Wind Farms Predictive Maintenance Based on Condition Monitoring System

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Abstract— **This article focuses on a new methodology based on fuzzy logic to predict the maintenance of wind farms. In wind systems, Vibrations present the main cause of the occurrence of failures. The prediction of these failures can be ensured by correct processing of the set of vibration signals collected by the Condition Monitoring System (CMS) and declaration of the appropriate maintenance action by the connected management system SCADA (Supervisory Control And Data Acquisition). In this paper, fuzzy logic is used as a new approach to processing vibration signals by exploiting their features for the generation of probabilities of occurrence of failures. The probabilities generated correspond to alarms (Green, Orange and Red) and the alarms correspond to maintenance actions to be applied.**

Keywords: alarms; CMS; fuzzy logic; maintenance; wind farms.

I. INTRODUCTION

The generation of electricity through inexhaustible flow energies and in particular by wind systems is becoming more of a necessity in our days. The maintenance of these systems also becomes one of the most challenging problems in the industry view their work under non-stationary operations which can cause catastrophic failures in the case of strong wind [1], [2].

The optimization of the maintenance planning is a crucial factor for the efficiency of the wind farms [3]. With this purpose, wind turbines (WT) can be monitored by SCADA or condition monitoring systems to detect failures [4],[5], risks [6] and to take necessary actions online. Several studies have proved the efficiency of this systems in the WTs [7] and other types of industries [4],[8], [9].

Some research is done to reduce false alarms generated in wind turbines. Zaher et al. [10] proposes a set of techniques combined in a single system for advance detection and the identification of the anomalies and failures in the wind turbines, based on the data processing of the SCADA system and this to give for the operator's sufficient time to make the appropriate decision to maintain their machines. Kim et al. [11] have taken the case of identifying failures within gearbox. They developed algorithms for detecting anomalies with the investigation of classification techniques using clustering algorithms and analysis of the main components to capture fault signatures. Schlechtingen et al. [12],[13] have proposed in a first part a system for monitoring the state of wind turbines using adaptive neuro-fuzzy interference systems (ANFIS) and a second part devoted to examples of application and evaluation of the efficiency of the system. Feng et al. [14] presented respectively in two different cases the analysis of signals coming from the SCADA and CMS systems and which are related to the Gearbox using retrospective data from 2 MW class variable speed and 1.3 MW two-speed WTs with gearbox faults. Yang et al. [15] have developed an effective method for processing data rows of the SCADA system, proposing an alternative state monitoring technique based on the search for correlations between SCADA data, carrying out quantitative evaluation of health state of a turbine under varying operational conditions with verification with tests. Igba et al. [16] have proposed some techniques based on three models (signal correlation, extreme vibration and RMS intensity) which are subsequently validated using a data of time domain approach using CM data of operational WT. S Zhong et al. [17] formulated a nonlinear multi-objective fuzzy optimization model with the goal of achieving an optimal maintenance plan for wind power systems by maximizing reliability and minimizing costs. P Qian et al. [18] have proposed Long Short-Term Memory (LSTM) algorithms as a new approach to predicting faults in wind turbines. J Wang et al. [19] Presented a new diagnostic and prognostic model to predict the remaining useful life of the bearing. This is why they used the wavelet transform to analyze the incipient defect signatures of the bearing, the health index algorithm is then exploited to merge the extracted characteristics and this in order to represent the defect conditions of the bearing. rolling.

FPG Márquez and Mayorkinos Papaelias [20] described the various maintenance models as well as the techniques and approaches for monitoring the condition of turbines. The fault tree analysis is also performed for a qualitative assessment and this in order to identify future research opportunities for fault detection and diagnosis. Bakir el al. [21] have developed an integrated framework that combines real-time degradation models and mixed integer optimization models and used solution algorithms whose goal is to make maintenance decisions in order to identify optimal repair times of every component of the wind turbine. A.P Marugán and F.P García Márquez [22] presented two methods based on neural networks and data collected by the SCADA system in order to extract the information necessary for the conditions of the wind turbines and to predict the activation of alarms.

In this paper, we propose a new approach based on fuzzy logic using as inputs the CMS data. In the inference system, only rules related to the main features of vibration are considered. This new approach can contribute positively to the organization of maintenance tasks based on the identification of alarms at the output of the fuzzy system. This new approach can positively contribute to real-time monitoring of the state of wind farms as well as to the organization of maintenance tasks based on the identification of alarms at the output of the fuzzy system.

II. PROPOSED METHODOLOGY

As aforementioned, the methodology presented hereby is based in a statistical use of the data of different CMSs. There are different monitoring techniques, being the most employed: vibrations (vibration-based damage detection) using sensors such as piezoelectric accelerometers; oil analysis to determine viscosity and levels of contaminants; acoustic emission; motor current signature analysis [23].

The CMS are aimed to provide a continuous monitoring of the condition of dynamic parts and power electronics of the wind turbines.

Figure 1 shows the general structure of a fuzzy system [24].

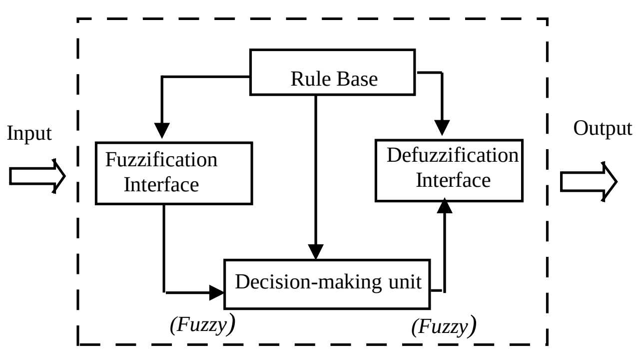

Fig.1. Basic configuration of a fuzzy logic system.

Fuzzy logic is a technique that is associated with the theory of fuzzy sets and the theory of possibilities [25]. The fuzzy system is composed of 3 main parts listed below:

✓ Fuzzification [26]

The aim of fuzzification is to convert any numerical value of each input data into a fuzzy subset I.e., a linguistic value between 0 and 1.Any fuzzy subset of each input variable requires a membership function whose shape is well defined (Sigmoid, Hyperbolic tangent, Exponential,…). and which can be defined in our example as follows:

-Input (1): Variable (1). Subsets: Good, Acceptable, and Inacceptable.

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-Input(n): Variable (n). Subsets: Good, Acceptable, and Inacceptable.

✓ Fuzzy Inference

Fuzzy inference is the process of formulating the mapping of input data based on membership functions, fuzzy logic operators (and / or), and If-Then rules at an output using the Fuzzy logic [27]. The Fuzzy rules (IF antecedent THEN consequent) in expert system are usually is following [28]:

IF Var (1) is A11 and/or Var (2) is A21… THEN y is B1
Else
IF Var (1) is A12 and/or Var (2) is A22… THEN y is B2
else
.
.
IF Var (1) is A1n and/or Var (2) is A2n… THEN y is Bn

Where Var (1), Var (2),…, Var(n) are the fuzzy input (antecedent) variables, y is a single output (consequent) variable, and A11 . . . A1n are the fuzzy sets [10]. The total rules used in the inference system are all possible combinations of the input variables. They depend on the number of linguistic variables that characterize the membership functions of the input data. If, for example, we have n input variables consisting of 3 fuzzy linguistic variables then the rules are in number of 3n.

There are two types of fuzzy inference methods [29]: Mamdani-Type and Sugeno-Type. The only difference between these two types is that the Type of Sugeno has an output membership function either linear or constant.

✓ Defuzzification

Defuzzification is the process of producing a quantifiable result given fuzzy sets and corresponding membership degrees. There are many types of defuzzification methods,

usually maximum membership and centroid techniques are used [19], [30].
In this paper, a novel methodology is presented to make an original treatment of the CMSs dataset.

The flowchart of the methodology proposed is shown by Figure 2.

In the diagram adopted for the identification of alarms, it is integrated the features of vibration measurements collected by CMS system with the fuzzy system.

The main features used in this paper are: RMS, Peak value, Kurtosis and Crest Factor.

In time domain technique, these parameters can be defined as follows [31]:

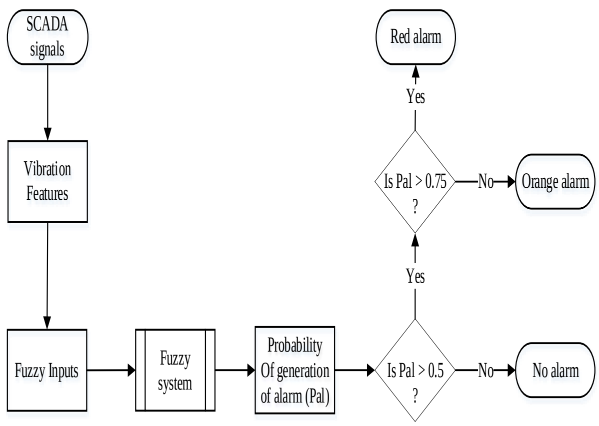

Figure 2: Alarm identification flowchart.

- Root Mean Square (RMS): This is a time analysis feature that corresponds to the measure of the signal power. It can be useful for detecting some out-of-balance in rotating systems. It can be calculated by equation 1:

$$RMS = \sqrt{\frac{\sum_{n=1}^{N}(y(n))^2}{N}} \quad (1)$$

-Peak value: is the maximum acceleration in the signal amplitude. It is calculated by equation 2:

$$Peak\ value = 1/2.[\max(yn) - \min(yn)] \quad (2)$$

-Kurtosis: This parameter corresponds to the scaled fourth moment of the signal. It is a measure of how concentrated the data are around a central zone of the distribution. It is calculated by equation 3:

$$Kurtosis = \frac{\sum_{n=1}^{N}(y(n)-Mean)^4}{(N-1)S^4} \quad (3)$$

-Crest Factor: This parameter is capable of detecting abnormal behaviors in an early stage. It is defined by equation 4:

$$Crest\ Factor = \frac{Peak}{RMS} \quad (4)$$

Where: N is the total number of discrete values of the signal y.

The fuzzy inference system is based on different rules to generate the occurrence probabilities of the alarms in the output.

The output of the fuzzy logic will correspond to three different scenarios:
-No alarm: The parameters analyzed have adequate values and the condition of the WT is correct. The output of the fuzzy logic is less than 0.5.
-Orange alarms: indicator of probable defects that do not cause problems for maintenance planning and can be programmed with daily or weekly preventive maintenance tasks. This alarm will be considered when the output of fuzzy system is between 0.5 and 0.75.
-Red alarms: critical states (maximum values for more than one physical variable), which requires diagnosis and urgent intervention to return the status parameters to acceptable levels. This alarm will be considered when the output of fuzzy system is more than 0.75.

III. Real Case Study

The data considered for this real case study is obtained from the European Project entitled OPTIMUS [32]. The datasets are come from the following CMSs installed in a WT:

- Vibration data from a Train Driver. The data available are signals of 1 second collected every three hours in 8 different points of the drive train from 01/04/2014 to 31/01/2015. Figure 3 shows the eight different regions of the drive train where vibration signals are collected. The signal will be identified regarding to this numeration, i.e. V1, V2 …V8.

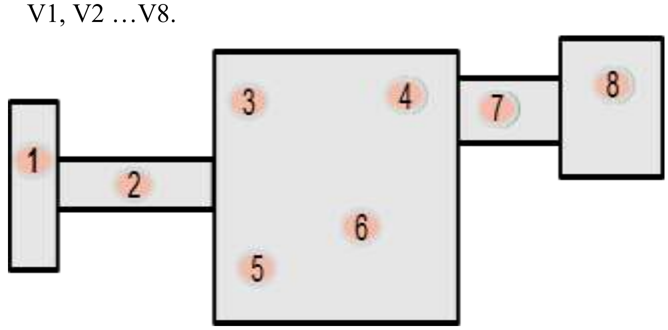

Figure 3. Location of the different sensors in the train system of the WT.

Figure 4 shows the evolution of vibration signals as a function of time.

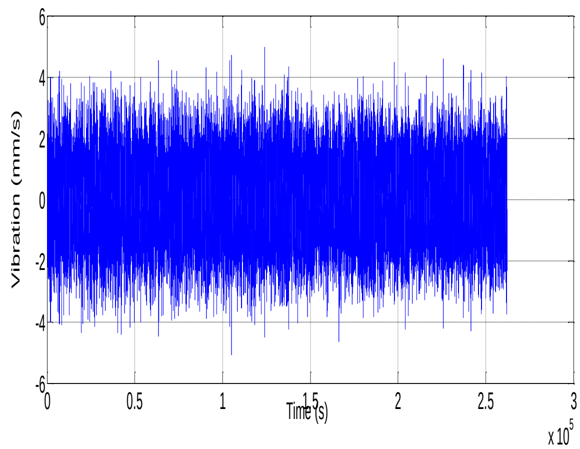

Figure 4. Evolution of vibration in time.

The main features of the vibration data will be the input of the fuzzy system and the output will be the probabilities of alarms generation.

Figure 5 shows the main vibration features in our study.

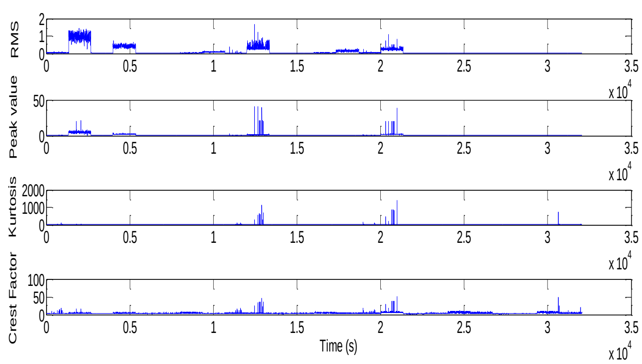

Figure 5. Evolution of Inputs data in time

Thus, some of the rules defined in this example are:

- IF RMS is Good and Peak is Good and Kurtosis is Good and Crest is Good THEN the output is green.
- IF RMS is Good and Peak is Acceptable and Kurtosis is Acceptable and Crest is Good THEN the output is orange.
- IF RMS is Unacceptable and Peak is Good and Kurtosis is Unacceptable and Crest is Unacceptable THEN the output is red.

More rules of the Fuzzy system are presented graphically in the Figure 6:

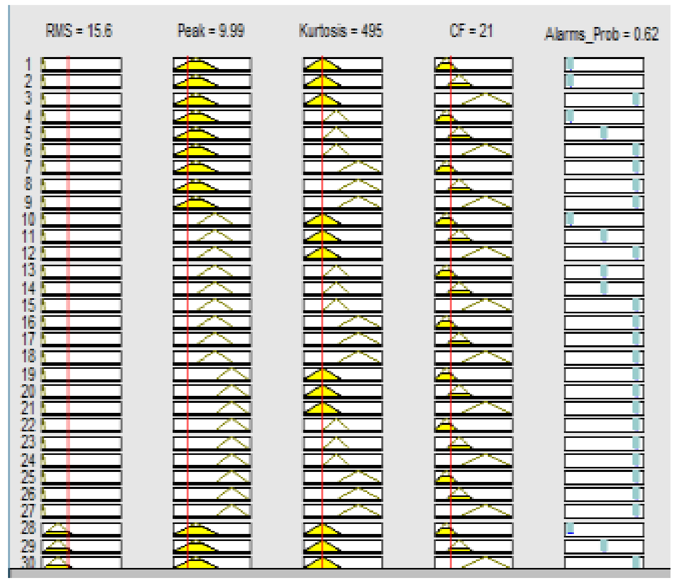

Figure 6. Rule based Fuzzy Inference System for generation of probabilistic alarms.

The red line of each variable shows the value of the variable. The displacements to the left or the right of these lines generates a new position of the output, and therefore, a new probability of alarm. Once, the fuzzy system is defined, it is possible to represent surfaces that explain the behavior of the system under different conditions. For example, Figure 7 represents the probability of alarm depending on RMS and Peak.

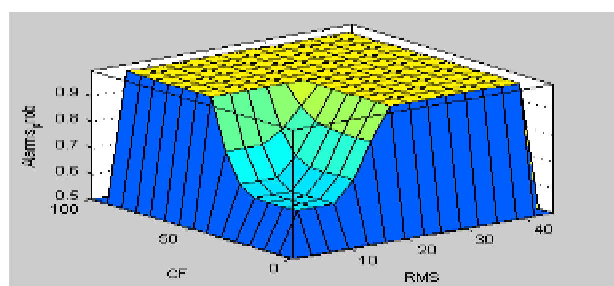

Figure 7. Surface view of alarms probability with respect to RMS and Peak.

The system built has been proved by performing a simulation with the CMS data. The results of the simulations are shown in Figure 8. The system provides a certain probability of alarm regarding to the inputs.

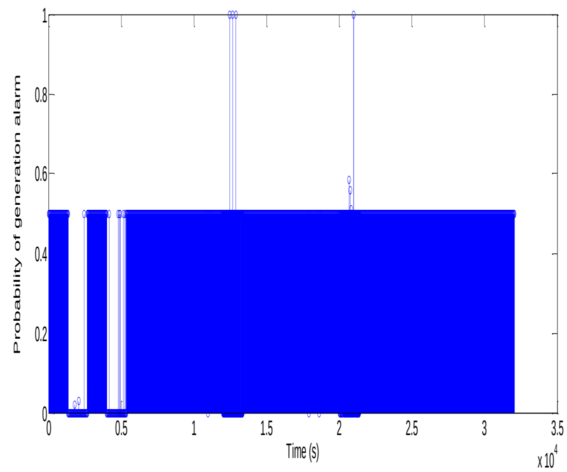

Figure 8. Probability of alarms generation.

Table 1. Number of alarms obtained by the fuzzy system

Fuzzy Inputs	Alarms number of Fuzzy Output		
	Green alarms	Orange alarms	Red alarms
Inputs	28160	3875	05

For the Inputs: A total of 32040 inputs have been analyzed through the created fuzzy system. The outcomes are:

- 28160 normal measures. This represents the 87.89 % of the total data
- 3875 orange alarms. This represents a 12.09 % of the total data.
- 05 red alarms. This represents a 0.02 % of the total data.

Our results can be validated by Adaptive network-based fuzzy inference system (ANFIS). Figs.9a and 9b. shows respectively the curves obtained before and after test with ANFIS. An error of 3.96% between the curves (FIS/ ANFIS) is observed which proves the effectiveness of our approach.

In addition, it is proved that the transformation of data collected by CMS into probabilities of alarms can be a useful information for complementing the decision making. The methodology can aid to reduce false alarms because when a critical alarm arises from the SCADA system, the response of the fuzzy system can reinforce that alarm.

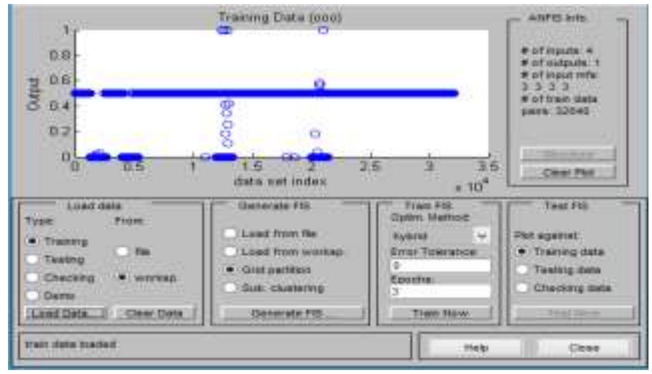

Figure 9.a. Fuzzy results before test

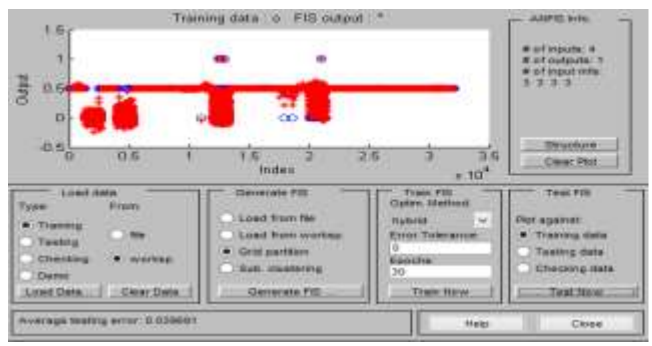

Figure 9.b. Results after test with ANFIS

IV. CONCLUSION

In this paper, a new methodology based on fuzzy logic is proposed in order to analyse the CMS data and provide an alternative decision support. The main purpose is to process the signals collected by the CMS system from a different perspective. A fuzzy system has been created using the vibration features data collected by the CMS system, membership functions and the fuzzy rules are thus determined. Three different results are distinguished at the fuzzy output: green, orange and red alarms. Firstly, the green alarms correspond to the values which are in the range of normal behaviour. Secondly, orange alarms where the probability of alarm reaches exceeds a defined threshold but it is not a critical point. Finally, red alarms when the probability is unacceptable.

Each type of alarm corresponds to an action or no action of maintenance. In the case of green alarms, no action is required. Orange alarms require preventive maintenance works to stop the evolution of vibrations in the wind power system. On the other hand, in the case of red alarms, the wind power system must be shut down with the need for urgent intervention to restore the system to its acceptable level.

V. References

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