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An approach to multiple fault diagnosis using fuzzy logic

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Abstract The development of systems capable of diagnosing new and multiple faults in industrial systems is an active research topic. In this paper a model-based diagnostic system capable of diagnosing new and multiple faults using fuzzy logic as a fundamental tool is proposed. Also, the wavelet transform is used for isolating noise present in measurements. The proposed model was applied to the Continuously-Stirred Tank Heater model benchmark. The results demonstrate the feasibility of the proposed model, improving the robustness in the diagnostic, without loss of sensitivity to incipient or small magnitude faults.

Keywords Fault diagnosis · Multiple faults · Fuzzy logic · Robustness · Sensitivity · Wavelet transform

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Abbreviations

CSTH	Continuously-Stirred Tank Heater model
CW	Cold water
DWT	Discrete wavelet transform
FDI	Fault detection and isolation
HW	Hot water
LTI	Linear time-invariant systems
MRA	Multi-resolution analysis
PI	Proportional-integral
SCADA	Supervisory control and data adquisition
SLAT	Single location at a time
WT	Wavelet transform

Introduction

There is an immediate and clear need of current industry to improve the efficiency of processes in order to produce higher quality goods, in addition to comply with environmental and industrial safety regulations (Heng et al. 2009; Hwang et al. 2010; Venkatasubramanian et al. 2003a). Unplanned stops and equipment faults can have an unfavorable impact in the availability of systems, the safety of operators, and the environment. In an industrial context, safety is associated with a set of specifications or standards that manufacturers must meet in order to reduce the accident risks. With this objective in mind, it is important to incorporate automatic control and supervisory systems into industrial processes, allowing satisfactory operation of these through compensating the effects of perturbations and changes that might occur in them. That is why in order to guarantee that the operation of a system satisfies performance specifications, faults need to be detected, isolated and eliminated; all of these tasks associated with FDI (Isermann 2011). Generally, these methods can be classified into two categories: model-based and process history-based methods.

Most of the research developed until now has beencircumscribedto the diagnosis of independently-occurring faults. The diagnosis of faults that occur simultaneously is a complex problem, due to the fact that the number of possibilities grows exponentially with the amount of faults. Also, multiple faults in dynamic systems can be difficult to detect, because the effects of a fault can be hidden or compensated with the effects of another type of fault, and because the same type of multiple fault can manifest itself in different forms, taking into account the order of occurrence in which they come about.

The diagnosis of simultaneous faults using artificial intelligence has been an area of research that has grown in the last few decades (Vong et al. 2014). Some researchers have focused in static systems (Sobhani-Tehrani et al. 2014). Other researchers have proposed solutions to the multiple faults problem based on observations on imperfect tests, to identify the evolution closest to the state of the fault (Ruan et al. 2009). In Wang et al. (2006), the authors propose an algorithm based in pattern recognition to perform diagnostics, and reported that although the algorithm demonstrates high efficiency and precision, the experimental data validates that there are cases in which some of the fault tests did not have a solution. In Bartenstein et al. (2001), SLAT patterns were used to diagnose multiple faults. A model-based methodology was proposed in Bachschmid et al. (2002) for the identification of multiple faults in rotor systems, requiring models of the system elements, and models of the faults. In this case, fault identification is achieved through a minimum squares adjustment in the frequency domain.

The development of new strategies that enhance the rate of correct fault diagnosis is a relevant research problem. Currently, the need of availability of diagnostic systems that perform rapid detection and that can also distinguish or correctly classify fault patterns, even when process measurements are affected by noise or external perturbations, is persistent. In the last few years, in model-based approaches (Miguel and Blázquez 2005; Simani et al. 2015; Simani and Patton 2008; Venkatasubramanian et al. 2003a, b; Zhang et al. 2015), as in those based on historical data (Bedoya et al. 2012; Botía et al. 2013; Perzyk et al. 2014; Uribe and Isaza 2011), fuzzy logic emerges as an alternative to classical logic, allowing the treatment of imprecise information which can describe many everyday life phenomena. The theory of Fuzzy Sets offers a mechanism for linguistically representing qualitative criteria, such as "small", "medium", and "tall", in inference systems, being capable of imitating human reasoning in decision making (Nooria 2015). Through fuzzy logic, any type of ambiguity or uncertainty can be dealt with, and systems that use this tool are fast and cost-effective, given the simplicity of their calculations. This theory, through the incorporation of expert knowledge, permits modeling non-linear processes and learning from data using a given set of knowledge algorithms such as neural networks, or genetic algorithms. Fuzzy systems also offer great advantages in applications where decision taking depends in the criteria of experts.

The objective of this research and its main contribution is to design a model-based diagnostic system with the ability to detect and classifymultiple and novel faults. The proposed algorithm based on fuzzy logic can achieve these objectives due to a modification of the fuzzy rule base in the steps of detection and fault isolation of the used basic scheme. Furthermore, a modification to the membership functions is proposed to improve the sensibility of the system. The WT in the pre-processing stage permits to isolate the noise measurements to improve the robustness of the diagnostic system.

This paper is organized in the following manner: in "Model-based fault diagnosis using fuzzy logic" section, the use of the FDI algorithm for the design of the diagnostic system is discussed. In "Case studies and experimental design" section, the testing process used, and the experiment design is discussed. "Results analysis" section contains the analysis of experimental results. Finally, the conclusions are presented.

Model-based fault diagnosis using fuzzy logic

Model-based fault diagnosis requires modeling all possible faults that can be present during normal functioning of a system. With this in mind, the dynamic system is composed by the plant or process, and the controllers, sensors and actuators in charge of supervision and control. Depending on the dynamics of the process and the objectives to be attained with the model, different types of system models can be used with the purpose of describing a process. LTI systems are the most ubiquitous and simple (Ding 2008; Camps Echevarría et al. 2010). There are two typical types of mathematical representations of LTI systems: Transference matrix and description in state-space. With regards to fault modeling, there are many ways of representing faults in a system (Ding 2008; Fantuzzi et al. 2002; Gertler 2000).

Proposed modification to the FDI algorithm

The algorithm proposed in this paper is based on the FDI scheme described in Mendonça et al. (2009), and shown in Fig. 1, where a model is used for normal operation of the process and another model is used for each one of the different faults. The main contributions of this paper are the modifications introduced to the algorithm in the construction of the membership functions and in the base of rules, with the objective of achieving the detection and isolation of new and multiple faults; and in the proposed incorporation of the WT as a pre-processing step to isolate noise present

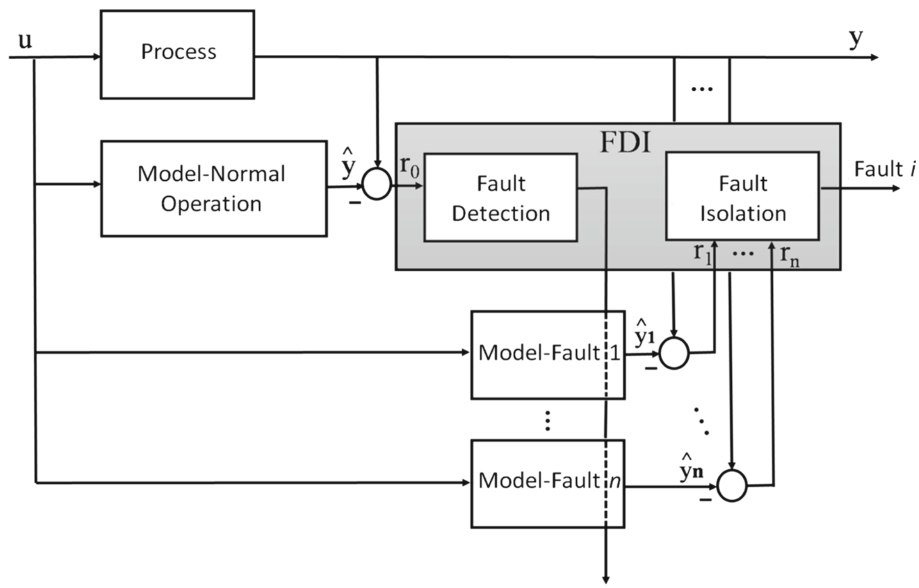

Fig. 1 Fault detection and isolation method

in the measurements, thus improving the robustness of the diagnosis system.The de-noising procedure has three steps:

1. **Decomposition.** Choose a wavelet, and choose a level N. Compute the wavelet decomposition of the signal s at level N.
2. **Detail coefficients thresholding.** For each level from 1 to N, select a threshold and apply soft thresholding to the detail coefficients.
3. **Reconstruction.** Compute wavelet reconstruction based on the original approximation coefficients of level N and the modified detail coefficients of levels from 1 to N.

In this work, theDWT was applied for signal decomposition using MRAwith 5 levels and the Daubechies Function as a mother wavelet. The parameters used for the signal decomposition are frequently used in applications of noise in fault diagnosis, achieving excellent results (Kunpeng et al. 2009; Rengaswamy et al. 2004; Wu and Hsu 2009).In order to achieve detection, the vector of residuals r_0 is defined as:

$$r_0 = y - \hat{y} \tag{1}$$

where y is the system's output and $\hat{y}$ is the model output in normal operation mode. If the system has more than one output, the residual r_0 is a vector of dimension m, where m is the number of outputs. Each scalar remainder can be denoted according to Eq. (2):

$$r_{0j} = y_j - \hat{y}_j \tag{2}$$

where y_j is the output j of the process, and $\hat{y}_j$ is output j of the model in normal operating mode, $j = 1, \ldots, m$.

In the proposed architecture, the isolation of faults is possible through evaluation of the residuals of the n models corresponding to the n faults to be diagnosed. According to Eq. (3), in each time interval k, a residuals vector r_i is calculated for each fault.

$$r_i(k) = y - \hat{y}_i \tag{3}$$

where $\hat{y}_i$ is the output of the fault model i, where $i = 1, \ldots, n$. If the system has more than one output, the residual $r_i$is a vector of dimension m, where m, is the number of outputs. Each scalar residual can be written according to Eq. (4):

$$r_{ij}(k) = y_j - \hat{y}_{ij} \tag{4}$$

where $\hat{y}_{ij}$ is the output of the model for fault i and output j, with $j = 1, \ldots, m$.

Detection

After the generation of the residuals vector r_0, trapezoidal membership functions are defined according to (5) and (6) to evaluate each of the residuals r_{0j}. Knowing that the noise in the process is bounded, it is possible to use expert knowledge to adjust the membership functions. As shown in Fig. 2, the fuzzy sets *Zero* and *One* are defined to represent the states of normal operation and with fault, respectively. The first contribution of the algorithm is in the construction of the membership functions step, where the fuzzy sets were defined asymmetrically in order to distribute uncertainty between them, giving more weight to the set *One* and in this way improving the certainty of fault occurrence. The parameter a_0 is obtained from the difference between the

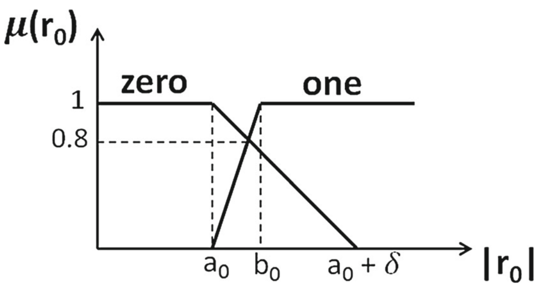

Fig. 2 Asymmetric membership functions for the detection step

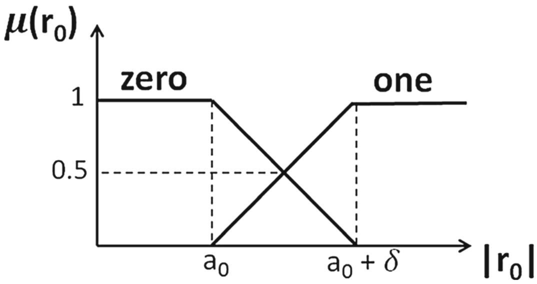

Fig. 3 Symmetric membership functions for the detection step

maximum andthe minimum noise valuesand δ is defined as the standard deviation of noise, both parameters defined by experts. The parameter b_0 is obtained such that the intersection point between the two fuzzy sets corresponds with a certainty factor of 0.8.

$$\mu_{zero} = \begin{cases} 0, & \text{if } |r_0(t)| > a_0 + \delta \\ \frac{a_0+\delta-|r_0(t)|}{\delta}, & \text{if } a_0 \leq |r_0(t)| \leq a_0 + \delta \\ 1, & \text{if } |r_0(t)| \leq a_0 \end{cases} \tag{5}$$

$$\mu_{one} = \begin{cases} 0, & \text{if } |r_0(t)| \leq a_0 \\ \frac{|r_0(t)|-a_0}{b_0-a_0}, & \text{if } a_0 \leq |r_0(t)| \leq b_0 \\ 1, & \text{if } |r_0(t)| > b_0 \end{cases} \tag{6}$$

where: $b_0 + a_0 + \frac{\delta}{4}$.

It is important to highlight that before using the asymmetric membership functions shown in Fig. 2, the classical asymmetric functions shown in Fig. 3 and defined in Eqs. (7) and (8) were analyzed.

$$\mu_{zero} = \begin{cases} 0, & \text{if } |r_0(t)| > a_0 + \delta \\ \frac{a_0+\delta-|r_0(t)|}{\delta}, & \text{if } a_0 \leq |r_0(t)| \leq a_0 + \delta \\ 1, & \text{if } |r_0(t)| < a_0 \end{cases} \tag{7}$$

$$\mu_{one} = \begin{cases} 0, & \text{if } |r_0(t)| < a_0 \\ \frac{|r_0(t)|-a_0}{\delta}, & \text{if } a_0 \leq |r_0(t)| \leq a_0 + \delta \\ 1, & \text{if } |r_0(t)| > a_0 + \delta \end{cases} \tag{8}$$

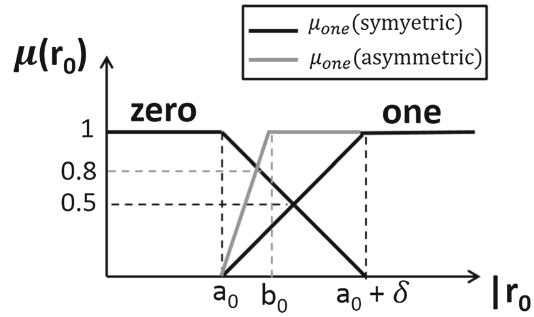

Fig. 4 Membership functions for the detection step

As observed in Fig. 4, these functions only differ from its asymmetrical counterparts in the fuzzy set *One*, where the region in which the set assumes values equal to 1 is smaller (the uncertainty is higher).

The second contribution of this research is the construction of the base of rules, which incorporates expert knowledge to detect the presence of multiple faults.

The rules for this block can be stated in this general form:

- If (r_{01} is *Zero*) and (r_{02} is *Zero*) and, …, (r_{0m} is*Zero*), then (State is "Normal Operation")
- If (r_{01} is *One*) and (r_{02} is *Zero*) and, …, (r_{0m} is Zero), then (State is "Single fault") $\vdots$
- If (r_{01} is *Zero*) and (r_{02} is *Zero*) and, …, (r_{0m} is *One*), then (State is "Single fault")
- If (r_{01} is *One*) and (r_{02} is *One*) and, …, (r_{0m} is *Zero*), then (State is "Multiple faults")

The first rule defines the normal operation of the system, whereas the n subsequent rules, where n is the dimension of the fault vector, establish the presence of single faults, if at least one of the residuals belongs to the Fuzzy set *One* over the threshold of $T = 0.8$. This threshold defines the region of fault and non-fault and can suffer minor changes in other processes. Finally, if the variables affected by each fault in a multiple fault are not correlated, then it is possible to construct in a simple way the last rule that allows detection of multiple faults if more than one residual belongs to the Fuzzy set *One* over the threshold of $T = 0.8$. It is important to state firstly that in order to determine the degree of membership of the consequences, the implication of the rule of minimum was used, and secondly that the consequences of the rules are only linguistic variables, and therefore there is no need for a defuzzyfication stage in order to obtain numerical values. The detection algorithm is the following:

Algorithm 1: Detection

Build membership functions $\mu_{r_{0j}}$for each residual according to output j using the parameters a_0 and δ.
for$l = 1$ to $l = k$ time intervals **do**
Calculate the residuals $r_{0j}(k)$ using (2)
  Calculate the degrees of membershipμ_{zero} and μ_{one} for each $r_{0j}(k)$ using (5) and (6)
  Determine the degree of membership of each one of the detection rules
  Compare the degree of membership to the threshold T to determine the state of the system
end for

Isolation

To evaluate the residuals r_{ij}, the trapezoidal membership functions shown in (9) and (10) are defined. As seen in Fig. 5, in this step the third contribution can be found in the construction of the membership functions, where the fuzzy sets where defined asymmetrically, giving more weight in this case to the set *Zero* such that the classification of corresponding faults is improved.

$$\mu_{zero} = \begin{cases} 0, & \text{if } |r_0(t)| > a_0 + \delta \\ \frac{|r_0(t)| - (a_0+\delta)}{b_0 - (a_0+\delta)}, & \text{if } b_0 \le |r_0(t)| \le a_0 + \delta \\ 1, & \text{if } |r_0(t)| < b_0 \end{cases} \tag{9}$$

$$\mu_{one} = \begin{cases} 0, & \text{if } |r_0(t)| < a_0 \\ \frac{|r_0(t)| - a_0}{\delta}, & \text{if } a_0 \le |r_0(t)| \le a_0 + \delta \\ 1, & \text{if } |r_0(t)| > a_0 + \delta \end{cases} \tag{10}$$

with:$b_0 = a_0 + \frac{3}{4}\delta$.

In this step, the classical asymmetric membership functions shown in Fig. 3 and defined in (7) and (8) were analyzed. As observed in Fig. 6, these functions only differ from its asymmetrical counterparts in the Fuzzy set *Zero*, where the region in which the set assumes values equal to 1 is smaller (the uncertainty is higher).

The fourth contribution of this research is the base of rules for fault isolation, be them single, multiple, or unknown. The classification of these is done if and only if the fault has been detected previously. For this base of rules, j indicates the output sensible to fault i. The rules of this block are stated in the following way.

- If (r_{1j} is *Zero*) and (r_{2j} is *One*) and, …, and (r_{nj} is *One*), Then (Fault is F_1)
- If (r_{1j} is *One*) and (r_{2j} is *Zero*) and, …, and (r_{nj} is *One*), Then (Fault is F_2) $\vdots$
- If (r_{1j} is *One*) and (r_{2j} is *One*) and, …, and (r_{nj} is *Zero*), Then (Fault is F_n)
- If (r_{1j} is *Zero*) and (r_{2j} is *Zero*) and, …, and (r_{nj} is *One*), Then (Fault is $F_1 - F_2$) $\vdots$
- If (r_{1j} is *Zero*) and (r_{2j} is *One*) and, …, and (r_{nj} is *Zero*), Then (Fault is $F_1 - F_n$)
- If (r_{1j} is *One*) and (r_{2j} is *Zero*) and (r_{3j} is *zero*) and, …, and (r_{nj} is *One*), Then (Fault is $F_2 - F_3$) $\vdots$
- If (r_{1j} is *One*) and (r_{2j} is *Zero*) and, …, and (r_{nj} is *Zero*), Then (Fault is $F_2 - F_n$) $\vdots$
- If (r_{1j} is *One*) and (r_{2j} is *One*) and, …, and ($r_{(n-1)j}$ is *Zero*) and (r_{nj} is *Zero*), Then (Fault is $F_{n-1} - F_n$)
- If (r_{1j} is *One*) and (r_{2j} is *One*) and, …, and (r_{nj} is *One*), Then (Fault is $F_?$)

The first n rules, where n is the dimension of the vector of faults, define the classification of single faults, if the residual corresponding to the fault model belongs to the fuzzy set *Zero* above the threshold of $T = 0.8$ and the remaining residuals belong to the fuzzy set *One* above the same threshold. As the variables affected by each fault are not correlated, the next block of rules permits the classification of all combinations of faults based on expert knowledge, if the residuals corresponding to the outputs of the fault models belong to the fuzzy set *Zero* above the threshold T

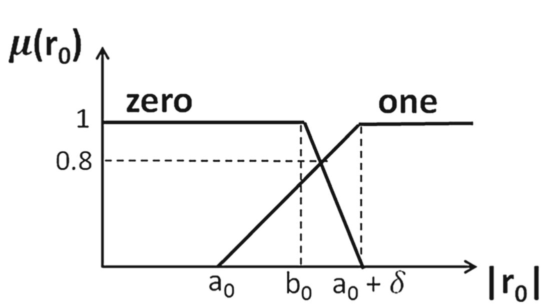

Fig. 5 Asymmetric membership functions for the isolation step

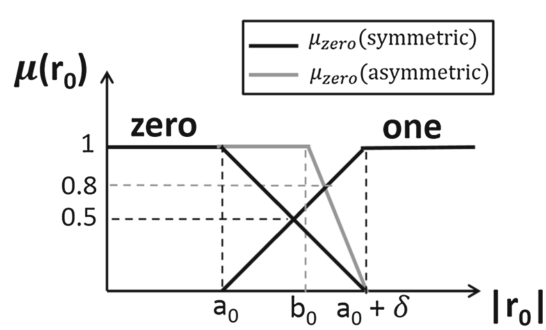

Fig. 6 Membership functions for the isolation step

and the remaining to the fuzzy set *One*, and this is possible because when multiple faults occur, the symptom variables of a fault have no influence over the other. This rule block, designed for multiple faults only reflects the combination of two faults, but based on expert criteria rules can be defined for the combination of n faults. With the last rule it is possible to know about the presence of unknown faults, given that if any fault was detected and no residual belongs to the fuzzy set *Zero* above T, then the fault affecting the system is a new fault. In this isolation step the consequences of the rule are also linguistic variables, and therefore there is no need for a defuzzyfication state to obtain numerical results. The algorithm for isolation of the faults is the following:

The relationship between the amount of heating vapor and the adjustment of the vapor valve is given by the following assumptions:

- The tank is well mixed; therefore the temperature of the output flow is the same as the temperature inside the tank. This is reasonable, given that the stirrer's action provides high velocity to the liquid around the heating coil and distributes rapidly and homogeneously the temperature inside the tank.
- The entire vapor condenses, and there is no wasted vapor. This is a reasonable assumption, unless the level is too low and the heating coils become exposed because of this. The maximum observed temperature under normal operating conditions is 65 °C when the vapor valve is completely open, and the vapor must condense completely under these conditions.

Algorithm 2: Isolation

Build membership functions $\mu_{r_{ij}}$ for each fault i and output j using the parameters a_0 and δ.
for $l = 1$ to $l = k$ time intervals **do**
Calculate the residuals $r_{ij}(k)$ using (4)
  Calculate the degrees of membership μ_{zero} and μ_{one} for each $r_{ij}(k)$ using (9) and (10)
  Determine the degree of membership of each one of the detection rules
  Compare the degree of membership to the threshold T to isolate the fault affecting the system.
end for

Case studies and experimental design

In the field of automatic control, the scientific research community has developed a set of model problems that are representative of different industrial processes, with the goal of using them to prove concepts and new ideas. For this work, the authors have chosen the Continuously-Stirred Tank Heater model (CSTH) from Thornhill et al. (2008), with the objective of validating the model-based diagnostic scheme proposed in this paper.

The CSTH, is a stirred tank of experimental use in which cold and hot water are mixed. This mix is also heated with vapor that circulates through a heat exchanger inside the tank. The tank shown in Fig. 7 has a height of 50 cm and a volume of 81 cm^3. The process has a tank, a stirrer, a heat exchanger, control valves, transmitters for level, flow and temperature, as well as controllers for these three variables. The control valves have pneumatic actuators that use a compressed air inlet of 3–15 psi. The flow sensors are orifice plate sensors with differential pressure transmitters with a nominal output of 4-20 mA. The level transmitter also uses differential pressure in its measurements, and the temperature instrument is a Type J metal-sheathedthermocouple that has been placed in the output tubing. The mass and energy balance equations, as well as the valves and sensors' calibration curves can be seen in Thornhill et al. (2008).

The process was simulated using Matlab-Simulink. The inputs and outputs are represented as electronic signals in the range of 4–20 mA. The inputs are cold water (CW), hot water (HW) and vapor. The outputs are the electrical measurements

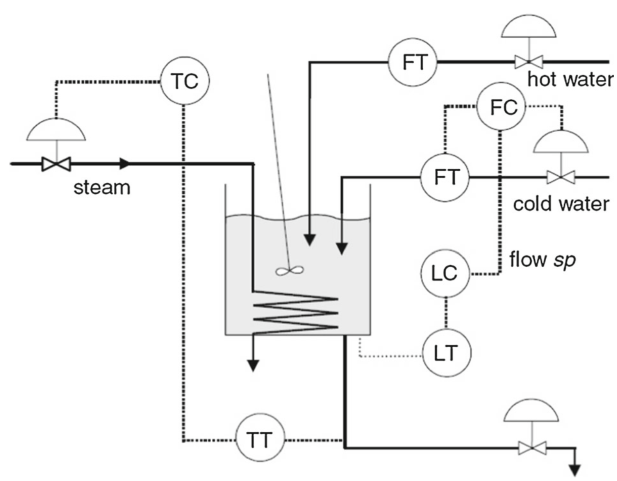

Fig. 7 Continuously-stirred tank heater model (CSTH)

Table 1 Nominal operating points

Variable	Op.pt.1	Op.pt.2
Level/mA	12.00	12.00
Level/cm	20.48	20.48
CW flow/mA	11.89	7.33
CW flow/$m^3 s^{-1}$	9.038×10^{-5}	3.823×10^{-5}
CW valve/mA	12.96	7.704
Temperature/mA	10.50	10.50
Temperature/°C	42.52	42.52
Vapor Valve/mA	12.57	6.053
HW valve/mA	0	5.500
HW flow/$m^3 s^{-1}$	0	5.215×10^{-5}

for level, cold-water flow, hot-water flow, and temperature. The control system is not part of the CSTH model, and was implemented directly in Simulink using the acquired data. The controllers are PI, and the controlled variables are level, and vapor temperature. The manipulated variable is cold-water input flow.

In Thornhill et al. (2008), two operating points are established; one defined only for the cold water inlet (Op.Pt.1) and the other for the hot-water inlet (Op.Pt.2). The nominal values for each case can be found on Table 1. This paper only deals with Op.Pt.1, not considering the hot-water input.

The simulated faults were the following:

1. Fault of the cold water input valve
2. Fault of the vapor input valve
3. Fault of the temperature transmitter

The faults in the valves correspond to problems associated with the free movement of the valve stems and the temperature transmitter fault is associated to an error in the instruments' calibration. In order to prove the sensitivity of the system, a fault of the temperature transmitter was simulated as an incipient fault. This way it is possible to have an estimate of how much the system takes to detect the presence of a fault that increments with the passage of time. The treatment of unknown faults needs to be considered when characterizing the diagnostics system. With this in mind, the malfunctions of the vapor input valve will be used as an unknown fault. Also malfunctions of the cold water input valve and the temperature transmitter will be simulated simultaneously, in order to assess the ability of the diagnostics system to classify multiple faults. All signals were corrupted with various levels of noise, corresponding to 2, 5, and 8 % of the signal, so that the robustness of the proposed diagnostics system can be evaluated.

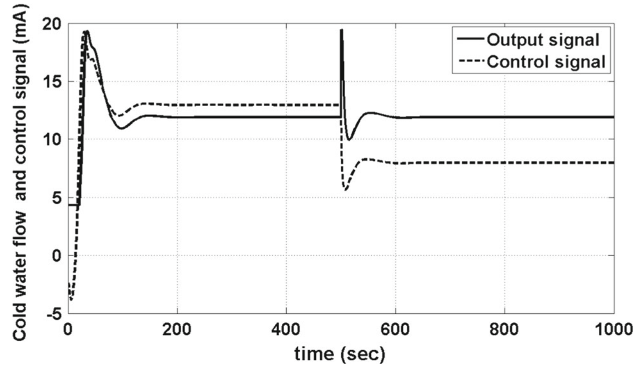

Fig. 8 CW input valve fault

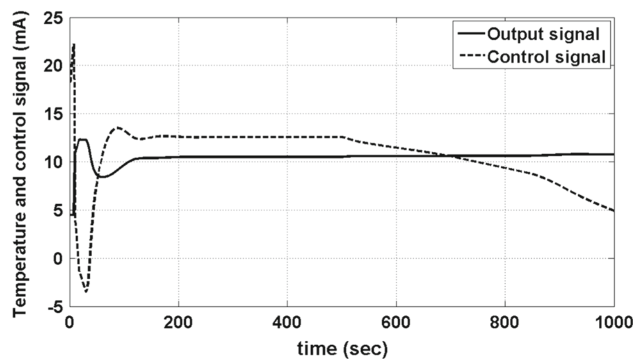

Fig. 9 Temperature transmitter fault

Symptom variables

Symptom variables are those in which changes caused by the presence of a fault are observed, and therefore are used to perform diagnostics of said faults. For the cases under study, the symptoms manifest as control signals of their respective control loops. In Figs. 8 and 9, the behavior of the cold water output flow and temperature can be observed, as well as their respective control signals in the presence of a fault of the cold water input valve, and the temperature transmitter. It can be seen that the outputs do not show significant changes when faults are present, due to the action of the controllers, whose behaviors are in fact altered, and this is the reason why the control signals will be used as symptom variables to perform the diagnostics.

For this process, the symptoms have no influence over each other. In Fig. 10 the control signals with the fault occurrence of the flow valve can be observed, and how this fault does not cause significant changes to the control associated to temperature. Figure 11 shows the control signals present when only the fault of the temperature transmitter is present. It shows how in this situation only the temperature control signal is affected. This demonstrates that the symptom variables are not correlated, which facilitates the diagnosis of multiple faults.

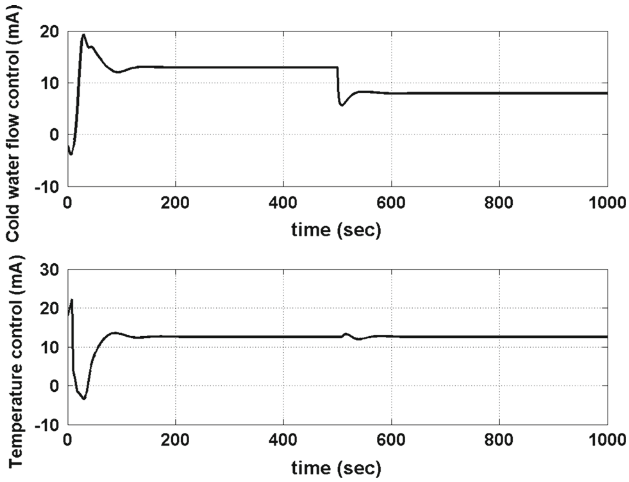

Fig. 10 Fault occurrence of the CW input valve

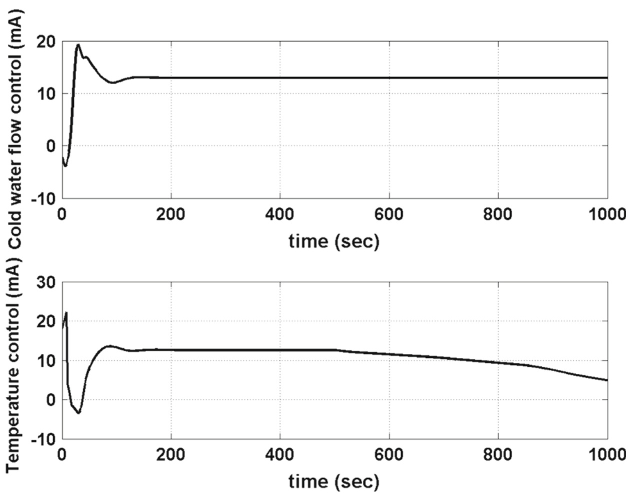

Fig. 11 Fault occurrence of the temperature transmitter

Results analysis

The experimental design in this research is aimed at the evaluation of the behavior of the FDI scheme discussed in Section 2 against single faults, multiple faults, and unknown faults, along with a robustness and sensitivity analysis. A comparison of the obtained results using the fuzzy membership functions proposed in this work and the symmetric membership functions, where the cross point between the fuzzy sets *Zero* and *One* corresponds to a membership degree of 0.5 is also discussed.

Single faults

In Tables 2 and 3, the results obtained from the fault diagnostics of the CW valve and the temperature transmitter respectively is shown. These were simulated independently for the three noise levels and the proposed scheme, with and without the Wavelet Transform. Also, the results using the membership functions proposed in this research and the symmetric membership functions are shown. It is important to highlight that the data shown in the next tables represent the amount of observations (expressed in percentages) that were detected or classified, depending on the case.

Here it is shown that the performance of the diagnostics system with the scheme proposed in section 2 is high, both in detection and classification, and the only remark is that for the 8 % noise level, the diagnostics system begins to show less performance. In the case of the fault of the CW valve, the diagnostics system classifies it with an accuracy of 93.75 % and an uncertainty of 6.25 % with a multiple fault of the CW input valve and the temperature transmitter. After introducing the Wavelet Transform, there is 96 % classification accuracy. It is highlighted that in this case that, being this fault an abrupt one, the results obtained are the same for both membership functions.

Also, for the membership functions proposed, a fault of the temperature transmitter is detected with 97.25 % accuracy. This is influenced by elevated time latency due to the fact that this fault is incipient, and to the magnitude of the noise present in the signal. A 97.25 % classification rate in the isolation stage is obtained, where 2.75 % are classified as unknown faults (malfunctioning of the vapor input valve). When introducing the Wavelet Transform a 100 % detection and classification rate is achieved. For the symmetric functions though, it is clearly seen how the classification per-

Table 2 Fault diagnosis of the CW valve

Scheme	Noise level (%)	Diagnosis—proposed membership functions		Diagnosis—symmetrical membership functions	
		Detection (%)	Classification (%)	Detection (%)	Classification (%)
Without wavelet transform	2	100	100	100	100
	5	100	100	100	100
	8	100	93.75	100	93.75
With wavelet transform	2	100	100	100	100
	5	100	100	100	100
	8	100	96	100	96

Table 3 Fault diagnosis of the temperature transmitter

Scheme	Noise level (%)	Diagnosis—proposed membership functions		Diagnosis—symmetrical membership functions	
		Detection (%)	Classification (%)	Detection (%)	Classification (%)
Without wavelet transform	2	100	100	100	100
	5	100	100	99.25	99.25
	8	97.25	97.25	93.75	93.75
With wavelet transform	2	100	100	100	100
	5	100	100	100	100
	8	100	100	96.25	96.25

Table 4 Multiple faultdiagnosis of the CW input valveand temperature transmitter

Scheme	Noise level (%)	Diagnosis—proposed membership functions		Diagnosis—symmetrical membership functions	
		Detection (%)	Classification (%)	Detection (%)	Classification (%)
Without wavelet transform	2	100	100	100	100
	5	100	100	99	99
	8	97.5	97.5	94.5	94.5
With wavelet transform	2	100	100	100	100
	5	100	100	100	100
	8	100	100	98.25	98.25

Table 5 Diagnosis of unknown faults

Scheme	Noise level (%)	Diagnosis—proposed membership functions		Diagnosis—symmetrical membership functions	
		Detection (%)	Classification (%)	Detection (%)	Classification (%)
Without wavelet transform	2	100	95.25	100	95.25
	5	100	88.25	100	88.25
	8	100	79.25	100	79.25
With wavelet transform	2	100	96.75	100	96.75
	5	100	90.5	100	90.5
	8	100	82.25	100	82.25

centage is less as noise increases, keeping also in mind that this fault is incipient and latency is an influential factor.

Multiple faults

As described previously faults in the CW input valve and the temperature transmitter were simulated simultaneously, with the objective of assessing the performance of the diagnostics system to classify multiple faults. In the results shown on Table 4 it can be appreciated the sensitivity and robustness of the diagnostics system when multiple faults are present. These results were possible because Algorithm 2 incorporates knowledge in the rule base to classify these types of situations. In these cases, there higher percentages of detection and classification are due to the fact that the simulated faults do not affect the same variable. In this case, it is shown that with the proposed membership functions better results are obtained than with the symmetric membership functions.

Unknown faults

In this experiment, a single fault was simulated to simplify the analysis. In this particular case, an abrupt malfunction of the vapor input valve was used. As seen in Table 5, when simulating the unknown fault using both the proposed membership functions and the symmetric membership functions, a single fault in the system is detected with 100 % accuracy in both schemes. Then, thanks to the fact that Algorithm

2 incorporates in its rule base the knowledge necessary to handle these situations, the classification of a new fault is achieved. The percentages of classifications begin to drop as the level of noise increases, having always some uncertainty with the fault of the temperature transmitter, because they affect the same variable.

Conclusions

The modifications proposed in this research, based in the aforementioned architecture, allowed the classification of new and multiple failures. These permit the FDI scheme proposed in Mendonça et al. (2009), and shown in Fig. 1, the detection and isolation of multiple and unknown faults, something that it would not do without these modifications. Also, the membership functions proposed here for isolation and detection stages improve the performance of the results obtained with the classical symmetric membership functions when the process is affected by incipient faults, thus enhancing the sensibility of the diagnosis. This work demonstrated also the robustness of this diagnostics system for different levels of signal noise, without it implying the loss of sensibility against incipient failures. With the help of the Wavelet Transform as a pre-processing stage, the noise present in the measurements was isolated, allowing a more robust diagnosis system.

For future research, an interesting idea is to design a fault diagnosis system based in historical data of the process with the ability to detect and classify multiple and novel faults. With the use of historical data it is possible to overcome the difficulties to obtain a model when the plant is big and complex. The most of the manufacture systems have installed a SCADA system; therefore the historical data is available. The use of the fuzzy clustering methods in combination with optimization techniques to tuning their parameters represents a good alternative.

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