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Condition Monitoring of Wind Turbines: A Case Study of the Gibara II Wind Farm

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ABSTRACT

The main objective of this study is to investigate the adaptation of wind turbines at the Gibara II Wind Farm in Cuba, which operates in a tropical climate that differs from the typical conditions in which these turbines are designed and manufactured in the northern hemisphere. The study utilizes condition monitoring techniques supported by Big Data acquired through a supervisory control and data acquisition (SCADA) system. By statistically processing normalized databases using multiple linear regression equations, the study establishes mathematical models that characterize the behavior of critical variables such as bearing, oil and winding temperatures, electrical generation, and specific climatic conditions unique to the wind farm under analysis. These models are essential for advancing condition-based maintenance (CBM) practices and developing preventive measures to mitigate functional failures. The significance of this research lies in the historical technical performance of the equipment under investigation, highlighting the importance of addressing the challenges posed by different environmental conditions. The study was conducted using the relevant regulatory technical documentation pertaining to the design of the wind turbines at the Gibara II Wind Farm.

1. INTRODUCTION

Condition monitoring (CM) is a technique used to assess the condition of machines and prevent failures by recommending maintenance actions when necessary. It is an integral part of condition-based maintenance (CBM), an advanced strategy that relies on monitoring equipment condition data [1, 2]. CM measurements can include various data sources such as vibration, acoustic emission, and oil analysis from wind turbine components [3]. The main objective of CBM is to optimize maintenance activities and reduce costs. Unlike traditional preventive maintenance, CBM is based on monitoring and analyzing system parameters, initiating maintenance when a condition variable crosses a threshold value [4, 5].

An essential component for an efficient maintenance procedure is the Condition Monitoring System (CMS), which plays a crucial role in early problem detection. By identifying potential issues at an early stage, maintenance tasks or repairs can be scheduled proactively, leading to improved machine availability and reduced maintenance costs [6]. According to [7], implementing condition monitoring, along with failure detection systems (FDS), is a viable approach to lowering maintenance costs. FDS provides an early warning system that complements the condition-based maintenance approach by enabling maintenance actions to be taken before failures occur. Therefore, the implementation of an FDS for wind turbines offers various benefits [8]:

- Early detection of faults or abnormal behavior.
- Improved equipment reliability and uptime.
- Reduction in unscheduled downtime.
- Optimal planning of maintenance activities.
- Cost savings through targeted maintenance interventions.
- Enhanced safety by preventing catastrophic failures.
- Improved performance and energy efficiency.
- Enhanced data-driven decision-making for maintenance strategies.
- Monitoring at remote sites.
- Capacity factor improvement.

The CM and FDS are essential tools for effective maintenance programs, especially in the wind turbine industry, as they enable proactive and cost-effective maintenance practices.

For the application of a correct CBM program, three fundamental steps must be followed [2, 9, 10].

- Data acquisition.
- Data processing.
- Maintenance decision making.

With favorable data acquisition and proper signal processing techniques, it becomes possible to detect faults in components while they are in operation. This enables the implementation of timely actions to prevent damage or failure of the mechanisms. As a result, maintenance tasks can be efficiently planned and scheduled, leading to improved reliability, availability, capacity, and safety during downtime.

Ultimately, this approach reduces maintenance and operating costs [11]. Monitoring techniques are employed to measure physical variables that serve as indicators of the machine's condition. These variables are then analyzed by comparing them to a range of normal values to evaluate the presence of deteriorating conditions [12].

By employing on-line condition monitoring systems equipped with fault detection algorithms, mechanical and electrical faults in various system components can be detected before they become visually or acoustically evident. This proactive approach helps prevent major defects that could lead to unscheduled turbine shutdowns, thereby avoiding significant economic costs [13]. Sensors monitor all these components, and the signals they capture are transmitted to the monitoring unit. Based on the collected data, the monitoring unit makes informed decisions, including issuing alarm signals or initiating turbine shutdowns when necessary [14]. Detecting failures in advance can prevent substantial losses caused by generator breakage or damage to other turbine elements. Additionally, it helps mitigate the costs associated with the ungenerated energy during equipment repairs. Turbine failures can stem from issues with the impeller, such as blade imbalances, torque oscillations, and flow problems, as well as external disturbances and transmission or coupling problems like shaft misalignment or gearbox failures [15].

The gearbox is responsible for the majority of turbine failures, even though electrical systems also frequently experience malfunctions. As a result, these components are considered critical within the turbine [16]. For this reason, our research focused on implementing condition monitoring techniques specifically for these components at the Gibara II Wind Farm. The use of CM techniques is prevalent throughout the industry, and their benefits are particularly evident in offshore wind farms. This is due to not only the high costs associated with offshore operation and maintenance but also the typically robust nature of these systems [17]. Figure 1 illustrates the concept of the P-F (Potential-Failure) period, which represents the time interval between the detection of a potential failure and its manifestation as a functional failure. Point P represents the moment when the failure cause is detectable using the chosen technique, while F signifies the failure point when the equipment's performance falls below the lower limit of the normal range [12, 18].

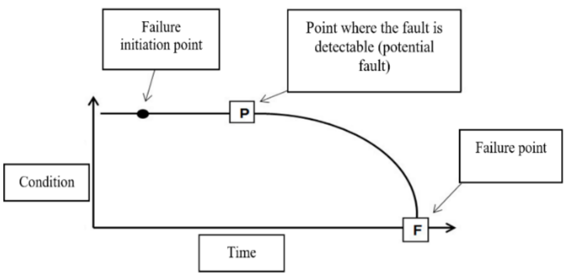

Figure 1. P-F interval [12, 18]

For each case, it is necessary to select the most appropriate technique that has the most convenient P-F interval, and to design the monitoring frequency appropriately, so that there is a time interval such that when a potential failure is detected, it is always possible to schedule and execute a corrective intervention, otherwise there is no sense in applying Condition Monitoring [18]. The main techniques for CM are vibration analysis, acoustic emission, temperature and oil residue analysis; these techniques are very well established in the industry [19].

Temperature monitoring is a widely used method in condition monitoring (CM) for identifying potential failures associated with temperature changes in equipment. This technique is frequently applied in the wind power industry to monitor components such as bearings, liquids, and generator windings. Various sensors, including optical pyrometers, resistive thermometers, and thermocouples, are utilized to measure temperatures [20]. However, due to the stochastic nature of wind turbines' operating environment, their performance and health status are significantly influenced by environmental and operating conditions. Therefore, gaining a better understanding of these factors is crucial for developing more reliable condition monitoring solutions for wind turbines [21]. Generally, there are three common approaches to temperature monitoring [22]:

1. Measurement of temperatures at local points, using surface or embedded temperature detectors.
2. Temperature monitoring of the larger area of the machine, using thermal imaging.
3. Measurement of temperature distribution in machine or bulk fluids.

Monitoring the operational temperature is a crucial aspect of performance monitoring. It has been observed that monitoring component temperatures, particularly in the trunnion bearing where lubrication issues may arise, is closely associated with wear in machine components [23]. While there has been an increase in wind turbine failures caused by excessive generator temperatures, the development of wind energy continues to be a prominent trend for the foreseeable future. Wind energy is recognized as one of the most efficient forms of renewable energy [24].

Cuba is embracing wind energy as a potential replacement for its conventional energy sources, taking advantage of the favorable wind speed conditions in the eastern region of the country. The Gibara II WF serves as an example of this transition. However, after several years of operation, specialists at the wind farm noticed the early occurrence of technical alarms detected by the SCADA system, specifically related to anomalies in aggregate temperatures and electricity generation. For this purpose, measurements of various parameters such as those listed in Table 1 were available, but the correlation between them was not known, posed a challenge in developing prediction models and limited the possible prediction models and limited their development.

Table 1. SCADA-monitored parameters chosen for CM studies at WT

	Parameters	U	Correlation
1	Temperature of generator bearing 1 (T1)	℃	
2	Generator Bearing 2 Temperature (T2)	℃	
3	Winding temperature (T3)	℃	
4	Gearbox oil temperature (T4)	℃	
5	Temperature of gearbox high shaft bearing (T5)	℃	¿?
6	Power (G)	kW	
7	Wind speed (Vv)	m/s	
8	Ambient temperature (T6)	℃	
9	Month (Month)		
10	Time (Hour)		

Temperature monitoring is a common practice in wind turbines, particularly for specific areas such as the stator core and cooling fluids in large electrical machines like WTGs. While these measurements can provide general indications of changes occurring within the machine, their effectiveness is greatly enhanced when strategically placed and continuously monitored. Generator temperatures are directly influenced by electrical loads and environmental conditions. Therefore, when temperature measurements are combined with information about the system's condition, it enables effective condition monitoring [25]. Various mathematical methods are employed to construct the normal operating model for wind turbine generator temperature. This model is then utilized to predict the generator temperature at each time step, facilitating ongoing monitoring of its behavior [26].

The rest of the document is structured as follows: Section 2 describes the proposed methodology. Section 3 presents the results and discussion, with the application of models to prevent functional failures. Finally, Section 4 shows the conclusions.

2. MATERIALS AND METHODS

The researchers at the Gibara II Wind Farm implemented condition monitoring (CM) techniques to investigate changes in the cooling system behavior of the Goldwind WT Model S50/750 turbines. The aim was to identify the underlying causes of temperature-related failures and prevent more significant failures from occurring. By detecting early warning signs of impending failures, prompt action can be taken to take the affected machine offline for repair. This proactive approach helps minimize the extent of damage to the components, thereby reducing repair costs. However, it is important to consider the cost of implementing and maintaining the monitoring system, ensuring that the potential savings outweigh the associated expenses [27]. It should be noted that temperature monitoring methods do not directly detect faults or their causes. Instead, they provide indications of potential failures that require attention [28]. In the studied WT model, six PT 100 sensors are used to measure temperatures, including gearbox oil temperatures, bearing temperature, and ambient temperature, at ten-minute intervals [29].

The bearing temperature should be in a certain range during normal wind turbine operating conditions. IEEE 841 states that stabilized bearing temperature increases at rated load should not exceed 45℃ [30]. An unforeseen rise in component temperature can be an indication of factors such as excessive load, inadequate lubrication, or potentially ineffective cooling mechanisms [26]. Furthermore, a sudden temperature increase during regular operation frequently signifies a failure in wind turbine bearings [31]. Similarly, gearbox oil temperature should be in a certain range during nominal wind turbine operating conditions [32]. Therefore, temperature monitoring can reveal the health status of wind turbine bearings and gearboxes [33].

CBM facilitates a shift from reactive maintenance to proactive strategies, leading to improved maintenance time optimization and the prevention of early system failures. The use of SCADA systems for monitoring wind turbines has gained increased prominence, primarily due to the availability of data without incurring additional costs [34]. Modern wind turbines are equipped with remote monitoring systems facilitated by SCADA, enabling continuous surveillance. Through these systems, operators can monitor various variables measured within the turbines, including alarms, warnings, and statuses, either in real-time or by accessing historical records [35].

A comprehensive overview of CM methods for various wind turbine components is presented in the study [36]. Temperature is commonly recognized as a crucial indicator for assessing the health of many wind turbine components and is often recorded automatically. It is widely agreed upon that SCADA-generated databases are essential for constructing the normal operating model [25, 37, 38]. However, there is a limitation to the reliability of these models due to the wide range of SCADA data values observed under varying operating conditions. Detecting early faults solely from SCADA data without appropriate data analysis tools can be challenging [39]. Consequently, for the specific study conditions, where ample data and measurements are available, twelve distinct operating conditions are identified. These conditions closely correspond to the four climatic seasons experienced throughout the year and the three variations in environmental conditions occurring within a day.

In the research [26], multiple linear regression analysis is recognized as a commonly employed statistical method for analyzing complex data involving multiple factors. It is utilized to examine and establish the relationship between various variables. To ensure dependable outcomes, it is crucial to carefully select and include logical variables in the analysis. Hence, MLRM can serve as a fundamental framework for a novel approach to accurately predict and monitor temperatures within WTs. This is achieved by calculating the correlation between observed and predicted values of the target variable, which is influenced by historical generator temperatures. By utilizing MLRM, it becomes possible to forecast temperature changes efficiently and reliably within WTs. With the use of professional software, the data collected was processed, allowing the following results to be obtained.

Overall, the research focuses on the importance of temperature monitoring, the role of SCADA systems in wind turbine monitoring, and the utilization of multiple linear regression analysis to predict and monitor temperatures effectively within wind turbines.

3. RESULTS AND DISCUSSION

To ensure the accuracy of the condition monitoring CM models and establish suitable models, the initial step was to examine the correlation between parameters. This process helped identify dependencies among variables. Based on these findings, closely related models were developed, which allowed for the identification of potential failure points, detection of potential failures, and establishment of conditions for functional failures.

Table 2 demonstrates a strong correlation between bearing temperatures and wind speed, highlighting the significant impact of wind speed on the monitored temperatures. Additionally, there is a positive correlation among variables such as electrical generation, winding temperature, gearbox oil temperature, gearbox bearing temperature, and wind speed. Conversely, researchers observed no relationship between ambient temperature and wind speed, as well as between time and month.

Table 2. Correlation between monitored variables

	T1	T2	T3	T4	T5	G	Vv	T6	Month	Hour
T1	1.00									
T2	0.82	1.00								
T3	0.84	0.70	1.00							
T4	0.86	0.68	0.90	1.00						
T5	0.86	0.72	0.83	0.95	1.00					
G	0.77	0.64	0.85	0.82	0.85	1.00				
Vv	0.77	0.64	0.83	0.81	0.84	0.99	1.00			
T6	0.10	0.16	-0.26	-0.09	0.04	-0.01	0.00	1.00		
Month	-0.20	-0.10	-0.30	-0.22	-0.23	-0.28	-0.26	0.13	1.00	
Hour	0.15	0.11	0.08	0.12	0.08	-0.03	-0.02	-0.12	0.00	1.00

It is apparent that there exists a complex interplay between temperatures and factors like time, month, and ambient temperature. From these observations, it is inferred that any predictive model should consider the monitored variables that influence the variable to be predicted. This highlights the importance of including relevant factors in the development of comprehensive predictive models.

This underlined the significance of analyzing the correlation between parameters in order to establish effective CM models. The findings demonstrated the strong influence of wind speed on bearing temperatures and identified several variables that exhibit interdependencies. These insights emphasize the need to consider relevant monitored variables when constructing predictive models to ensure their accuracy and reliability.

As in any entity dedicated to energy production, the first question that could be answered with the CM was the behavior of generation as a function of wind speed, an analysis of which is shown in Figure 2.

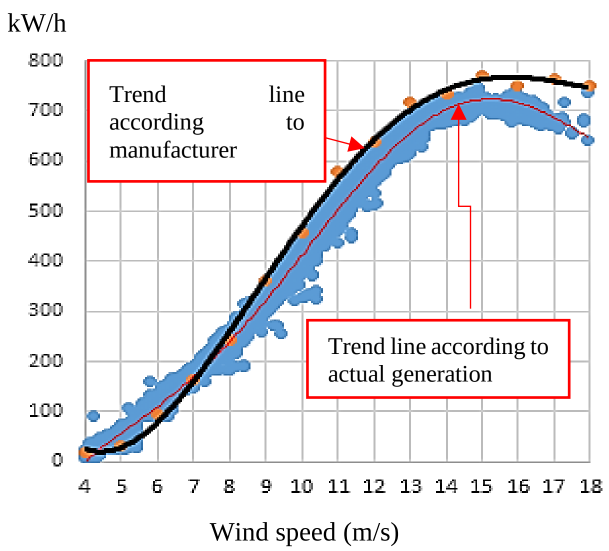

Figure 2. Generation behavior as a function of wind speed

Considering that each wind speed range corresponds to a specific range of generation, the research suggests that anomalies in the functional state of the wind turbine WT occur when the expected condition for each wind speed range is not met. The graph above illustrates the behavior of generation throughout the monitored period, showing a higher frequency of anomalies during the afternoon. A polynomial function can be used to predict the behavior of electric generation based on wind speed, as indicated by the trend of normal behavior. It is evident that the trend line predicted by the manufacturer for generations contradicts the actual behavior. Consequently, the researchers derived a mathematical model using the advantages of Excel. This model allows for the establishment of condition monitoring in generation and facilitates behavior prediction.

$$y(x) = 0{,}0107x^5 - 0{,}5917x^4 + 11{,}732x^3 - 103{,}01x^2 + 465{,}77x - 825{,}94$$

The fifth order polynomial equation determined allows predictions with an $R^2 = 0.99$, guaranteeing a high level of accuracy. Previous research [37, 40, 41], established the relationship between T1 temperature and potential failures and failure points in the WT of the Gibara II WF, but the existing relationships with the rest of the parameters monitored by the SCADA system were not exposed.

Hence, condition monitoring (CM) is necessary for T3 and T4, crucial variables in understanding the heat dynamics within the nacelle. These variables are influenced by wind speed and power generation, which in turn impact the variations of T1. The mathematical models developed through MLRM in this study enable WF specialists to compare actual behaviors with established patterns and identify any abnormal behaviors. Following several months of data collection and analysis, Table 3 provides the coefficients and models for predicting the behavior of T1, a critical parameter indicative of the operational state of the studied wind turbines.

With the coefficients of the previous table and the following model, T1 CM can be performed for the four seasons of the year in Cuba for the most unfavorable schedule.

$$y(T1)°C=(B+(B_1X_1)+(B_2X_2)+(B_3X_3)+(B_4X_4)+(B_5X_5)+(B_6X_6)+(B_7X_7)+(B_8X_8)+(B_9X_9))$$

The coefficients for predicting T3 are presented in Table 4, indicating that the estimated values have an adjusted quadratic error exceeding 0.94. This suggests a remarkably accurate estimation of the actual behavior, with potential discrepancies only occurring in cases of temperature variations exceeding 10°C and wind speeds surpassing 11.5 m/s. Such instances would be recognized and investigated as potential starting points for failures due to the frequent occurrence of anomalous behaviors during afternoon hours, as well as the strong correlation observed between T3 and variables Vv, G, and T4.

The CM of T3 based on the mathematical model obtained, made it possible to identify potential faults in the winding of two generators, which during capital maintenance showed the development of some failure points.

$$y(T3)°C=(B+(B_1X_1)+(B_2X_2)+(B_3X_3)+(B_4X_4)+(B_5X_5)+(B_6X_6)+(B_7X_7)+(B_8X_8))$$

Table 5 shows the coefficients corresponding to the model for the calculation of T4.

Table 3. Coefficients to calculate T1 using a model based on MLRM

		Coef 1 Quarter	Coef 2 Quarter	Coef 3 Quarter	Coef 4 Quarter
Intercept	B	8.143573	0.704019	-12.8766	-28.8062
Variable X1 (T2)	B1	0.243525	0.352493	0.110034	0.250373
Variable X2 (T3)	B2	0.407339	0.433852	0.565685	0.286583
Variable X3 (T4)	B3	0.815199	0.148774	0.677963	0.709729
Variable X4 (T5)	B4	0.377585	0.081446	-0.289872	0.003187
Variable X5 (T6)	B5	0.045615	0.596639	0.7842845	0.688820
Variable X6 (Vv)	B6	0.041979	0.372969	-0.142988	-0.980194
Variable X7 (G)	B7	0.010003	0.013355	-0.008785	0.008218
Variable X8 (Mouth)	B8	-0.54017	2.831710	-2.803893	0.029041
Variable X9 (Hour)	B9	0.019288	0.261460	0.713358	0.078044
Adjusted R^2		0.98	0.93	0.94	0.84

Table 4. Coefficients to calculate T3 using a model based on MLRM

		Coef 1 Quarter	Coef 2 Quarter	Coef 3 Quarter	Coef 4 Quarter
Intercept	B	-4.35189	-39.6000	-17.91224	6.320143
Variable X1 (T2)	B1	0.061094	0.151660	0.133250	0.164532
Variable X2 (T3)	B2	0.812575	0.335468	0.246464	0.323034
Variable X3 (T4)	B3	2.920794	0.015358	2.274582	3.210162
Variable X4 (T5)	B4	-1.39507	2.243055	-0.392217	-1.424929
Variable X5 (T6)	B5	-1.28480	-0.13296	-0.395577	-0.492166
Variable X6 (Vv)	B6	0.388847	-0.01631	0.003767	0.003767
Variable X7 (G)	B7	0.042179	-8.23043	-9.501416	-9.501416
Variable X8 (Mouth)	B8	-9.81310	2.556498	0.727049	0.727049
Adjusted R^2		0.97	0.95	0.94	0.94

Table 5. Coefficients to calculate T4 using a model based on MLRM

		Coef 1 Quarter	Coef 2 Quarter	Coef 3 Quarter	Coef 4 Quarter
Intercept	B	5.680592	20.18035	7.947909	1.103971
Variable X1 (T2)	B1	-0.00497	-0.02560	-0.022952	-0.016165
Variable X2 (T3)	B2	0.059067	0.008406	0.030974	0.024013
Variable X3 (T4)	B3	-0.03202	-0.01394	-0.008316	0.003645
Variable X4 (T5)	B4	0.078348	0.161162	0.176715	0.099341
Variable X5 (T6)	B5	0.660395	0.417801	0.500191	0.702797
Variable X6 (Vv)	B6	0.100671	-0.13554	0.001922	0.052038
Variable X7 (G)	B7	0.143553	1.723730	1.411983	0.710072
Variable X8 (Mouth)	B8	0.148088	-0.84591	-0.311128	0.057597
Variable X9 (Hour)	B9	0.004126	0.013589	0.006997	0.003888
Adjusted R^2		0.97	0.97	0.95	0.96

4. CONCLUSIONS

After acquiring the mathematical models using MLRM and processing the data obtained from the SCADA system, it was able to diagnose and predict technical behaviors. This breakthrough enabled informed decision-making in maintenance, going beyond the preventive maintenance plans suggested by the manufacturer. It marked the initiation of new Condition-based Maintenance activities at the Gibara Wind Farm. These CBM tasks were supported by a combination of condition monitoring and the Statistical Data Fusion technique applied to the cooling system of the Goldwind WT model S50/750. This combination ensured a reliable assessment of the wind turbine (WT) status and enhanced the prevention of failures. The study's outcome was the successful development of mathematical models using MLRM and the utilization of SCADA data. This provided valuable insights into the technical behavior of the WT and facilitated maintenance decision-making. By implementing CBM strategies beyond traditional manufacturer recommendations, the study paved the way for more effective and targeted maintenance actions at the Gibara WF. The integration of CM and SDF techniques specifically targeted the cooling system of the Goldwind WT model S50/750, resulting in improved evaluation of WT conditions and a proactive approach to failure prevention.

In essence, the research delves into the tropicalization of wind turbines by investigating their operational performance and establishing mathematical models to understand and predict critical variables. This knowledge enables condition-based maintenance strategies and serves as a foundation for preventing functional failures. The study recognizes the importance of adapting wind turbine technologies to different climatic conditions, especially in tropical regions like Cuba, in order to optimize their performance and longevity.

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