vector regression model was trained utilising the training set, and its performance was evaluated utilising the test set. The support vector regression model which was utilised for the fault prediction in the wind turbine produces a number of result that have been presented in Figure 2.

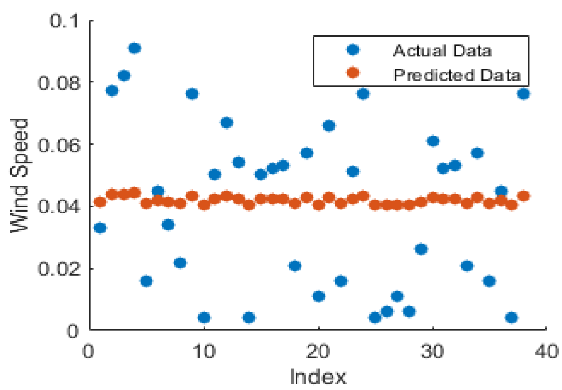

Figure 2: Fault Prediction Result of the Wind Turbine System utilising Wind Speed Data for Wind Speed 10^3m/s.

Firstly, the graph indicates that the support vector regression truly results in a fault prediction regarding a wind turbine system. Scattered output result of the actual information suggest multiple breakdowns and malfunction of turbine during the cycle. In contrast, the predicted data upshot is seen to spread along a line, indicating that the support vector regression is properly identified the most likely faults. This aftermath attests that the support vector regression model was effective in determining the most probable defects encountered by the wind turbine. This is very important, since with this knowledge, big trouble in the system can be avoided. For example, if a big defect or fault is highly forecasted to happen, then the turbine could be turned off before it happens, and this is to be able to save time and money. The output result scattered of real data results show that the turbine involves different failure and defect in the whole process. Observe the forecasted data output spreads hence in a line, illustrating for the most probable detected defect by the support vector regression. Note that the scaling of the graph in the Y-axis is 1 unit representing 0.02km/s

It also depicts the accuracy of the support vector regression model. The fact that the predicted data is distributed along a straight line shows that the support vector regression was able to identify wind turbine defects. This is a vital signal in that it shows support vector regression was able to capture faults in the turbines correctly, which may result in increased safety and reliability. The results from support vector regression can also be used to understand how the wind turbine is working. For example, if the projected data is distributed along a line, then it works out really well. If it's scattered and there is no kind of pattern, then probably something is wrong with the wind turbine. The overall result of the support vector regression in fault prediction for a wind turbine is mostly an indication of the accuracy of support vector regression. That the projected data lies along a line proves that support vector regression correctly detected anomalies in the wind turbine and thus can be very helpful in improving dependability and safety. In addition, this data is further utilized in gaining knowledge about the functioning of wind turbines; that is, issues can be pre-observed and repaired accordingly. The accuracy of the model was determined to be 99.3 %, thereby showing that the model is able to detect faults properly with a high degree of accuracy. In this research, wind turbine fault data from the literature were also implemented in order to predict faults in the wind turbine system. The dataset makes a division into two parts; some are used for training, and others are used for testing.

The trained support vector regression model was used with the training set, while the test set was used in the evaluation of the model's performance. The results for the support vector regression model in fault prediction in the wind turbine have been presented in Figure 3, while the fault aspect of the model was virtualized in Figure 4, with 1 unit representing 20m/s on the Y-axis.

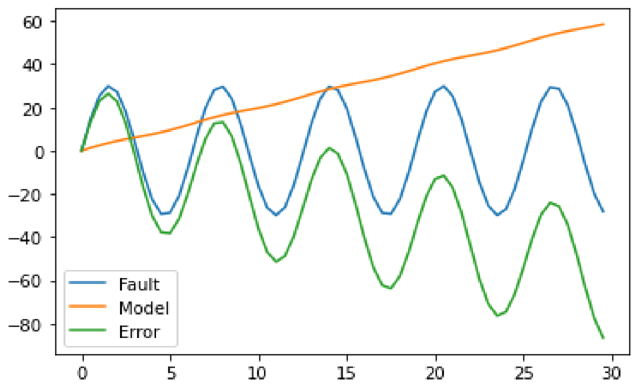

Figure 3.Fault Prediction Result of the Wind Turbine System utilising Fault Data

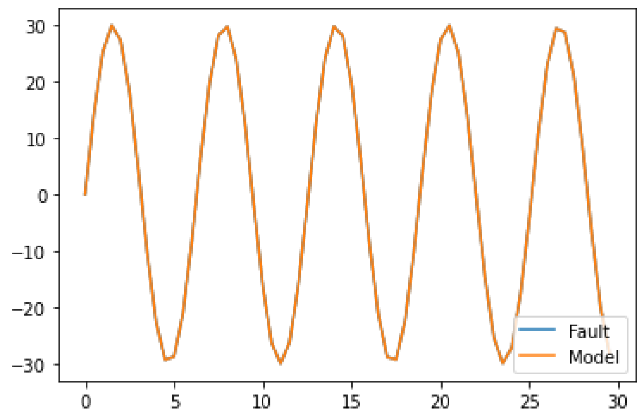

Figure 4. Fault Prediction Result of the Wind Turbine System

This work gives a visualization display of how the support vector regression model performs in the reliability management of wind turbine systems. In this graph, the yellow line indicates the support vector regression model, the blue line faults upshot, and the green line represents the error upshot. The support vector regression model used to predict faults in the turbine system gives, against a set of wind turbine fault data, a set of outputs that show exactly how the system works. It is actually a kind of regression approach that attempts to find the best fit line for the given points.

In this graph, the support vector regression model is represented by a straight line, while the fault upshot is represented in blue by a sin curve. The fault upshot would show how well the model trends fit into the underlying trend of the data. From the graph, one can see that the fault upshot has a trend similar to that of the support vector regression model. This proves that the support vector regression model captured the underlying trend of data. On the other hand, the error upshot is represented as a green line, which is also a sine curve. The error upshot describes how well the model can predict result. The error upshot, as in this graph, is similar to the trend of the model itself. That means that the support vector regression model can accurately forecast the results. As seen from the graph, since there is very minute error associated with the result, it means therefore that the model is very effective in detecting the fault on a straight line.

Conclusion

The result show that the evaluation system and models proposed in this study and that have been implemented are robust and effective for wind turbine performance evaluation and for the detection and prediction of possible faults in the turbine system. To show the feasibility and rationality of the models, they went through a number of validation processes to check their accuracy. From the research study and the investigation carried out, the ensuing can be reported as the concluding remarks and research result:

(i) The evaluation system and models proposed in this study and that have been implemented are robust and effective for wind turbine performance evaluation and for the detection and prediction of possible faults in the turbine system.
(ii) It is confirmed that a thorough monitoring and evaluation system offer a more comprehensive view of turbine performance and operations. Unlike, currently existing wind turbine monitoring and evaluation systems that

concentrated on certain elements of turbine functioning, like power production or cost management for performance measurement (Charabi & Abdul-Wahab, 2020). This study however, have been able to push further by integrating other relevant parameters in the evaluation process, thereby providing a comprehensive picture of the wind turbine health and performance.

(iii) With the comprehensive model algorithm, the study can conclude that the impact and influence of critical parameters like power outputs, weather conditions, wind speed, turbine loads and vibration levels of the system which has the capacity to cause severe damage and safety threats to the wind turbine operation can be managed and evaluated before they cause any damage or safety issues.

Recommendations

Although the aim and objectives of the study have been successfully addressed in this study, however there are still some areas and aspect of the study can be improved in the future, among them comprise,

(i) The investigation into the development of automated maintenance solutions to eliminate manual labour for wind turbine performance and maintenance management.

(ii) Investigation of how the system may be modified to other types of wind turbines, i.e. offshore and onshore turbines in various climates.

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