FAULT DETECTION AND DIAGNOSIS USING FUZZY MODELS

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Abstract

The inherent characteristics of fuzzy logic theory makes it suitable for fault detection and diagnosis (FDI). Fault detection can benefit from nonlinear fuzzy modeling and fault diagnosis can profit from a transparent reasoning system, which can embed operator experience, but also learn from experimental and/or simulation data. Thus, fuzzy logic-based diagnostic is advantageous since it allows the incorporation of a-priori knowledge and lets the user understand the inference of the system. In this paper, the successful use of a fuzzy FDI based system, based on dynamic fuzzy models for fault detection and diagnosis of an industrial servo-actuated valve is presented. Only real plant data is used for the design and validation of the fuzzy FDI system. The validation results show the effectiveness of this approach.

1 Introduction

There is an increasing demand for man-made dynamical systems to become safer and more reliable. These requirements extend to process industry plants, which are basically controlled by servo-actuated flow control valves. Taking into consideration that malfunction of a valve in many hazardous applications can cause serious consequences, the fault diagnosis of industrial servo-actuated valve is a very important task. When the malfunction is detected and isolated, a quick response might prevent the monitored system from expensive damages and loss of efficiency and productivity. A system that includes the capacity of detecting, isolating and identifying faults is called a fault diagnosis and isolation system (FDI) [5]. During the years, many research has been carried out using analytical approaches, based on quantitative models. The idea is to generate signals that reflect inconsistencies between normal and faulty system operation. Such signals, the residuals, are usually generated using analytical approaches, such as observers, parameter estimation or parity equations. Early detection and isolation of abrupt and incipient faults can be achieved with model-based processing of all measured variables, using either qualitative or quantitative modeling.

Generally, the methods of fault detection can be divided into two groups: process variable monitoring and model based methods, which are more complex. For a simple fault that can be detected by a single measurement, a conventional threshold check may be appropriated. However, since in complex industrial systems it is usually very difficult to directly measure the state of the process, more sophisticated solutions are needed. In this case a model-based approach will be more suitable. This requires process modeling, which proves to be a very demanding task, especially when dealing with a nonlinear process.

The idea of model based fault detection is to compare output signals of the model with the real measurements available in the process, thereby generating the residuals, which are fault indicators giving information about the location and timing of a fault. This FDI approach requires precise mathematical relationships relating the model to the process, to allow the detection of small abrupt and incipient faults quickly and reliably. Different methods of model estimation are available. The most popular are analytical, being examples of these the Kalman filter, the Luenberger observer, between others [5]. However, the requirements for precise and accurate analytical models imply that any resulting modeling error will affect the performance of the resulting FDI system. This is particularly true for dynamically nonlinear and uncertain systems, which represent the majority of real processes. Therefore, the main assumption made when using model based FDI approach is that a precise mathematical model of the plant is required. This makes quantitative model-based approaches very difficult to use in real systems, since any un-modeled dynamics can affect the performance of the FDI scheme. A way to overcome this problem is to design robust algorithms, where the effects of disturbances on the residual are minimized, and the sensitivity to faults maximized. Many approaches have been developed including unknown input observers and eigenstructure assignment observers, as well as frequency domain techniques for robust FDI filters, such as the minimization of multi-objective functions, without much success for nonlinear cases. Recently other methods like neural networks, expert systems, fuzzy systems and neuro-fuzzy systems have been used with relative success [4].

Fuzzy techniques have received much attention due to their fast and robust implementation, their capacity to embed a-priori knowledge, their performance in reproducing nonlinear mappings, and their abilities of generalization. Thus, fuzzy logic techniques are now being investigated in the FDI research community as a powerful modeling and decision-making tool, along with neural networks and others more traditional techniques such as non-linear and robust observers, parity space methods and hypothesis-testing theory. To circumvent this precision modeling problem, more abstract models based on qualitative approaches may be used. Alternatively, fuzzy-logic rules may be developed to either assist or replace the use of a model for diagnosis. The key advantage of fuzzy logic is that it enables the system behavior to be described by "if-then" relations. The main trend in developing fuzzy FDI systems has been to generate residuals using either parameter estimation or observers, and allocate the decision-making to a fuzzy-logic inference engine. By doing so, it has been possible to combine symbolic knowledge to quantitative information and, thereby, minimize the false alarm rate. Indeed, the key benefit of fuzzy-logic is that it lets the operator describe the system behavior or the fault-symptom relationship with simple if-then rules. In this paper a step forward approach will be presented. The symptoms will be generated using fuzzy observers and plant measurements. 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 residual will then be a weighted difference between the predicted and the actual outputs. In our approach fuzzy observers are built for normal and faulty operations allowing the detection and isolation of the considered faults.

The paper is organized as follows. The architecture for fault detection and diagnosis proposed in this paper is described in Section 2. This FDI structure needs the identification of fuzzy models, which are briefly presented in Section 3. The pneumatic servo-actuated industrial valve used as test bed for the FDI architecture is described in Section 4, and the respective design of the FDI scheme for this system is explained in Section 5. The validation results are presented in Section 6, and some conclusions are drawn in Section 7.

2 Architecture for fault detection and diagnosis

This paper proposes a simple architecture to detect, isolate and identify faults. The FDI system is based on fuzzy observers (models) identified directly from data. The model-based technique uses a fuzzy model for the process running in normal operation, and one observer (model) for each of the faults to be detected. 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. 1. The multidimensional input, $\mathbf{u}$, of the system enters both the process and a model (observer) in normal operation. The vector of residuals $\boldsymbol{\varepsilon}$ is defined as

$$\boldsymbol{\varepsilon} = \mathbf{y} - \hat{\mathbf{y}}\,, \tag{1}$$

where $\mathbf{y}$ is the output of the system and $\hat{\mathbf{y}}$ is the output of the model in normal operation. When any component of $\boldsymbol{\varepsilon}$ is bigger than a certain threshold δ, the system detects faults. In this case, n observers (models), one for each fault, are activated, and n vectors of residuals are computed. Each residual i, with $i = 1, \ldots, n$ is computed as

$$\boldsymbol{\varepsilon}_{\mathrm{F}_i} = \mathbf{y} - \hat{\mathbf{y}}_{\mathrm{F}_i}\,, \tag{2}$$

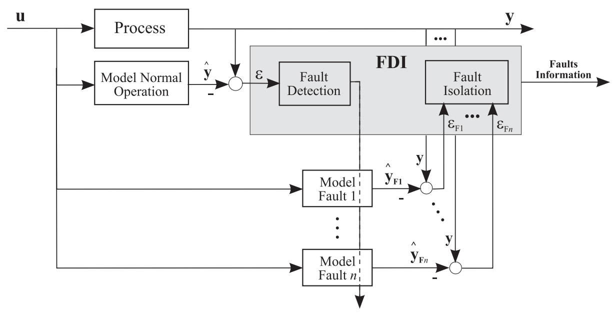

Figure 1: Fault detection and identification scheme.

where $\hat{\mathbf{y}}_{\mathrm{F}_i}$ is the output of the observer for the fault i. The residuals $\boldsymbol{\varepsilon}_{\mathrm{F}_1}, \ldots, \boldsymbol{\varepsilon}_{\mathrm{F}_n}$ are evaluated, and the fault or faults detected are the outputs of the FDI system. In this paper, all the models, i.e., the observer for normal operation and the observers for the n faults, are fuzzy models reproducing the dynamic behavior of the process, for each condition considered. This technique revealed to be adequate to identify models extracted from real data, as in the example described in this paper. Next section describes fuzzy modeling in detail.

3 Fuzzy Modeling

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 on the basis of system measurements. Note that the fuzzy observers used in the architecture for fault detection and diagnosis proposed in this paper are fuzzy models. In the following, we consider data-driven modeling based on fuzzy clustering [1, 8]. This approach avoids the well-known bottleneck of knowledge acquisition. The fuzzy model is acquired from sampled process data, utilizing the functional approximation capabilities of fuzzy systems.

Assume that data from an unknown system $y = F(\mathbf{x})$ is observed. The aim is to use this data to construct a deterministic function $y = f(\mathbf{x})$ that can approximate $F(\mathbf{x})$. The function f is represented as a collection of fuzzy if–then rules. Depending on the form of the propositions and on the structure of the rule base, different types of rule-based fuzzy models can be distinguished. The system to be identified can be represented as a MIMO nonlinear auto-regressive (NARX) model. These MIMO system can be decomposed into several MISO models, without loss of generality [1]:

$$\hat{y}(k+1) = f(\mathbf{x}(k)), \tag{3}$$

where $\mathbf{x}(k) \subset \mathbb{R}^n$ is the state of the system and is represented by previous inputs and outputs. Only MISO models are considered in the following for the sake of simplicity.

3.1 Takagi–Sugeno fuzzy model

We consider rule-based models of the Takagi-Sugeno (TS) type [9]. It consist of fuzzy rules which each describe a local input-output relation, typically in an affine form. The representation of (3) as a TS model is given by

$$R_i : \textbf{If } x_1 \text{ is } A_{i1} \textbf{ and } \ldots \textbf{and } x_n \text{ is } A_{in} \textbf{ then } y_i = \mathbf{a}_i\mathbf{x} + b_i \tag{4}$$

with $i = 1, 2, \ldots, K$. Here, R_i is the ith rule, $A_{i1}, \ldots, A_{in}$ are fuzzy sets defined in the antecedent space, $\mathbf{x} = [x_1, \ldots, x_n]^T$ is the antecedent vector, 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:

$$\hat{y} = \frac{\sum_{i=1}^{K} \beta_i y_i}{\sum_{i=1}^{K} \beta_i}, \tag{5}$$

where β_i is the degree of activation of the ith rule:

$$\beta_i = \Pi_{j=1}^{n} \mu_{A_{ij}}(x_j), \quad i = 1, 2, \ldots, K, \tag{6}$$

and $\mu_{A_{ij}}(x_j) : \mathbb{R} \to [0, 1]$ is the membership function of the fuzzy set A_{ij} in the antecedent of R_i.

3.2 Identification by fuzzy clustering

The nonlinear identification problem is solved in two steps: structure identification, and parameter estimation.

3.2.1 Structure identification

The designer must choose first the order of the model, and the significant state variables $\mathbf{x}$ of the model. This step is crucial in the identification of fuzzy observers for FDI, since the smaller the vector $\mathbf{x}$ the faster the model. Note that fuzzy observers for FDI must be both simple and accurate models in order to detect the faults as fast as possible. To identify the model (4), the regression matrix X and an output vector $\mathbf{y}$ are constructed from the available data:

$$\mathrm{X}^T = [\mathbf{x}_1, \ldots, \mathbf{x}_N], \quad \mathbf{y}^T = [y_1, \ldots, y_N]. \tag{7}$$

Here $N \gg n$ is the number of samples used for identification. The objective of identification is to construct the unknown nonlinear function $\mathbf{y} = f(\mathbf{x})$ from the data, where f is the TS model in (3).

3.2.2 Parameter estimation

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 $\mathcal{X} \times \mathcal{Y}$ [10, 11, 1]. Hence, the data set Z to be clustered is composed from X and $\mathbf{y}$:

$$\mathrm{Z}^T = [\mathrm{X}, \mathbf{y}]. \tag{8}$$

Given Z and an estimated number of clusters K, the Gustafson-Kessel fuzzy clustering algorithm [6] is applied to compute the fuzzy partition matrix U. This provides a description of the system in terms of its local characteristic behavior in regions of the data identified by the clustering algorithm, and each cluster defines a rule. Unlike the popular fuzzy c-means algorithm [3], the Gustafson-Kessel algorithm applies an adaptive distance measure. As such, it can find hyper-ellipsoid regions in the data that can be efficiently approximated by the hyper-planes described by the consequents in the TS model.

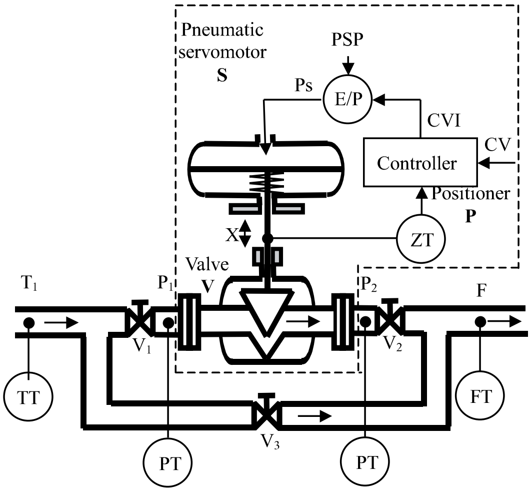

Figure 2: Diagram of the industrial servo-actuated pneumatic valve considered.

The fuzzy sets in the antecedent of the rules are obtained from the partition matrix U, whose ikth 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 ith row of the partition matrix by projections onto the space of the input variables x_j:

$$\mu_{A_{ij}}(x_{jk}) = \mathrm{proj}_j^{\mathbb{N}\, n+1}(\mu_{ik}), \tag{9}$$

where proj is the point-wise projection operator [7]. The point-wise defined fuzzy sets A_{ij} are approximated by suitable parametric functions in order to compute $\mu_{A_{ij}}(x_j)$ for any value of x_j. In this paper like [1] after clustering The consequent parameters for each rule are obtained as a weighted ordinary least-square estimate. Let $\theta_i^T = \left[\mathbf{a}_i^T; b_i\right]$, let X_e denote the matrix $[\mathrm{X}; \mathbf{1}]$ and let W_i denote a diagonal matrix in $\mathbb{R}^{N \times N}$ having the degree of activation, $\beta_i(\mathbf{x}_k)$, as its kth diagonal element as defined in (6). Assuming that the columns of X_e are linearly independent and $\beta_i(\mathbf{x}_k) > 0$ for $1 \le k \le N$, the weighted least-squares solution of $\mathbf{y} = \mathrm{X}_e\theta + \varepsilon$ becomes

$$\theta_i = \left[\mathrm{X}_e^T \mathrm{W}_i \mathrm{X}_e\right]^{-1} \mathrm{X}_e^T \mathrm{W}_i \mathbf{y}. \tag{10}$$

Rule bases constructed from clusters are often unnecessary redundant due to the fact that the rules defined in the multidimensional premise are overlapping in one or more dimensions.

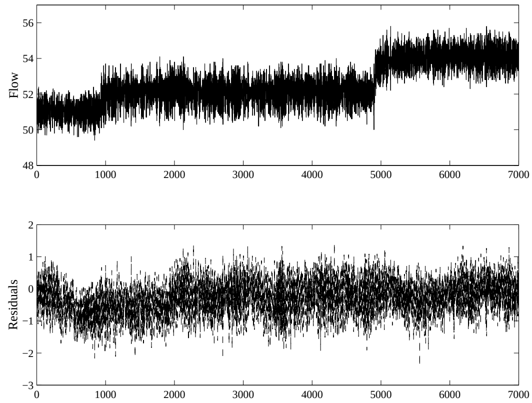

Figure 3: Validation of the flow output. Top: Flow output. Bottom: Flow residuals.

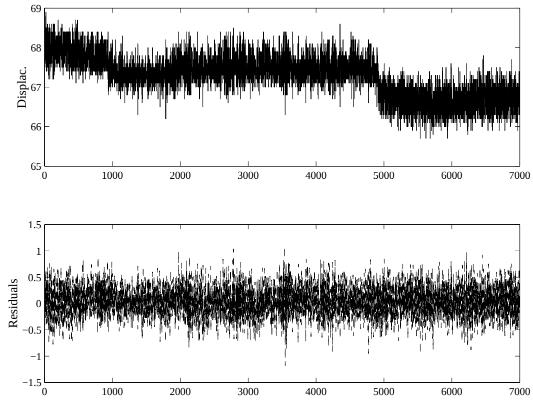

Figure 4: Validation of the rod displacement output. Top: Rod displacement output. Bottom: Rod displacement residuals.

4 Description of the process

A pneumatic servo-actuated industrial control valve is used as test bed of the fault detection and diagnosis approach proposed in this paper [2]. The valve is situated on the outlet of thick juice from the fifth section of evaporation station of the Lublin Sugar Factory in Poland. The actuator-valve is depicted in Fig. 2. The actuator consists of three main parts: control valve, V; pneumatic servomotor, S; and positioner, P. Furthermore, each of the three main parts contains other components shown in Fig. 2, which are the following: positioner supply air pressure, PSP; air pressure transmitter, PT; volume flow rate transmitter, FT; temperature transmitter, TT; rod position transmitter, ZT; electro-pneumatic converter, E/P; cut-off valves, V_1 and V_2; by-pass valve, V_3; pneumatic servomotor chamber pressure, Ps; and controller output, CVI.

The designer of the system must choose carefully the most relevant variables in order to keep the models (observers) as simple as possible. Therefore, the parameters of models identified for the valve have been carefully chosen. Namely, the variables to be considered in the models and the orders for each variables have been selected in order to minimize the complexity of the models, which must still be very accurate to detect and identify correctly the faults.

5 Design of the FDI system

This section presents the design of the fuzzy observers for the FDI scheme presented in Section 2. Fuzzy models for the normal operation and for each fault considered were identified using the *Fuzzy Modeling and Identification Toolbox* [1]. Real data for the industrial servo-actuated valve have been used. This data obtained from the Lublin sugar factory including normal operation and operation with faults. Considering all the factory constraints and the difficulties to obtain the faults operation in this paper are used only two faults. From a thorough analysis of the variables described in Section 4, it can be concluded that for FDI purposes, the most relevant variables are the flow process value, PV, and the servomotor rod displacement,

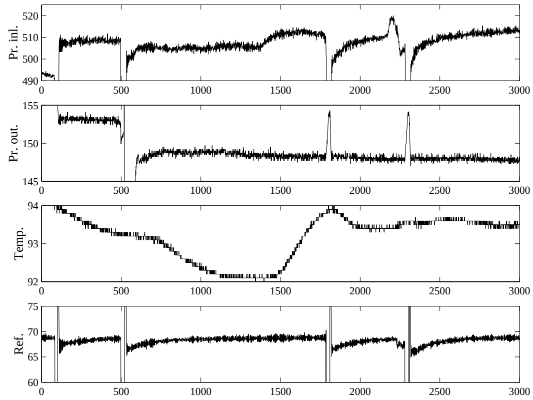

Figure 5: Identification (id.) and validation (val.) of input data.(See Table 1).

X. Therefore, these variables have been considered as outputs of the fuzzy model identified for normal operation. Moreover, the variables that revealed also to be relevant for this model are the following: pressure inlet valve, P_1; pressure outlet valve, P_2; temperature at the inlet, T; and control value for the inlet valve, CV.

Three clusters revealed to be sufficient for each output, and as so, the TS fuzzy observer has 6 rules, 3 for each output. The clusters are projected into the product-space of the space variables and the fuzzy sets A_{ij} are determined, with $i = 1, \ldots, K$ and $j = 1, \ldots, n$, where $n = 6$ is the size of the state vector, in this case. The rules for the output PV and for the output X are not included due to lack of space.

The set of identification data used to build the valve model in normal operation contains 7000 samples. The same number of data points is used for validation. Figures 3 and 4 presents both the validation of the fuzzy model under normal operation, and the residuals obtained for these data. The *variance accounted for* (VAF) obtained for each output, flow and rod displacement, are 91.2 and 86.9, respectively. Thus, the models are very accurate as desired.

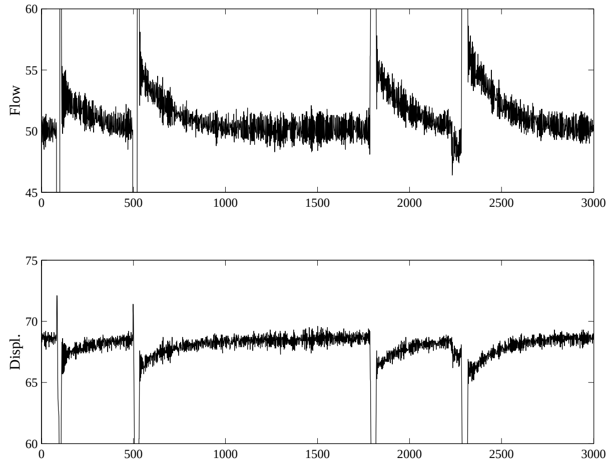

Figure 6: Identification (id.) and validation (val.) of output data.(See Table 1).

From the set of possible faults, two were considered: F17, which is an unexpected pressure change across the valve reflected either in the upstream or downstream pressure, and F19, which is a flow sensor fault. Figures 5 and 6 shows 3000 input and output data samples collected from the industrial servo-actuated valve. The sampling time is 1s. The faults F17 and F19 are located at the sampling points presented in Table 1, which has two faulty windows for each fault. Therefore, one part was used for identification, noted as (id.) in and the other for validation, noted as (val.) in Table 1. Two fuzzy observers

Faults	Samples	
	begin	end
F17 (val.)	80	94
F17 (id.)	493	515
F19 (id.)	1782	1817
F19 (val.)	2277	2315

Table 1: Faults in real data.

have been identified, one for each fault. Again, a thorough analysis of the variables described in Section 4 has been made, and the more relevant ones have been chosen. Only two clusters are now sufficient for each output, and as so, the TS rules for the fuzzy observer F17 has 4 rules, 2 for each output. The rules for the output PV are the following:

1. **If** $\mathrm{PV}(k)$ is A_{11} **and** $\mathrm{X}(k)$ is A_{12} **and** $P_1(k+1)$ is A_{13} **and** $P_2(k+1)$ is A_{14} **then**
   $\mathrm{PV}(k+1) = 1.23\mathrm{PV}(k) + 4.74 \cdot 10^{-2}\mathrm{X}(k)$
   $-0.138P_1(k+1) + 0.459P_2(k+1) - 68.8$

2. **If** $\mathrm{PV}(k)$ is A_{21} **and** $\mathrm{X}(k)$ is A_{22} **and** $P_1(k+1)$ is A_{23} **and** $P_2(k+1)$ is A_{24} **then**
   $\mathrm{PV}(k{+}1) = -0.67\mathrm{PV}(k){-}2.9\mathrm{X}(k){+}6.1{\cdot}10^{-3}P_1(k{+}1)$
   $-7.17 \cdot 10^{-2}P_2(k+1) + 2.91 \cdot 10^2$

The fuzzy rules for the output X are:

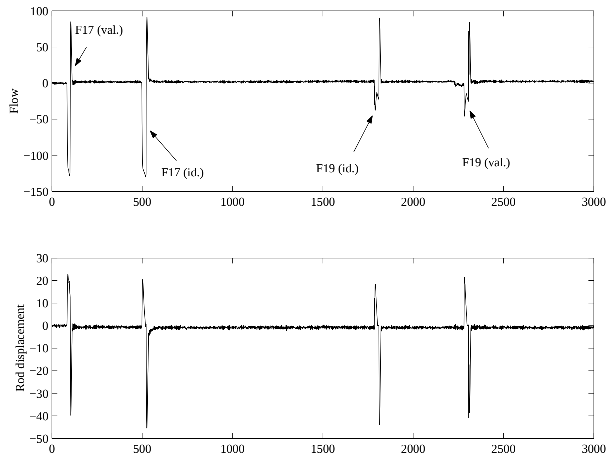

Figure 7: Residuals using the fuzzy observer under normal operation. Top: Flow. Bottom: Rod displacement.

1. **If** $\mathrm{X}(k)$ is A_{11} **and** $P_1(k+1)$ is A_{12} **then**
   $\mathrm{X}(k+1) = 0.96\mathrm{X}(k) + 3.77 \cdot 10^{-2}P_1(k+1) - 0.18$

2. **If** $\mathrm{X}(k)$ is A_{21} **and** $P_1(k+1)$ is A_{22} **then**
   $\mathrm{X}(k+1) = 0.48\mathrm{X}(k) + 0.1P_1(k+1) - 17.9$

The VAF obtained for each output, flow and rod displacement, are 95.3 and 93.7, respectively. Thus, the fuzzy observer F17 is again very accurate as desired.

Three clusters are considered for each output, and as so, the TS rules for the fuzzy observer F19 has 6 rules, 3 for each output. The rules for the output PV and for the output X are not included due to lack of space.

The VAF obtained for each output, flow and rod displacement, are 93.2 and 98.9, respectively. Again, the fuzzy observer F19 is very accurate as desired.

6 FDI validation

The FDI system proposed in this paper, which is presented in Fig. 1, was applied to the industrial valve to detect and identify the faults F17 and F19 based on real data. Two fuzzy models were identified, one for each fault. The residuals obtained using the fuzzy model in normal operation, are shown in Fig. 7. It can be seen that both residuals ε present four zones with large values. This result confirm the four faults in the real data. When the block Fault Detection in Fig. 1 detects faults, the faulty models, in our case the fuzzy observers for F17 and F19, are activated. When the plant data used corresponding to normal plant operation the block Fault Detection no detects fault and the faults observers are not activated.

The real data and the residual $\varepsilon_{\mathrm{F}_{17}}$ obtained for fault F17 considering the output rod displacement are depicted in Fig. 8. It is clear that the residual is very close to zero, and thus the fault F17 is isolated using the fuzzy observer. The figure for the output flow and it residual are not included due to lack of space.

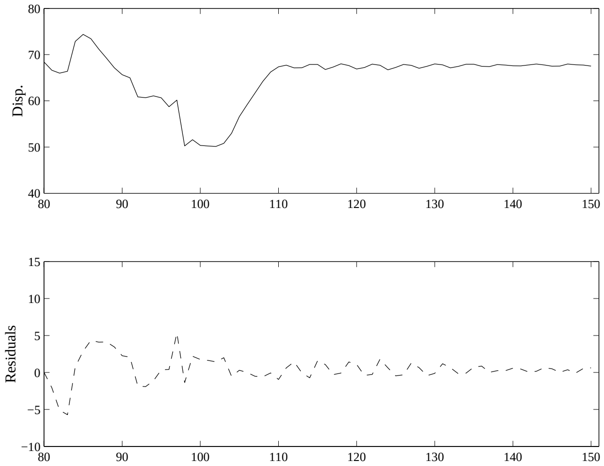

Figure 8: Output and residual obtained using the fuzzy observer F17. Top: rod displacement. Bottom: rod displacement residuals.

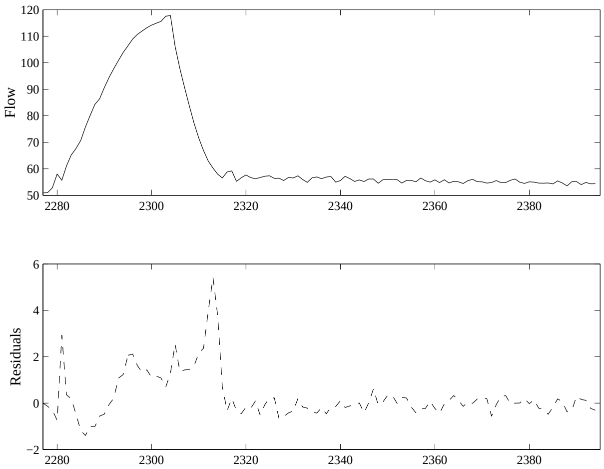

Figure 9: Output and residual obtained using the fuzzy observer F19. Top: flow. Bottom: flow residuals.

Further, the real data and the residual $\varepsilon_{\mathrm{F}_{19}}$ obtained for fault F19 considering the output flow are shown in Fig. 9. Again, the residual is very close to zero, and the fault F19 is isolated using the fuzzy observer. The figure for the output rod displacement and it residual are not included due to lack of space. Considering the obtained results, it can be concluded that the FDI system proposed in this paper was able to detect and identify the faults selected (F17 and F19) in the industrial servo-actuaded pneumatic valve, using fuzzy observers identified from real data.

7 Conclusions

This paper proposes a simple FDI scheme using fuzzy observers to compute the residuals. The fuzzy observers are identified from real input-output data of a possibly faulty system. The application to a pneumatic servomotor actuated industrial valve shown that the FDI scheme was able to detect two different faults. Future work will consider the extension of the proposed FDI scheme to a large number of faults, and the inclusion of incipient faults to be detected, isolated and identified.

Acknowledgements

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