Fuzzy Inference System for fault detection in internal combustion engines in Thermoelectric Power Generating Plants

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Abstract—In this work, an approach to implement a simplified fuzzy inference model for monitoring the conditions of workings of power generators through the pressure values of combustion temperature and engine water pressure is displayed. The model helps the supervisory system, through real-time evaluation of the operating conditions of the engine in percentage rates. The application of tools based on computational intelligence, have shown efficiency in various areas of industrial engineering.

Keywords— Computational intelligence, Fuzzy logic, Internal combustion engine, Monitoring.

I. INTRODUCTION

Generation of Electric Energy (EE) is increasing in developing countries due to the massive consumption of EE, although in Brazil the main source of EE be Hydraulic generation with 66% of total generation (Trindade, Sperling, & Bourbon, 2017), Still have a significant percentage coming from non-renewable energy sources accounting for 18%, in northern Brazil 18.2% of the total energy are Thermoelectric(EPE, 2017).

In Brazil, it uses the thermal energy in a strategic way, as it can be produced in a constant amount throughout the year, unlike hydropower, which have the dependent production level of rivers(Lima & Souza, 2014).

Power generation by motor generator (MG) is strategic but with a high cost of deployment and maintenance.

Because of this high cost, predictive maintenance based on the MG's runs parameters, is earning more and more importance in preventing failure of these engines. Because of the critical features that this equipment is for power systems, especially in developing countries. Several techniques for fault detection in MG's have been applied, such as: Martinez uses a model-based approach with a multi-variable generation of waste from the main fault situations, arranged in a matrix characteristic of fault signatures, establishing a standard reference to continuously evaluate waste in on-line operating conditions(Coronado-Martinez, Ruiz-Sanchez, & Suarez-Cerda, 2017). Fonseca performs a diagnosis of the technical conditions of the engine using a lubricating analysis, vibration analysis, and thermography (Fonseca, Bezerra, Brito, Leite, & Nascimento, 2018).

A new technique for failure prediction in a plant controlled by computerized SCADA system (Mayadevi, Vinodchandra, & Ushakumari, 2012), A method that detects combustion failures caused by a fuel deficiency in a cylinder, even in its early stages is presented by Nieto (Nieto, Blazquez, Platero, & Casado, 2017). A cylinder balancing method is disclosed which minimizes the crankshaft torsional vibrations at medium speed internal combustion engines (Ostman & Toivonen, 2008).

A systems Supervisory Control and Data Acquisition are designed to allow human operators supervise, maintain and control critical infrastructure (Samtani, Yu, Zhu, Patton, & Chen, 2016), Sanchez and Suarez for fault

detection in fossil power plants operation using recurrent neural networks (Sanchez, Suarez, & Ruz, 2004).

This paper proposes a fuzzy inference model for detection and modeling of incipient faults in combustion engine components of the power generators.

The proposed method allows detection of incipient faults in the main motor, whereas the values of the following quantities: the combustion pressure in the cylinder, and cooling water temperature and pressure.

The proposed failure patterns are based on values set in the characteristic structure of the machine so that they can be reproduced in a wide range of sets of motorcycle generators. The advantages of the proposed system are its low intrusiveness, simplified deployment and cost efficiency.

II. LITERATURE REVIEW: FUZZY INFERENCE SYSTEMS

Fuzzy logic was initially defined by Zadeh (Zadeh, 1965)And presented in scientific circles through his article "Fuzzy Sets" published in the journal Information and Control (Chenci, Rignel, & Lucas, 2011). Zadeh introduced the concept of fuzzy sets defining them in terms of mapping a set in the unit interval on the real line(Brown, 1971).

The problem of making decisions to classify the objects of the universe into two or more classes was considered appropriate in the context of the theory of fuzzy sets(Capocelli & De Luca, 1973). Fuzzy logic is a logic based on the theory of fuzzy sets(Gonçalves, Junior, Leite, da Costa Junior, & de Lima Tostes, 2013).

It differs from traditional logic systems in their characteristics and their details. In this logic, the exact reasoning corresponds to a limit case of approximate reasoning, being interpreted as a writing process of fuzzy relations(Gomide & Gudwin, 1994).

The fuzzy logic is the point of an input spatial map to an output space, and the main mechanism to define this space is a list of if-then rules called instructions. Unlike conventional logic, Fuzzy logic uses the idea that all things admit membership degrees(Marro, Souza, Cavalcante, Bezerra, & Nunes, 2010)(Pereira, Bighi, Gabriel, & Gabriel, 2008).

The fuzzy inference model adopted for the failure prediction system of the engine is based on computer simulations of the combustion pressure in the cylinder values and cooling water temperature and pressure, selected as relevant variables for analysis.

So it can be built the system that interprets the rules, you must first define all terms adjectives that describe them.

As an example, the description of the membership functions with numeric range and the linguistic value of each selected variable, are presented in Table 1:

Table.1: System Suitability functions.

Type	Linguistic variables	set Cloudy	Numeric range	description
Input	Water temperature (TAGUA)	Low	[0 - 100]	The expected value for the water temperature is between 40 and 80 degrees Celsius.
		Normal		
		High		
	Water Pressure (Pagua)	Low	[0 - 6]	The expected value of the water pressure is between 2 and 5 bar.
		Normal		
		High		
	combustion pressure (PComb)	Low	[0 - 220] to	The expected value for the combustion pressure is between 40 and 180 bar.
		Normal		
		High		
Output	CondFunc	Normal	[0 - 100]	The expected value for stability is up to 50 points.
		Not normal		

In Fig. 1, is shown implementing the inference model proposed for failure prediction in the GUI area of the user.
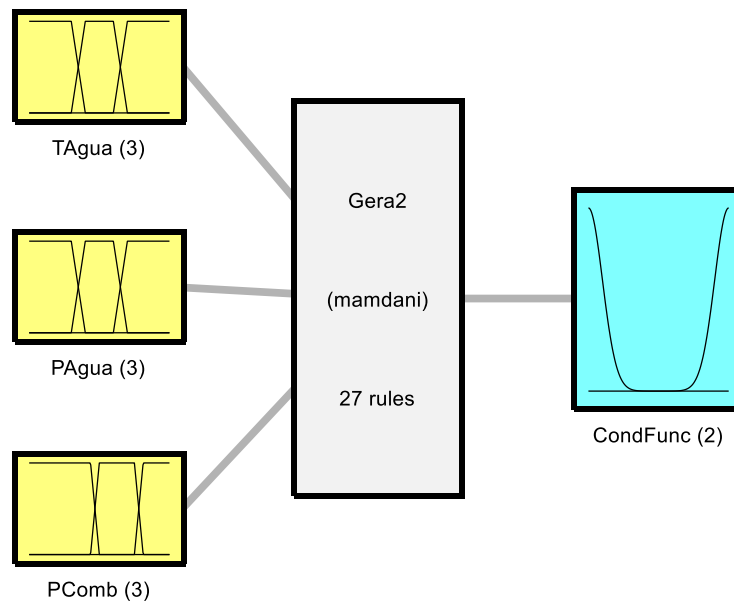
System Gera2: 3 inputs, 1 outputs, 27 rules

Fig.1: Input variables and system output.
Source: Author (2018)

Once selected the number and shape of the membership functions, it must be determined for each of the membership functions, the values associated with the high and the low relevance, and the amounts of the maximum of 1 (one) and the values associated the minimum membership is equal to 0 (zero)(Medeiros, de Mello, & Campos Filho, 2007). This procedure is different for the different shapes of the membership functions available on MFLT. The most commonly used formats for membership functions are triangular (trimf), trapezoidal (trapmf) and Gaussian (gaussmf).

Regarding the description of the variables they represent the knowledge of the expert in the fuzzy inference being termed as input variables and system output, matched linguistically representing inaccuracy mode (Nogueira & Nascimento, 2017)(Poletti & Meyer, 2009). Thus, the variables of the proposed system are:

Tagua- The limits for the variable values of water temperature are set between 40 and 80 degrees Celsius. The fuzzification of this variable is trapezoidal, seen in Fig. 2.
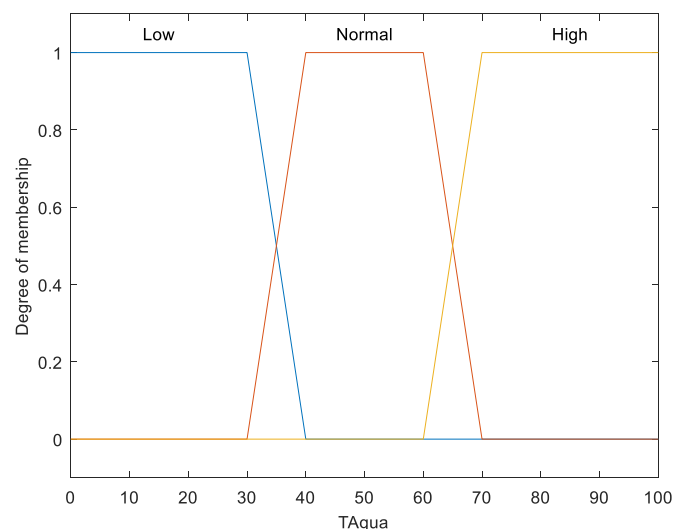

Fig.2: Tagua input variable.

Pagua- The limit values for the water pressure are set variable between 3 and 5 bar. The fuzzification of this variable is trapezoidal, as shown in Fig. 3.
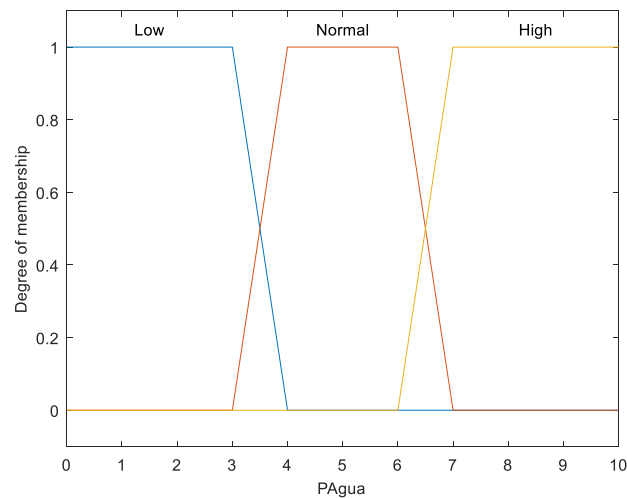

Fig 3: Pagua input variable.

pComb- The limit values for the combustion pressure variable are set between 80 and 120 bar. The fuzzification of this variable is trapezoidal, as shown in Fig. 4.
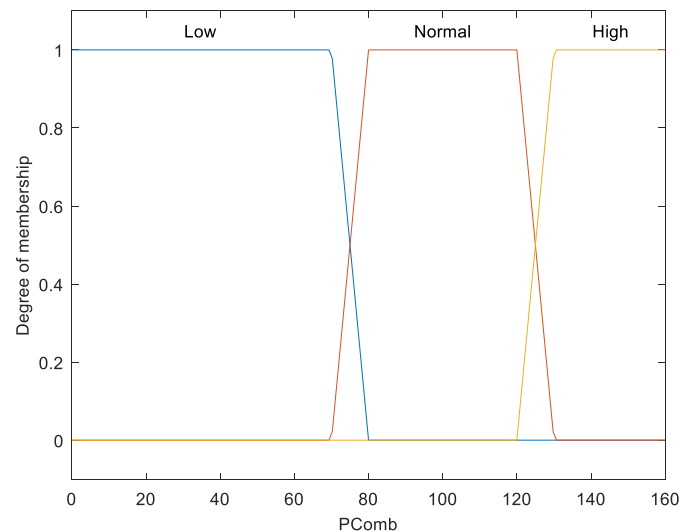

Fig.4: Pagua input variable.

CondFunc - associations of input variables are related to the output variable operating conditions, which has a fuzzification shown in Fig. 5.
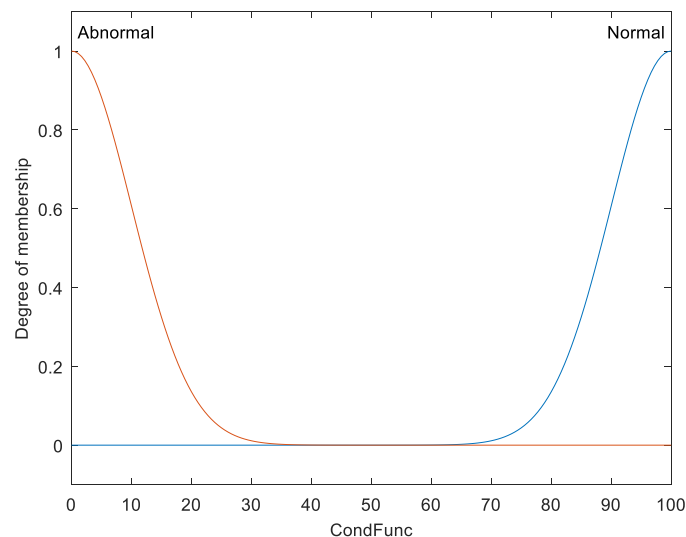
Fig.5: Output variable CondFunc

The demonstration of the basic inference rules of the language variables of the proposed system, resulted in 27 combinations applied in this fuzzy solution, which part can be seen in Fig. 6.

Fig.6: Combination of Inference Rules

III. ANALYSIS OF THE APPLICATION OF THE PROPOSED SYSTEM

In the viewer rules, the data is arranged in a graphical interface that facilitate the simulation and interpretation of various scenarios by combining values for the variables of the system inferences, showing the functions that reflect the overall result of the system. Adopting hypothetical input values, considering them wherein for the water temperature input variables is 50 Celsius, the water pressure of 5 bar and combustion pressure of 100 bar, resulting is an operating condition 99.5 %, i.e. a favorable environment for the operation of the motor generator. By varying the input values, it is possible to evaluate the outputs of the proposed system, obtaining a value that allows a correct analysis of the efficiency of the method adopted for fault detection in motor operation, seen in Fig. 7.
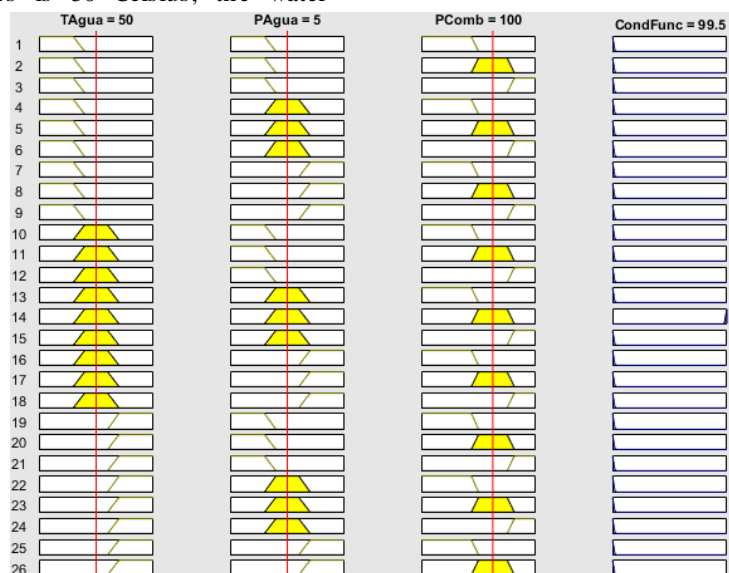

Fig.7: Viewer of Inference Rules

In Fig.7, it can be seen that for values within defined limits established for each input variable, the machining condition is present in 99.5%, a reliable value for the continued operation.

In any other operating condition exceeds the upper or lower limits of normal for the variables defined, has a worst case scenario for operation of the motor generator, is indicated shutdown for maintenance of the same, observable in FIG. 8.
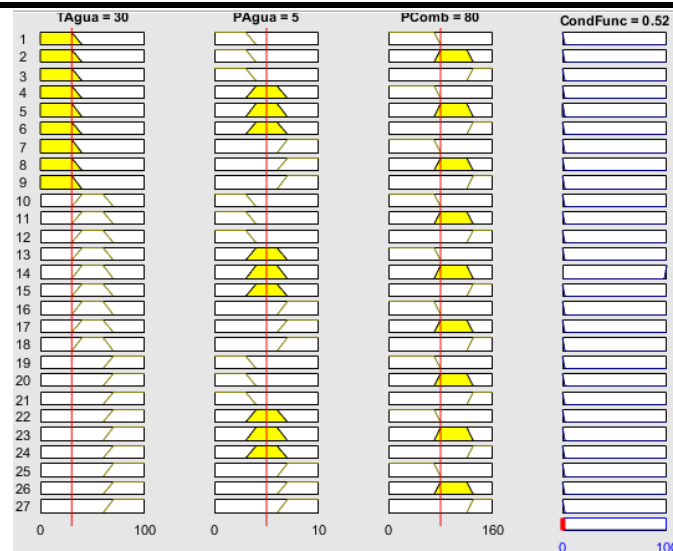
Fig.8: Viewer of Inference Rules

Fig. 8 shows the machine operating conditions (0.52%) unacceptable for continuity of operation due to the fact that the temperature of the water (30) is outside the predefined limits.

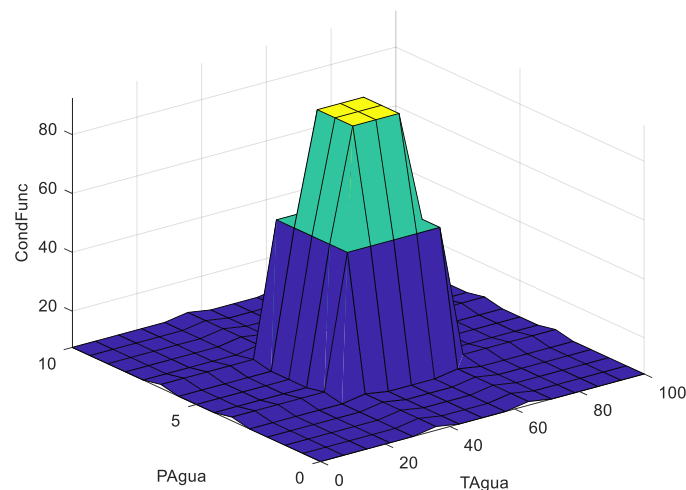Fig. 9 shows the resultant surface plot of the proposed system.

Fig.9: Surface Chart

IV.   CONCLUSION

The approach proposed by the model of Fuzzy Inference proved to be streamlined and efficient for monitoring and fault detection in the operating conditions of the engine generator, enabling greater reliability and security for the protection systems. The monitoring of the variables pressure and the combustion temperature and the engine water pressure with the application of fuzzy logic proved adequate to support decision making regarding the operating conditions of the power plant generators.

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