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# Fuzzy logic methodology to study the behavior of energy transformation processes based on statistics $T^2$ and Q

Y Cárdenas<sup>1</sup>, G E Carrillo<sup>2</sup>, A Alviz<sup>3</sup>, and G Carrillo<sup>4</sup>

<sup>1</sup> Universidad de la Costa, Barranquilla, Colombia

<sup>2</sup> Universidad Tecnológica de Bolívar, Cartagena de Indias, Colombia

<sup>3</sup> Universidad Industrial de Santander, Bucarmanaga, Colombia

<sup>4</sup> Corporación Politécnico de la Costa Atlántica, Barranquilla, Colombia

E-mail: gcarrillo@utb.edu.co

**Abstract.** In the processes of energy transformation, to carry out an adequate follow-up of the process parameters represent an opportunity to propose strategies to improve the processes' performance. For this reason, it is essential to analyze the behavior of process variables under the quantitative and qualitative optics supported by the experts. Thus, this work proposes a methodology of fuzzy Mandani type logic that allows the analysis of energy transformation processes (such as internal combustion engines) based on  $T^2$  and Q statistics, as a way to identify whether the operation limits are kept within the normal or exceed the limits, achieving to identify the anomaly in the process. In the initial stage, MATLAB implements two diffuse systems; the first system aims to determine the impact variables have on the generation of an anomaly, without identifying the type of defect. In the second stage, it's defined as a function of the number guests, the kind of monster that occurs in the observations made from the transition range in the operation of the system analyzed, until the last measurement obtained. In the third stage, the statistics  $T^2$ , Q, and its limits are determined from the operating variables of the selected system. Finally, the previously calculated statistics are graphically processed in the diffuse systems. The results obtained in this work show that the analysis of processes or phenomena based on qualitative observations, the methodology implemented, is a useful tool for decision making in the industrial sector.

## 1. Introduction

Social development has been considerably boosted by the development of the industrial sector and the different systems incorporated into the processes, which in this environment are required [1]. In the execution of each function, it is essential that each process or equipment maintains optimal operating conditions [2], as a way of ensuring the safety of equipment, operators, business assets and reducing the costs associated with their maintenance, fuel and input costs, as well as the various implications for business interests [3]. Because of this possibility of variation in operating conditions or malfunctioning, enabling operators to carry out analysis and early detection of anomalies or undesirable operating conditions has become a subject of considerable research interest [4,5]. Diverse are the techniques or systems used to analyze the behavior of the operating variables and the various conditions of a process, in which various equipment is involved [6]. However, because of all these conditions, the operators must interact in order to of neural networks. Khelil *et al.* [7] presented a methodology for the diagnosis of marine engines, using neural networks, as a way to control the operating conditions of the machine. Tayarani and Khorasani [8] designed a failure detection, and isolation scheme for gas turbines by



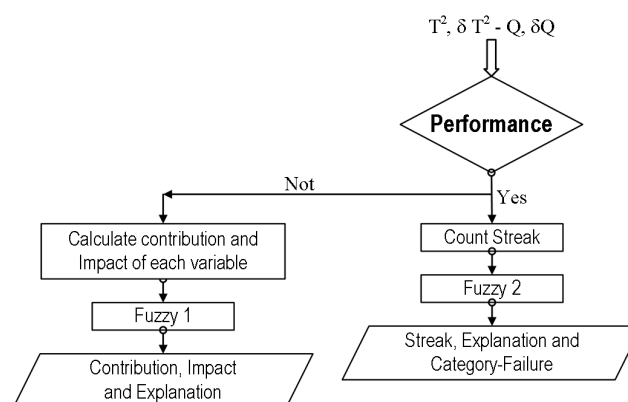
implementing neural networks, dynamic neural networks and time-delayed neural networks were used. Delvecchio *et al.* [9] propose a strategy based on vibro-acoustic signals that can monitor and diagnose the malfunctioning of internal combustion engines. Çeven *et al.* [10] use the fuzzy logic technique to determine the operating behavior and range of an electric vehicle, using the Mamdani type fuzzy logic approach, as it is one of the most versatile methodologies for this type of study. Given this panorama of the industrial sector and the imminent operational need, the leading scientific contribution of this work consists of the implementation of a methodology for the analysis of internal combustion engine (ICE) operating conditions that allows the detection of failures in this type of equipment, based on a Mandani type fuzzy logic technique, parameters that will enable the monitoring of the operating state of a system, such as  $T^2$  and  $Q$ , and the observations based on the experiences of the operators of this type of system. Make decisions [11]. In this sense, to be able to incorporate the experience and observations made by the operators, to the process of detection of failures using computer tools, represents one of the aspects in the industry that has a more significant impact in the optimization of the methods, used resources, reliability, and maintainability of the equipment [12,13]. Some of the research carried out is presented below: Sangha *et al.* [14] developed a car engine failure detection analysis using dynamic data and the application.

The main contribution of this research is based on the development of a methodology used to analyze the behavior of process variables, based on the qualitative description that in many occasions are carried out by experts in the process of electric power generation, such as internal combustion engines, as a machine for energy transformation.

## 2. Methodology

This section shows the main stages and concepts that help describe the methodology implemented in this research. In Figure 1, the sequence of analysis used to study the behavior of the variables involved in the energy conversion process is shown. In Figure 1, the statistics  $T^2$  and  $Q$  correspond to the parameters that allow the monitoring of the operating state of a system from principal component analysis (PCA). However, these results are generated separately, therefore, in this stage a diffuse system type Mandani is designed that allows to evaluate both parameters to determine from  $k$  (Streaks), contributions, impact and joint explanation of variables and the kind of anomaly (failure, fault, incorrect operation) presented in the action of the ICE.

The methodology shown in Figure 1, uses expert analysis (ICE operator) and the algorithm implemented to identify the type of anomaly, with the aim of providing the operator with sufficient information to enable to analyze the process correctly. For this purpose, two fundamental techniques are established: the first one called fuzzy system based on variable contributions, and the second one called fuzzy system based on operational streaks. The fuzzy system developed in this research; it was implemented by using a library of MATLAB. Below, it will be describing the main stages of fuzzy system.



**Figure 1.** Steps for implementing fuzzy logic.

### 2.1. Technical bases of the fuzzy logic principle

A fuzzy system performs a non-linear mapping of one or more inputs to a set of one or more outputs, Mandani main stages are:

2.1.1. *System of fuzzification.* A fuzzy set was define as a set containing elements that have a degree of belonging and are governed precisely by a membership function. Therefore, be  $Y$  a set of objects whose parts are denoted by  $y$  A fuzzy set  $A$  of  $Y$  is meant as a set of ordered pairs Equation (1) [15]:

$$A = \{[y, f_A(y)] | y \in Y\}. \quad (1)$$

To  $f_A(y)$  is the membership function or membership function.

2.1.2. *Inference system.* Interface between input and output diffusion assemblies. It consists of a set of rules that represent the knowledge base for performing a particular task through a set of rules.

a) Fuzzy rules: A rule can be formed as follows [15]. IF  $I_a$  ( $x$  is  $A$ ) AND ( $y$  is  $B$ ) THEN ( $z$  is  $C$ ).

To  $A, B, C$  correspond to linguistic values gathered by the diffuse sets that fuzzification entries in values or degrees of belonging according to their respective functions of belonging. The clause found before "THEN" is called the antecedent or premise, while the part after that word is called the consequent or conclusion [15].

b) Implication It is the process that through the fuzzy rules takes the fuzzy sets of input and generates a fuzzy set at the output. The three logical operators: (AND), (OR), (NOT), function to group the membership values for the antecedent or premise. Therefore, there are three methods to evaluate the fuzzy rules [15].

- The rule  $[f_A(x) \text{ AND } f_B(y)]$  is evaluated by the  $\min(f_A(x), f_B(y))$ .
- The rule  $[f_A(x) \text{ OR } f_B(y)]$  is evaluated by the  $\max(f_A(x), f_B(y))$ .
- The rule  $\text{NOT}[f_A(x) \text{ OR } f_B(y)]$  is evaluated by the fuzzy complement  $[1 - f_A(x)]$ .

2.1.3. *Defuzzification.* This process consists of taking the fuzzy set resulting from the aggregation process and generating a scalar value at the output. There are different methods to carry out this process [15].

- Centroid method: calculates the center of gravity of the area under the curve.
- Maximum methods: Three ways are higher than maximum, average of maximums, and lower than peaks.
- Bisector method: calculates the line that divides the fuzzy set into two regions of equal area.

## 3. Results

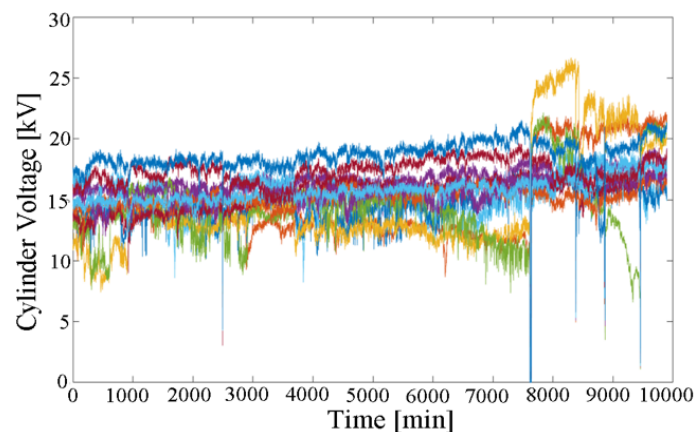
In this section the main results obtained with the methodology proposed in this work will be presented. In addition to some descriptions of the analyzed system, analysis conditions, discussions and analysis of the results. This section starts by the results of the fuzzy 1 system and later, it will be present the result of the fuzzy 2 system.

### 3.1. Operational parameter of the internal combustion engine

To develop the analysis and implementation of the methodology proposed in this work, real data from the operation of a natural gas engine (JGS 612 GS-N. L) were used. This engine is used as the electricity

generation system of a company in the industrial sector of Colombia. In Figure 2 is shown the behavior of one of the operating variables of this system.

Figure 2 shows the behavior of the voltage of the engine cylinder, used as one of variables to develop the study presented in this research. Analysis that is complemented with the observations made by the experts involved in the process, to finally process this information with the fuzzy logic methodology integrated into the study of the statistics.  $T^2$  y Q. From Figure 2, it is essential to highlight the variation in the voltage behavior of the 12 cylinders of the engine. For these values obtained from the operation of the machine, the experts of the process made various assessments on the variation of the conditions in different states of engine operation. Findings that will be verified, through fuzzy systems 1 and 2, implemented in this study and that will be shown below.



**Figure 2.** Voltage behavior as a function of operating time.

### 3.2. Fuzzy system based on variable contributions

The first system is based on measuring each variable when its contribution level is low, medium, and high. Understanding as low, medium and increased contribution the values that oscillate between  $x < 5$ ;  $6 \leq x \leq 10$ ;  $x > 10$ . The characteristics of the fuzzy system that were used in this analysis are shown in Table 1. Thus, as Table 1 shown, three membership functions have been generated for each entry, the names of these fuzzy sets are high (H), medium (M), high (H). The choice of trapezoid membership functions was made. Since it has a degree of value belonging by rank. Also, three membership functions were implemented for the outputs named: does not explain, some measure, yes explains. So, the defuzzification of the system will indicate the variables that impact on the detection of anomalies.

**Table 1.** Characteristics of the contribution-based system.

Characteristic's	Type
Number of inputs	2 parameters (contribution and impact)
Input range	High (H), Medium (M), High (H)
Output	3 Does not explain, some measure, if explains
Fuzzy system type	Mandani

Figure 3 and Figure 4 shows the implemented topology of the fuzzy system called "Impact vs. contribution" which has four inference rules, described in Table 2. For the fuzzy system shown in the Figure 5 five fuzzy rules are proposed, based on the analysis carried out and condensed in the Table 2. From the defined standards, the surface of fulfillment of the 5 functions is obtained, Figure 5. Which indicates the association of each stipulated rule *i.e.* the result of the Table 2 in graphic form. For variables with low, medium or high impact and no contribution to the process, they cannot be considered to give explanations for the variation in engine operating conditions. In the case of variables, with low impact and low-medium contribution, descriptions can be obtained, and it would be necessary to carry out some type of additional monitoring of behavior, in order to have a definitive proof of the behavior of the

system. Finally, for variables with high contributions in the process and high impact, they allow an apparent explain description variation in the operating condition of the motor. Therefore, they must be subject to constant supervision and control, as a way to guarantee the appropriate process.

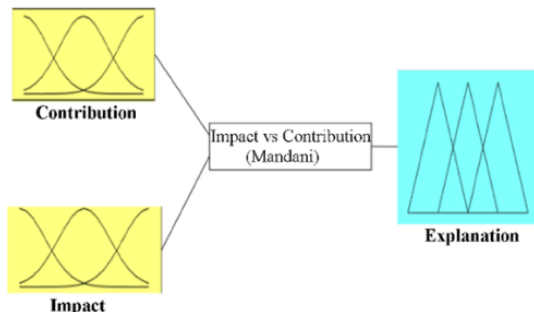


Figure 3. Fuzzy system topology.

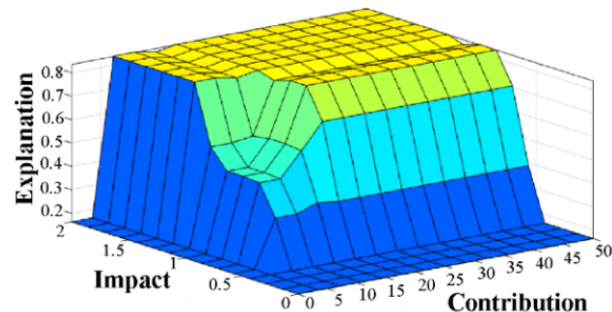


Figure 4. Fuzzy1 rule compliance area.

Table 2. Expert impact assignment.

		Contribution (C)		
		Low (B)	Medium (M)	High (A)
Impact (I)	0 Low (L)	No impact	Impact	No impact
	1 Medium (M)	No impact	Impact to some extent	Impact
	2 High (H)	No impact	Impact	Impact

3.3. Fuzzy system based on operational streams

The second fuzzy system is based on the ratio of the number of spurts when the degree of explanation, is unexplained (No), short and if explained. Understanding as range of low, medium and high gusts the values that oscillate between:  $x < 3$ ;  $7 \leq x \leq 10$ ;  $x > 11$ ; respectively. The characteristics of the fuzzy system that were used in this analysis are shown in the Table 3.

Thus, as Table 3 shown, three membership functions are generated for each entry, the names of these fuzzy sets are Low (L), Medium (M), High (H). The choice of trapezoid membership functions was made. This type procedure was chosen because it has a degree of value belonging by range. Also, three membership functions were implemented for the outputs called Incorrect operation, failure. Therefore, the defuzzification of the system will indicate what type of anomaly is presented in the system.

Table 3. Characteristics of the diffuse streak-based system.

Characteristic	Type
Number of inputs	2 parameters, 3 conditions: streak and explanation
Input range	Low(L), Medium (M), High(H)
Output	3: Incorrect operation, Failure, Fault
Fuzzy system type	Mandani

The Figure 5 shows the implemented topology of the fuzzy system called “Streak vs. Explanation” that has four inference rules. From Figure 5, it is possible to infer that in order to make a conclusion about a type of failure, it is necessary to have streak values of the variable to be analyzed. From medium of streaks, it is possible to reach conclusions about the types of failures present in the process. Average values and explanations of the experts allow to obtain an answer off or the failure, which may be affecting the engine. Until reaching the condition of having high streak values, with high value in the explanation of the experts, as a desired way to fully identify the cause of the failure caused.

For this fuzzy system, fuzzy rules are proposed, based on the analysis carried out and condensed in the Table 4 From the defined rules, the area for fulfilling the functions is obtained as shown Figure 6.

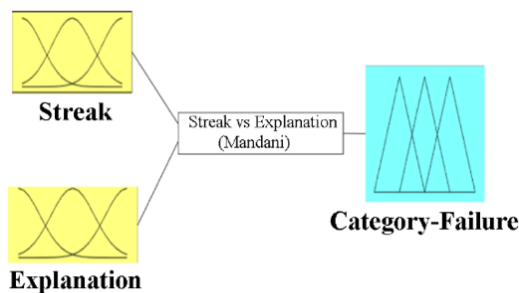


Figure 5. Fuzzy system topology.

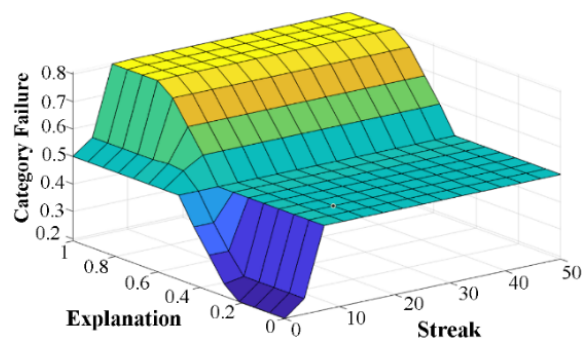


Figure 6. Fuzzy 2 rule compliance surface.

Table 4. Expert explanation assignment.

		Streaks		
		Low (L)	Medium (M)	High(A)
Level of explanation	NO	Incorrect operation	Failure	Failure
	To a small extent (SE)	Fault	Failure	Failure
	YES	Fault	Breakdown	Breakdown

#### 4. Conclusions

Based on the research carried out in this work and based on the review of the specialized bibliography, it is possible to conclude that with the implementation of the methodology presented in this work, it was possible to develop a useful tool for decision-making in transformation processes of energy, as are internal combustion engines. This proposed method takes into consideration the analysis of process variables, multivariate statistics, and the descriptions made by the experts, which, as it was possible to observe, by reviewing the literature, there are no references of works carried out on this type of analysis.

From the results obtained from the operation of the JGS 612 GS-NL engine and from the observations of the experts, the fuzzy systems created in this work allowed the securing of surface graphs, which facilitate the interpretation of the behavior of the variables and the effects they are having on the process, as a practical tool to classify these behaviors, such as changes in operating conditions or process failures. These surface graphs can additionally be used to identify variable by variable, which are more representative for the process and how much they can affect the desired operating conditions.

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