INTELLIGENT FAULT DIAGNOSIS OF MARINE EQUIPMENTS

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Abstract
The automatic and intelligent diagnosis of faults in marine equipment is a task that is considered to be of great importance considering the numerous tasks that are associated with professionals working on ships. The possibility of including automatic and intelligent processes on a ship makes it possible to monitor equipment more effectively and make more informed decisions. This approach has received a lot of attention in the academic and industrial fields as it can offer considerable economic and safety advantages. Some fault diagnosis approaches can be found in the literature, where mathematical and control theory models are considered. However, in complex processes not all their characteristics are always known exactly, so mathematical modelling of processes is an extremely difficult task. Fault diagnosis can therefore be based mainly on data or heuristic information. The inherent characteristics of fuzzy logic theory make it suitable for processing this type of information, which is why it will be used to model and diagnose faults in a marine pneumatic servo-actuated valve. The fault diagnosis architecture proposed in this paper is based on analysing the discrepancy signals obtained between the outputs of the fuzzy models and the outputs process under study. These discrepancies, the residuals, are used to detect and isolate faults in the equipment. Fault isolation is carried out using an intelligent decision-making approach. Fault isolation indicates which fault is occurring in the process. The proposed approach will be used to diagnose abrupt faults in a marine pneumatic servo-actuated valve.

1 INTRODUCTION

The need to produce with higher quality and productivity requirements has led to a continuous increase in the complexity of technical processes. This situation increases the demand for safety and reliability, which have become important requirements in the production of marine systems (Lazakis, I., *et al* 2018). In the past, a type of maintenance known as predictive maintenance was used. In this case, maintenance work was carried out by assessing the condition of the equipment obtained through sensors and based on the equipment's degradation time. This type of maintenance was highly dependent on human intervention and expertise (Lazakis, I., *et al* 2019) and (Raptodimos Y. and Lazakis I., 2018). The increase in the complexity of technical processes leads to an increase in the probability of faults occurring. Marine equipment has subsystems that are connected to

each other. Thus, the occurrence of a small fault can cause a chain effect for other related subsystems, resulting in an amplification of the original fault (Tan Y., *et al* 2021). If control systems include automatic supervision of process control, faults can be detected and isolated when they are still in the early stages of development. Different approaches have been developed in fault diagnosis. The development of model-based fault diagnosis began in the early 1970s. This method of fault detection in dynamic systems has been receiving more and more attention over the last few years. Fault detection and isolation methods are used to detect any discrepancy between the system outputs and the model outputs, and if this occurs it is a fault. However, the same difference signal can correspond to model-plant mismatches or noise in real measurements, which are erroneously detected as a fault. The availability of a good model of the monitored system can significantly improve the performance of diagnostic tools, minimizing the probability of false alarms (Sun, X., *et al* 2016). The residual is the inconsistency between the data from the system measurements and the corresponding signals of the model. The residual generation is then identified as an essential problem in model-based fault diagnosis, since if it is not performed correctly, some fault information could be lost. To make marine systems safer and more reliable, there has been a growing demand for more effective fault diagnosis systems. (Aslam, S., *et al* 2020). Given the wide variety of equipment on board a ship, fault diagnosis of a pneumatic servo-actuated valve in operation on a ship can prevent faults situations and serious consequences. Diagnosing pneumatic servo-actuated valve faults is therefore a very important task. When the fault is detected and isolated, a rapid response can prevent the monitored system from suffering costly damage and loss of efficiency and productivity.
This paper proposes a model-based fault diagnosis architecture combining synergetically fuzzy modeling and an intelligent decision-making approach. Fault diagnosis consists of fault detection and fault isolation. First, fuzzy models for normal operation and for each fault are identified. The underlying idea is to predict the system outputs from the available inputs and outputs of the process, thus identifying a fuzzy model directly from data. The detection is made using the residual computed using the comparison of real data with the fuzzy model of the system running in normal operation. When a fault is detected, each faulty model output is compared to the real outputs of the process. After the detection, a fault must be isolated. The residuals obtained from each fault model are evaluated using an intelligent decision-making approach and the fault can be isolated.
This paper is organized as follows. The next section presents some bibliography developed by some authors on fault diagnosis as well as the fault diagnosis redundancy methods. The fuzzy modeling is presented in section 3. The proposed intelligent fault diagnosis is presented in section 4. The application exemple, marine equipment, is presented in section 5. The experiments and results obtained when applied the proposed approach of fault diagnosis are presented in section 6 and finally some conclusions are drawn in section 7.

2 FAULT DIAGNOSIS

Many different Fault Detection and Isolation (FDI) approaches have been developed over the last few years, in a wide variety of installations. One of the first was the failure detection filter, applied to linear systems (Beard, 1971). After that, different methods and approaches were developed such as the application of identification methods to the fault detection of jet engines (Rault, Richalet, Barbot, and Sergenton, 1971) and the correlation methods applied to leak detection (Siebert & Isermann, 1976). Isermann introduced process fault detection methods based on modeling parameters and state estimations (Isermann, 1984). Model-based methods for fault detection and diagnosis applied to chemical processes were presented in Himmelblau (1978). In the frequency domain, FDI is applied using the frequency spectra as criterion to isolate the faults (Ding and Frank, 2000). Other FDI approaches are based on residual generators, including physical or hardware redundancy methods, or analytical or functional redundancy methods (Chen and Patton, 1999). Techniques based on transfer learning have more recently been applied to Marine Diesel Engines (Guo, Yu & Zhang, Jundong 2023). Fault diagnosis using adaptive neural network were applied in ship power equipment (Zhang, D. 2022). (Young, J.K., *et al* 2023) proposes a hierarchical level of fault detection and diagnosis method that combines domain knowledge of ship engines and advanced data analysis techniques. As you can see, fault diagnosis has been widely accepted by the academic community and is widely applied in the maritime environment, particularly on ships.
The next section presents the technique used in this paper, which is based on redundancy-based fault diagnosis.

2.1 Fault diagnosis redundancy methods

When redundant systems are used in fault diagnosis, the reliability of these systems is improved. A fault diagnosis method based on causality has therefore been proposed for systems that use redundancy (Yin *et al*

2022). Fault diagnosis can be carried out using a traditional approach based on hardware redundancy. Using this technique, several sensors, actuators and components are used to measure, and control a given variable. However, there are some problems with using this technique, such as extra equipment and maintenance cost, as well as the additional space required to accommodate this equipment (Isermann and Ballé, 1997). These disadvantages increase the necessity of using other methods, easier to use and with smaller costs.
Analytical or functional redundancy methods can be used instead. These methods use redundant analytical relationships among several measured variables of the monitored system (Chen and Patton, 1999; Kinnaert, 2003). These variables are measured signals with estimated values, generated by a mathematical model of the considered system. In the analytical redundancy scheme, the resulting difference generated from the comparison of different variables is called residual or symptom signal. The residual should be zero when the system is in normal operation and when the fault occurs the residual should be different from zero. This property of the residual is used to determine whether or not faults have occurred. Some examples of residual generators based on the analytical redundancy scheme are the Kalman filter, Luenberger observers, state and output observers or parity relations (Chen and Patton, 1999). The model-based FDI method can be defined as the detection and isolation of faults on a system by means of methods that extract features from measured signals. The model-based fault diagnosis technique has been used in a wide variety of equipment and areas, most recently in marine diesel engines (Kougiatsos N. *et al* 2022). The first operation is used to generate residuals by means of the available inputs and outputs from the monitored system. The residuals can be generated by the comparison of measured outputs, y, and the estimated outputs, $\hat{y}$. The residual evaluation is carried out using a mechanism that checks the residual increase compared to a reference value. In this way, a fault can be detected. For a simple fault that can be detected by a single measurement, a conventional threshold check may be appropriate (Chen and Patton, 1999). Figure 1 presents the fault detection approach based on residuals analysis. In model-based fault detection, the accuracy with which the model characterises the process under analysis is of great importance. Without a well-performing model, fault diagnosis cannot be carried out correctly.
The second operation of model-based fault diagnosis consists of an intelligent decision-making approach. A number of residuals can be designed, where each must be sensitive to individual faults occurring in different locations of the system. The analysis of each residual, once the threshold is exceeded, leads to the fault isolation. The evaluation of the residuals via a set of statistical tests was made in (Kinnaert, M. *et al* 2000). However, the impossibility of obtaining complete knowledge and understanding of the monitored process increases the uncertainty in the model. The reduction of sensitivity to modeling uncertainty can be used in fault diagnosis. This sensitivity reduction, sometimes, does not solve the problem since the sensitivity reduction may be associated with a reduction of the sensitivity to faults (Chen and Patton, 1999; Gertler, 1998). Thus, the main problem with using the model-based fault diagnosis approach is the uncertainty arising from modelling, which is unavoidable in real industrial systems. Model-based, data-driven, knowledge-based and hybrid approaches to fault diagnosis in marine equipment are presented in (Lv Y. *et al*, 2024). It also offers perspectives on the potential future directions of this field.

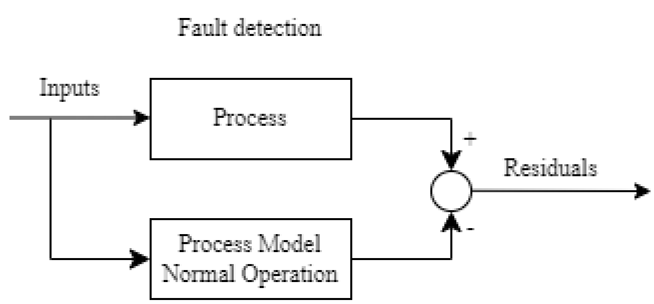

Fig. 1 Fault detection approach

3 FUZZY MODELING

Expert systems use inference techniques to solve complex problems that normally require specialised human knowledge. These systems offer several advantages, such as rapid response, greater reliability, cost reduction and flexibility. Considering these characteristics, expert systems have been used in a wide variety of applications. In the approach presented in this paper, the expert system is based on the principles of fuzzy logic through fuzzy modelling. Fuzzy modeling often follows the approach of encoding expert knowledge expressed in a verbal form in a collection of if–then rules, creating a model structure. Parameters in this structure can be adapted using input-output data. When no prior knowledge about the system is available, a fuzzy model can be constructed entirely based on system measurements. The models that will be used in the fault diagnosis approach proposed in this paper are fuzzy models. In the following, data-driven modeling based on fuzzy clustering will be considered (Sousa and Kaymak 2002).

Let's consider rule-based models of the Takagi-Sugeno (TS) type (Takagi and Sugeno 1985). It consists of fuzzy rules, where each of them describe a local input-output relation, typically in an affine form:

$$R_i\text{: If } x_1 \text{ is } A_{i1} \text{ and ... and } x_n \text{ is } A_{in} \text{ then } y_i = \mathbf{a}_i\mathbf{x}+b_i \tag{1}$$

where $i = 1,2, \ldots, K$. Here R_i is the i^{th} rule, $\mathbf{x} = [x_1,\ldots,x_n]^T$ is the antecedent vector, $A_{i1},\ldots,A_{in}$ are fuzzy sets defined in the antecedent space, and y_i is the rule output variable. K denotes the number of rules in the rule base, and the aggregated output of the model, $\hat{y}$, is calculated by taking the weighted average of the rule consequents:

$$\hat{y} = \frac{\sum_{i=1}^{k} \beta_i y_i}{\sum_{i=1}^{k} \beta_i} \tag{2}$$

β_i is the degree of activation of the i^{th} rule defined as $\beta_i = \prod_{j=1}^{n} \mu_{A_{ij}}(x_j)$, $i = 1,2,\ldots, K$ and $\mu_{A_{ij}}(x_j)\colon \mathbb{R} \rightarrow [0,1]$ is the membership function of the fuzzy set A_{ij} in the antecedent of Ri.

To identify the model (2), the regression matrix $\mathbf{X}$ and an output vector $\mathbf{y}$ are constructed from the available data $\mathbf{X}^T = [\mathbf{x}_1,\ldots,\mathbf{x}_N]$; $\mathbf{y}^T = [y_1,\ldots,y_N]$. Here, $N \gg n$ is the number of samples used for identification.

The number of rules, K, the antecedent fuzzy sets, A_{ij}, and the consequent parameters, $\mathbf{a}_i$, b_i are determined in this step, by means of fuzzy clustering in the product space of $X \times Y$ (Babuška 1998). Hence, the data set $\mathbf{Z}$ to be clustered is defined as $\mathbf{Z}^T = [\mathbf{X},\mathbf{y}]$. Given $\mathbf{Z}$ and an estimated number of clusters K, the Gustafson-Kessel fuzzy clustering algorithm (Gustafson and Kessel 1979) is applied to compute the fuzzy partition matrix $\mathbf{U}$.

The fuzzy sets in the antecedent of the rules are obtained from the partition matrix $\mathbf{U}$, whose ik^{th} element $\mu_{ik} \in [0,1]$ is the membership degree of the data object $\mathbf{z}_k$ in cluster i. One-dimensional fuzzy sets A_{ij} are obtained from the multidimensional fuzzy sets defined point-wise in the i^{th} row of the partition matrix by projections onto the space of the input variables x_j.

The consequent parameters for each rule are obtained as a weighted ordinary least-square estimate. Let $\theta_i^T = [a_i^T; b_i]$ where $\mathbf{X}_e$ denote the matrix $[\mathbf{X};\mathbf{1}]$ and let $\mathbf{W}_i$ denote a diagonal matrix in $\mathbb{R}^{NXN}$ having the degree of activation, $\beta_i(\mathbf{x}_k)$, as its k^{th} diagonal element. If the columns of $\mathbf{X}_e$ are linearly independente and $\beta_i(\mathbf{x}_k) > 0$ for $1 \leq k \leq N$, the weighted leastsquares solution of $\mathbf{y} = \mathbf{X}_{eq} + \varepsilon$ becomes

$$\theta_i = [\boldsymbol{X}_e^T \boldsymbol{W}_i \boldsymbol{X}_e]^{-1} \boldsymbol{X}_e^T \boldsymbol{W}_i \boldsymbol{y} \tag{3}$$

4 PROPOSED INTELLIGENT FAULT DIAGNOSIS

This paper presents a model-based architecture for fault diagnosis based on fault detection and isolation. These two steps, fault detection and fault isolation, are presented below.

The proposed approach is based on fuzzy modelling and the models are obtained directly from the available process data. However, in this approach it is possible to use any type of white or black box model (fuzzy, neural, etc.), since only the outputs of the models are used in the proposed architecture. The model-based technique proposed in this paper uses a fuzzy model for the process running in normal operation, and one model for each of the faults to be isolated. The fuzzy model used to detect faults is obtained using process data without faults. Faults are detected when the obtained residual comparing the outputs of the process with the outputs of the fuzzy model exceeds a previously defined threshold. To isolate the faults, is used a fuzzy model for each fault. The fuzzy models for each fault are obtained using data from the process with faults. The fault is isolated when the obtained residual comparing the outputs of the process with the outputs. Suppose that a process is running, and n possible faults can be detected. The fault detection and isolation system proposed in this paper for these n faults is depicted in Fig. 2. The multidimensional input of the system enters both the process and a model (observer) in normal operation. The vector of residuals ∈ is defined as:

$$\in = \boldsymbol{y} - \widehat{\boldsymbol{y}} \tag{4}$$

where **y** is the output of the system and $\widehat{\boldsymbol{y}}$ is the output of the model in normal operation. When any component of $\in$ is bigger than a certain threshold δ, the system detects a fault. After detected the fault, n models, one for each fault, are activated, and n vectors of residuals are computed.
In the proposed fault diagnosis architecture presented in Fig. 2, fault isolation is obtained by residual evaluation of each of the n models, one for each fault. At each time instant k, a residual $\in_i$ is computed for each fault

$$\in_i (k) = \boldsymbol{y_i} - \widehat{\boldsymbol{y}}_{\boldsymbol{i}} \tag{5}$$

where $\widehat{\boldsymbol{y}}_{\boldsymbol{i}}$ is the output of the observer for the fault i, with i = 1,…,n. Note that the residual $\in_i$ is a vector with dimension m, which is equal to the number of outputs.
Next, the intelligent decision-making methodology for fault isolation will be presented. The detection of faults leads to the activation of models for each of the faults, as shown in Fig. 2. After obtaining the residuals for each of the fault's models, they are aggregated with a range between time instant k and time instant k-p. The p value should be selected according to the variability of the outputs of the processes being analysed. This value may increase in situations where the variability of the system's outputs is greater and decrease if the variability of the system's outputs is smaller. The use of a range from time instant k and time instant k-5 allows the proposed method to absorb possible momentary changes in the outputs of fault models, when they are not actually faults. Considering that the fault model can have several outputs, this paper proposes determining the maximum values of the aggregate values of the residuals corresponding to the various outputs. In this way, an aggregate residual value is obtained for each fault model. Considering the possibility of the existence of several faults, the sum of the aggregate values of the residuals of each fault model is evaluated. The fault is isolated by identifying the model with the lowest aggregate residual value.

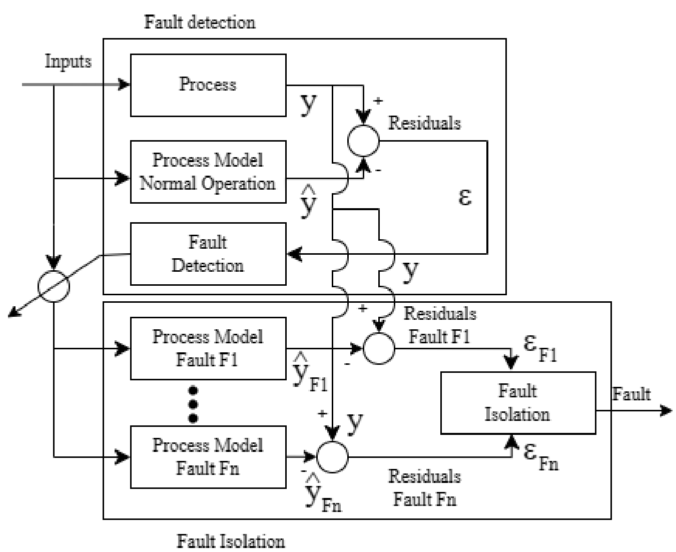

Fig. 2 Fault detection and isolation approach

5 MARINE EQUIPMENT

A pneumatic servo-actuated valve for marine control, which is presented in Fig. 3, is used as test bed of the fault diagnosis approach proposed in this paper. The actuator consists of three main parts: control valve, V; pneumatic servomotor, S; and positioner, P. Each of the three main parts contains other components: the positioner supply air pressure PSP, the air pressure transmitter PT, the volume flow rate transmitter FT, the temperature transmitter TT the rod position transmitter ZT the electro-pneumatic converter E/P and the controller output CVI. From the analysis of the variables presented for the pneumatic servo-actuated valve, it can be concluded that the most relevant variables for fault diagnosis are the flow process, PV, and the rod displacement of the servomotor, X, which are considered outputs of the model to be considered.

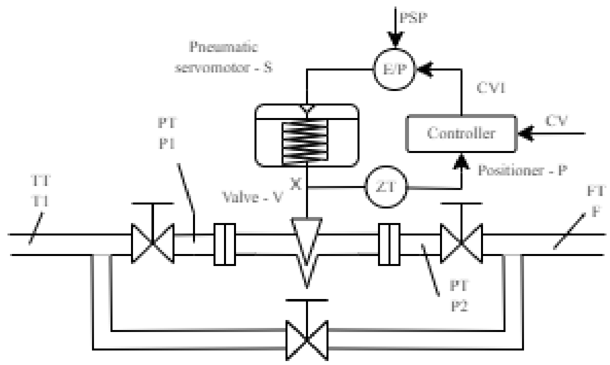

Fig. 3 - Diagram of the pneumatic servo-actuated valve

6 EXPERIMENTS AND RESULTS

6.1 Process data

The analysis of the process variables led to the conclusion that the most important input variables for modelling are: input pressure, output pressure, temperature and reference. The most important output variables are: flow and the rod displacement. Process data without fault are presented in Fig. 4.

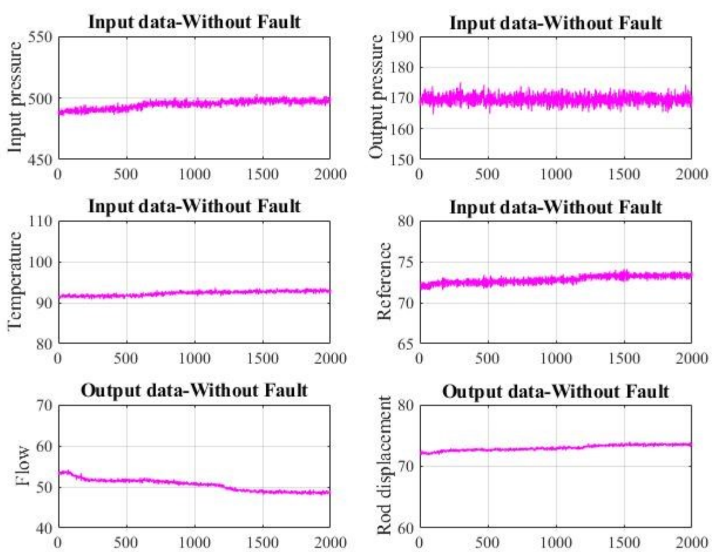

Fig. 4 - Process data without fault
Process data with fault F1 are presented in Fig. 5.

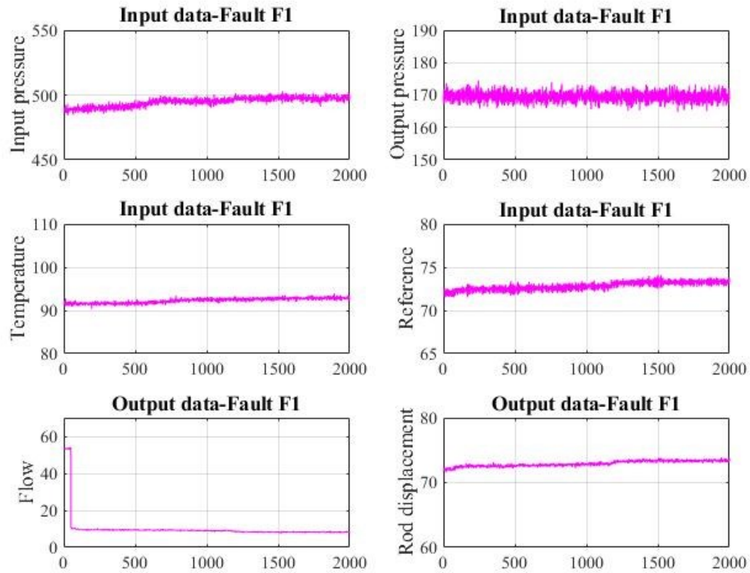

Fig. 5 - Process data with fault F1

Process data with fault F2 are presented in Fig. 6.

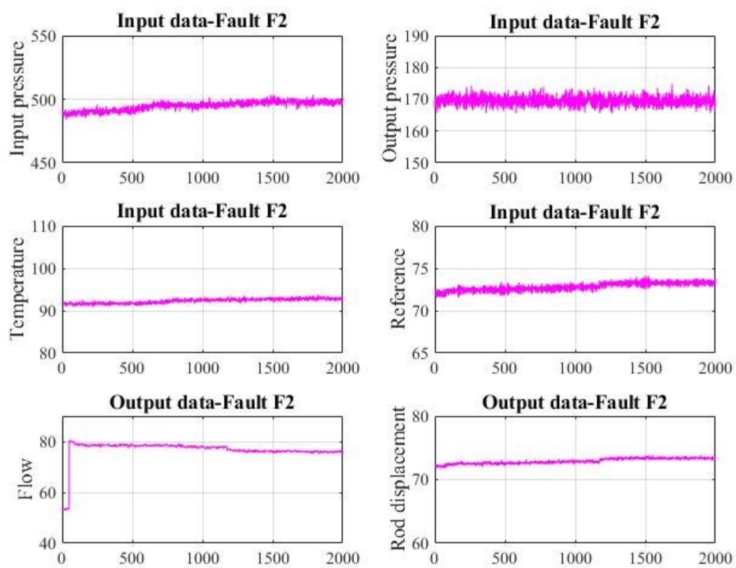

Fig. 6 - Process data with fault F2

Process data with fault F3 are presented in Fig. 7.

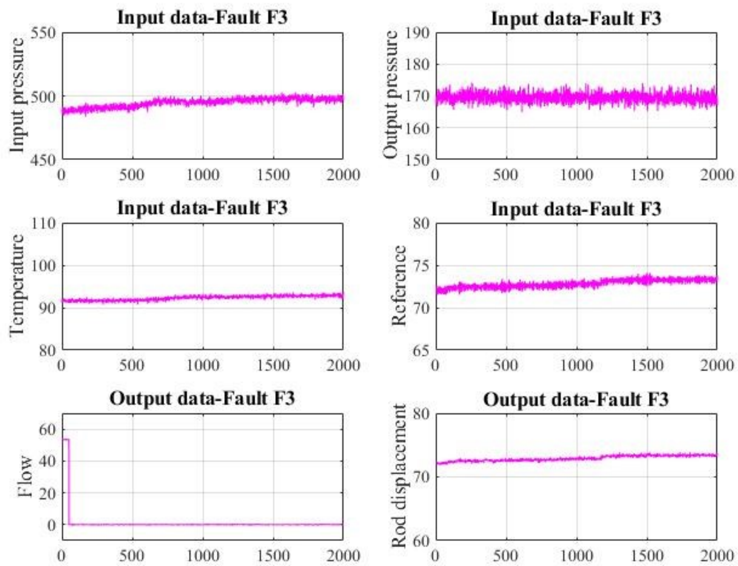

Fig. 7 - Process data with fault F3

6.2 Identify models

The weighted least squares solution shown in (3) was determined for each of the output variables of the models without faults and with faults F1, F2 and F3. The following matrices correspond to the obtained values for the output flow (PV) and output rod displacement (X). The process without faults, output flow (PV):

$$\theta_{PV} = \begin{bmatrix} 0.1815 & -0.3866 & 71.2045 \\ 0.5835 & -0.3788 & 49.4296 \\ 0.5859 & -0.2232 & 38.4875 \end{bmatrix}$$

Process without faults, output rod displacement (X):

$$\theta_X = \begin{bmatrix} -0.1262 & -0.0552 & 0.2540 & -0.4726 & 117.8472 \\ 0.2064 & 0.0204 & 0.0119 & 0.3035 & 24.1329 \\ -0.5721 & 0.0788 & -0.7599 & 2.6410 & -46.1430 \\ -1.1126 & -0.0714 & 0.6246 & -2.4737 & 309.1027 \\ 1.4325 & -0.0017 & 0.0823 & 0.4739 & -72.3240 \\ -1.7284 & -0.0133 & -0.0885 & -0.4039 & 241.4274 \end{bmatrix}$$

Process with fault F1, output flow (PV):

$$\theta_{PVF1} = \begin{bmatrix} 1.0135 & 0.8193 & -143.5841 \\ 0.9566 & 0.0495 & -3.9807 \end{bmatrix}$$

Process with fault F1, output rod displacement (X):

$$\theta_{XF1} = \begin{bmatrix} 0.9570 & -0.0536 & 10.0766 \\ 1.0115 & -0.8982 & 155.6135 \end{bmatrix}$$

Process with fault F2, output flow (PV):

$$\theta_{PVF2} = \begin{bmatrix} 1.0112 & -0.0848 & 13.6251 \\ 0.9478 & 0.0463 & -4.1712 \\ 0.5368 & 0.0461 & 26.2229 \\ 0.8348 & 0.0613 & 1.5096 \end{bmatrix}$$

Process with fault F2, output rod displacement (X):

$$\theta_{XF2} = \begin{bmatrix} 3.8695 & 0.0150 & 0.0484 & -0.2912 & -218.8394 \\ -4.7910 & -0.0351 & -0.0191 & 1.7986 & 316.4989 \\ 3.4144 & -0.0247 & 0.0934 & -1.3228 & -112.3224 \\ -4.1929 & 0.0614 & -0.1297 & 0.5842 & 365.9917 \\ 5.7223 & -0.0903 & 0.0370 & 0.1444 & -325.1669 \end{bmatrix}$$

Process with fault F3, output flow (PV):

$$\theta_{PVF3} = \begin{bmatrix} 1.0123 & -0.9941 & 70.7522 \\ 0.9554 & -0.3503 & 28.9153 \\ 0.5422 & -0.3263 & 59.8856 \end{bmatrix}$$

Process with fault F3, output rod displacement (X):

$$\theta_{XF3} = \begin{bmatrix} -1.0460 & 0.1633 & 0.3385 & 94.9887 \\ -1.7498 & 0.2497 & -1.2573 & 247.1444 \\ 3.1628 & -1.0110 & 0.1432 & 5.2099 \\ 0.5065 & -0.0363 & -0.0294 & 43.9048 \\ -0.1286 & 0.0538 & 0.6125 & 28.3033 \\ -0.2368 & 0.4790 & -0.2297 & 24.1267 \\ 0.2110 & -0.1097 & -0.1963 & 90.7247 \\ -0.4276 & 0.2118 & -0.2958 & 89.7600 \end{bmatrix}$$

6.3 Results

The FDI approach proposed in this paper, which is presented in Fig. 2, was applied to the pneumatic servo-actuated valve to detect and isolate the abrupt faults. From the set of possible faults 3 were considered: F1, F2 and F3. Table 1 presents some descriptions about these faults.

Faults	Description
F1	Valve clogging
F2	Fully or partly opened bypass valve
F3	Flow rate sensor fault

Table1 - Faults description

Table 2 present the results obtained when each input fault occurs in the system. Each row in the Table 2 correspond to the imposed fault to occur in the simulation, and each column indicates the model of the fault used to isolate the fault. The residual for the fault considered in each line is depicted in bold. The fault diagnosis approach proposed in this paper can detect and isolate correctly all the three faults considered. By checking the values in bold (Table 2), they are the smallest residual value in the respective row.

Input Faults	Fuzzy Model		
	F1	F2	F3
F1	**483.91**	8.0751e+04	3.5397e+05
F2	7.9139e+04	**186.77**	2.2061e+05
F3	3.5563e+05	2.2435e+05	**761.06**

Table2 – Residual fault isolation ($\in_i$)

In the following, several figures showing the behavior of the fault detection and isolation approach presented in this paper. Figure 8 shows the residuals for fault detection and the detection time. The value of the residual corresponding to the flow output is very high and exceeds the defined threshold, thus indicating the occurrence of a fault. This conclusion is confirmed because the proposed fault diagnosis approach took as input the data corresponding to the behaviour of the process with fault F1. The threshold value is defined using an approach based on learning and knowledge of the process behaviour.

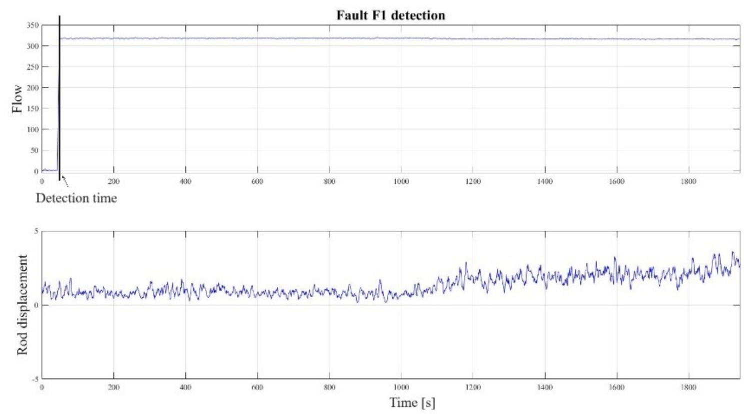

Fig. 8 - Fault F1 detection

Once the fault has been detected, in the first stage of the fault diagnosis approach shown in Fig.2, the second stage of fault isolation begins. Figure 9 shows the obtained results when the fault diagnosis approach takes as input the data corresponding to the behaviour of the process with fault F1. The residuals obtained from the model corresponding to fault F1 are very close to zero, indicating that the fault has been correctly isolated. On the other hand, the values of the residuals corresponding to the F2 and F3 faults models are very far from zero, meaning that these faults are not occurring.

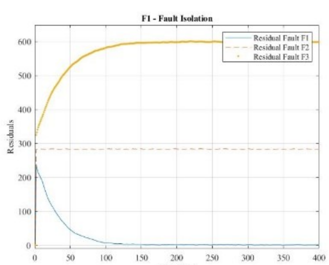

Fig. 9 - Fault F1 isolation

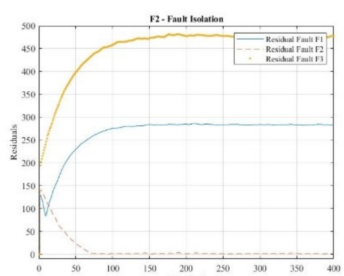

Fig. 10 - Fault F2 isolation

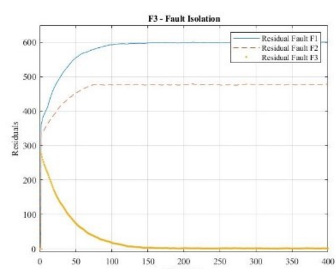

Fig. 11 - Fault F3 isolation

The results obtained when the input data corresponding to the behaviour of the process with fault F2 are shown in Figure 10. The residuals obtained from the model corresponding to fault F2 are very close to zero, indicating that the fault has been correctly isolated. On the other hand, the residual values corresponding to the F1 and F3 faults models are very far from zero. This confirms the non-occurrence of faults F1 and F3.
Figure 11 also shows the results obtained from the perspective of isolating fault F3, when the data input from the fault diagnosis process corresponds to the behaviour of the process with fault F3. Residuals obtained from the model corresponding to fault F3 are very close to zero, indicating that fault F3 is correctly isolated. Also, the residual values corresponding to the F1 and F2 faults models are very far from zero. Therefore, these faults are not occurring.

7 CONCLUSIONS

This paper proposes a fault diagnosis architecture based on fuzzy modeling and an intelligent decision-making approach to indicate the occurrence of faults. Fuzzy models are used in the fault diagnosis architecture presented in this document. Fault diagnosis includes fault detection and fault isolation. The fuzzy model used in fault detection was obtained with data from the process operating without faults. The fuzzy models used in fault isolation were obtained with data from the process operating with faults. The detection and isolation of faults are based on residual evaluation. An intelligent decision-making approach was proposed to isolate the faults. The isolation is performed by evaluating the residuals of each fuzzy fault models. The fault diagnosis architecture proposed in this paper was applied to a pneumatic servo-actuated marine valve, and it was able to detect and isolate 3 faults. Note that the data contains noise, which increases the difficulty to detect and isolate the faults.
Future research will consider extending the proposed FDI scheme to a greater number of faults, including other types of faults and more complex ones, developing an intelligent system to determine the threshold value and an intelligent system to determine the number of time instants to consider when analysing the residuals. Further, the proposed method will be integrated in fault tolerant control.

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