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Granger causality procedeture to diagnosis and failture in industrial systems

Procedimiento de causalidad de Granger para diagnóstico y localización de fallas en sistemas industriales

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Abstract
Industrial process supervision is an important subject nowdays due to the increased requirement for safer processes for operators and effective for companies. Control loops affected by disturbs, are grouped with PCA, based on their increased variability and the causal relationships between them are detected via Granger causality. A graph drawing algorithm allows indicating the source of the disturbance. The procedure is applied to data from a simulated chemical process CSTR. The proposed procedeture correctly indicated the sources of disturbances.
Key words: fault diagnosis, Granger causality, system identification

Resumen
La supervisión de procesos industriales es un tema importante en la actualidad debido a la creciente necesidad de procesos más seguros para los operadores y efectivos para las empresas. Los lazos de control afectados por perturbaciones se agrupan con PCA, en función de su mayor variabilidad y las relaciones causales entre ellos se detectan mediante la causalidad de Granger. Un algoritmo de dibujo de gráficos permite indicar la fuente de la perturbación. El procedimiento se aplica a datos de un proceso químico simulado CSTR. El procedimiento propuesto indicaba correctamente las fuentes de perturbaciones.
Palabras clave: diagnóstico de fallas, causalidad de Granger, identificación del sistemas

1. Introduction

Technical improvements in recent years have improved quality and productivity in the industry, but they have also resulted in the creation of increasingly complex systems to study and keep until their final stage of life. Just managing new equipment and performing process maintenance does not guarantee a safe environment for operators. Process plant management remains predominantly a manual activity, equally is the detection of process abnormalities and the diagnosis of their probable causes. Knowledge about the relationships between

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process variables is important to support decisions that take you back to your normal and safe operating state. According to industry statistics, 70 % of accidents are caused by human error (Nor, N. et al., 2020). Recent events at large plants, such as the detonation of the Kuwait Mina Al-Ahmed petrochemical refinery, had estimated damage of $ 400 million. Some other case is the explosion of Petrobras's offshore platform, Brazil, which resulted in losses of $ 5 USD billion (Nor, N. et al., 2020). Although these types of large-scale accidents are not usual, minor accidents are common, generating both economic and human losses. This indicates that there is still a long way to go to improve supervisory and fault diagnosis performance for industrial processes.

Fault detection and diagnosis is a major problem in control systems (Alauddin, M. et al., 2018). Chemical processes, power plants, factories and others are cases where an undetected failure can contribute to disastrous economic, environmental and social effects. Investigations have been conducted to diagnose faults and monitor equipment degradation. Artificial intelligence systems such as neural networks and fuzzy systems have been applied to alleviate these difficulties and enhance the process monitoring system. (Kirilova, E. G. et al., 2022) provide an extensive review of the various applications of neural networks for chemical engineering purposes, and comparisons to existing conventional methods are also shown, both in simulation and online implementation. Isolation of faults that propagate their effects on the plant are investigated in (Yong, G. et al., 2015). Causality detection methods are used, and a new method has been proposed in (Marques, V. et al., 2015). In a similar way to the parameter estimation failure detection methods in (Lindner, B. et al., 2019) seeks to detect failures through changes in the causal relationships between variables. In addition, allowing the detection of changes in the causal relationship, the data generated in each iteration can be used to test the relevance of statistical causality, which is very important to increase the reliability in this type of research. This character test was performed for Granger causality using surrogate series in (Sysoev, I. et al., 2015).

Faults or disturbances are detrimental in moving process variables away from their references. Its detection and indication of the source is more problematic because its effect disappears over time (He, Z. et al., 2018). The usual procedure is to search the databases for the variables affected by the disturbance and investigate their cause from the knowledge of the process. This paper proposes a methodology for automatic indication of the source of disturbances. Indicating an incipient fault detection approach via detrending and denoising is proposed.

The article is organized as follows: The next section offers a method for detecting disturbances and grouping control loops that have been affected using PCA, and discusses the steps required to calculate Granger causality and proposes a methodology based on it. The methodology for diagnosing system failures will be outlined step by step in subsection 2.10 as the application of the proposed procedeture. Section 3 application to data from a simulated industrial system CSTR. The conclusions are presented in Section 4.

2. Fault Detection in industrial systems

An industrial process has numerous variables, some of which are explicit in its importance to the process and some are difficult to know if the process truly depends on them, but the relationship between them must be considered. The propose of fault detection is to determine whether a potential fault has occurred in the sensor network. A model is generally constructed through the fault-free health-monitoring in structural health monitoring (SHM) field data to describe the normality, after that a sensor fault detection index can be defined. Due to the difference of model building, the fault detection stage can be divides into unilabiate control chart-based , multivariate statistical analysis –base and residual based methods. The fault detection index is then computed for the currently measured sensor data and compared to a decision threshold. The potential sensor fault is determinate to occur after the fault detection index exceeds its corresponding threshold. (Yi, T. et al., 2018)

A SHM system is usually equipped with different types of sensors , which constitute a sensor network, to collect structural responses. Therefore, it is necessary to use multivariate statistics that allows the joint monitoring of variables. Typically the and statistics are used to calculate thresholds for monitoring non-normal situations, for that reason in SHM field, these are grouped using the PCA method (Huang, H. . et al., 2017) ,which in addition to reducing the number of data worked, is one of the most frequently used due to simplicity of its application, high diffusion in the literature and the possibility of statistical analysis of the process through fault detection index that present a superior performance to univariate control diagrams.

2.1. Principal component analysis

Consider $X \in \Re^{Nxm}$ as a vector of N samples of m sensors, so each line represents a sampling of each sensor. The matrix *X* must be normalized. It has zero mean and unit variance. The matrix *X* can be decomposed according to the singular value decomposition algorithm (SVD) (Kruger, U. et al., 2012).

$$\frac{1}{\sqrt{N-1}}X = U\Sigma V^T \tag{1}$$

Covariance matrix

$$S \approx \frac{1}{N-1}X^T X = V\Lambda V^T \tag{2}$$

Where $U \in R^{nxn}$ and $V \in R^{mxm}$ are unitary matrices, and $\Sigma \epsilon R^{nxm}$ contains the non –negative real singular values of decreasing magnitude along its main diagonal and zero off diagonal elements. Solving the equation (1) is equivalent to solving an eigenvalue decomposition of the sample covariance matrix *S*. The eigenvalues of the matrix *S* are placed from largest to smallest representing the variance of each component, being the first eigenvalue representing the greatest variability of the set of variables (Kruger, U. et al., 2012).

$$\Lambda = \Sigma^T\Sigma = diag\{\lambda_1, \lambda_2, ...\lambda_m\} \tag{3}$$

Where the matrix *P* is related to the highest eigenvalues of the matrix *S* and the columns of the orthogonal matrix V. To find the projections of the matrix *X* it is necessary to calculate the projection score matrix T (Kruger, U. et al. 2012).

$$T = XP \tag{1}$$

The projection of the T is the estimated $\hat{X}$

$$\hat{X} = TP^T \tag{2}$$

Residue values and estimated values $\hat{X}$ can be obtained (Kruger, U. et al. 2012).

$$r = X - \hat{X} = (I - PP^T)x \tag{3}$$

2.2. Hoteling's Statistic

From the equation (2), assuming invertible *S*, it's possible to define equation (9):

$$z = \Lambda^{-1/2}V^T x \tag{4}$$

Hoteling's statistic is given by (Chiang, L. et al., 2001):

$$T^2 = z^T z \tag{5}$$

The T^2 statistic is the square 2-norm of a normalized observation vector *x*. From the equation (7) a threshold can be found to characterize the variability of the data in all observed dimensions. Turned over a significance level, appropriate values for the T^2 statistic threshold can be automatically determined by using the *F* distribution. Given a *α* significance level, the threshold can be calculated (Chiang, L. et al., 2001):

$$T_\alpha^2 = \frac{m(n-1)(n+1)}{n(n-m)} F_\alpha(m, n-m) \tag{6}$$

2.3. Statistic Q

The *Q* statistic is the 2-norm square standard that measures the deviation of the residue generated by the difference between the estimate and the observations made, since *r* is the residue, the statistic is given by (Chiang, L. et al., 2001):

$$Q = r^T r \tag{7}$$

The Q distribution threshold was approached by Jackson and Mudholkar (Chiang, L. et al., 2001).

$$Q_\alpha = \theta_1 \left[\frac{h_0 c_\alpha \sqrt{2\theta_2}}{\theta_1} + 1 + \frac{\theta_2 h_0 (h_0 - 1)}{\theta_1^2} \right]^{\frac{1}{h_0}} \tag{8}$$

Where $\theta_i = \sum_{j-a+1}^{n} \sigma_j^{2i}, h_0 = 1 - \frac{2\theta_1\theta_3}{3\theta_2^2}$ and c_α is the normal deviation corresponding to the percentage $(1 - \alpha)$ where α is the significance level.

2.4. Statistical contributions Hoteling's Statistic and Q

Once a fault is detected, it is necessary to determine which variables have left the control zone, which can be extremely complex for systems with many variables. One way to distinguish affected variables is to calculate the contributions of each variable to the statistics at the time of failure and to obtain the set of variables that contributed to the violation. For the T^2 statistic, the contributions at failure times are calculated using the *T* score matrix. Negative contribution values are taken to zero.

$$CONT_{T^2} = \frac{t_i}{\lambda_i^2} P_{j,i} X_{i,j} \tag{9}$$

where λ_1 is the eigenvalue corresponding to the score matrix column and $X_{i,j}$ is the normalized sample. To calculate the contributions of the residue, the squared residue itself is used (Chiang, L. et al., 2001).

$$CONT_Q = (r)^2 \tag{10}$$

2.5. Granger causality

In diverse studies of science, causal relationships are inferred by using temporal signals of interest collected from a given physical process. Thus, methodologies that may infer from these data such relationships with a certain property have been created and discussed. In 1956, the mathematician Wiener intuitively formulated the idea of causality in the prediction of time series (Wiener, N. et al. 1956), which was formalized in the field of Econometrics using linear regression models by economist Granger (Granger, C. W. et al. 1969). According to Granger causality, given two variables *x* and *y*, if the inclusion of past observations of *x* helps reduce the prediction error of *y* then *x* causes *y*. This method was used in a financial market application to investigate the uncertainty in predicting output growth in emerging markets (Balcilar, M. et al. 2022) and used to determine cause and effect relationships in the social sciences studying life expectancy versus air pollution trajectories in Nigeria. (Nwani, S.E. et al. 2022), neuroscience (Barnett et al. 2014), (Seth, A. et al. 2015), in the field of industrial process engineering for root cause detection of disturbance or oscillation (Lindner, B. et al. 2019), (Lucke, M et al. 2022), and recent Granger causality review and advances (Shojaie, A. et al. 2022)

In most of the causal investigations we try to discuss single causes in deterministic situations and two conditions are important for causal determinations suppose that an event *x* is a cause for event *y*:

Granger causality assumes that the future can cause neither the present nor the past. In the case of the variables *x* and *y*, you can have the following situations:

1. *y* causes *x* : ($y \rightarrow x$)

2. *x* causes *y* : ($x \rightarrow y$)

3. Feedback occurs between the two variables: ($x \leftrightarrow y$)

4. There is no causal relationship.

Thus, what matters is whether there is a statistically significant cause and effect relationship between the variables *x* and *y*, which only occurs if there is a correlation and temporal precedence relationship between them (Granger, C. W. et al. 1969).

Some procedures must be performed before applying the Granger method to a set of variables of interest. It is first necessary to check if there is a requirement to perform some kind of preprocessing to the signals and to verify their seasonality. The definition of the order of the estimated models should be chosen based on some selection criteria (AIC or BIC, for example), just as the models should be validated using some specific techniques. One should also choose the statistical method to infer causality and the correct method for multiple comparisons performed (Aguirre, L. A. et al. 2004).

2.6. Mathematical modeling

A model is the simplified representation of a real system whose purpose is to identify its most relevant aspects without worrying about all the details. A system can be modeled using black box modeling. This modeling, also known as identification, assumes that little or no prior knowledge of the process is required, so having only available inputs and outputs, it is possible to obtain a mathematical model of the system under study (Ljung, L. et al. 1998), (Aguirre, L. A. et al. 2004).

Among these forms of representation, we can highlight the representation by transfer function, by state space and the discrete time representation. Regarding this last representation, consider the following model:

$$A(q)y(t) = B(q)u(t) + \varepsilon(t) \tag{11}$$

Where $y(t)$ and $u(t)$ are the system output and input respectively, q is the delay operator,$\varepsilon(t)$ is the white noise residue and all variables are measured in time where $t = 1,2,3 \ldots T A(q)$, and $B(q)$ are arbitrary polynomials defined by $A(q) = 1 - a_1 q^{-1} - a_2 q^{-2} \ldots - a_{n_y} q^{-n_y}$ and $B(q) = 1 - b_1 q^{-1} - b_2 q^{-2} \ldots - b_{n_u} q^{-n_u}$ the parameters n_y and n_u refer to the number of parameters or the order of the chosen model. For this work it will be considered that $n_y = n_y = p$ in all cases analyzed, that is the number of poles is the same number of zeros. The model presented in Equation (14) is called the autoregressive model with exogenous inputs (ARX), where the acronym AR refers to the autoregressive part of the model given by $A(q)u(t)$ the letter *X* refers to the entry $B(q)u(t)$ is called exogenous variable *x*.

In this work, system identification techniques use models whose representation is the ARX. The estimation of its parameters made using the least squares method, to properly adjust the input and output data and verify if there is a cause and effect between these data. Significantly, for causality analysis, it is not known who is entering or leaving the model. For this reason, we seek the causal relationship between the variables by testing them all as input and output and verifying if the variables included in obtaining the models help to predict the variable tested as output.

2.7. Model order selection criteria

To estimate a model using the ARX structure in Granger analysis, is necessary to choose the order of the model. One way to make this choice is to use information criteria that minimize a residual function that is penalized by the number of regressors used, thus looking for the most parsimonious model. In this direction, we look for the model that regards the minimum possible parameters to estimate and explain the behavior of the study variable (small error) (Aguirre, L. A. et al. 2004). In this work the following criteria are used: Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) (Ljung, L. et al. 1998).

$$AIC_p = \ln|\Sigma| + \frac{2pn^2}{T} \tag{12}$$

$$BIC_p = \ln|\Sigma| + \frac{\ln|T|\,pn^2}{T} \tag{13}$$

Where $ln|\Sigma|$ is the napierian logarithm that determines the residual covariance matrix of unrestricted models and measures the suitability of the model. Increasing the number of parameters allowed increases the number of degrees of freedom, generating less prediction error variation or allowing for more accurate data adjustment. Reducing error variability by increasing the number of parameters is balanced by a penalty imposed by the reporting criterion. Therefore, how the beginning parts of the equations (15) and (16) measure the reduction in residual variation, while the second parts penalize the inclusion of each condition. If the penalty is less than the reduction in residual variability, the regressor should be integrated into the model. Differently, the regression will bring more cost than benefit and should be excluded from the model, allowing selection of the order that minimizes the criterion applied.

2.8. Granger Conditional Causality

When the number of variables are greater than $2(n > 2)$, the bivariate Granger analysis can be extended to a multivariable case (Seth, A. K. et al. 2010). Suppose, for example, that exist three variables x_1, x_2, x_3 and is necessary to know if the x_3 variable causes the x_1 variable. So if excluding the x_3 variable significantly increases the model prediction error with the x_1 variable output as compared to the x_1 model prediction error including all variables, then it can be said that $x_3 \rightarrow x_1$. To demonstrate the mathematical formulation of this analysis, consider *n* variables. An y_t vector of dimension n_{x_1} will be used to represent the observed values of all variables at the time instant *t*. Thus, the autoregressive vector of order *p* can be expressed by:

$$y_t = \sum_{l=1}^{p} A_l X_{t-1} + \varepsilon_t \tag{14}$$

Where A_l is the square array of parameters of the VAR model. Systems can be represented in matrix form or by the equation (15).

$$Y_{(m\times n)} = X_{(m\times np)} B_{(np\times n)} + \Sigma_{(m\times n)} \tag{15}$$

The condition is $m > np$ necessary to avoid singularities in the matrix product $x^T x$, so that the *B* coefficients of the *B* matrix can be estimated using the least squares method by the equation (19).

$$\hat{B} = (X^T X)^{-1} X^T Y \tag{16}$$

To detect the causal relationship of the variable x_3 in the variable x_1, first estimate the quadratic sum of the residuals with the variable x_1 as output and all others as input (unrestricted model):

$$RSS_1 = \left(y - X\hat{\beta}\right)^T (y - X\hat{\beta}) \tag{17}$$

Where *y* and β correspond respectively to *y* column and $\hat{B}$ Then, we estimate the quadratic sum of the constrained model residues in the same way using the equation (13), having the $x_1$variable as output and excluding only the x_3 variable as input RSS_{31}.Then the *F* distribution test statistic applies $F^{\alpha}(p, m - np)$ under the null hypothesis that the variable x_3 does not cause the variable x_1:

$$f_{x_3 \rightarrow x_1} = \frac{\frac{RSS_{31} - RSS_1}{p}}{\frac{RSS_1}{m - np}} \tag{18}$$

The null hypothesis will be rejected if $f_{x_3 \rightarrow x_1} > F^{\alpha}$ or the calculated p-value is less than the significance level α used in the test. Thus, it is said that $x_3 \rightarrow x_1$. To apply the Granger conditional analysis, the prerequisite that $m \geq np$ must be attended. Knowing that $m = T - p$ the condition for applying the conditional Granger analysis is:

$$T \geq p\left(n+1\right) \tag{19}$$

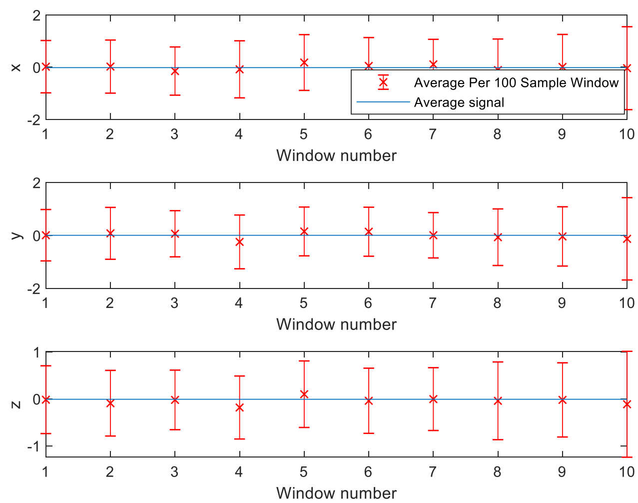
2.9. Granger multiple variable Causality

Consider that it is desired to infer causality between the variables by considering the following models found in (Seth, A. K. et al. 2010).

$$\begin{aligned} x(k) &= 0.8x(k-1) - 0.5x(k-2) + 0.4z(k-1) + 0.2y(k-2) + \varepsilon_1 \\ y(k) &= 0.9y(k-1) - 0.8y(k-2) + \varepsilon_2 \\ z(k) &= 0.5z(k-1) - 0.2z(k-2) + 0.5y(k-1) + \varepsilon_3 \end{aligned} \tag{20}$$

This model contains 3 different variables which have an autoregressive structure, and for this case, the variable *x* depends on itself and a regressor of *z* and one of *y*; The *y* variable does not depend on another variable, it just depends on itself, and finally the *z* variable depends on itself and *y*. All variable models are simulated, and white noise has been introduced. ε_1, ε_2 and ε_3.The first step is to determine if the data is stationary, because as a requirement, the statistics applied to infer causality assume the stationary of the variables. In the Figure 1, 10 windows with 100 samples each showing the mean and standard deviation of the variables are presented. The graphical result indicates that the data is stationary, as expected, as it was generated to satisfy this requirement. If the data had not met this condition, the data should be differentiated until the prerequisite is met. (Ljung, L. et al. 1998).

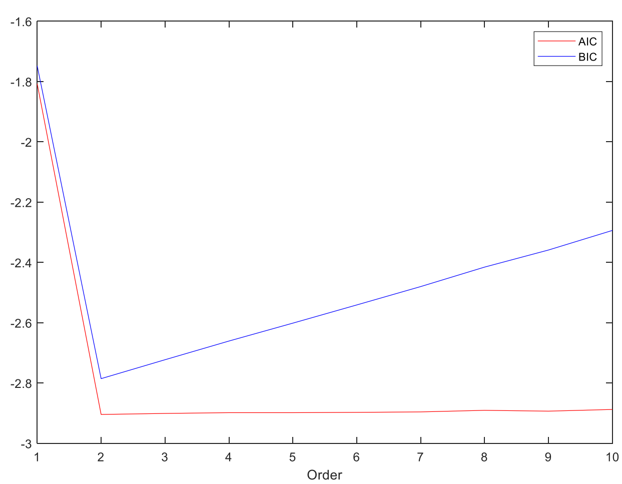
Figure 1
Variability stationary test



Source: Authors

The following step is established on the AIC or BIC criteria to estimate a minimum order to model the information (Aguirre, L. A. et al. 2004). In the Figure 2 The AIC and BIC criteria for the signal set are presented. The criteria indicate a minimum order of 2 to model all signals, which is coherent if we compare the equation (23).

Figure 2
AIC and BIC criteria for x,y and z



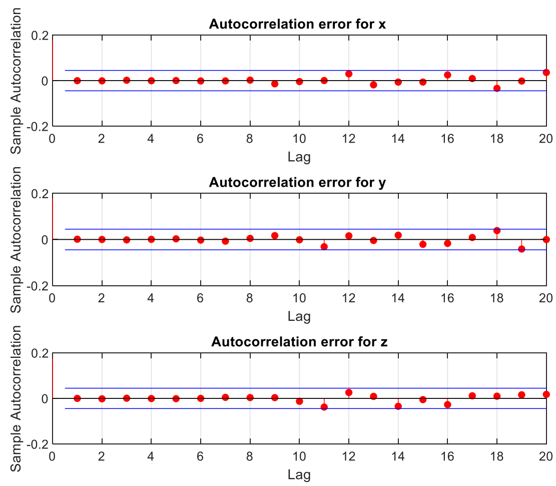
Source: Authors

Determining the minimum order according to the criteria, the following step is to analyze the autocorrelation of residuals that are within the confidence interval for all regressors. In Figure 3, it is possible to verify that the second order models adequately represent the signals, so the residue is white noise.

In order to infer causality between the set of three variables *x, y* and z, to solve this case it is necessary to perform 6 independent hypothesis tests or $M = n(n-1)$ where *n* is the number of variables. Only will be considered significant casualties, when the p-value is less than or equal to fF^{α} for each direction tested.

In the Figure 4 The graph found by applying the Granger causality method is shown. Comparing the result obtained with the original equation models in equation (23), all causal relationships between *x*, *y* and *x* is caused by the other.

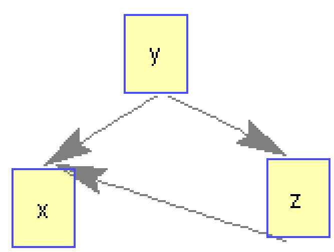
Figure 3
AIC and BIC criteria Autocorrelation of residues for x, y and z



Source: Authors

Two variables, just as *y* is not caused by any other variable, so no arrow is pointing at her. Being verified the method with this simple example; the following will be presented the methodology to solve the problem of fault diagnosis in a complex system.

Figure 4
Granger causality graph for x, y and z



Source: Authors

2.10. Proposed procedeture to fault diagnosis

To properly diagnose the failure the following steps were defined:

Step 1 Define and select data for system operation point, this amount of time series must be sure that does not have any disturbance, so the system is working properly. Then extract information such as mean and standard deviation of the variables, to normalize the data. With this normal dataset, the PCA model include a number of components representing as initial test recommendation at least 70% of the variance of the variables, this percentage is chosen arbitrarily or by the knowledge about the system, it may be too low or too high for a particular application. When the number of observation variables is large and the amount of data available is relative small, the T^2 statistic tends to be inaccurate representation of the in-control process behavior, especially in the loading vector corresponding to the smaller singular values. Additionally, the smaller singular values are prone to errors because these values contain small signal noise. Therefore, in this case the loading vectors associated only with the larger singular values should be retained in calculating the T^2 statistic (Chiang, L. . et al., 2001).

Step 2. Using the normalized system operation point data, following the equations (9) and (11) to calculate statistical thresholds T^2 and *Q.*

Step 3. For each new sample compute the statistical thresholds $T^2$and *Q*, if the thresholds are violated. After a failure is indicated, calculate with the equations (12) and (13), the contributions of each variable to the failure are calculated for a time window before and after the failure to raise a sign of the failure with the contributions of the two statistics. Select the variables with the highest contribution.

Step 4. Using the variables separated by the calculation of the contributions, use the Granger causality method, to infer causality between the affected variables to find the root cause or the relationship map between the variables, but before of that follow the next considerations:

- To calculate causality relations between variables use the same data used for the normalized system operation point data in step 1, but only use the suggested variables indicated by the contribution in the step 3.
- Determine if the data is stationary, because as a requirement, the statistics applied to infer causality assume the stationary of the variables. If the data do not have this condition, the data should be differentiated until the prerequisite is met (Ljung, L. et al. 1998).
- To estimate a model using the ARX structure in Granger analysis is necessary to choose the order of the model using AIC and BIC criteria.

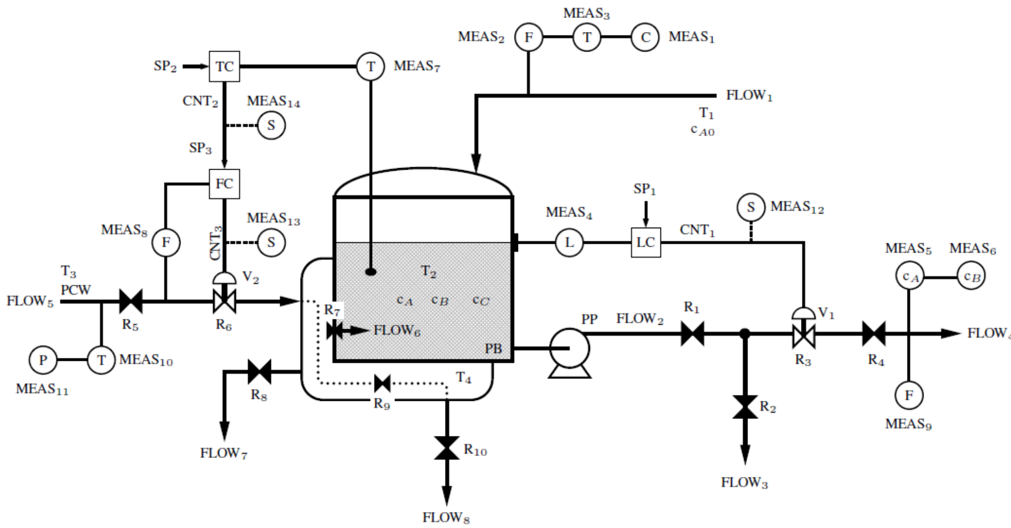
Step 5. Identify the source or the sources that originated the fault through a search in the directed graph produced by the Granger causality method.

The main objective in fault diagnosis area is to determine the cause of the fault. Even if the cause is not detected using this steps, the information about the control loop where the fault took place is very close to the cause of the fault. This information is very useful for process knowledge and may help to complete the diagnosis.

3. Experimental development, case study

Continuous stirred tank reactor (CSTR), this system is a simulator modeled in the Fortran language of a chemical reactor that takes an exothermic reaction work where the original Fortran code is available in (Finch, F. E. et al.1989). The MIT-CSTR software consists of a single file that can be easily compiled by a standard Fortran compiler using MATLAB. The system has 18 variables and allows you to enter 22 different faults. The process diagram is presented in Figure 5. A substance “A” is inserted into the tank to bring out an exothermic chemical reaction to obtain two different products B and C. This system accepts level and temperature control circuits and valve actuators and a fluid pump. In Table 1 the names of the system variables and Table 2 list the 22 faults that can be introduced. In this work we will use fault number 19, which is the fault that affects the level controller reference SP_1.

Figure 5
CSTR system diagram



Source: Finch,F.E .1989

Table 1
CSTR variable list

Number	Variable	Acronym
1	Feed concentration	C_{A0}
2	Feed flow rate	Q_1
3	Feed temperature	T_1
4	Reactor level	L
5	Product A Concentration	c_A
6	Product B concentration	c_B
7	Reactor temperature	T_2
8	Coolant flow rate	F_5
9	Product flow rate	F_4
10	Coolant inlet temperature	T_3
11	Coolant inlet pressure	PCW
12	Level controller output	CNT_1
13	Coolant controller output	CNT_2
14	Coolant set point	CNT_3
15	Inventory	r_1
16	Mol balance	r_2
17	Cooling water pressure drop	r_3
18	Effluent pressure drop	r_4

Source: Finch,F.E. 1989

Table 2
CSTR fault list

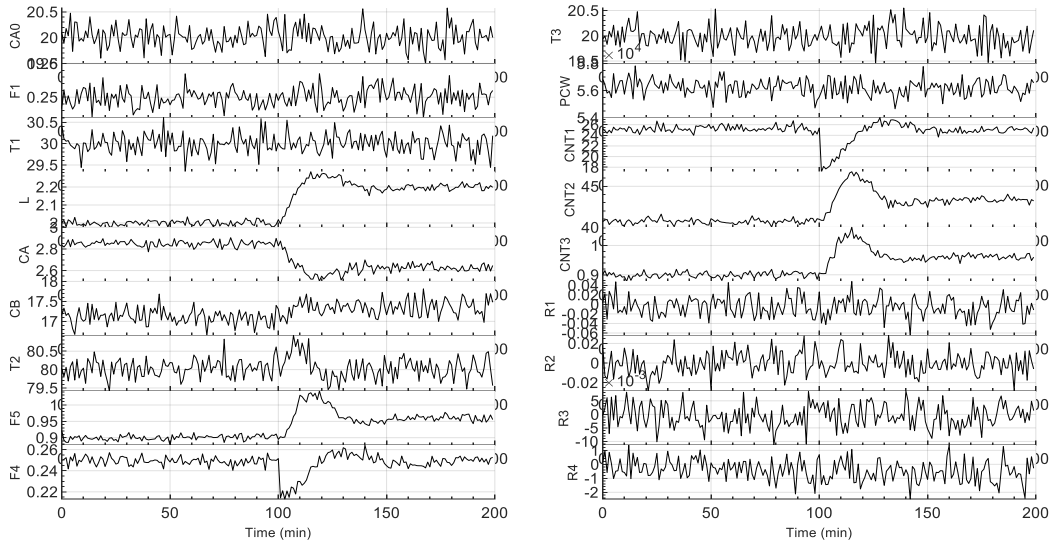
Number	Fault	Acronym
1	No fault	-
2	Blockage at tank outlet	R_1
3	Blockage in jacket	R_9
4	Jacket leak to environment	R_8
5	Jacket leak to tank	R_7
6	Leak from pump	R_2
7	Loss of pump pressure	*PP*
8	Jacket exchange surface fouling	*AU*
9	External heat source (sink)	Q_{ext}
10	Primary reaction activation energy	β_1
11	Secondary reaction activation energy	β_2
12	Abnormal feed flowrate	F_1
13	Abnormal feed temperature	T_1
14	Abnormal feed concentration	c_{A0}
15	Abnormal cooling water temperature	T_3
16	Abnormal cooling water pressure	PCW
17	Abnormal jacket effluent pressure	JEP
18	Abnormal reactor effluent pressure	*REP*
19	Abnormal level controller setpoint	SP_1
20	Abnormal temperature controller setpoint	SP_2
21	Control valve 1 stuck	V_1
22	Control valve 2 stuck	V_2

Source: Finch,F.E. 1989

3.1. Simulation

The system was simulated for 200 minutes where the first 100 minutes the system was in its normal operating mode, then at minute 100 fault number 19 from Table 2 is inserted, Note that this failure affects the SP_1 level controller reference. In the **¡Error! No se encuentra el origen de la referencia.** is shown in the time domain the 18 simulation variables.

Figure 6
CSTR simulation with fault number 19 at 100 min



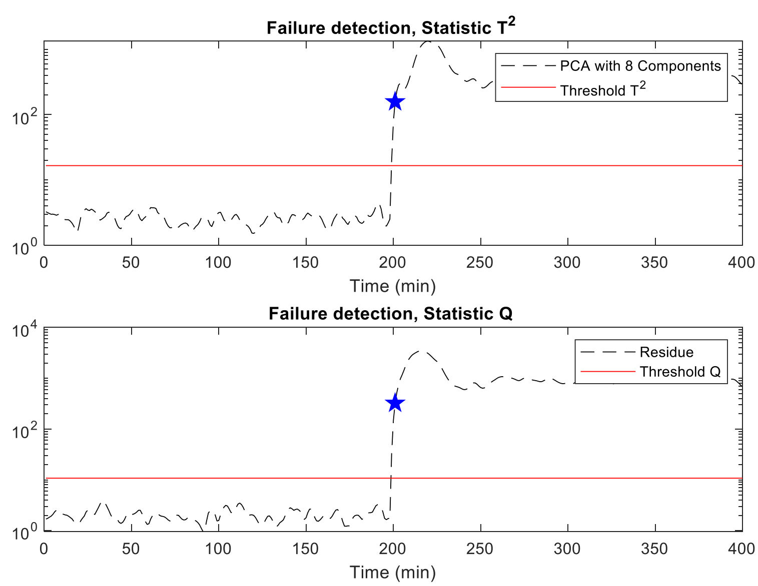
Source: Authors

It is possible to observe how many of the variables left their normal operating point, some of them did not return to the previous operating point as others that, having a controller, it compensated the failure through its procedure and returned to normal system operation.

3.2. Fault detection

The **¡Error! No se encuentra el origen de la referencia.** shows the fault indication in the system, the PCA is trained with the normal operation data (first 100 minutes), and was reduced to 8 components, representing the 70% of the variability of the data set, the algorithm correctly indicated the time when the system left its normal operation using the statistics T^2 and Q.

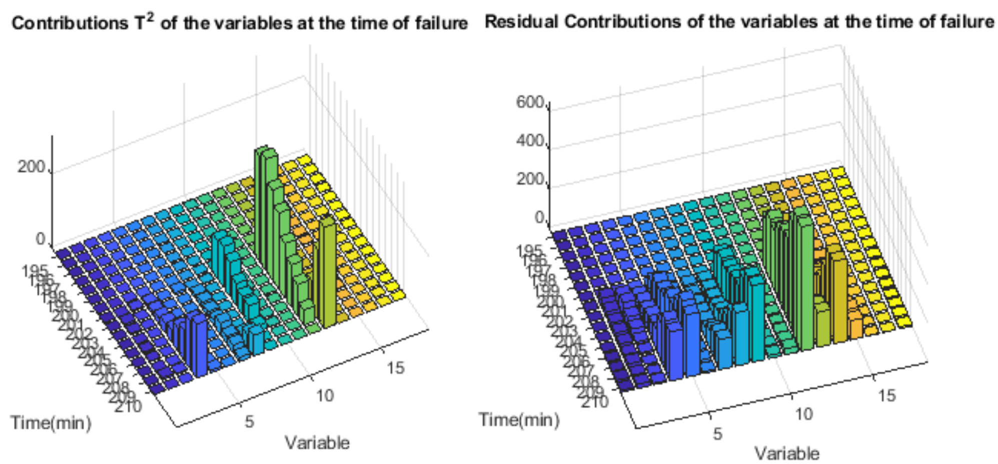
Figure 7
Failure indication with Statistics T^2 and Q at minute 200



Source: Authors

In the **¡Error! No se encuentra el origen de la referencia.** the contributions of the statistics for the failure interval presented, that is, the scores of each variable. This interval contains the set of samples of the 18 variables from minutes 195 to 210 or 5 minutes before failure and 10 minutes after detection. The purpose of this graph is to analyze which variables contributed at the time of failure so that the statistics exceeded their thresholds.

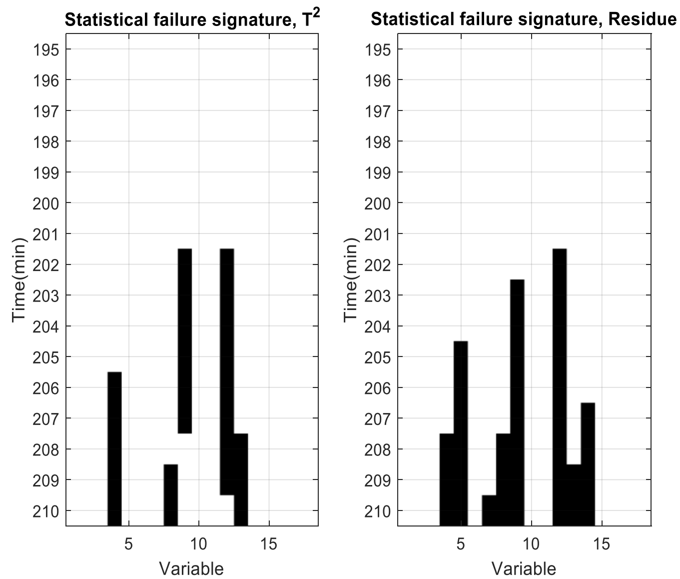
Figure 8
Contributions of variables to fault 19 in the 195 to 210 minute interval



Source: Authors

Based on the contributions of fault 19, it is possible to find a pattern or signature of the fault by filtering out those moments that are most significant. For this, the sum of all contributions in the time window was performed to calculate obtaining 100% of the contribution and from this value a threshold of 1% was used to indicate how significant a variable was determined to exceed the threshold. The result of this procedure is shown in **¡Error! No se encuentra el origen de la referencia.**. This figure shows how from the 200th minute that fault 19 was inserted in the system, the variables affected in the T^2 statistic were 4, 8, 9, 12 and 13; for the Q statistic, variables 4, 5, 7, 9, 12, 13 and 14. As expected, there are several variables in common between the two signatures; these significant variables are used to infer causality between them in order to check the causal map.

Figure 9
Fault 19 in 2D signature, in the interval 195 to 210 minutes

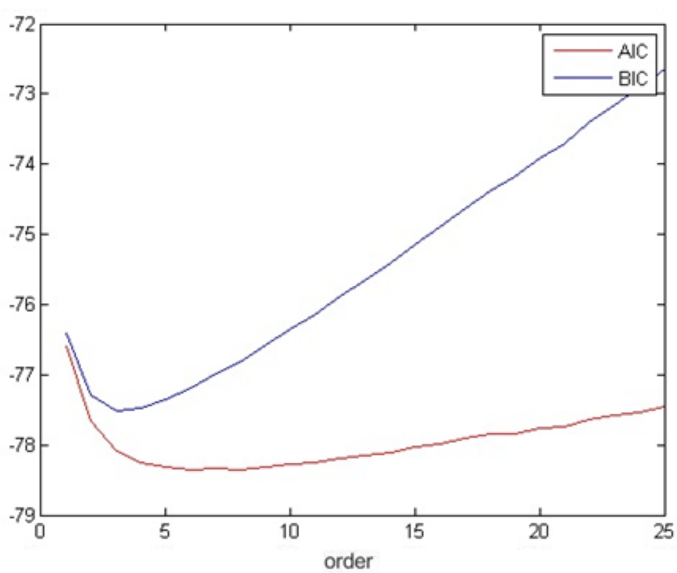


Source: Authors

3.3. Result analysis, Granger's causality inference on the affected variables

Succeeding, the next step is to assess whether the data set is stationary in order to apply the Granger method. The set of variables chosen with the help of the failure signatures was 4, 5, 7, 8, 9, 12, 13 and 14 the test result to check the variables seasonality was negative so it was necessary to differentiate once the data (Aguirre, L. A. et al. 2004). After differentiating the data, the test was positive. The next step is to apply the AIC or BIC criteria to establish a minimum order for the set of signals.

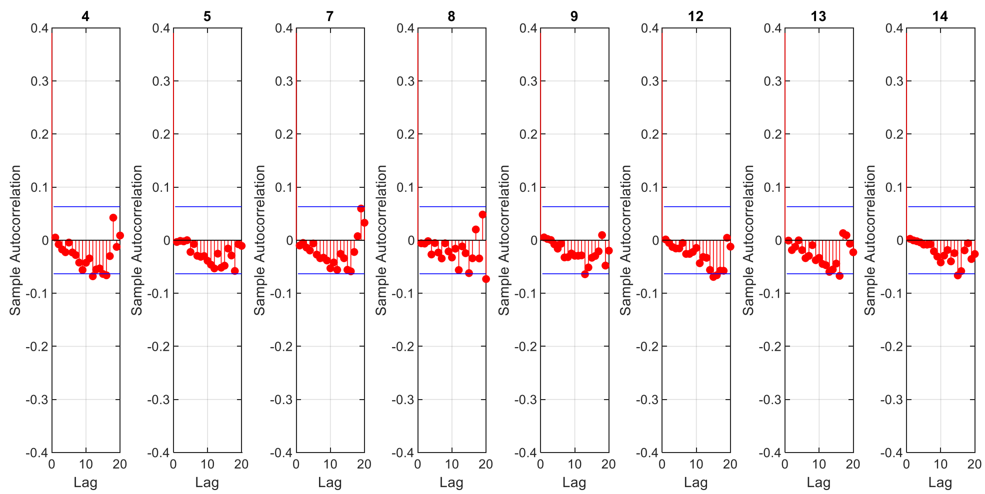
Figure 10
AIC and BIC criteria for selected CSTR variables



Source: Authors

The **¡Error! No se encuentra el origen de la referencia.** shows the result of the AIC and BIC criteria. These criteria indicate the minimum order to estimate the set of signals, for the AIC the order is close to 10 and in the BIC it is in 4, these orders are an approximation or starting point since it must be verified if the autocorrelation of the residue is in mostly within the confidence interval. Fulfilling this condition, we can say that the model adequately represents the data set since the residue does not contain any more useful information for the model. In this case, order 15 was found. The **¡Error! No se encuentra el origen de la referencia.** corroborates that the residues can be called white noise.

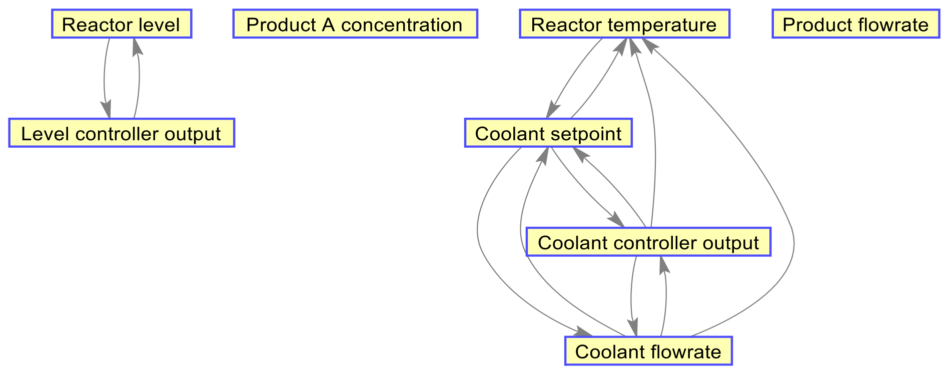
Figure 11
Autocorrelation of the residue with model of order 15 for selected variables CSTR



Source: Authors

The result of Granger's causality method can be seen in **¡Error! No se encuentra el origen de la referencia.** the graph shows the cause and effect interactions between the variables that were selected with the fault signature. The gain obtained with the subscription managed to reduce the search area by selecting the variables that most contributed to the failure. In the graph, the arrow indicates that the pointed variable is caused by the variable where the arrow starts. By the graph, fault 19, which affects the SP_1 controller reference, directly affects three variables and generates a reciprocal effect, between the temperature variables. Therefore, even without knowing the source of the failure, it would still be possible to identify it. The concentration of product A was not indicated with relation to cause or effect of any other variable, which does not indicate that it does not have, only that the method was unable to infer.

Figure 12
Granger causality graph for selected variables CSTR



Source: Authors

4. Conclusions

The proposed procedure to fault diagnosis with Granger's causality method is reviewed under identification framework which can be useful in detecting the root cause of a failure in an industrial system. As stated, the order of the model must be done with caution, because, if it is poorly dimensioned, the causal relations between the variables may appear or disappear. However, even when not chosen in an appropriate way, they provide guidance for investigating the root of a failure. When system identification techniques are used to fit models to paired combination of variables, and if the models are deemed to be inadequate as per the correlation tests, then one can quickly infer that the variables do not interact. It is shown that, for a given order, the models are fitted in both directions, then the cross-correlation between the input and residues allow one to infer causality between the two variables. Since the method only requires that the model capture the information contained in the input, the method is naturally extended to the multivariate case, when one variable can be affected by others.

The proposed procedure is applied to simulated data from a benchmark problem; indicate the source of these disturbances was proposed, only needing the indication of the normal operation period. The affected data by the disturbance are grouped checking those whose error signal variance increased significantly. To diagnose the source, Granger causality method was used, since it allows to build a directed graph that relates the grouped variables. The method can be applied automatically each time that a disturbance is detected by the operation the results are then validated and compared with Granger's method. Measuring the similarity between the current operating conditions and historical operating conditions, which can identify abnormal behavior. Thus it would be possible to automatically detect the presence of disturbances and immediately indicate its source.

The Granger method assumes linearity on data. This assumption is fulfilled in this approach since during training the variations of process variables keep close to their steady state values. An extension of the method for plants with multiple operation points is possible using the concept of data clustering, selecting multiple PCA training sets for different operation points. A test to calculate the distance from each new sample to each cluster is performed to select the PCA model to be used.

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