Modeling a Fuzzy Inference System for a Wind Turbine Condition Monitoring

O. Montserrat Reyes[1], P. Malaquías Quintero[2], Pablo H. Ibargüengoytia[3]

[1, 2]Technological Institute of Apizaco, Apizaco, Tlaxcala, México

[3]National Institute of Electricity and Clean Energies, Cuernavaca, Morelos, México

Abstract: ***Condition monitoring systems have been used to determine the need for equipment maintenance and successful results have been achieved, however, these systems in combination with fuzzy logic have not been sufficiently explored, and one area of application is wind turbines. In this paper, the state of the art of wind turbine condition monitoring is briefly reviewed and it is proposed to use fuzzy logic for the diagnosis of wind turbine condition, in order to detect the abnormal behavior of the signals through a system of fuzzy inference that can be used as a fundamental element in the diagnosis of turbine condition. The system is based on data from a Komai wind turbine whose specifications were used to model the system. The results of the tests indicate that this system can be used to represent human knowledge and the diagnosis is reliable.***

Keywords: Fuzzy logic, condition monitoring, wind turbine

1. Introduction

Fuzzy inference systems (FIS) have demonstrated the ability to solve complex and ambiguous problems, applying this technique in wind turbine condition monitoring is important because the number and size of turbines increases. At the moment the consumption of energy has had a strong increase due to the globalization, the demographic growth, the human establishment, among other factors; consequently, clean energies play a fundamental role in satisfying the demand for energy as well as helping to conserve the planet [1].

According to the Mexican Association of Wind Energy in Mexico there are 42 wind farms in operation with 1935 wind turbines (WT) in operation (2016 data). In addition, the 2.5% is the percentage of the world's electricity supplied by wind power and it is expected that by 2020 this percentage will be between 8-12% and in Mexico 40% of the national renewable energy target depend of wind energy [2]. Achieving that this type of energy is competitive with other sources of energy is crucial, therefore, the availability, reliability and life of the turbines should improve [3].

Due to the increase in the production of wind energy it is important to monitor the condition of the WT to determine their need for maintenance in order to reduce inspection or maintenance costs due to the increase in the size and quantity of turbines. On the other hand, the remote location of the turbines currently used makes availability crucial if maintenance is required [4].

The article is organized as follows: section two includes a relevant background of the research area. The third section is about the importance of a WT condition monitoring. The four section shows the methodology for the development of the FIS. In the five section the experimental work is shown and finally section six is the conclusion about the work done.

2. Literature survey

Some of the turbine condition monitoring techniques used are vibration analysis that continues to be “the most popular technology employed in WT, especially for rotating equipment” [5]. the Acoustic monitoring is a technique that has some similarities with vibration monitoring but whereas “vibration sensors are mounted on the component involved” [6] so as to detect movement, acoustic sensors are attached with flexible glue with low attenuation and record sound directly.

The Ultrasonic testing (UT) techniques are used extensively by the wind energy industry for the structural evaluation of WT towers and blades. UT is generally employed for the detection and qualitative assessment of surface and subsurface structural defects [7]. The oil analysis it is used for the of guaranteeing oil quality or the condition of the various moving parts, “oil analysis is mostly executed off-line by taking samples” [5].

The radiographic inspection is used to obtain radiographic imaging of critical structural turbine components using X-rays is only rarely used although it does provide useful information regarding the structural condition of the component being inspected [8]. The thermography is often used for monitoring electronic and electric components and identifying failure [9]. The technique is only applied off-line, and often involves visual interpretation of hot spots that arise due to bad contact or a system fault.

Regardless of the technique, the capability of the condition monitoring relies upon two basic elements: the number and type of sensors, and the associated signal processing and simplification methods utilized to extract important information from the various signals [10].

Regarding signal processing methods are the statistical methods [11], the trend analysis [12], filtering methods [13], time-domain analysis that are typically used for vibration analysis [14] and oil analysis [15], among others methods.

There are also Artificial Intelligence techniques that are applied in the field of clean energies in order to optimize production costs and have better energy efficiency [1]. Some of these techniques are fuzzy logic, neural networks and probabilistic reasoning (genetic algorithms, Bayesian networks, chaotic systems).

The fuzzy and neuro-fuzzy logic, and the probabilistic reasoning deals mainly with the imprecision and approximate reasoning, the neural networks of learning and the probabilistic reasoning of the uncertainty [16]. To consider these efficient techniques, a correct choice of data and the technique to be used must be made in order to infer faults or anomalies in the turbines in the best way [17].

Fault detection and diagnosis is an adaptation of condition monitoring that involves intelligent algorithms for detection of incipient faults [18]. Neural networks have the advantage of high data processing speeds due to parallelism [4]. Bayesian networks are also used for the intelligent diagnosis of WT in order to detect anomalies in the behavior of the data [19].

On the other hand, fuzzy systems are useful for highly complex systems whose behavior is not easy to understand, they can also be applied where an approximate but fast solution is desired [20].

Monitoring equipment condition is important in order to detect unexpected failures mainly of large components, which can result in excessive downtime, however, failures in auxiliary equipment or small components can also cause costly downtime. Therefore, it is worthwhile to perform an adequate monitoring of the equipment to reduce unscheduled downtime and consequently the operation times [10].

Such monitoring can be online by providing instant feedback or offline. With a good data acquisition and adequate processing, failures can be detected while the components are operating, so appropriate actions can be programmed, this results in greater reliability, safety and availability of the turbines, thus reducing downtime and thus the costs involved in maintenance.

Condition monitoring and the diverse mathematical methods for processing signals and data analysis are based on different elements of the wind turbine. The techniques mentioned are some of those available.

3. Importance of wind turbine condition monitoring

Wind turbines are machines that convert the kinetic energy of wind into electricity. The amount of electricity produced by a wind turbine depends on its size and the wind speed. The electrical energy can be stored in batteries or used directly. Due to the advantages of using this type of energy as inexhaustible, sustainable and non-polluting with a low impact on the environment. Wind turbines are a fundamental part of wind power generation, so the diagnosis of the equipment and the detection of faults help determine the need for maintenance of the equipment to prevent major problems.

Condition monitoring of wind turbines is very important nowadays because the size and location of the turbines has as a consequence that their availability is crucial. Unexpected failures in large or small components lead to costly downtimes that can be excessive. Therefore, monitoring the condition of the turbines is important in order to reduce the unscheduled downtime costs and consequently the operating costs [11].

The high temperatures in the components of the turbine, for example, can cause overheating of the same and therefore generate some failure. These problems have a negative impact on the life of the turbine and to make a diagnosis expert in the area are needed. However, making diagnoses through human operators is slow and may have errors.

Therefore, the development of a fuzzy inference system that captures human knowledge and is able to adequately diagnose and in the shortest time possible the condition in which the turbine is located can help identify the need for maintenance and improve its reliability. The condition of the turbines in this research work is based on SCADA data.

3.1 Komai wind turbine

For this research work we used data from the SCADA system of a turbine brand *Komai,* model: KWT300. Some features of the turbine are:

- It has a horizontal axis power generation system. It is equipped with a gearbox with active pitch regulation of three variable speed blades.
- The generator is a three-phase induction motor of 400V. It is connected to the network through an IGBT (Insulated Gate Bipolar Transistor) converter with an AC-DC-AC link system.

The Komai wind turbine located in the Regional Wind Technology Center (CERTE) of the National Institute of Electricity and Clean Energies (INEEL), located in Juchitán, Oaxaca, México; is the wind turbine from which data were obtained for the development of this research and is shown in Figure 1. The basic specifications [21] are described in Table 1, where data are indicated as the power that the turbine is capable of generating, the type of turbine, the height, position and diameter of the rotor, the wind speed and the rotor, the temperature ranges and the life of the turbine.

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Figure 1: Wind turbine Komai, CERTE

Table 1: Specifications of the *Komai* wind turbine

Rated power	300 kW
Type	Horizontal Axis
Hub height	43.5 m
Rotor position	Up-wind
Rotor diameter	33 m
Rated wind speed	11.5 m/s
Nominal rotor speed	40.5 rpm
Cut-in wind speed	3.0 m/s
Cut-out wind speed	25 m/s (10 min average) 28 m/s (3 seg average)
Survival wind speed	70 m/s
Temperature range in operation Temperature range out of operation	-15 °C to 45 °C -20 °C to 55 °C
Design life time	20 years

The ambient conditions [21] for the turbine to function correctly are described in Table 2 where temperature and humidity are indicated.

Table 2: Ambient conditions

Ambient temperature	Operating temperature:	-15 °C a 45 °C
	Idling temperature:	-20 °C a 55 °C
	Average temperature:	15 °C
Humidity	Average humidity:	65% a 75%

The turbine *Komai* KWT300 generates power with the wind speed between 3 m / s and 25 m / s. The table 3 shows the ideal performance values of the turbine [21] and Figure 2 shows the behavior.

Table 3: Output performance

Wind speed (m/s)	*Rotor rotation (rpm)*	*Generated power (kW)*
3	12.0	0.5
4	17.4	5.4
5	21.7	24.2
6	26.0	43.2
7	30.4	72.0
8	34.7	112.3
9	39.1	165.5
10	40.5	228.2
11	40.5	297.7
12-25	40.5	300.0

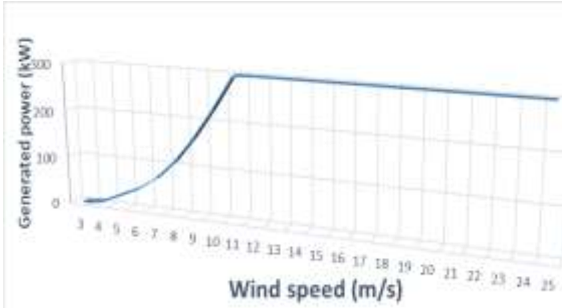

Figure 2: Power curve of the wind turbine *Komai*

4. Modeling of a fuzzy system for monitoring the condition of a wind turbine

For the modeling of fuzzy inference system, the following methodology was used:

a) Obtain the historical data base of the SCADA system on which it will be worked.
   - Select the relevant input signals.
   - Determine the number of linguistic terms for each input and output variable.
   - Design a collection of fuzzy rules type If - Then
b) Represent the behavior model of the wind turbine
c) Evaluate the model
d) Interpretation of results

The Figure 3 shows a block diagram of the proposed methodology.

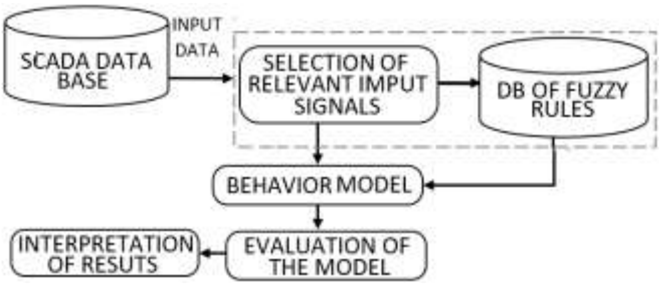

Figure 3: Block diagram of the proposed methodology

4.1 Fuzzy modeling

Generally speaking, how it might construct a fuzzy inference system for a specific application. The standard method for constructing a fuzzy inference system, a process usually called fuzzy modeling, has the following features: The rule structure of a fuzzy inference system makes it easy to incorporate human knowledge about the target system directly into modeling process (domain knowledge).

When the input-output data of a target system is available, conventional identification techniques can be used for fuzzy modeling (numerical data also plays an important role in fuzzy modeling) [16].

The fuzzy modeling can be pursued in two stages. The first stage is the identification of the surface structure, which includes the following tasks:

1) Select relevant input and output variables
2) Choose a specific type of fuzzy inference system
3) Determine the number of linguistic terms associated with each input and output
4) Design a collection of fuzzy if-then rules

After the first stage, is obtained a rule base that can more or less describe the behavior of the target system by means of linguistic terms. The meaning of these linguistic terms is determined in the second stage, the identification of the deep structure, which determines the membership functions (MFs) of each linguistic terms. This stages includes the following tasks:

1) Choose an appropriate family of parametrized MFs
2) Interview human experts familiar with the target system
3) Refine the parameter of the MFs using optimization techniques

4.2 Historical database of the SCADA system

The database consists of 35 SCADA signals. With records dating from March 19, 2013 to December 8, 2015. Which were taken from the turbine *Komai*. Consists of 61290 records. Table 4 shows the relevant SCADA system data signals.

Table 4: Relevant SCADA data signals

Name of variable	*Unit*	*Short description*
PitchAngle	°	Inclination angle
GearOilTemperature	°C	Gear oil temperature
GeneratorSpeed	Rpm	Generator speed
ActivePower	Kw	Output power
WindSpeed	m/s	Wind speed
NacelleTemperature	°C	Temperature inside the nacelle

4.3 Structure of the fuzzy inference system

The structure of the proposed fuzzy inference system Sugeno type is illustrated in Figure 4, it has three input signals (oil temperature, gondola temperature and output power) and an output variable which in this case is the condition. The membership functions used are triangular and illustrate a fuzzy rule of type If-Then.

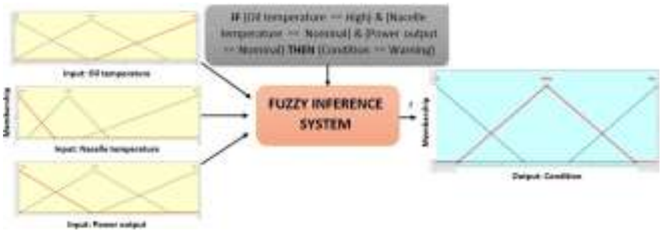

Figure 4: FIS with three inputs and one output

Linguistic terms. In this step, the linguistic terms for the input/ output variables of the fuzzy inference system are defined. For the development of the fuzzy inference system, three linguistic variables were used in the antecedent part, which are described in the Table 5, the linguistic variables 'OilTemp', 'NacelleTemp' and 'Power' are defined by the fuzzy sets 'Very Low' (VL) 'Low' (L), 'Nominal' (N), 'High' (H) and 'Very High' (VH). For the consequent part, the parameters are described in Table 6, the linguistic variable 'Condition' are defined by the fuzzy sets.

Table 5: Definition of linguistic terms of the input variables

Input variables (SCADA Signals)	*Linguistic Terms*
Oil temperature of gearbox (GearOilTemp)	VL: Very low L: Low N: Nominal H: High VH: Very High
Nacelle temperature (NacelleTemp)	
Output power (ActivePower)	

Table 6: Definition of linguistic terms of the output variable

Output variable	*Linguistic Terms*
Condition	N: Nominal W: Warning AL: Alert

Once the linguistic terms have been defined, the membership functions with their respective parameters are defined. For this case, triangular functions are used. Table 7 shows the membership functions for the input variables with their respective parameters which were obtained from the specifications of the Komai turbine.

Table 7: Parameterization of the triangular MFs (inputs)

Oil temperature	*Nacelle temperature*	*Output power*
VL: [0, 0, 0.2]	VL: [0, 0, 0.05]	MB: [0, 0, 0.25,]
L: [0, 0.25, 0.5]	L: [0, 0.5, 0.1]	B: [0, 025, 0.5]
N: [0.35, 0.5, 0.65]	N: [0, 0.1, 0.3]	N: [0.25, 0.6, 0.7]
H: [0.6, 0.8, 1]	H: [0.25, .065, 1]	A: [05, 0.75, 1]
VH: [0.75, 1, 1]	VH: [0.3, 1, 1]	MA: [0.75, 1, 1]

In the consequent part of the fuzzy system, the linguistic variable corresponds to the 'Condition', which is defined by the fuzzy sets 'Normal Condition' (N), 'Warning Condition' (W), 'Condition Alert' (A) and are shown in the Table 8. The definition of the parameters is based on the level of impact according to the behavior of the input variables, with a rating from 0 to 1, where 0 is a normal condition coefficient and 1 is a bad condition.

Table 8: Parameterization of the triangular MFs (output)

Triangular
N: [0, 0, 0.4]
W: [0.1, 0.5, 0.9]
A: [0.6, 1, 1]

The Figure 5 shows the triangular type membership functions used for a fuzzy inference system with 3 input variables (gearbox oil temperature, nacelle temperature and output power) and one output (condition).

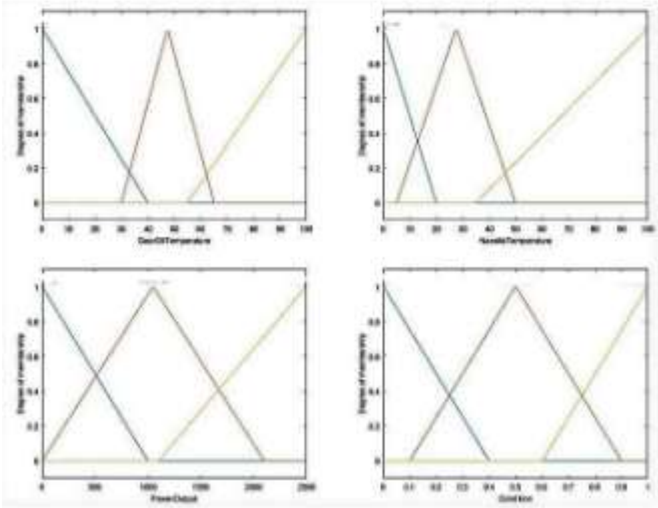

Figure 5: MFs of linguistic variables

Fuzzy rules. In this step, the linguistic terms for the input/ output variables of the fuzzy inference system are defined. For the development of this system some of the fuzzy inference rules that were considered are shown in Table 9, these rules are of the Yes-Then form and they have the 3 input linguistic variables mentioned above (oil temperature, temperature of the gondola and power output). In the part of consequent, the condition of the wind turbine.

Table 9: Parameterization of the triangular MFs (inputs)

Rule	*Antecedent (If)*			*Consequent (Then)*
#	OilTemp	NacelleTemp	Power	Condition
1	High &	Low &	Low	Warning
2	High &	Low &	Nominal	Warning
3	High &	Low &	High	Warning
4	High &	Nominal &	Low	Alert
5	High &	Nominal &	Nominal	Alert
6	High &	Nominal &	High	Alert
7	High &	High &	Low	Alert
8	High &	High &	Nominal	Alert
9	High &	High &	High	Alert
10	Nominal &	Nominal &	Nominal	Normal
11	Low &	Low &	Low	Normal
12	Low &	Low &	Nominal	Normal
13	Low &	Low &	High	Warning
14	Nominal &	Nominal &	Low	Alert
15	Low &	Nominal &	Nominal	Normal
16	Low &	Nominal &	High	Normal
17	Low &	Nominal &	Low	Alert
18	Nominal &	High &	Nominal	Alert
19	Nominal &	Low &	High	Alert
20	Nominal &	Nominal &	Low	Normal

5. Experimental work

To observe the behavior of the model made in this section, it was implemented using 20 data in the fuzzy logic toolbox to perform a comparison of results between the fuzzy inference system Mamdani and Sugeno.

In order to verify the performance of the fuzzy system, the Mamdani model of the min-max form was performed, in the same way the Sugeno type model was implemented, both in the Matlab Fuzzy Logic ToolBox, 10 of the results obtained are shown in the Table 10 using triangular functions.

Table 10: Parameterization of the triangular MFs (output)

OilTemp (◦C)	*NacelleTemp (◦C)*	*Potencia (kW)*	*Mamdani*	*Sugeno*
55.85	38.90	29.66	0.44	0.59
40.18	33.90	99.80	0.18	0.00
65.50	49.00	186.91	0.82	1.00
62.90	44.27	134.26	0.55	0.94
62.90	45.46	234.31	0.55	0.92
43.91	26.95	122.66	0.18	0.00
44.28	31.90	193.69	0.18	0.00
32.06	27.90	30.602	0.19	0.00
64.90	47.90	199.79	0.80	0.99
50.00	30.00	1000.00	0.13	0.00

The experiments throw a difference between the fuzzy system type Sugeno and Mamdani, however; both correctly indicate the condition in which the wind turbine is located according to the data.

6. Conclusion

In this research, with the aim of improving the wind turbine condition monitoring activities and due to the good performance of the fuzzy systems in the maintenance area, a fuzzy Mamdani system is proposed for the diagnosis of wind turbine conditions considering factors impact (temperatures, power, speeds), which in undesirable conditions, have a negative impact on the life of the turbine as it is the case of an increase in temperature caused by insufficient cooling that can be a consequence of a contaminated filter, this temperature increase generates more heat than the turbine is able to support under optimal conditions, which critically affects its useful life and therefore affects the wind turbine cycle.

To achieve this objective, a knowledge base was acquired through the SCADA system of the wind turbine, in addition to the available documentation, the standards of the international electrotechnical committee (IEC), and the knowledge of experts in the area. From this knowledge the fuzzy rules were extracted and a fuzzy system was developed with which the diagnosis of wind turbine condition is proposed.

The proposed system was implemented contemplating 20 data sets and using the Fuzzy Logic Toolbox of Matlab, obtaining similar results with two models of fuzzy inference system (Mamdani and Sugeno) and according to the experts consulted, both expected performance was obtained.

The application of the proposed fuzzy inference system has as a benefit the reduction of time in diagnoses made by human operators, reduction of the human error factor, improvement in the maintenance schedule of the turbines if necessary, which results in the reduction of maintenance costs and the increase in the reliability of operation of the wind turbine, which are a fundamental part in any industrial process.

As future research work, it is contemplated that the system of inference not only of the condition of the turbines to alert operators, but also be able to detect failures incipiently and also indicate the possible cause.

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Author Profile

O. Montserrat Reyes, Computer Engineer, graduated from the Faculty of Engineering of the Autonomous University of Tlaxcala in 2014. Currently a student of the Masters in Computational Systems at the Technological Institute of Apizaco.

P. Malaquías Quintero. PhD. in Computer Science by l'université Montpellier and the Laboratory of Research in Computer Science, Robotics and Microelectronics of Montpellier of the Centre national de la recherche scientifique (CNRS) of France, a Masters in Computational Sciences by the Technological Institute of Toluca, in the State of Mexico. Department of Systems and Computing of the Technological Institute of Apizaco and of the Faculty of Engineering of the Autonomous University of Tlaxcala.

Pablo H. Ibargüengoytia. PhD. in Computer Science. Researcher of the Management of Control, Electronics and Communications of the National Institute of Electricity and Clean Energies.