Enhancing Wind Turbine Reliability through Intelligent Fault Prediction Techniques

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Abstract:
Wind turbines (WTs) stand as one of the main sources of renewable energy, playing a crucial role in achieving sustainability objectives and increasing the proportion of renewable energy in the global energy matrix. Nevertheless, WTs are often exposed to various types of stresses during their operation in external environments. This scenario negatively affects the operation of WTs, accelerating their aging and leading to critical failures. Consequently, the costs associated with operation and maintenance (O&M) actions increase, while the financial appeal of such power sources diminishes. To address these issues, WT condition monitoring techniques have become indispensable, aiming to detect failure patterns prior to the occurrence of the failure event. However, most of the papers found in literature focus on forecasting critical failures based on the detection of incipient failures. The primary drawback of this approach lies in the fact that there are no viable models that allows to infer the evolution of a incipient failure into a critical one. In this paper, a novel methodology is developed for predicting the time until critical failure occurrence. This methodology relies on simple machine learning (ML) methods that are fed with WT's supervisory control and data acquisition (SCADA) system data, eliminating the need for complex sensor hardware. It is expected that this method will provide a valuable tool for energy companies to optimize their O&M processes.

Keywords: Fault Diagnosis; Wind Turbines; Machine Learning; Condition Monitoring

1. INTRODUCTION

In 2020, wind turbines were in the third position among renewable technologies in terms of installed capacity and in the second position when considering power generation. Furthermore, they accounted for nearly 20% of the entire renewable energy production IRENA (2022). The increase of wind based energy generation in the world energy matrix can be attributed to growing environmental concerns, that aim at replacing conventional fossil fuel-based energy sources with renewable and environmentally friendly alternatives Jin et al. (2021).

Both onshore and offshore WTs operate in harsh external environments, being subjected to adverse climate conditions such as excessive sunlight, sand, rain, wind and electrical discharges. These challenging environmental factors may lead to abnormal operation due to mechanical or electrical stresses. In severe conditions, this situation might escalate to energy supply interruption, causing financial losses Tang et al. (2020).

Traditionally, wind turbines are composed by four primary components the rotor, the nacelle, the tower, and the foundation, as illustrated in Figure 1. Due to the operational characteristics of WTs they are among the energy sources related to the highest failure rates Qiao and Lu (2015). A failure can be concentrated in one of the WT's components or can occur in a generalized way. Regarding the WT's rotor, that is the focus of this paper, Scheu et al. (2019) defines seven critical failure modes. Some of these FM are related to material failures, such as cracks, chipping and deterioration, whereas others are related to the aging process, such as wear out and fatigue. Moreover, these failure modes affect the rotor's components in different manners, the rotor's blades are prone to adjustment errors, whereas the rotor's axis is prone to fatigue, for example.

These aspects contribute to the increase in the O&M costs of wind farms, which can diminish their financial appeal. The O&M costs of wind farms are responsible for between 11% and 30% of the levelized cost of electricity (LCOE) of such enterprises, increasing as the WT ages. Moreover, the O&M costs associated with offshore wind farms are traditionally higher than those found for onshore wind farms, because the former are often located in remote and hard to access areas and their maintenance actions involve complex coordinating labor and transportation of spare parts IRENA (2012).

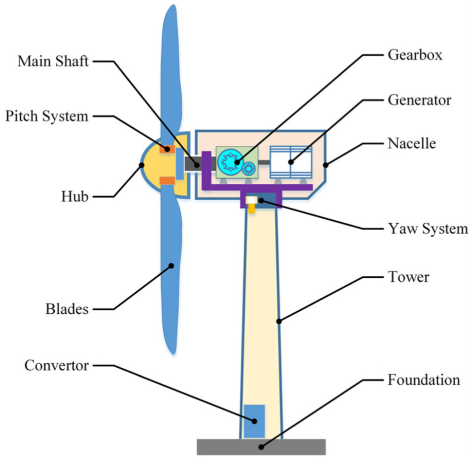

Figure 1. Generic structure of a Wind Turbine. From: Wang et al. (2017)

Condition monitoring of WTs is essential to reduce the occurrence of faults, diminishing undesirable costs and avoiding unplanned supply interruptions. Condition monitoring (CM) in wind turbines are capable of continuously or periodically assessing the state of the WT's parameters to identify potential behavioral changes that could indicate an potential failure. This monitoring enables maintenance actions to be taken before critical failure occurs, thereby mitigating its adverse consequences Qiao and Lu (2015). Condition monitoring approaches can be implemented in three different ways:

- Condition monitoring based on sensor systems designed for specific purposes, as can be found in references Gong and Qiao (2015); Chen et al. (2016);
- Condition monitoring based on data from the WT SCADA system, such as in Zhang and Wang (2014); Santolamazza et al. (2021); Vidal et al. (2018);
- Condition monitoring based on a combination both methods in order to improve the monitoring performance, such as in Morshedizadeh et al. (2023); Feng et al. (2011).

Based on the previous information, in this paper, an innovative intelligent approach based on SCADA data is presented to predict faults in WT's rotor. This approach is able to identify the specific time window during which a fault is most likely to occur. Several machine learning techniques were assessed to compose the methodology, and the final model's performance was validated using data obtained from 58 wind turbines. The authors expect that the methodology provides a tool for the electric sector towards increasing power generation predictability, reducing corrective maintenance actions, reducing machine downtime and elevating power generation rates.

2. DATA DESCRIPTION

For this work, data gathered over a two-year period (2017 - 2018), at two different wind power plants, were used to compose the dataset for the methodology. This data was extracted from both the SCADA system and the maintenance history records of 58 wind turbines. The methodology proposed in this paper relies on supervised learning techniques, which indicates that the dataset must be composed by pairs of inputs and corresponding desired outputs. In this context, the SCADA system data was employed as the input, while the maintenance history data was employed as the desired output.

Table 1. Type of maintenance processes

Maintenance events	Frequency
Unscheduled Corrective	80.1%
Preventive	13.7%
Requested by the Customer	3%
Scheduled Corrective	2.87%
Inspection with shortage	0.235%
Predictive	0.0281%

The SCADA system comprises measurements collected at 10 minutes interval from several sensors installed in the WTs and provided 609 features for each one of the WTs. For each measurement collected by the sensors, four parameters are calculated are provided to the operator: maximum and minimum value, mean value and standard deviation.

The historical data contains information regarding WT failures and unavailability events, indicating the machine that suffered the defect, the date of the outage, the duration of the outage and the affected system. The information regarding the date in which the failure happened was used to create an dataset in which the target output was the time remaining to the fault. Considering that the SCADA data present a 10-min resolution, the input dataset will also have samples with 10-min resolution. Therefore, the time remaining to failure was obtained for each one of the samples.

For instance, if a failure happened in instant t, for each sample, the time remaining until instant t was used as target output. Considering an classification approach, these targets were grouped in time intervals. In this paper, four time intervals were used as output: less than seven days, between seven and third days, between third and sixty days and over sixty days. This intervals were defined together with the maintenance team, which indicated that they were appropriate periods of time for preventive actions.

Furthermore, considering that interventions by the maintenance team are only required for failures that led to supply interruption periods greater than one day, only this type of failure was considered. The analysis of the maintenance history data revealed that a significant portion of the faults were related to unscheduled maintenance events. The percentage for each type of maintenance is presented in Table 1.

The methodology that is proposed in this paper aims to prevent the occurrence of unscheduled maintenance events, that are usually associated with the greatest costs. Therefore, only the instances associated with unscheduled maintenance events were included in the analysis.

Furthermore, based on the dataset analysis, it was verified that the rotor was the WT's subsystem most prone to failure - representing approximately 30% of the faults for both power plants considered. Moreover, this subsystem was among the systems that led to greater operation downtime. These characteristics were considered when

ISSN: 2175-8905 / 2177-6164

DOI: 10.20906/SBAI-SBSE-2023/3848

selecting the system as a focus for this paper. Nevertheless, the model can be generalized and adapted to other systems in wind turbines.

3. FAULT PREDICTION IN WIND TURBINES

The methodology proposed in this paper intends to perform predictive diagnosis of failures in WTs. Hence, this methodology must be able to identify if the analyzed subsystem presents any abnormal behavior, and must indicate the expected time until the occurrence of a failure. As previously stated, the implementations will concentrate on failures associated with the rotor, however, any WT subsystem might benefit from such methodology. The pipeline of the proposed methodology is depicted in Figure 2.

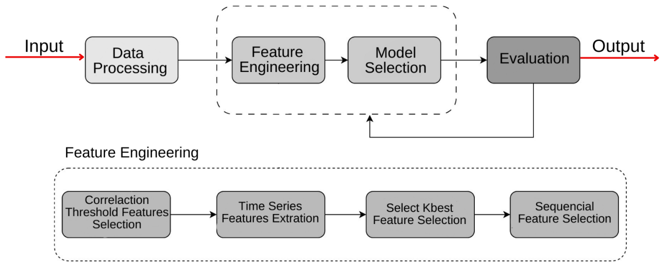

Figure 2. Pipeline of the proposed methodology

3.1 Data Processing

Before training the ML model, it is necessary to preprocess the dataset, in order to remove errors and identify if any transformation is required for the data. Moreover, it is important to have test and validation datasets, that allows the trained model's performance assessment when considering unknown samples. With this intend, the original dataset was divided into three, one for training, one for test and one for validation purposes. Considering the two-year data available, the division between the datasets was made as follows:

- Training dataset: One year data, containing the entire year of 2017;
- Validation dataset: Two-month data, containing January and February of 2018;
- Test dataset: Ten-month data, containing data from March until December of 2018.

An entire year of data was employed to construct the training set, enabling the model to learn the seasonal behavior of the faults. The distribution of faults within each of the datasets is illustrated in figures 3, 5, and 4. In these figures, the WT identification is presented in the vertical axis, and the color bar describes the time remaining to the fault in days. Consequently, the lighter the color, the closer the fault is to happening. In Figure 3, for instance, wind turbine WTG13 suffers two faults during the analyzed period, one occurring between March 19^{th} and April 2^{nd} and the other one between August 20^{th} and September 3^{rd}.

As previously explained, the failure data was used as target output for the learning model. In Figure 6 is depicted an example of the targets that were considered. In this figure,

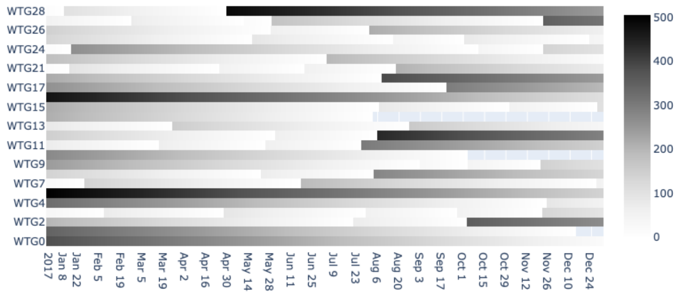

Figure 3. Training dataset fault distribution

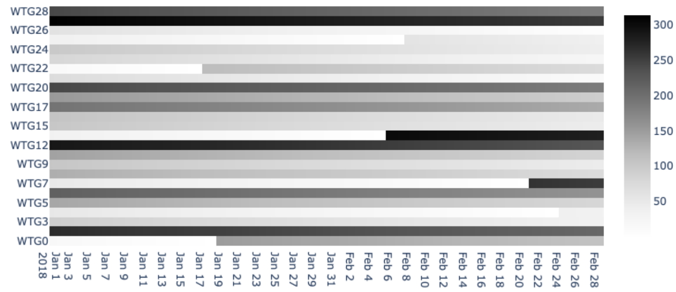

Figure 4. Validation dataset fault distribution

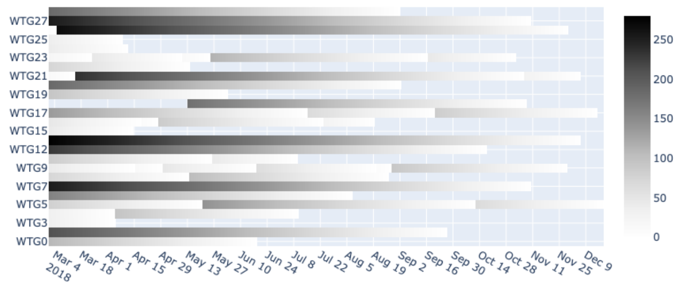

Figure 5. Test dataset fault distribution

each time the line intersects the horizontal axis, represents the occurrence of a failure. In this example, six failures are identified. The initial failure occurred between May and June of 2017. Along the vertical axis, which indicates the time until failure in days, it is observed that the second fault took place 90 days after the first one, happening in September of 2017. Similarly, the third fault occurred 45 days after the second, and so forth.

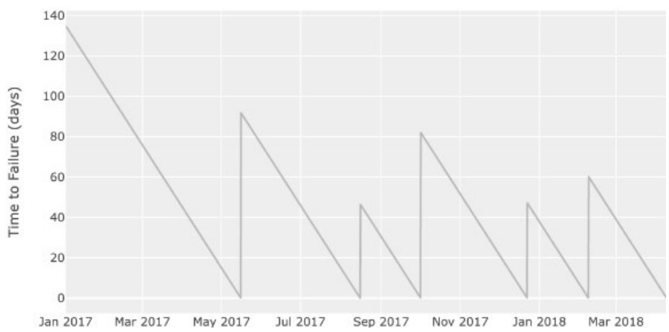

Figure 6. Target definition

3.2 Feature Engineering

Prior to the model selection, a feature engineering process was executed towards identifying the features that best characterize the dataset. Feature selection is a process as important as the model selection one, because the quality of the dataset determines the level of difficulty that the model will encounter when modeling the data. Multiple techniques for feature selection exist, and they can be used individually or combined with each other. The methods that were used in this paper will are showcased in the following sections in order of implementation.

Correlation Threshold Feature Selection The initial feature selection method applied to the data was the correlation threshold feature selection method. Within this method, features were either included or excluded from the dataset based on their correlations. The aim of this technique is to maintain only those features that exhibit low correlations with each other, thereby eliminating highly correlated features. This analysis is useful for mitigating model overfitting and training bad conditioning.

Time Series Feature Extraction Subsequently, the TS-Fresh feature extraction method was implemented to eliminate temporal features, including lags and trends. This technique was executed using three distinct time windows for the analysis of lags and trends. These time windows were determined considering that a minimum of two days is typically needed to organize a team for intervention in a wind turbine. As a result, time windows of one week, three weeks, and six weeks were chosen, representing short, medium, and extended time intervals, respectively.

SelectKBest Following the procedures that eliminated undesired features, the SelectKBest method was employed to select the best features present in the dataset. In this study, the value of k was set to 150. Considering their distinct characteristics, each subsystem of the WT will have different features with more of less relevance for the failure process.

Sequential Feature Selection Finally, after narrowing down the original features to 150 selected features, the sequential feature selection method is applied to eliminate features that have weak influence over the model's response.

3.3 Model Selection

To perform the time until critical failure identification, a classification approach was developed. Therefore, the result of the method will indicate the time interval with the highest probability of critical failure occurrence. The schematic for the classification approach is presented in Figure 7.

As depicted in the in Figure 7, the classification method works in three stages that are serially concatenated. In each stage, an simple random forest (RF) model implemented in Python performs a binary classification, indicating if the input sample with WT data represents a state that will lead to a critical failure within the time period that is being evaluated. The RF model was chosen

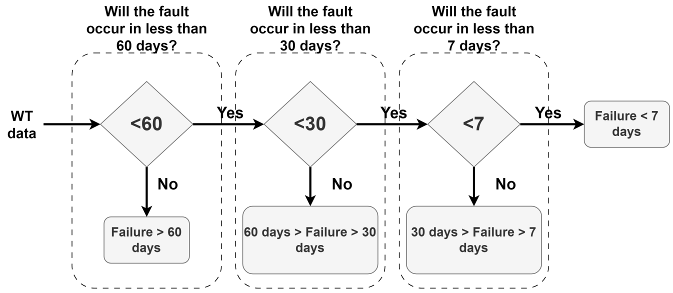

Figure 7. Classification approach

Table 2. Metrics for the first stage classification

Class	Precision	Recall	F1- Score	Accuracy
< 60	0.829	0.923	0.873	0.867
≥ 60	0.915	0.813	0.861	

for its classification capabilities, which offer a combination of high accuracy and a minimal number of adjustable parameters. In this study, priority was given to selecting the simplest machine learning method, towards concentrating on the feature engineering process. Furthermore, the RF model could be substituted by other classification methods with comparable levels of accuracy without negatively affecting the approach.

The logic for each stage of the proposed approach is presented as follows:

- For the first stage, the RF model verifies if a failure will occur in less than 60 days. If the classification returns true, the method follows to the next stage, if not, it outputs that this state might lead to a critical failure in a period greater than 60 days.
- In the second stage, the binary RF classification model inquires if the critical failure will occur in less than 30 days. If true, the method follows to the next stage; if false, the result indicates that the critical failure will occur between 30 and 60 days.
- Finally, the last classification stage analyzes whether the WT will present a critical failure in less than 7 days. If the result is true, this is the output of the model; if not, the model returns that a critical failure is likely to happen between 7 and 30 days.

These time intervals were defined together with an maintenance team, based on their daily needs in maintenance planning.

4. RESULTS AND DISCUSSIONS

The results presented in this section were analyzed based on different classification metrics. These metrics were: precision, recall, F1-score, accuracy. In the following subsections, the classification results are presented for each time interval that was considered.

4.1 First stage

For the first classification stage, that indicates if a critical failure will or not occur within 60 days, the model's accuracy was 86.7%. The metrics for this stage are presented in Table 2.

Table 3. First stage classification - Confusion Matrix

		Predicted label	
		< 60	≥ 60
True label	< 60	8499	711
	≥ 60	1756	7636

Table 4. Metrics for the second stage classification

Class	Precision	Recall	F1- Score	Accuracy
< 30	0.792	0.957	0.867	0.832
≥ 30	0.921	0.667	0.773	

Table 5. Second stage classification - Confusion Matrix

		Predicted label	
		< 30	≥ 30
True label	< 30	5598	253
	≥ 30	1467	2937

Table 6. Metrics for the third stage classification

Class	Precision	Recall	F1- Score	Accuracy
< 7	0.716	0.719	0.717	0.856
≥ 7	0.904	0.903	0.904	

The confusion matrix is presented in Table 3. According to it, out of the 18602 samples that were analyzed in the test phase, 8499 were correctly categorized as over 60 days and 7636 were correctly classified as having less than 60 days until the critical failure. In contrast, 2,467 samples were wrongly classified within one of the classes.

More than twice the number of samples were misclassified as having less than 60 days remaining. This type of error is less harmful than wrongly classifying samples that would occur in less than 60 days as greater than 60 days. In the former case, the maintenance team will anticipate the maintenance actions, while in the latter case, maintenance actions would not take place, even though a failure could occur.

4.2 Second stage

The second classification stage usually presents results with lower accuracy than the first stage because there is an error propagation from the first part of the method. For the test dataset, the second stage classification model presented 83.2% of accuracy. The metrics for this stage are presented in Table 4.

Analyzing the confusion matrix presented in Table 5 it is inferred that 10255 samples were passed from phase one to phase two. The other 8347 samples were classified as critical failures that might occur in a time interval greater than 60 days. Once again, the number of samples wrongly classified as under 30 days, while being truly over 30 days, was significantly greater than the opposite case. Which indicates that the method is conservative in terms of safety.

4.3 Third stage

In Table 6, is shown that the accuracy for the final classification stage is $85,6\%$.

Table 7. Final stage classification - Confusion Matrix

		Predicted label	
		< 7	≥ 7
True label	< 7	1288	504
	≥ 7	511	4762

The final classification stage's confusion matrix is illustrated in Table 7. According to this figure, 4762 samples were correctly classified as over than 7 days until critical failure, whereas 1288 were truly identified as a failure probably occurring in less than 7 days. The number of misclassified samples was balanced, in contrast to what was observed for the previous stages of classification.

4.4 Discussion and future work

All of the classification stages presented high levels of accuracy, surpassing 80%. It was verified that, the initial stage demonstrated higher accuracy compared to the subsequent stages. This situation could be attributed to error propagation across the method's stages. Nevertheless, the levels of accuracy obtained for last stage remains competitive for this type of application.

In terms of other metrics, both the first and second stages exhibited lower precision for the true class and lower recall for the false class, which demonstrates that the method is conservative. In the final classification stage, the method's performance for predicting failures that will occur in less than 7 days was comparatively lower than that of the previous stages. This may have occurred because less samples from this class were available. However, the stage's overall accuracy is still over 85%, without the need of synthetic samples.

The proposed methodology could be easily implemented within an operational environment, as an autonomous monitoring software. This software would receive measurements collected from the SCADA system. It is important to highlight that in this scenario, the machine learning techniques integrated into the software must be adjusted to the data specific to the locally installed WTs. Furthermore, updates to the machine learning training are necessary whenever there are modifications to the configuration of the WTs. Lastly, it's important to emphasize that the computational effort associated with machine learning techniques, such as the RF model, is primarily a concern during the training phase of the method, when parameter adjustments are made. In the case of the RF model, even this training phase is brief due to the limited number of parameters. Following the training phase, during the operational phase, machine learning models demonstrate a respectable response speed.

For future work, this methodology could be assessed for different WT subsystems. Additionally, this paper only evaluated the incidence of critical failures without distinguishing between different types of failure modes that might lead to these events. As part of future work, incorporating the analysis of failure modes into the dataset and integrating it into the model would be valuable to further assist the maintenance planning process.

5. CONCLUSIONS

This paper presented a methodology for time to failure prediction using machine learning techniques based on SCADA and maintenance history data. One of the method's first contributions relies in the use of SCADA data, that dismisses the necessity of using high cost hardware for implementing customized CM systems. Furthermore, another contribution consists in the implementation of an intelligent approach with high accuracy levels that uses simple ML models instead of high complex ones. Most of the work is dedicated to dataset preprocessing, manipulation, and framing the problem as a classification task. Moreover, another important aspect of the paper is the fact that real data extracted from wind farms was used, and no synthetic samples were needed to validate the results. Demonstrating the validity of the method for practical applications.

The main contribution of the proposed methodology is the fact that it provides the time until critical failure as a result, not only identifying the presence of an incipient failure. Incipient failures often evolve to critical failures, which is why most of the papers found in literature focuses on forecasting the occurrence of the former. The issue with this approach is that there is no recognizable pattern that can be used to determine when a critical failure will occur after the occurrence of an incipient one. As a result, this conventional methodology is not particularly effective to support maintenance planning. To overcome this limitation, the methodology introduced in this paper is capable of determining the time until the occurrence of a critical failure without the prior knowledge of incipient faults occurrence. Therefore, being a valuable tool for companies in the electric sector, optimizing their maintenance processes, and, consequently, reducing the O&M costs.

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