FAULT DETECTION OF A CONTROL VALVE USING STRUCTURED PARITY EQUATIONS

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Abstract— In this paper a model based fault detection system is developed for a control valve. The features extracted by the fault detection system are produced using the structured parity equations technique; therefore, linearized mathematical models of the control valve are obtained. At the end of the work, 17 of 25 faults are detected.

Keywords— Fault Detection, Fault Diagnosis, Structured residuals, Control Valve

1 Introduction

Fault detection is a field of study of constant development, as characteristics like safety and fault tolerance are always desired in engineering projects. To achieve such requirements, several methods of fault detection have been developed, with great range of applications.

In this paper, a model based fault detection system will be applied to a control valve, whose faulty operation is known as one of major cause of scarce performance of control loops (Scali et al., 2011).

2 Fault Detection Based on Structured Residuals

A general scheme of the model based fault detection method is shown in figure 1 (Isermann, 2006): it consists of the identification of the analytical

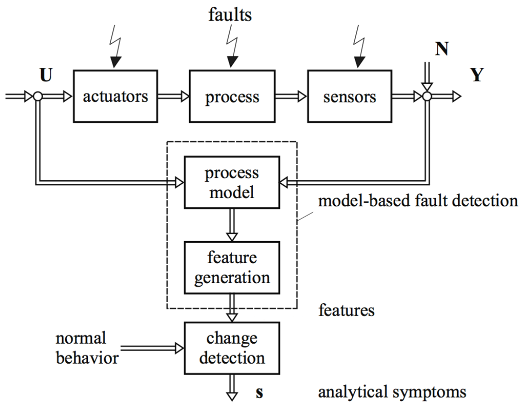

Figure 1: Model based fault detection method

symptoms (also called fault signatures) in some feature produced with data from the process and from a mathematical model that simulates the behavior of the process in the absence of faults. The fault signatures are patterns produced in the feature when a fault is acting on the process.

One of the main features used for model based fault detection are the output error residuals: it consists of the difference between the outputs of the process and the model. Thus n residuals can be produced for a process with n outputs.

Ideally if no fault is present in the process, the residuals are null; otherwise a fault is said to be acting on the process. In this situation the residuals are influenced only by the faults. However, factors like measurements noise and modeling errors also affects the residuals, so thresholds are usually adjusted in order to avoid false detections.

A further improvement that can be done is the use of *structured residuals*: in this approach, the faults will influence some residuals, and some not (Isermann, 2006). This is done by canceling the effects of some measured process signals in some of the residuals: For example, if a residual r_1 is not affected by a signal u_1, r_1 is considered *independent* of u_1. In the structured residual technique, every residual is independent of one measured signal from the process. This enhances the distinction between the fault signatures, as every residual belong to certain subspaces in the residual space.

3 Experiment Description

The structure used for the experiment consists of a pneumatic linear servo motor, positioner and a control valve with equal-percentage inherent flow characteristic. The servo motor has a stroke of $38.1mm$, while the valve has a maximum flow of $40t/h$, with water as the operation fluid. There is a bypass valve, which only opens when a specific fault is acting on it; otherwise it remains fully closed all the time. All the components and faults were simulated with the DAMADICS Actuator Benchmark (Syfert et al., 2002).

The measured signals are the flow F across the valve, the servo motor stem displacement X and the input signal to the valve CV, that is the output from a controller, all of them being measured in a percentual scale.

The servo motor, positioner and control valve are subjected to the occurrence of 25 faults, shown in table 1, where the signal $(*)$ indicates the faults with two directions; that means these faults can deviate the behavior of the process to a higher or lower value.

Table 1: Faults

Control Valve Faults	
f1	Clogging
f2	Plug or seat sedimentation
f3	Plug or valve seat erosion
f4	Increase of valve stem friction $(*)$
f5	External leakage
f6	Internal leakage
f7	Medium evaporation or critical flow
Pneumatic Servo Motor Faults	
f8	Twisted servo-motor's stem
f9	Servo-motor housing tightness
f10	Servo-motor's diaphragm perforation
f11	Servo-motor's spring fault
Positioner Faults	
f12	Electro-pneumatic transducer fault $(*)$
f13	Stem displacement sensor fault $(*)$
f14	Air supply pressure sensor fault $(*)$
f15	Positioner feedback fault
External Faults	
f16	Positioner supply pressure drop
f17	Unexpected pressure change $(*)$
f18	Fully or partly opened bypass valves
f19	Flow rate sensor fault $(*)$

4 Valve Mathematical Model

In order to construct the structured residuals based on the output error, a mathematical model describing the non-faulty behavior of the valve has to be found. This step is of major importance, since the more accurate the model, the more accurate the fault detection system will be; however, it's known that when the process is of great complexity, it becomes impracticable to obtain its complete description; in cases like that some assumptions can be made in order to simplify the model, and it's up to the engineer to find a good relation between simplicity and accuracy.

Regarding the control valve, the flow across it is dependent of the input signal, the servo motor stem displacement, and the fluid temperature and pressures at the valve inlet and outlet; in this work the fluid temperature and its pressure drop across the valve were maintained constant at values that prevented effects like flashing, cavitation and choked flow to occur. Therefore the only variables able to modify the flow are the input signal CV and the stem displacement X. Given the relations between these 3 variables, and the fact that X is measured in the experiment, 2 models can be constructed: the first represents the dynamics of the servo motor and positioner, while the second represents the dynamics of the valve, as can be seen on figure 2. Theoretically, this approach is better than considering an unique model relating F with CV, because more residuals are able to be constructed, increasing the numbers of faults signatures that can be produced.

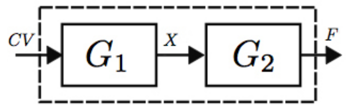

Figure 2: Model Structure of the valve

A ramp signal is applied at the control valve to identify any nonlinear behavior; the response is given at figure 3: it can be seen that the most significative nonlinearity is in the valve dynamics: it has reverse action response, and the flow only starts to change when the stem displacement becomes higher than approximately 45%.

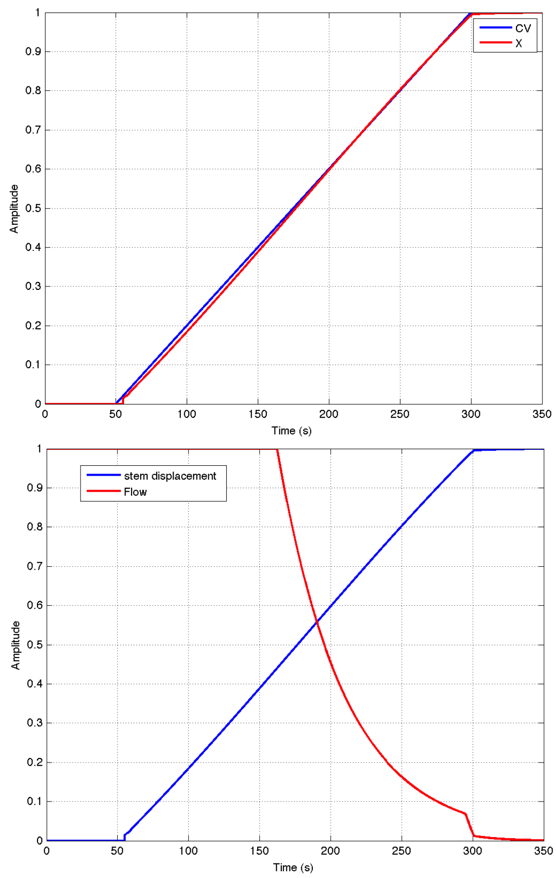

Figure 3: Valve Ramp response

Despite the nonlinearities observed, it is desirable to obtain linear models for G_1 and G_2; this is a very common procedure when dealing with valves (Smith and Corripio, 1985); so the input signal CV is going to be restricted around the operation range of (80% $\sim$ 95%). This procedure will keep the error between the responses of the valve and its linearized model inside acceptable boundaries.

The linear models G_1 and G_2 are going to be calculated with the MATLAB System Identification Toolbox, and three model structures are going to be tested: first-order, second-order (under-damped or critically damped) and second-order over-damped, where only the minimum-phase case is considered for all structures. The models with better accuracy, (validated with different excitation signals then the ones used in the identification case) are going to be selected.

The excitation signals used in the identification case is the GBN - Generalized Binary Noise, known to improve the identification results considerably, due to its capability of specifying the frequency band desired to concentrate more power; that makes possible to define an optimum GBN signal to identify a particular system. This procedure was done for each model structure tested for G_1 and G_2, according to the guidelines of Tulleken (1990).

Neglecting the positioner dynamics, the best model calculated for the servo motor is:

$$G_1(s) = \frac{1.017}{0.3933s^2 + 1.254s + 1} \quad (1)$$

The MATLAB System Identification Toolbox is not able to estimate a satisfactory model for the valve, due to its inverse action characteristic; so, knowing that the relation between inverse and direct action response of a linear model can be expressed by:

$$\begin{aligned} Y_{ia} &= 1 - Y_{da} \\ Y_{ia} &= 1 - G_{da}U; \end{aligned} \quad (2)$$

where Y_{ia} and Y_{da} are, respectively, the inverse and direct action response of a model, the equivalent direct action response of the valve was calculated, and this data was used to estimate the direct action model G_{2ad}:

$$G_{2ad}(s) = \frac{0.968}{1.07s + 1} \quad (3)$$

Then, the response of the inverse action model of the valve is calculated using the model G_{2ad} and the relation expressed in equation (2).

A comparison of the step response of the servo motor and the valve and its corresponding models is given in figure 4: it can be noticed that even with the limitation of the input signal CV at the range (80% $\sim$ 95%), some nonlinearity still were present in the valve dynamics, in the form of a variable gain relating the flow with the stem displacement; as the gain calculated for the model $G_2(s)$ is a constant, some errors were noticed, but were considerable acceptable, given all the simplifications made.

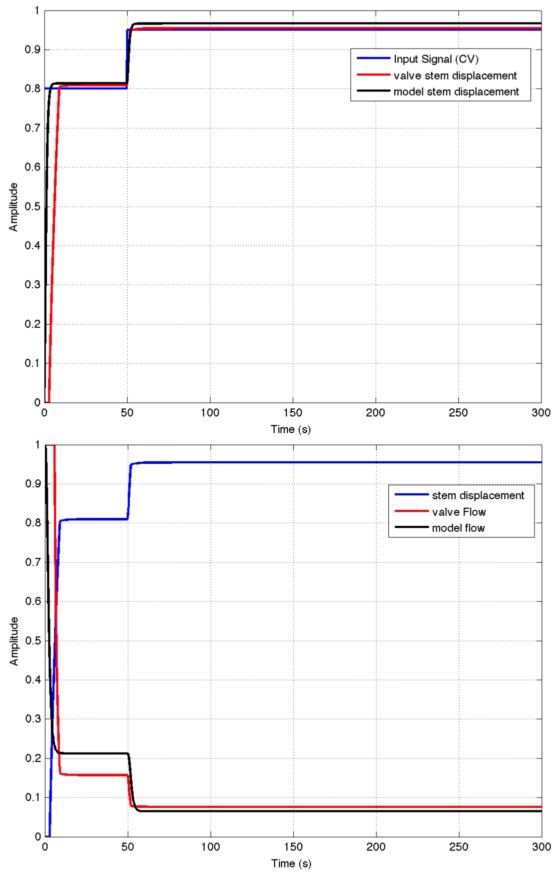

Figure 4: Step responses of valve and model

5 Structured Parity Equations

The structured parity equations were obtained based on the output error equations (Isermann, 2006); regarding figure 2, and considering G_2 as the inverse action model of the valve, two equations can be written:

$$\begin{aligned} r_1 &= X - X_{est} \\ &= X - G_1(s)CV \end{aligned} \quad (4)$$

$$\begin{aligned} r_2 &= F - F_{est} \\ &= F - G_2(s)X \end{aligned} \quad (5)$$

In matrix notation:

$$\begin{bmatrix} r_1 \\ r_2 \end{bmatrix} = \begin{bmatrix} 1 \\ -G_2(s) \end{bmatrix} X + \begin{bmatrix} -G_1(s) \\ 0 \end{bmatrix} CV + \begin{bmatrix} 0 \\ 1 \end{bmatrix} F \quad (6)$$

To produce the structured residuals r^*, equation (6) has to be multiplied by a matrix W, resulting in a vector of 3 components, each one independent of one variable, as shown:

$$r^* = \begin{bmatrix} r_1^* \\ r_2^* \\ r_3^* \end{bmatrix} \begin{matrix} \text{(Independent of } X) \\ \text{(Independent of } CV) \\ \text{(Independent of } F) \end{matrix}$$

The matrix W that satisfies these conditions is:

$$W = \begin{bmatrix} G_2(s) & 1 \\ 0 & 1 \\ 1 & 0 \end{bmatrix} \quad (7)$$

Therefore, the structured residuals are given by:

$$\begin{aligned} r^* &= W \begin{bmatrix} r_1 \\ r_2 \end{bmatrix} \\ &= \begin{bmatrix} G_2(s) & 1 \\ 0 & 1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} X - G_1(S)CV \\ F - G_2(s)X \end{bmatrix} \\ &= \begin{bmatrix} F - G_1(s)G_2(s)CV \\ F - G_2(s)X \\ X - G_1(s)CV \end{bmatrix} \end{aligned} \quad (8)$$

Equation (8) can be written as:

$$r^* = \begin{bmatrix} r_1^* \\ r_2^* \\ r_3^* \end{bmatrix} = \begin{bmatrix} F - G_2(s)X_{est} \\ F - G_2(s)X \\ X - X_{est} \end{bmatrix} \quad (9)$$

A block diagram showing how the structured residuals are related to the Control valve and its models is shown in figure 5:

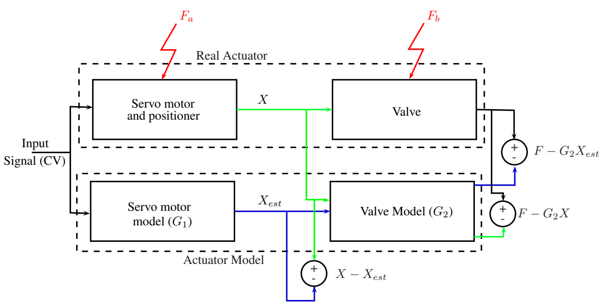

Figure 5: Structured residuals block diagram

The group of all possible faults that can act on the servo motor and positioner are represented by F_a, while F_b is the group of faults that can act on the valve. From figure 5 it can be concluded that the structured residual r_1^* is sensitive to all the faults belonging to F_a or F_b, that may occur in the whole actuator assembly; however, the structured residual r_2^* and r_3^* will only be sensitive to one of these groups: r_2^* is sensitive only to faults in the valve body, while r_3^* is sensitive only to faults acting in the servo motor and positioner. Those relations are expressed in the table 2, where the signal "$\neq 0$" means that a residual is sensitive to the occurrence of a specific fault group, while "$= 0$" means that the residual is insensitive.

Table 2: Residuals behavior

	Residuals		
Fault	r_1^*	r_2^*	r_3^*
F_a	$\neq 0$	$= 0$	$\neq 0$
F_b	$\neq 0$	$\neq 0$	$= 0$

6 Experiment Methodology

To verify the efficacy of the structured residuals projected in (9), a step signal with initial and final value of 80% and 95% is applied at CV for $300s$ (the same step signal can be seen at figure 4); this procedure is done first to the valve without faults, to give a reference behavior of the structured residuals, and can be seen in figure 6:

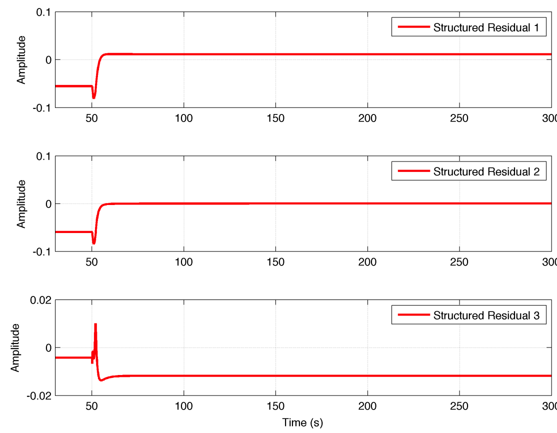

Figure 6: Residuals for the valve without fault

Then the same procedure is repeated for all the faults shown at table 1, with maximum fault strength, abrupt development at the time instant $t = 60s$, and duration of 240 seconds. Only the residuals that deviate to a constant value are considered in the identification of the fault signatures.

7 Results

The detection results are given in table 3, giving necessary information to perform fault diagnosis.

At total, 17 faults are able to be detected, with 11 distinct fault signatures: the faults $f7$, $f9$, $f13$ (with fault direction -1), $f15$, $f19$ (with fd$= 1$), f_2 andf_3 can be isolated, but the group of faults ($f1$, $f10$, $f16$), and ($f6$, $f13$(fd=1), $f18$) can't; this means that if the value of the vector r^* in a given moment is $[4(+)\ 5(+)\ (0)]^T$, we can only be sure that at least one of the faults in the group ($f6$, $f13$(fd=1), $f18$) is acting on the valve.

Although the fault signatures caused in the vector r^* in the occurrence of $f17$ and $f12$ have two distinct patterns, the detection system isn't able to conclude the fault direction; therefore, the statement that the faults $f17$ and $f12$ can be iso-

Table 3: Detection Results

Fault	r_1^*	r_2^*	r_3^*
f1	4(+)	0	4(-)
f10	4(+)	0	4(-)
f16	4(+)	0	4(-)
f6	4(+)	5(+)	0
f13 (fd=1)	4(+)	5(+)	0
f18	4(+)	5(+)	0
f17 (fd=1)	4(+)	5(+)	4(-)
f17 (fd=-1)	4(+)	5(+)	4(-)
f12 (fd=1)	3(+)	0	2(-)
f12 (fd=-1)	3(+)	0	2(-)
f7	4(+)	4(+)	3(-)
f9	(+)	0	(-)
f13 (fd=-1)	0	2(-)	4(-)
f15	0	(+)	0
f19 (fd=1)	3(+)	3(+)	0
f2	0	(-)	2(-)
f3	2(+)	2(+)	0

$(*)$ stands for fault direction -1

lated depends on what's required of the fault detection system: only to detect a fault presence, or to also determine its direction.

Regarding $f12$, a electro-pneumatic transducer fault, its development time had to be changed to $t = 10s$ for its fault signature to be detected. This has to be done due to the fact that the step signal applied in CV only excites the system (therefore altering the transducer output) at the time instant t = 50s.

The behavior of the structured residuals when the valve is subjected to the fault $f16$, a pressure drop in the positioner supply is given at figure 7; it can be seen that, although the structured residual r_2^* shows some deviation, it isn't considered, because in order to simplify the detection system, only the residuals that deviate to a constant value are used. The residuals r_2^* of faults $f1$ and $f10$, and r_3^* of $f3$ also have irregular deviations that were ignored; the fault signature of $f3$ can be seen at figure 8.

In the overall case, the detection results are in accordance with table 2 (containing the predictions of the structured residuals behavior in the occurrence of 2 groups of faults); the residual r_1^* is sensitive for all the faults simulated in the experiment; it has null value for the faults $f15$, $f2$ and $f13(fd = -1)$ because the deviations presented don't exceed the thresholds, as can be seen in figure 9.

Comparing tables 1 and 2, the residual r_2^* should only be sensitive to the faults $f1$ to $f7$, and be insensitive to faults $f8$ to $f11$; the results show that r_2^* is sensitive to 8 faults, where 4 of them ($f2$, $f3$, $f6$ and $f7$) are predicted. On the other hand, it is insensitive to 6 faults, where 2

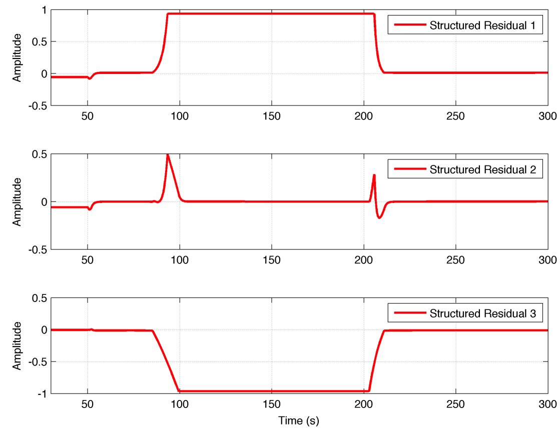

Figure 7: Residuals for the valve with fault $f16$

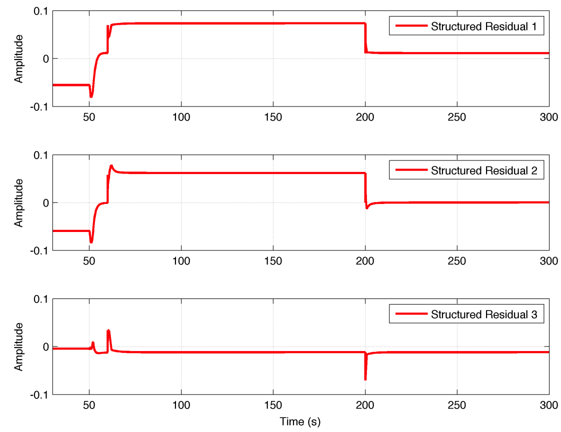

Figure 8: Residuals for the valve with fault $f3$

of them ($f9$ and $f10$) are predicted. The unpredicted detections happens with faults that act in components not included in the models G_1 and G_2 (positioner and external faults).

The residual r_3^* should only be sensitive to the faults $f8$ to $f15$, and insensitive to faults $f1$ to $f7$; the results show that r_3^* is sensitive to 11 faults, where 4 of them ($f9$, $f10$, $f12$ and $f13$) are predicted. From the remaining 7 faults, 3 ($f1$, $f2$ and $f7$) are valve faults. Besides that, r_3^* is insensitive to 6 faults ($f3$, $f6$, $f13$, $f15$, $f18$ and $f19$), where 2 of them ($f6$ and $f3$) are predicted. Again, the faults in components not included in the model affected the performance of the detection system.

8 Conclusion

This paper presents the development of a fault detection system for the control valve. The output error equations are used to produce the vector of structured residuals r^*; to achieve, two simplified linear models, G_1 and G_2, describing the behavior of the pneumatic servo motor and the valve without the influence of faults had to be calculated. The choice of two models instead of one is made due to the higher number of fault signatures that

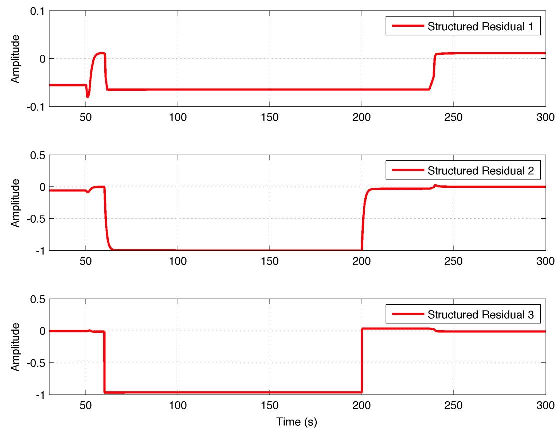

Figure 9: Residuals for the valve with fault $f3(fd = -1)$

could be produced.

As the valve response to a ramp input revealed a nonlinear behavior, some restrictions has to be made, like keeping the input signal to the valve within the range of ($80\% \sim 95\%$), to prevent the error between the valve and the model to become too high.

After the implementation of the fault detection system, 17 of 25 faults were able to be detected, and 7 could be isolated. This result proved to be good, given the fact that the fault detection system was constituted of 2 simplified linear models used to represent the behavior of such an complex and nonlinear system as a control valve.

The experiment results are consistent to the predicted behavior of the structured residuals, and it became clear that better results can be achieved if a more detailed model, that includes the dynamics of the positioner and the modeling of external faults, is used. Besides that, the structured residuals are known as an efficient tool in the detection of additive faults, that change the process output by adding an offset to it, and not depending on the process input. For the detection of parametric faults, like e.g., the change of some valve parameters, some parameter estimation method have to be used, and again a detailed structure of the process model is going to be required.

9 Acknowledgments

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