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Variable control tool in MATLAB for energy transformation processes

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Abstract. During the stages of transformation of energy in a process, exercise control over the variables that intervene in it, improve its performance, and identify undesirable conditions in these. Thus, this study is developed as a graphical interface to implement a methodology for controlling variables of energy conversion processes, such as internal combustion engines. The control tool developed in MATLAB variables is based on multivariate statistics. The methods for developing this tool of Graphic User Interface is based on the statistics of principal component analysis and failure statistics such as T^2 Hotelling and the Q statistic that allows the control of anomalies presented in the operation's behavior. About the methodology, first, the input data are normalized, achieving standardization of the observation matrix vs. variables, then the spectral decomposition of the normalized data is performed, reaching the generation of the matrix of auto-values, allowing the age of the projection space of the data. With this based and delimited, it is possible to establish the ranges of observation of the mentioned statisticians. The result obtained from this research corresponds to software that allows the constant observation and analysis of the behavior of each variable of the generation engine. It describes the upper limit, lower limit, arithmetic mean, principal components, graphics of the statistics, and detects the failures in real times.

1. Introduction

Today, the concepts and methods of statistical process control have become a fundamental aspect for monitoring operations in the manufacturing and energy-generating industries [1]; it is worth mentioning that both the concepts and the methods of the internal combustion engine (ICE) are complementary to those of the control of the automatic feedback process. The control tools allow monitoring the performance of a process over time to verify that it is maintained in a "statistical control state" [2]. Such a control state exists if the process or product variables remain close to their desired values or in the "normal" operating range [3]. Based on this idea, what is expected through the variable's operational control is to identify the root causes of the failure, achieve improvements in the process chain, avoid corrective maintenance, and apply bases of preventive care.

Conventional multivariate statistical process control schemes focus on monitoring the stability of the arithmetical mean of the process, limiting the analysis of the "weighting" or valuable variables that directly affect the process to a value higher than 80 % of the total incidence [4]. Thus, detecting and diagnosing the variables that cause failures has become one of the most widely used methods worldwide to identify abnormalities that impact any decision-making point. However, the growing complexity of



operating electricity generation plants means that these activities are carried out with more exceptional care by the personnel in charge, requiring computer platforms that facilitate this work [5]. One of these platforms has been the so-called graphic user interfaces (GUI), which allows visual interaction composed of Image, and graphic objects of the process with the user or operator role [6]. The use of GUI has been developed as a control information tool in the industrial sectors. Usually, the software systems have been built on platforms based on events or functional parameters that allow the variability of the analysis independence of the study's settings. The software-driven by technical parameters is contained by a GUI that enables the user to use digital buttons as a tool to t variables [7]. Statistical studies show that 70% of industrial events are caused by human error [8,9], requiring the incorporation of control techniques for industrial automation and methods of fault detection and diagnosis (FDD) in different industrial environments; an example FDD development is the petrochemical industries [10], transport [11] and energy specifically in generation engines [12] among others.

Although the conventional control is based on robust statistical and graphical control settlements, it suffers from a lack of applicability in data-rich environments, typical of modern processes such as power generation supported by ICE's [13]. To monitor the state of the process from the principal component analysis (PCA), different statistics are used to build control charts to monitor the process's condition. Thus, it is possible to follow the process in a univariate way and see the reality in the threshold. The most widely used statistics at the industrial correspond T^2 of hotelling and statistical Q [14]. Thus, multivariate statistical projection methods, such as PCA, where both statistics are used, are used to reduce the surveillance space's dimensionality by projecting the information of the original variables in low dimensional subspaces defined by a few latent variables.

The main contribution of this research is the development of a tool that provides a constant analysis of the variables of operation of an internal combustion engine, in which transformation of the chemical energy of a fuel such as natural gas, mechanical work of rotation of a shaft and then electricity, in a generator system occurs. This tool is developed under the MATLAB environment with the fundamentals of multivariate analysis of principal components.

2. Methodology

This section presents the mathematical description of the principal component analysis used for the GUI design based on ICE's failure behaviour. This methodology allows for constant monitoring of the variables involved in energy transformation [15].

2.1. Statistical components

It is considered a data set consisting of observation variables and observations for each variable, which is arranged in a matrix arrangement $X_0 \in \mathbb{R}^{n \times m}$ as shown in the agreement, Equation (1) [15].

$$X_0 = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1m} \\ x_{21} & x_{22} & \dots & x_{2m} \\ \vdots & \vdots & \dots & \vdots \\ x_{n1} & x_{n2} & \dots & x_{nm} \end{bmatrix}. \quad (1)$$

The matrix X_0 should be normalized or standardized in such a way as to allow analysis without the tendency to the units of each m . From this matrix, it is possible to calculate the covariance matrix as defined by Equation (2) [16].

$$S = \frac{1}{n-1} X^T \cdot X, \quad S \in \mathbb{R}^{m \times m}. \quad (2)$$

Spectral decomposition of S can be obtained if their values or self-values and their respective individual vectors or self-vectors are found. You can find the eigenvalues, λ_i , of S solving the Equation (3) [15].

$$\det(\lambda I - S) = 0 \rightarrow \lambda_1, \lambda_2, \dots, \lambda_m, \quad (3)$$

I is the identity matrix. Self-assessments must be organized in such a way that the conditional expressed in the condition of Equation (4).

$$\lambda_1 \geq \lambda_2 \geq \dots \lambda_m. \quad (4)$$

The spectral decomposition is then performed obtaining Λ and V where the auto-value matrix Λ is obtained with the arrangement as shown by the expressed in the condition of Equation (5) [15]:

$$\Lambda = \begin{bmatrix} \lambda_1 & 0 & \dots & 0 \\ 0 & \lambda_1 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \lambda_m \end{bmatrix}, \Lambda \in \mathbb{R}^{m \cdot m}, \quad (5)$$

and the autovector matrix expressed in the vector of Equation (6).

$$V = [v_1 \ v_2 \ \dots \ v_m], V \in \mathbb{R}^{m \cdot m}, \quad (6)$$

the decomposition of S then, the disintegration of is done as shown by the Equation (7) [17].

$$S = V \cdot \Lambda \cdot V^T. \quad (7)$$

Projection $y = V^T \cdot x$ of an observation vector $x \in \mathbb{R}^m$ converts the observation space into a set of uncorrelated variables corresponding to the elements of y . The variance of the $i = \text{ésimo}$ element of y is equal to $i = \text{ésimo}$ self-worth in the matrix Λ . Where S is invertible (since it is a symmetric matrix), it is possible to apply the definition shown by the Equation (8) [17].

$$z = \Lambda^{-1/2} \cdot V^T \cdot x \quad (8)$$

So, the statistician T^2 hotelling is given by Equation (9) [15].

$$T^2 = z^T \cdot z. \quad (9)$$

The projection of the observations, contained in X , in a smaller dimensional space will be included in the scoring matrix described by the Equation (10) [15].

$$T = X \cdot P \in \mathbb{R}^{n \cdot a}, \quad (10)$$

where the first self-values are contained in a matrix $P \in \mathbb{R}^{m \cdot a}$ and the projection T back to the space of observation $m = \text{dimensional}$ is, Equation (11).

$$\hat{X} = T \cdot P^T \quad (11)$$

The residual matrix is defined as follows, as shown in the Equation (12) [15].

$$E = X - \hat{X}, \quad (12)$$

where the initial data set is expressed by the selected main components and the noise space.

3. Results

This section presents the results based on the design of the control tool based on the multivariate analysis under the PCA statistics described in the methodology. The algorithm or steps that were for the development of this GUI tool are broken down; additionally, it is shown how the normalized values of failures of the ICE and number of principal components according to their weighting in the spectral space are projected in the designed tool. These results allowed a constant monitoring of the variables involved in the process of energy transformation.

3.1. Description of the design algorithm

Using MATLAB, interface Figure 1 was designed for fault detection based on the algorithm used in this study. Below is a flowchart that shows the general content of the GUI developed. Figure 1 describes step by step the content of the GUI. Initially, the tool is designed with a presentation of the authors, also contains an installer for those users who do not have MATLAB on their computers. Then the platform is designed to receive the information from the matrix described in the methodology; this matrix contains observations vs variables, if it includes the requirements described in the tutorial, conditions such as that the excel has no special features such as NAN, among others, it continues to the analysis of the behavior of variables individually, Next, the process of quantifying and characterizing the main components is carried out, identifying the anomalies with the T^2 Hotelling and the Q statistic, finally, the detection and identification of the failure to monitor the variables involved in energy transformation.

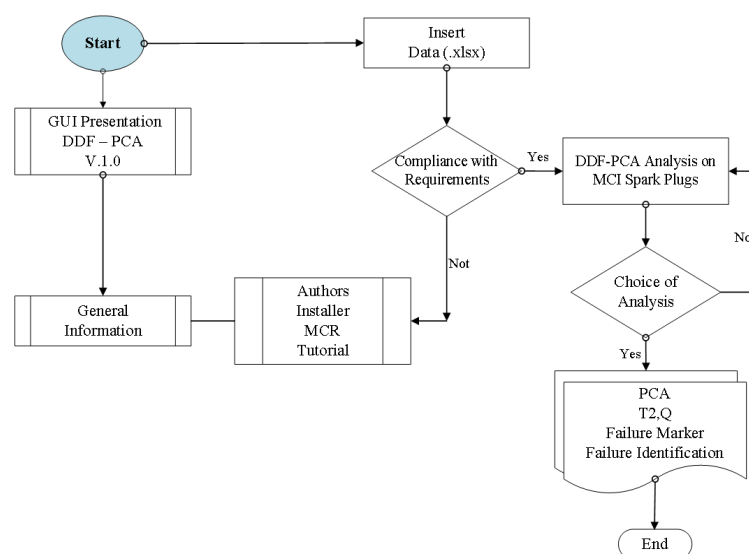


Figure 1. Graphic user interface flowchart.

3.2. Graphic user interface

The program FDD-PCA v1.0 is a graphic user interface that operators in charge of ICE's control can use; the interface allows multivariate statistical analysis based on PCA; the GUI's presentation is shown in Figure 2. Figure 2 shows the general presentation of the platform; this presentation is contained by general graphics of what the software presents. It should be noted that the two statistics are shown with what the data processing is done.

Figure 3 shows the behaviour of the statisticians T^2 Hotelling and the Q statistic, the measurement of the variability of the 9898 measurements performed.

The observations made in the observations from 1 to 1000 indicate that the level of operation with respect to the following observations is low, this level of normal operation, is consistent with the regular behavior of the variables in control status. However, they present instantaneous disturbances in very short periods of time, which does not symbolize alarms in the operators because the behavior returns

quickly to its average. Additionally, there is the Q statistic, which shows the residual error behavior that have the variables in space T^2 . Figure 4 shows the individual behavior of each variable, it is presented the ranges of upper limit, lower limit and arithmetic mean of the behavior of the variables, facilitating the operator the visualization of the real behavior. The first a vectores column in the autovector matrix V indicate the main direction of the space in which the variables move with their respective auto-values Λ or scale factor. The criterion of choice of a corresponds to the explanation of at least 95% of the variability contained in the matrix that initially entered.

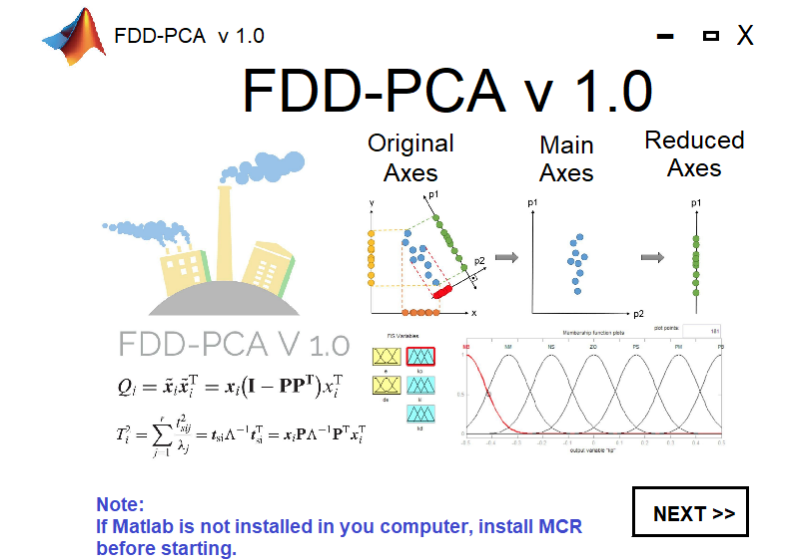


Figure 2. Presentation of the graphic user interface.

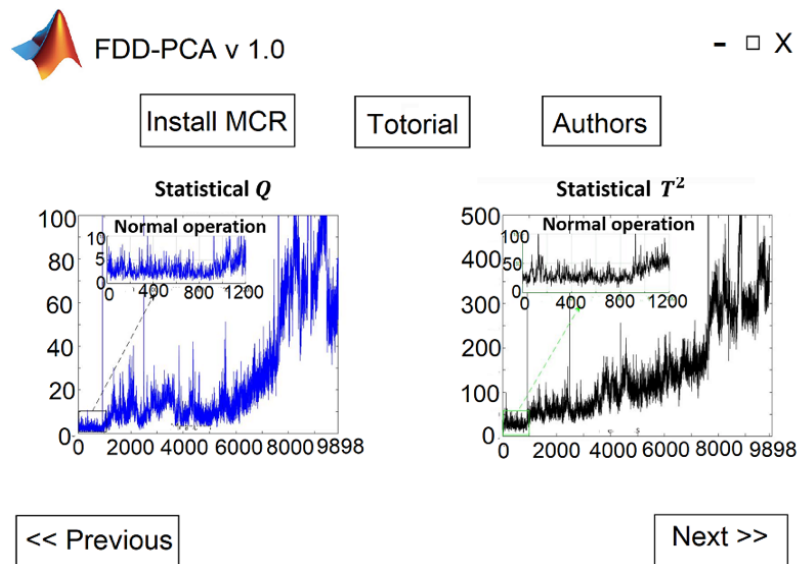


Figure 3. Installer, tutorial, and authors' section.

In the Figure 5. the principal components are quantified and characterized according to the input matrix's nature. According to the gobblers, the case study of the internal combustion engine presents 30 members with their respective weights. Finally, the GUI becomes a useful tool in detecting the failure in the ICE process. The exciting thing about the tool is that it allows us to visualize the moment of observation in which the system presents loss.

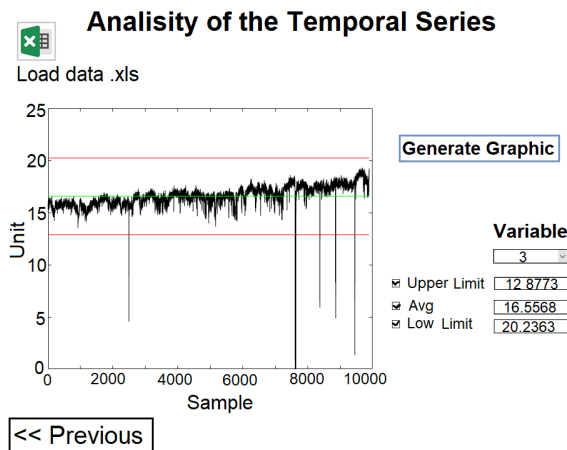


Figure 4. Individual analysis of the variables.

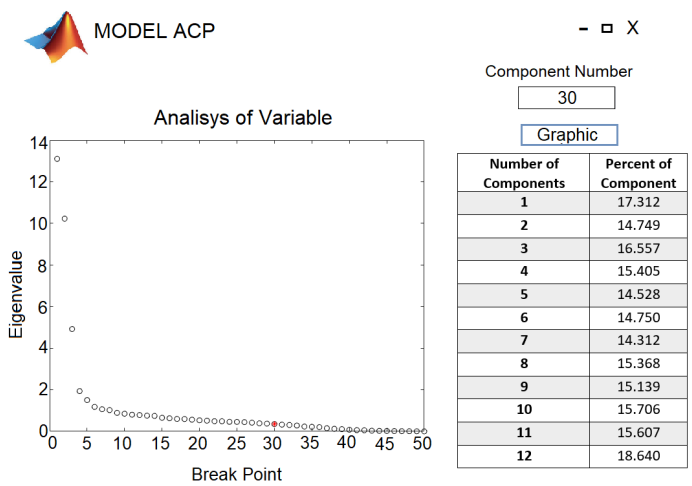


Figure 5. Characterization of the principal components.

4. Conclusions

It is a GUI tool that manages to detect and identify failures and the origin of these during the ICE operation. This educational tool can be used at the industrial level by operators as an instrument of association with policies of proper use of energy resources and sustainability policies, since early detection of faults will help to prevent the system from operating outside acceptable or permissible operating conditions, preventing fuel consumption and increased emissions of gases such as CO₂, and generating gases such as NO_x, SO_x, etc., created during the combustion process in gasoline, natural gas, diesel, gas turbine, boiler-steam turbine assembly engines.

The inclusion of the GUI in energy generation processes addresses one of the lines (preventive and corrective maintenance) in energy management systems in industries, managing to facilitate observation and monitoring of the behavior of each of the fundamental components for the operation of the energy transformation machine.

The results obtained in the analysis show that for the study of the energy transformation machine or an internal combustion engine, the variable of greater significance corresponds to the Voltage of the cylinder 8 (x8), with a percentage of 38% throughout the 9898 observations in units of time. The algorithm developed in the GUI step by step shows the precise time the anomaly begins that corresponds to the comment 1000, which means that the monster was presented before the operators' report since the operators show abnormality in the analysis 7600.

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