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

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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.](image-url)
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, and the main stages are:

2.1.1. System of fuzzification. A fuzzy set was defined 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 $y$ and $A$ a fuzzy set of $Y$ is meant as a set of ordered pairs Equation (1) [15]:

$$A = \{[y, f_A(y)]|y \in Y\}.$$  (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 $x$ 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 min ($f_A(x), f_B(y)$).
- 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. 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.

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.

| 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
Finalmente, para variables con altos contribuciones en el proceso y alto impacto, permiten una explicación aparente de la variación de las condiciones de operación de la máquina. Por lo tanto, deben ser sujetas a supervisión constante y control, como una manera de garantizar el proceso adecuado.

**Figure 3.** Fuzzy system topology.  
**Figure 4.** Fuzzy rule compliance area.

### Table 2. Expert impact assignment.

| Impact (I) | Contribution (C) | Low (B) | Medium (M) | High (A) |
|------------|------------------|---------|------------|----------|
| 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

El segundo sistema difuso está basado en la razón de número de bruscos cuando la gravedad de explicación es no explicada (No), corto y si explicado. Entendiendo como rango de valores de bruscos medianos y altos los que oscilan entre: $x < 3; 7 \leq x \leq 10; x > 11$ respectivamente. Las características de dicho sistema fueron mostradas en la Tabla 3.

| 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                            |

El Gráfico 5 muestra la topología implementada del sistema difuso llamado “Streak vs. Explanation” que tiene cuatro reglas de inferencia. Desde Gráfico 5, es posible inferir que en orden a hacer una conclusión sobre un tipo de fallo, es necesario tener valores de bruscos del variables a analizar. Desde el punto de vista de los bruscos, es posible llegar conclusiones sobre los tipos de fallos que presentan el proceso. Los promedios de los valores y las explicaciones de los expertos permiten obtener una respuesta sobre el fallo o la falla, que puede afectar el motor. Al llegar a la condición de tener valores de bruscos altos, con alto valor en la explicación de los expertos, como un deseo con el que se identifica de manera total la causa del fallo causado.

Para este sistema difuso, reglas difusas son propuestas, basadas en el análisis realizado y condensado en la Tabla 4. De las reglas definidas, el área para cumplir con las funciones se obtiene como se muestra en el Gráfico 6.
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.

References
[1] Li Z, Sun L, Geng Y, Dong H, Ren J, Liug Z, Tian X, Yabara H, Higanoa Y 2017 Examining industrial structure changes and corresponding carbon emissionreduction effect by combining input-output analysis and social network analysis: A comparison study of China and Japan J. Clean. Prod. 162(61) 70-82
[2] Islam J, Hu Y, Haltas I, Balta-ozkan N, G Jr, Varga L 2018 Reducing industrial energy demand in the UK: A review of energy efficiency technologies and energy-saving poten ia in selected sectors Renew. Sustain. Energy Rev. 94(23) 1153–1178
[3] Franciosi C, Voisin A, Miranda S, Riemma S, Iung B 2020 Measuring maintenance impacts on the sustainability of manufacturing industries: from a systematic literature review to a framework proposal J. Clean. Prod. 260(14) 121-129
[4] Waligórski M, Batura K, Kucal K, Merkisz J 2020 Research on airplanes engines dynamic processes with modern acoustic methods for fast and accurate diagnostics and safety improvement Measurement 12(13) 123-129
[5] Diéguez M, Urroz J, Sáinz D, Machin J, Arana M, Gandia L 2018 Characterization of combustion anomalies in a hydrogen-fueled 1.4 L commercial spark-ignition engine using in-cylinder pressure, block-engine vibration, and acoustic measurements Energy Convers. Manag. 172(13) 67–80
[6] Alblawi A 2020 Fault diagnosis of an industrial gas turbine based on the thermodynamic model coupled with a multi feedforward artificial neural networks Energy Reports 6(13) 1083–1096
[7] Khelil Y, Graton G, Djaziri M, Ouladsine M, R Outbib 2012 Fault detection and isolation in marine diesel engines-a generic methodology IFAC Proc. 45(20) 964–969
[8] Tayarani S S, Khorasani K Fault detection and isolation of gas turbine engines using a bank of neural networks J. Process Control 36(22) 41-48

[9] Delvecchio S, Bonfiglio P, Pompoli F 2018 Vibro-acoustic condition monitoring of internal combustion engines: A critical review of existing techniques Mech. Syst. Signal Process 99(14) 661–683

[10] Çeven S, Albayrak A, Bayır R 2020 Real-time range estimation in electric vehicles using fuzzy Comput. Electr. Eng. 34(13) 83-89

[11] Ansari F 2020 Cost-based text understanding to improve maintenance knowledge intelligence in manufacturing enterprises Comput. Ind. Eng. 141(12) 106-115

[12] Lin Q, Zhang Y, Yang S, Ma S, Zhang T, Xiao Q 2020 Full length Article A self-learning and self-optimizing framework for the fault diagnosis knowledge base in a workshop Robot. Comput. Integer Manuf. 65(12) 101-121

[13] Tso W, Burnak B, Pistikopoulos E 2020 HY-POP: Hyperparameter optimization of machine learning models through parametric programming Comput. Chem. Eng. 139(13) 106-113

[14] Sangha M, Gomm J, Yu D, Page G 2005 Fault detection and identification of automotive engines using neural networks IFAC Proc. 38(12005) 272–277

[15] Zumoffen D 2008 Desarrollo de Sistemas de Diagnóstico de Fallas Integrado al Diseño de Control Tolerante a Fallas en Procesos Químicos (Colombia: Universidad Nacional de Rosario)