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# NEURAL APPROXIMATORS FOR FAULT DETECTION OF ACTUATORS IN THE PRESENCE OF FRICTION: THE CASE OF THE DAMADICS BENCHMARK PROBLEM

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Abstract: The problem of actuator fault detection (FD) for mechanical systems with friction phenomena is addressed. A novel methodology based on an on-line neural approximation scheme is applied to the DAMADICS benchmark problem. The FD algorithm is based on the well known dynamic LuGre model characterizing mechanical friction effects. This friction model is suitable for use in the simulation model of the DAMADICS benchmark which is developed in order to approximate the industrial process in a sugar factory located in Lublin (Poland). The approximation scheme makes it possible to evaluate on line suitable thresholds for the detection of incipient or abrupt faults regarding the friction and the spring models of the considered actuator.


Keywords: Fault detection. Actuators with friction. Neural networks. DAMADICS Benchmark

## 1. INTRODUCTION

Monitoring complex nonlinear plants for the purpose of automated fault detection is a task of fundamental importance in many areas of control engineering. Therefore, since the early '70s, a lot of approaches to fault diagnosis (FD) have been developed that may be roughly classified as (i) model-based FD approaches and (ii) model-free FD approaches. In this paper, we focus on a model-based technique (for overviews on these research activities, we refer the reader, for instance, to the classical books (Gertler, 1998; Patton *et al.*, 1989), and to the references cited therein).

In a wide range of physical systems such as mechanical systems, electro-magnetic systems, actuators, sensors etc., non-smooth nonlinearities such as friction, backlash and hysteresis, severely limit their performance and reliability. In this work, we concentrate on detecting faults in mechanical systems with friction with emphasis on the application to the DAMADICS actuator benchmark problem. In this connection, it is worth noting that friction is present in any system that involves mechanical motion. It may cause large steady state errors and oscillations generated by a combination of friction, which counteracts motion, and an instability mechanism, thus making friction a very complicated phenomenon. The aforementioned reasons impose extra complexity to any scheme that is targeted at diagnosing faults in such systems.

Several research activities (Armstrong and Hélouvry, 1991), (Armstrong *et al.*, 1994) have shown that

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a friction model involving dynamics is necessary to describe accurately the friction phenomena. Various dynamic models have been proposed (Canudas de Wit *et al.*, 1995; Armstrong and Hélouvry, 1991; Rice and Ruina, 1983). However, the unknown structure of the incoming faults significantly magnifies the level of system uncertainty. Neural networks with their good adaptability and inherent approximation capabilities, have already been utilized mainly towards the friction compensation problem (Canudas de Wit and Ge, 1997b; Kim and Lewis, 2000; Huang *et al.*, 2002).

In the framework of the DAMADICS research network funded by the European Union, a benchmark model was developed to approximate the behavior of the evaporation stage of a sugar factory in Lublin (Poland). Actuators under consideration consist of a control valve, a pneumatic linear servomotor and a positioner. In such a kind of electromechanical systems, the presence of friction phenomena is unavoidable and significantly increases the complexity of the FD problem.

In this paper, we apply a methodology described in a companion paper [1] (Papadimitropoulos *et al.*, 2003) (aimed to detect faults in mechanical systems with friction that perform linear motion) to the DAMADICS benchmark for actuator fault detection. The basic module in the proposed architecture is an on-line approximator which is based on linear-in-the-weights neural network structures (the on–line approximations approach to FD dates back to the seminal work (Polycarpou and Helmicki, 1995)). To model the effects of friction, the dynamic LuGre model (Canudas de Wit *et al.*, 1995) is used. However, we don't assume knowledge of system nonlinearities. Furthermore, the friction internal state is not assumed to be available for measurement. By means of the on-line approximation scheme, it is possible to learn the system dynamics under nominal operating conditions. This, in turn, allows to design an appropriate threshold function for the purpose of actuator FD.

## 2. THE DAMADICS BENCHMARK

In this section, a brief description of the actuator that will be investigated in the paper is given. The plant under concern is the sugar factory Cukrownia Lublin S.A located in Lublin (Poland). Specifically, we consider the evaporation process where the main task is to thicken the beet juice coming from the cleaning and filtering stages, at the minimum heat-energy consumption. The first three sections work with natural juice circulation and the last two work with juice circulation forced by pumps. We focus on the first section, consisting of one evaporator and containing an important actuator, located on the inflow of thin juice and controlling its level in the first stage of evaporation station.

As shown in Fig. 1, the actuator is made of three main components (Bartys, 2002):

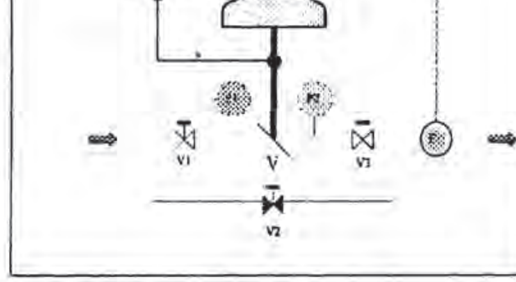


Fig. 1. A control valve-pneumatic servomotor-positioner device.

- Control valve driven by a servomotor, which is used to prevent, to allow and/or to limit the flow of fluids.
- Spring-and-diaphragm pneumatic servomotor; this is a compressible fluid powered device where the fluid acts upon the flexible diaphragm thus providing linear motion of the servomotor stem.
- Positioner; this device is used to eliminate control-valve stem miss-positions due to external or internal sources such as friction, hydrodynamic forces, etc..

Fig. 2 shows a more detailed overview of the servomotor as well as its physical layout; the effects (forces) of the other two components are emphasized (the meaning of the symbols is straightforward and is not presented for the sake of brevity). A rather detailed dynamic model of the above evaporation process (and of the actuator as well) has been developed and validated in the context of the DAMADICS research training network. The unavoidable friction effects are modelled by means of suitable hysteresis functions. As we shall see later on, in this paper the friction effects will be described by a different dynamic model, namely the LuGre model.

## 3. PROBLEM FORMULATION

In this section, the LuGre (Canudas de Wit *et al.*, 1995) model of friction and the basic ideas on which our work is based, are presented. As it is

[1] This paper can be obtained on request to the authors.

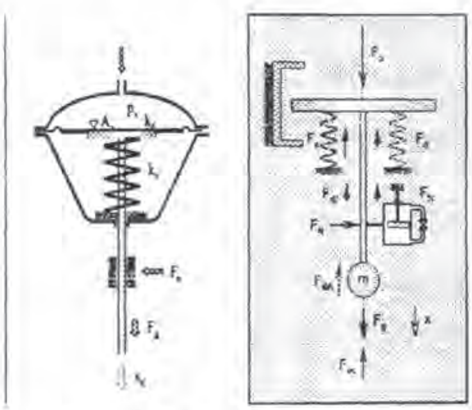

Fig. 2. The pneumatic servomotor and its physical layout.

mentioned before, the reason to use this friction model is that it is able to capture important phenomena such as presliding displacement, frictional lag, stick-slip motion, etc.. Another important reason is that, in the considered actuator, the motion corresponds to a low-velocity motion. In such a case, the friction nonlinearities dominate and the LuGre model is very suitable to characterize these nonlinear effects.

Consider the linear motion of a mass $m$ driven by an input force $u$:

$$m\ddot{x} + Kx + F = u \tag{1}$$

where $F$ represents the friction force, $K > 0$ denotes the spring constant, $x$ the mass position, and $\dot{x}$ its velocity. To model the effects of friction, the dynamic LuGre model (Canudas de Wit *et al.*, 1995) is used:

$$F = \sigma_0 z + \sigma_1 \dot{z} + \sigma_2 \dot{x} + \omega(x, \dot{x}, z) \tag{2}$$

$$\dot{z} = -\alpha(\dot{x})|\dot{x}|z + \dot{x} \tag{3}$$

where the friction internal state $z$ describes the averaging deflection of the contact surfaces during the sticking phases and $\omega(x, \dot{x}, z)$ denotes a friction modelling error. This modelling error term has been included in the standard LuGre friction model (2) to take into account possible uncertainties, disturbances, etc. We assume that $|\omega(x, \dot{x}, z)| \leq \bar{\omega}$, where $\bar{\omega} \geq 0$ is an ***unknown*** but small constant. Furthermore, the parameters $\sigma_0$, $\sigma_1$, $\sigma_2$, (stiffness, damping and viscous coefficients, respectively) that appear in (2) are positive and are considered unknown, too. In (Canudas de Wit *et al.*, 1995), the function $\alpha(\dot{x})$ is given by

$$\alpha(\dot{x}) = \frac{\sigma_0}{f_c + (f_s - f_c)e^{-(\dot{x}/v_s)^2}}$$

where $f_c$ is the Coulomb friction, $f_s$ is the stiction force and $v_s$ is the Stribeck velocity. It is apparent that $0 < \sigma_0/f_s \leq \alpha(\dot{x}) \leq \sigma_0/f_c$. In practice, $\alpha(\dot{x})$ depends on several factors such as material properties, temperature etc.

Defining $x_1 \triangleq x$, $x_2 \triangleq \dot{x}$, it follows that

$$\dot{x}_1 = x_2 \tag{4}$$

$$\dot{x}_2 = -\alpha_1 x_2 + (\alpha_3 \alpha(x_2)|x_2| - \alpha_2)z + \alpha_4 u - \\ -\alpha_4 \omega(x_1, x_2, z) - \alpha_5 x_1 \tag{5}$$

$$\dot{z} = -\alpha(x_2)|x_2|z + x_2 \tag{6}$$

where $|x_2|\alpha(x_2) \geq 0$, $\alpha_1 \triangleq (\sigma_1 + \sigma_2)/m$, $\alpha_2 \triangleq \sigma_0/m$, $\alpha_3 \triangleq \sigma_1/m$, $\alpha_4 \triangleq 1/m$, and $\alpha_5 \triangleq K/m$.

For system (4)-(6), the following assumptions are introduced:

*Assumption 1.* The state variables $x_1$ and $x_2$ are available for measurement.

*Assumption 2.* Let $\mathcal{U}$ be the class of piecewise continuous and bounded signals. Then, for any $u \in \mathcal{U}$ and any initial condition, the state trajectories $x_1$, $x_2$ are uniformly bounded.

It is worth noting that the internal friction state $z$ is not assumed to be available for measurement, and the function $\alpha(x_2)$ as well as the positive parameters $\alpha_i$, $i = 1, \ldots, 5$ are considered unknown.

The faults considered in this paper are modelled as additive perturbations (occurring at some unknown time instant $T_f$) $\Delta F_1(x_1, x_2, t)$ and $\Delta F_2(x_1, x_2, t)$ to the nominal $F$ and $K$ in (1), respectively. In this respect, the following further assumption is introduced (no multiple faults are considered in this paper).

*Assumption 3.* Only one single fault may occur at a given time $T_f$.

After occurrence of a fault, the dynamics of the systems becomes:

$$\dot{x}_1 = x_2 \tag{7}$$

$$\dot{x}_2 = -\alpha_1 x_2 - \alpha_5 x_1 + \alpha_4 u + (\alpha_3 \alpha(x_2)|x_2| - \alpha_2)z - \\ -\alpha_4 \omega(x_1, x_2, z) + [(\alpha_3 \alpha(x_2)|x_2| - \alpha_2)z - \\ -\alpha_1 x_2 - \alpha_4 \omega(x_1, x_2, z)]\Delta F_1 - \alpha_5 x_1 \Delta F_2 \tag{8}$$

$$\dot{z} = -\alpha(x_2)|x_2|z + x_2 \tag{9}$$

*Remark 1.* The additive perturbations $\Delta F_1(x_1, x_2, t)$ and $\Delta F_2(x_1, x_2, t)$ to the nominal values of $F$ and $K$, respectively, reflect variations in the normal forces in contact, temperature changes and material wear, as well as spring's stiffening and relaxation phenomena. These malfunctions are typically encountered for instance in actuators installed in harsh plant environments as is the case of the DAMADICS actuator described in Section 2.

It is important to clarify that the above-described dynamic model for a mechanical system with friction phenomena in both nominal and faulty modes of operation has a different structure with respect to the DAMADICS model. However, the complexity of the DAMADICS model rules out the possibility of using it in the framework of a nonlinear model-based FD algorithm. Therefore, the key idea is to determine a suitable LuGre model to make its behavior very similar to the DAMADICS one from an input–output perspective. This will allow us to use the LuGre model to design a model-based FD scheme. In the next section, this task will be achieved by using an on-line approximation scheme. In Fig. 3, this intuitive idea is shown in a schematic way. [2]

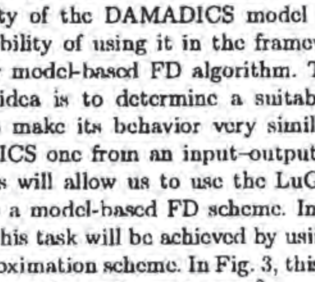


Fig. 3. Architecture of the adaptive on–line approximation scheme.

## 4. ON-LINE APPROXIMATION SCHEME

In the previous section, the need to design an on–line approximation scheme to learn the input–output behavior of the LuGre model (which, in turn, is very similar to the DAMADICS model nominal input–output behavior) has been highlighted. The approximator's output will serve as the residual signal for fault detection. In this respect, as will be seen later on, a key role is played by the functional approximation scheme that in this work is implemented by one–hidden–layer neural structures with a linear output layer. Such a class of neural approximators can be characterized as $y = W^T S(v)$, where $y \in \Re^{n_1}$ and $v \in \Re^{n_2}$ denote the neural net output and input, respectively, $W$ is an $L$-dimensional vector of synaptic weights, and $S(v)$ is a $L \times n_1$ matrix of regressor terms. In this paper, we assume that the regressor terms contain high order connections of sigmoidal functions (Rovithakis and Christodoulou, 2000). Several other choices are of course possible (see the discussion in (Papadimitropoulos *et al.*, 2003)).

It is well known that, if the number of regressor terms $L$ is sufficiently large, then there exist a weight vector $W^*$ such that ${W^*}^T S(v)$ can approximate $f(v)$ to any degree of accuracy, in a given compact set. This property allows us to focus on linear in the weights neural networks without loss of generality and with great advantage in terms of simplicity of algorithm design.

Now, consider the following on-line approximator

$$\dot{\hat{x}}_1 = x_2 + k_1\tilde{\xi}_1 - \hat{\alpha}_5\tilde{\xi}_2 \tag{10}$$
$$\dot{\hat{x}}_2 = -\hat{\alpha}_1\hat{x}_2 - \hat{\alpha}_5\hat{x}_1 + \hat{\alpha}_4 u + k_2\tilde{\xi}_2 - \phi \tag{11}$$

where $k_1, k_2 > 0$ are design constants and $\phi$ denotes a function that will be defined later on. Moreover, let us introduce the estimation error

$$\tilde{\xi}_i \stackrel{\triangle}{=} x_i - \hat{x}_i, \quad i = 1, 2 \tag{12}$$

Then, from (4),(5), and (10)-(12), it follows that

$$\dot{\tilde{\xi}}_1 = -k_1\tilde{\xi}_1 + \tilde{\alpha}_5\tilde{\xi}_2 \tag{13}$$
$$\begin{aligned}\dot{\tilde{\xi}}_2 = &-\alpha_5\tilde{\xi}_1 - (k_2+\alpha_1)\tilde{\xi}_2 + \tilde{\alpha}_1\hat{x}_2 + \tilde{\alpha}_5\hat{x}_1 - \\ &-\tilde{\alpha}_4 u + [\alpha_3\alpha(x_2)|x_2| - \alpha_2]z - \\ &-\alpha_4\omega(x_1, x_2, z) + \phi\end{aligned} \tag{14}$$

where $\tilde{\alpha}_i \stackrel{\triangle}{=} \hat{\alpha}_i - \alpha_i$, for $i = 1, 4, 5$.

Basing on Lyapunov stability analysis [3] arguments, it turns out that the function $\phi$ introduced in (11) takes on the form

$$\begin{aligned}\phi \stackrel{\triangle}{=} &-[|x_2|\hat{w}_1^T S_1(x_2, |x_2|) + \hat{w}_2^T S_2(|x_2|) \\ &+|x_2|\hat{\epsilon}_1 + \hat{b}_1]sigm(\tilde{\xi}_2)\end{aligned} \tag{15}$$

where $\hat{w}_1^T S_1$ and $\hat{w}_2^T S_2$ are the neural approximators, and $sigm(\cdot)$ denotes a sigmoidal smooth approximation of the signum function, that is $sigm(x) = sgn(x) + \epsilon_s(x)$, where $sgn(x)$ is the sign function, and the error $\epsilon_s(x)$ satisfies $|\epsilon_s(x)| \leq 1$.

In (13) and (14), $k_1$, $k_2 > 0$ are design constants and the parameters $\hat{\alpha}_1$, $\hat{\alpha}_4$, $\hat{\alpha}_5$ are given by the following adaptive rules:

$$\dot{\hat{\alpha}}_1 = -\hat{x}_2\tilde{\xi}_2\,; \ \dot{\hat{\alpha}}_4 = u\tilde{\xi}_2\,; \ \dot{\hat{\alpha}}_5 = -\tilde{\xi}_2(\tilde{\xi}_1 + \hat{x}_1)$$

Analogously, also the weights $\hat{w}_1$, $\hat{w}_2$ and the parameters $\hat{\epsilon}_1$ and $\hat{b}_1$ are given by

[2] The use of the LuGre model needs the velocity measurement which is not available in the DAMADICS actuator case. However, the velocity can be estimated using the position measurements by means of a suitably designed Kalman filter.

[3] The analysis is omitted due to space limitations.

$$\dot{\hat{w}}_1 = |\tilde{\xi}_2||x_2|S_1(x_2, |x_2|)\,;\ \dot{\hat{w}}_2 = |\tilde{\xi}_2|S_2(|x_2|)$$
$$\dot{\hat{\epsilon}}_1 = |\tilde{\xi}_2||x_2|\,;\ \dot{\hat{b}}_1 = |\tilde{\xi}_2|$$

The robustness of the above adaptive laws and the convergence properties of the on–line approximation scheme are not reported due to space limitations and can be found in (Papadimitropoulos *et al.*, 2003) where suitable projection methods are exploited.

### Residual evaluation

The faults concerning friction may introduce variations in the normal forces in contact, temperature changes and material wear or to uniformly alter the parameters of the dynamic friction model. Let us define the following quantity

$$\Phi \triangleq [\ |x_2|\hat{w}_1^T S_1(x_2, |x_2|) + \hat{w}_2^T S_2(|x_2|) + \\ +|x_2|\hat{\epsilon}_1 + \hat{b}_1\ ]$$

Owing to the convergence analysis presented in (Papadimitropoulos *et al.*, 2003), it follows that $\Phi$ can be used to define the threshold function $\rho$ as:

$$\rho = \frac{|\Phi|}{k_2} \qquad (16)$$

Choosing now as a residual signal $\tilde{\xi}_2$ with its correspondent threshold (16), we can say that a fault will be detected when $\tilde{\xi}_2 \geq \rho$.

## 5. DAMADICS SIMULATION RESULTS

In this section we present the simulation results when a fault that concerns friction or the servomotor's spring occurs. The results were taken according to the scheme that is depicted in Fig. 4. $P_1$ and $P_2$ represent the pressure before and af-

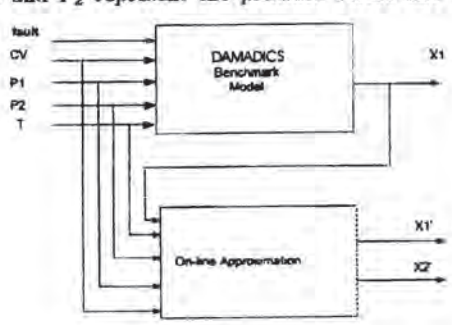


Fig. 4. Architecture used for DAMADICS simulation trials.

ter the control valve and were set to be $3.5 \cdot 10^6$Pa and $2.6 \cdot 10^6$Pa respectively. $T$ represent the water temperature and was 20°C. $CV$ is the control value that takes values in $[0, 1]$. A value of "1" expresses that the valve is closed where a value of "0" a fully-opened valve. The output of the benchmark model $X1$, represents the rod's displacements. To implement the on-line approximator we have employed High Order Neural Networks (HONNs), with sigmoid activation function of the form $s(x) = \frac{m}{1+e^{-l(x-c)}} + \lambda$. Specifically, by trial and error method for the term $\hat{w}_2^T S_2(|x_2|)$ we have chosen a $5^{th}$-order HONN with $(m, l, c, \lambda) = (0.8, -4, 2.119, -1.5)$, while for $\hat{w}_1^T S_1(x_2, |x_2|)$ a $2^{nd}$-order HONN with $(m, l, c, \lambda) = (1.41, -10.0225, 0.5974, -2.11)$. The design constants $k_1$ and $k_2$ were set to be 100 and 400 respectively. The outputs $X1'$ and $X2'$ of the on-line approximator represent the estimated position and velocity respectively. As simulations have been carried out in a noise-free environment, the velocity was estimated by introducing a high-pass filter. According also to benchmark definition, the faults are standardized to the range of $[-1\ 1]$. The limiting values "-1" and "1" corresponds to some pre-defined states or physical values $(\Delta f_{min}, \Delta f_{max})$. Fault notations are given in Table. 1. Furthermore, the fault concerning

| Friction fault | | Servomotor spring fault | |
|---|---|---|---|
| -1 | No friction | -1 | Spring's perforation |
| 0 | Unchanged friction | 0 | No fault |
| 1 | Advanced friction | 1 | Spring's tightness |

Table 1. Fault specifications.

friction is an incipient one. The fault that we simulated occurs at $t = 70$ sec and takes its final value "1" after 20 sec. A detection decision (0-no fault, 1-fault) is being made when $|\tilde{\xi}_2| \geq \rho$ for more than one sample time. The simulations results are depicted in Fig. 5.

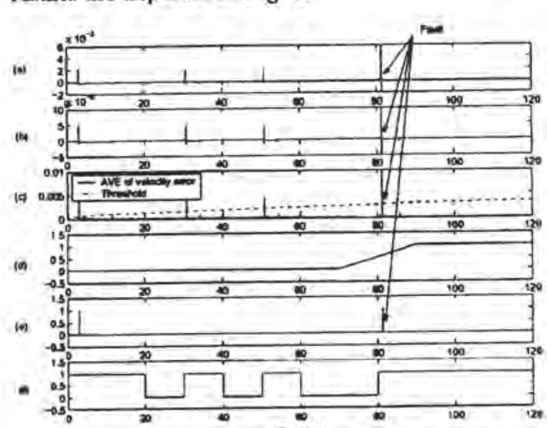


Fig. 5. Behaviors of (a) position error $\tilde{\xi}_1$. (b) velocity error $\tilde{\xi}_2$. (c) absolute value of velocity error, $|\tilde{\xi}_1|$ threshold $\rho$. (d) A fault evolution. (e) detection decision. (f) control Value (CV).

The conclusions that can be drawn from Figs. 5(a)-(b) are that the adaptive scheme is able to learn on line the behavior of the model with very small errors. In Fig. 5(c) a parallel graph of $|\bar{\xi}_2|$ and of the corresponding threshold $\rho$ is plotted. As it mentioned before, a fault decision is taken when $|\bar{\xi}_2| \geq \rho$ for more than one sample time. Specifically:

$$|\bar{\xi}_2(t)| \geq \rho(t)$$
$$\&$$
$$|\bar{\xi}_2(t+\Delta t)| \geq \rho(t+\Delta t)$$

where $t$ is the time instant at which $|\bar{\xi}_2| \geq \rho$ and $\Delta t$ is the sampling step. This is the reason why no fault indication is turned on before the actual occurrence of the fault (see Fig. 5(c)), despite some spikes occurring before the time of fault occurrence (see Fig. 5(c)).

As can be noticed from Fig. 5(c), the fault is detected at $t = 81.12$sec. The fault strength on this time–instant is of about 50% of its final value (Fig. 5(d)), a characteristic which can prevent on time the overall system from serious damages. Similar comments can be made when we simulate the system with the servomotor spring fault (see Fig. 6), which, according to the benchmark definition, is an abrupt fault. In this case, the fault is detected at $t = 70.005$sec.

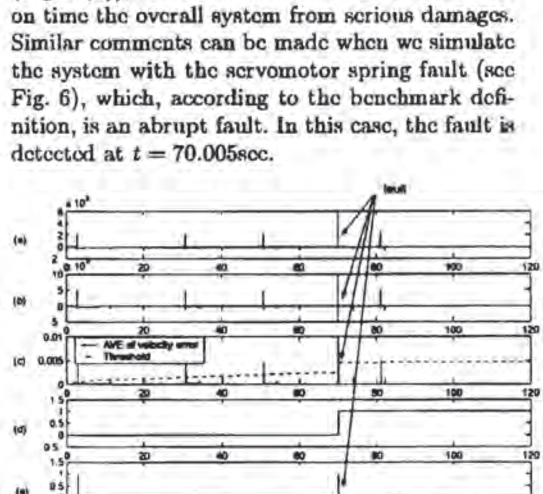


Fig. 6. Behaviors of (a) position error $\bar{\xi}_1$. (b) velocity error $\bar{\xi}_2$. (c) absolute value of velocity error, $|\bar{\xi}_1|$ threshold $\rho$. (d) A fault evolution. (e) detection decision. (f) control Value (CV).

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