A new method for fault detection in a free model context ⋆

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Abstract: This paper presents a new method of fault detection based on residual signal generation. Most of the existing diagnostic methods that use the residual to detect a failure are often based on the knowledge of the system model. The developed method does not require a precise knowledge or deep information about the system model. It is based on the reconstruction of the system output via an ultra-local model and a model-free controller. The reconstructed/estimated output is used to build the residual signal which is the fault indicator. Several simulation tests have been performed to evaluate the potential of the proposed approach for fault diagnosis. A fault on an actuator of the system is simulated in linear, non-linear and multi-input non-linear case studies. The simulation results reveal that the fault is successfully detected for all these systems under a noisy environment.

Keywords: Fault detection; Actuator fault; Model Free Control; Model Free Fault Detection.

1. INTRODUCTION

A fault can be defined as an unauthorized deviation of one or more system parameters from normal operation to unusual function. In recent years, researchers have become increasingly interested in Fault Detection and Diagnosis of systems due to their sensitivity which requires a high level of security Venkatasubramanian et al. (2003). The presence of a fault can be detrimental to both the machine and the human user when the detection is not performed in time.

Several fault detections tools have been developed in recent years. They can be classified in two main approaches: the first one based on data and signal processing Schwab et al. (2018). Libal and Hasiewicz (2018) proposed new wavelet representation rules for fault detection. Sánchez et al. (2018) introduced a variable frequency sinusoidal signal into the closed loop to examine the consistency of the output signal with the fault signature. The second one is based on the analytical model Gertler (1991). The latter is also called the model-based approach; it relies on knowledge of the system dynamics to build a model that reflects the most realistic behavior of the system. In the model-based approach, fault detection can be performed by evaluating a residual signal Fliess et al. (2004) or by estimating and identifying fault variables Join et al. (2005). The residual signal is generated by comparing the output of the controlled system with the estimated output. Observers are widely used for fault detection, either with the estimation of the system output or with the system states whose measurement is not accessible. Meziane et al. (2015) designed a sliding mode observer for the diagnosis of three-cell power converters. The objective is to detect a parametric fault that leads to a change in the value of the capacitor, which is characterized by a deviation in the dynamics of the system. An estimation of states and defects is made via a takagi-sugeneo observe in García et al. (2018). Rozas et al. (2018) applied the concept of analytical redundancy by residue generation to detect faults associated with changing on lithium-ion battery parameters. Model-based methods are relevant for fault detection, but information and knowledge of the model is mandatory. The main challenge before fault detection is to find a model that accurately describes the behavior of the system.

In this paper a novel Model-Free Fault Detection (MFFD) method is presented. This MFFD relies on the model-free control (MFC) strategy introduced by Fliess and Join (2013). In MFC, an ultra-local model that represents the behavior of the system in a very small time frame is

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used to design the controller. In the proposed MFFD method, the system output is estimated through the ultra-local model employed by the MFC. A residual signal is generated between the actual output of the system and the estimated output in order to detect the fault. Therefore, no information about the system model is needed to detect the fault. In addition, the ease of online implementation with a low computational cost are the main advantages of the proposed method. The MFFD aims to detect at least one fault on the actuator for a real-time application.

The paper is structured as follows: in section 2, the MFFD strategy is detailed. Section 3 presents the simulation results obtained for linear and non-linear systems. Conclusion and prospects are presented in section 4.

2. MODEL FREE FAULT DETECTION

As evoked in the previous section, the proposed method is based on the model-free control. A brief overview of the principle of MFC is presented below.

2.1 Model free control:

Model-free control or intelligent PID controllers is suitable for the control of non-linear systems due to the advantage of replacing the global model of the system with an ultra-local model, which is described in more detail in Fliess and Join (2008). The estimation of the system dynamics is done on-line via the input and output of the system, this method suitable for the control of complex systems Barth et al. (2020). The ultra-local model is defined by:

$$y^{(v)} = F + \alpha.u \tag{1}$$

Where: α is a non-physical parameter. F represents the dynamics of the system. (v) is the order of derivation of the output y and u is the input of system.

Polack et al. (2019) presented a method to identify the α parameter. In most applications this parameter is fixed, however Yaseen and Bayart (2018) considered α as a time varying parameter. In fact, the model-free control relies on the good estimation of F. Mboup et al. (2009) proposed an algebraic estimation method that is robust in a noisy environment. The estimate of this function is given by:

$$\hat{F} = \frac{-6}{T^3}\int_{t-T}^{t} (T-2t)y(t) + \alpha t(T-t)u(t)\mathrm{d}t \tag{2}$$

Where $T > 0$ might be quite small and $[t-T; t]$ corresponds to the sliding windows of integration interval. Closing the loop with the intelligent controller iP:

$$u(t) = \frac{1}{\alpha}\left(-\hat{F} + \dot{y_d} + k_p e\right) \tag{3}$$

Where: y_d is the desired trajectory, e is the tracking error defined as $e = y_d - y$ and k_p is the gain of the proportional controller to be tuned.

2.2 Model free fault detection:

The developed method is based on the generation of a residual between the measured output and the estimated output from the ultra-local model in (1). Estimating this

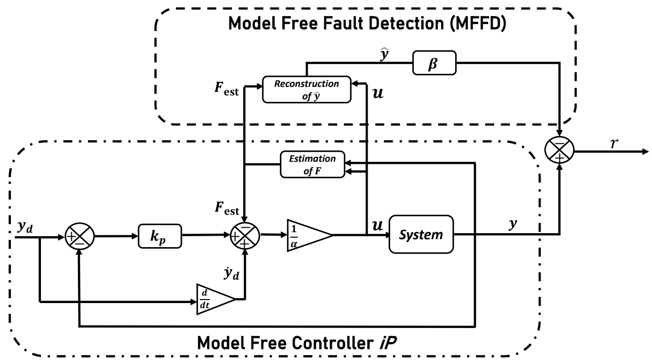

Fig. 1. Diagram of the MFFD and MFC

output does not require any prior knowledge of the system design, which is the main advantage over traditional methods. The idea is based on the reconstruction of the y from the command u and the function $\hat{F}$ which represents the dynamics of the system. The Fig. 1 shows the diagram of MFC and MFFD.

In a continuous and theoretical sense, y for any multi-order system can be written as:

$$y = \int_0^t \left(F(\tau) + \alpha u(\tau)\right) d\tau \tag{4}$$

However, for various reasons (mainly numerical), the estimate of F is erroneous, can be written as follows:

$$\hat{F} = F - \Delta F \tag{5}$$

Substituting (5) into (4) yields:

$$y = \int_0^t \left(\hat{F}(\tau) + \alpha u(\tau) + \Delta F(\tau)\right) d\tau \tag{6}$$

In the case where the estimation error $\Delta F = 0$, the estimated $\hat{y} = y$ in the presence or absence of defect. But in a more realistic context and in practice the estimation error is not 0 ($\Delta F \neq 0$). The sources of this error are multiple: variation of the system dynamics, noise, perturbations, variation of the model-ultra-local due to a defect, disturbances.
Since the ΔF is unknown the calculated $\hat{y}$ becomes:

$$\hat{y} = \int_0^t \left(\hat{F}(\tau) + \alpha u(\tau)\right) d\tau \tag{7}$$

Due to the absence of the ΔF terms in (7) mainly for numerical reasons, the calculated $\hat{y}$ is different from the measured output y. For this raison, $\hat{y}$ requires a correction, a β parameter is introduced to adjust this estimation error. The residual can be written in the following form:

$$r = y - \beta\hat{y} \tag{8}$$

Any bias is interpreted as a fault, there is no distinction between a defect and a disturbance.
When a fault appears, the estimation error is no longer directly related to y/y_d, causing a bias on the residual.

Calculation of β: The β parameter is introduced to compensate the estimation error. In the case of linear systems, this parameter is permanently determined at the first change of the desired trajectory. With the assumption that the system is not affected by a fault during the first

setpoint change.
For non-linear systems case, β does not result from a linear combination of inputs/outputs and their derivatives. The evolution of this parameter depends on the dynamics of the system which is linked to the changes of the setpoint. Therefore, a new determination of this parameter is necessary for each new setpoint change. The calculation of β is performed as follows:

Algorithm 1 β calculation procedure

1: **if** $\dot{y}_d = 0$ and $e \approx 0$ **then**
2: $\quad \beta \leftarrow \beta$
3: **else**
4: $\quad \beta \leftarrow \frac{y}{\hat{y}}$
5: **end if**

For linear systems, β is calculated via Algorithm 1 just for the first setpoint. The retained value remains fixed for all setpoint changes.

3. SIMULATIONS RESULTS

To illustrate the proposed fault detection method, simulation tests are performed for linear and non-linear systems. All systems are controlled by MFC, the fault is simulated by a power loss on the actuator. A white Gaussian noise is added to the output to assess the robustness of this approach in a noisy environment.

3.1 Linear systems

First order system: A first order linear system described as follow is considered:

$$\dot{y} = -5y + 5.u.f$$

Where the iP controller parameters are: $\alpha = 5$, $Kp = 10$ and $Te = 10ms$. An actuator fault is associated with the variable f. In case of normal operation $f = 1$, and in case of fault $f < 1$.
First, to better illustrate the method, a case with no faults is considered, i.e. $f = 1$. Fig. 2 shows the measured output y and the estimated output $\hat{y}$. It can be seen that the estimated output has a different magnitude than y due to the ΔF term which is not calculated. For this reason, the parameter β is added to correct this difference. The β is calculated with Algorithm 1. The obtained value of β is 0.643 and is constant. As shown in Fig. 3, at $31s$, the actuator fault occurs with $f = 0.6$. From this point, the estimation of the output diverges from the measured value. As seen in Fig. 4, before the fault, the residual is null whatever the setpoints. After the fault occurs, the residual is 0.20 which means that the fault has been successfully detected. It should be noticed that the iP is fault tolerant controller. The fault compensation is done immediately, it is interesting to determine if the system is in a fault situation or not.

The Fig. 5 shows the evolution of the parameter β calculated by Algorithm 1. For the three amplitude changes of the desired trajectory, β varies for a while but converges after each trajectory change to a fixed value. This value is retained at the first setpoint change for linear systems. The value where β converges for this example is 0.643. The variations of β in the transient mode are due to the change of the dynamics of $\hat{F}$ which represents the behavior of the system.

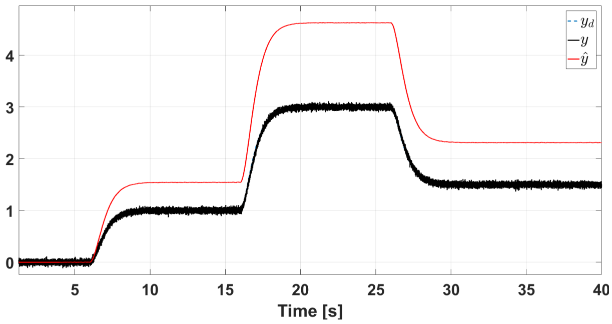

Fig. 2. y and $\hat{y}$ without correction

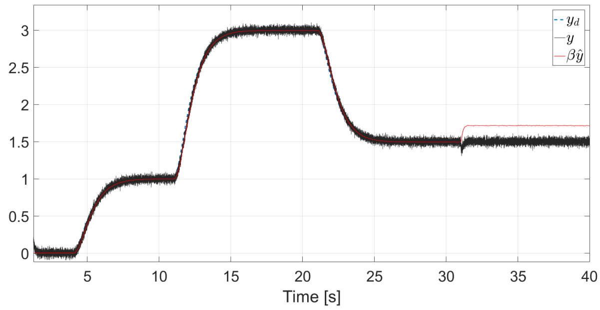

Fig. 3. y and $\beta\hat{y}$ for first order linear system

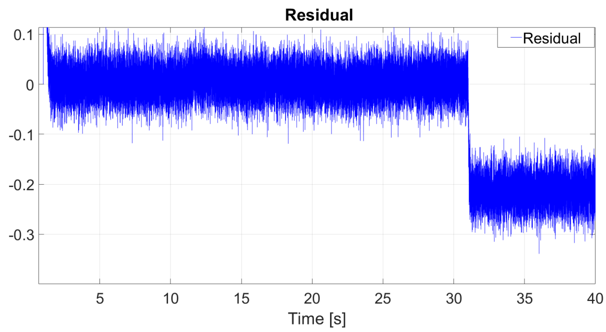

Fig. 4. Residual fault indicator

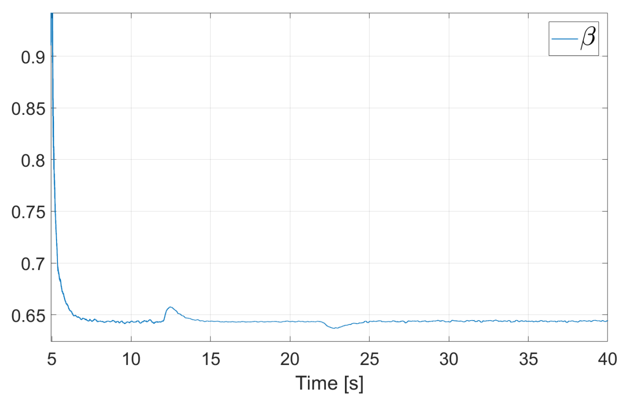

Fig. 5. Evolution of the β calculated by Algorithm 1

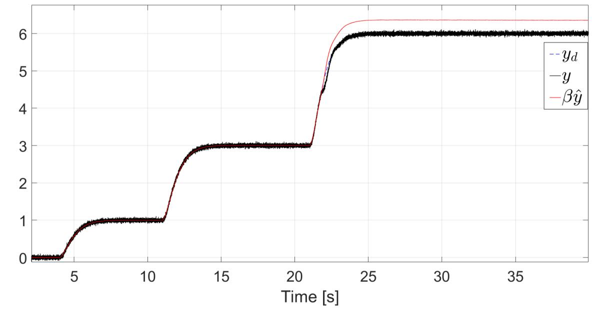

Fig. 6. y and $\beta\hat{y}$ for third order linear system

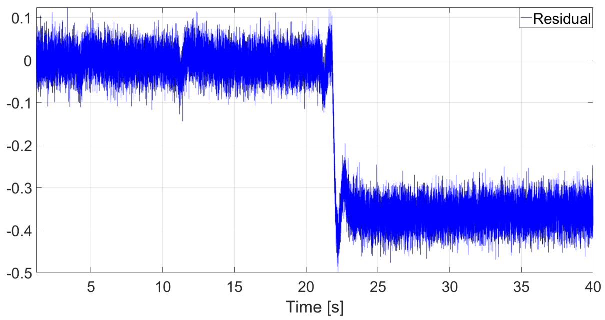

Fig. 7. Residual fault indicator

Third order system: A third order system described as follows is considered:

$$\dot{X} = AX + BU.f$$
$$Y = CX + DU$$

Where:

$$A = \begin{bmatrix} -3 & -1.5 & -0.5 \\ 2 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix}, B = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}, C = [1 \;\, 4 \;\, 4], D = 0$$

The iP controller parameters are: $\alpha = 2.5$, $Kp = 3.5$. The actuator fault is simulated as in the previous example. The β is fixed after the first change of setpoint, the value retained is 0.94.

For this system the fault appears at the time of change of the set point as shown in Fig. 6. The presence of the fault causes a discrepancy between the estimated and the measured output, which results in a divergence of the residual signal as shown in Fig. 7. Of course, the controller quickly recovers the deviation from the measured output to follow the desired trajectory.

3.2 Non-linear systems

First non-linear system: A non-linear system described by the following equation is considered:

$$\dot{y} = y^2 + u.f$$

The parameters of iP controller are: $\alpha = 3$, $Kp = 5$. However, as mentioned in the previous section the value of β changes with the magnitude of the setpoint change. The Fig. 9 shows the evolution of β calculated with Algorithm 1 during the setpoint changes. This can be explained by the fact that $\hat{F}$ is not linear. A fault on the actuator is assumed by changing the value of the parameter f. As shown in Fig.

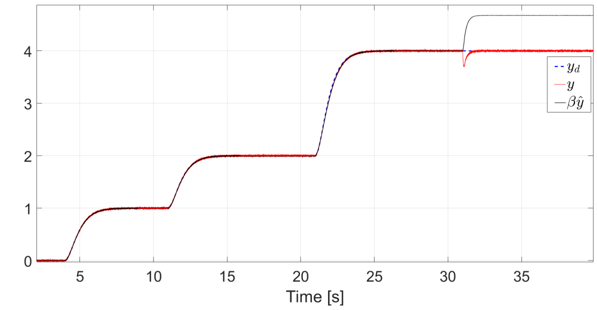

Fig. 8. y and $\beta\hat{y}$ for non linear system

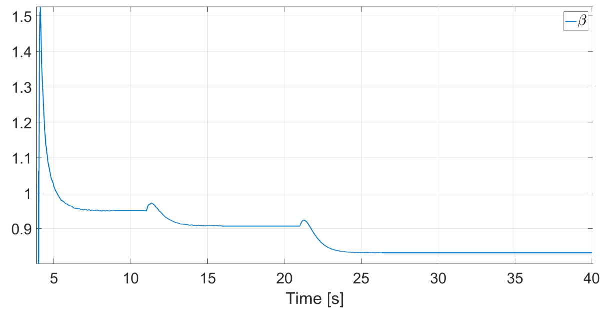

Fig. 9. Evolution of β

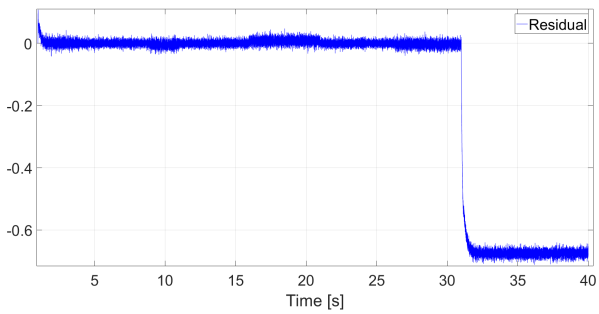

Fig. 10. Residual fault indicator

8 and Fig. 10, as soon as the fault appears at time $31s$, the residual signal deviates indicating the presence of a fault.

Three tank system: To examine the abilities of the proposed method to detect acuator faults, a multivariable nonlinear known as a three-tank system is investigated. Several fault detection methods have been applied for this system: Theilliol et al. (2000) use an observer with unknown input to detect a sensor fault. Mesbah et al. (2014) proposes a probabilistic approach for active tolerant control. The three-tank system is shown in Fig. 11, this system can be represented as in Fliess et al. (2005) by:

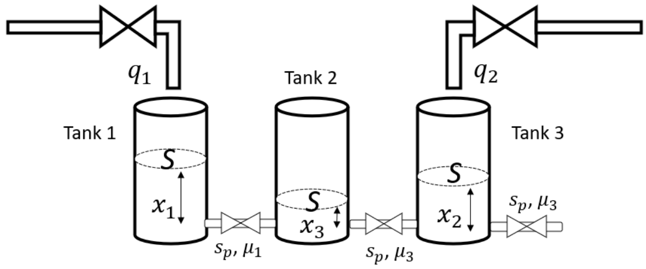

Fig. 11. Three tanks diagram

$$\begin{cases} \dot{x_1} = -C_1 sign(x_1 - x_3)\sqrt{\mid x_1 - x_3 \mid} + \dfrac{u_1.f_1}{S} \\ \dot{x_2} = C_3 sign(x_3 - x_2)\sqrt{\mid x_3 - x_2 \mid} - \\ C_2 sign(x_2)\sqrt{\mid x_2 \mid} + \dfrac{u_2.f_2}{S} \\ \dot{x_3} = C_1 sign(x_1 - x_3)\sqrt{\mid x_1 - x_3 \mid} - \\ C_3 sign(x_3 - x_2)\sqrt{\mid x_3 - x_2 \mid} \\ y_1 = x_1 \\ y_3 = x_3 \\ y_3 = x_3 \end{cases}$$

Where $x_i, i = 1, 2, 3$ is the fluid level in tank i. The control variables u_1 and u_2 are the flow input. The parameter $f_i, i = 1, 2$ is associated with the actuator fault, if $f_i < 1$ fault is present. The constant C is defined as: $C_n = (\frac{1}{S}).S_p \mu_n.\sqrt{2.g}, n = 1, 2, 3$, $S = 0.0154m$, $S_p = 5.10^5$,$g = 9.81m.s^-2$, $\mu_1 = \mu_3 = 0.5$, $\mu_2 = 0.675$.

The closed loop control with an iP controller is expressed by:

$$u_1 = \frac{1}{150}\left(-\hat{F}_1 + \dot{y}_{1d} + 1e_1\right)$$

$$u_2 = \frac{1}{150}\left(-\hat{F}_2 + \dot{y}_{2d} + 2e_2\right)$$

where: $e_1 = y_{1d} - y_1$ and $e_2 = y_{2d} - y_2$. Join et al. (2004) defined y_{2d} by:

$$y_{2d} = y_{3d} - \left(\frac{-\dot{y}_{3d} + C_1 sign(y_1 - y_3)\sqrt{\mid y_1 - y_3 \mid}}{C_3}\right)^2$$

For fault detection, the residues are designed as follows: $r_1 = y_1 - \beta_1 \hat{y}_1$ and $r_2 = y_2 - \beta_2 \hat{y}_2$. The evolution of the parameters β_1 and β_1 is illustrated in Fig. 14. The evolution of the parameter β does not converge to a constant value after the change of trajectory contrary to the case of linear systems.

The trajectory tracking is well provided with the iP controller as shown in Fig. 12. Actuator faults are simulated at $200s$ for the first pump and $2400s$ for the second pump. Fig. 13 confirms that the iP controller tolerates the fault, i.e. the output is maintained at the desired level in the presence of a fault.

However, the estimate of the output y_1 diverges at the time of the fault occurrence on u_1 as shown in Fig. 15. The residual r_2 remains stable around 0 until the fault occurs on pump 2. The parameter β is calculated for each new setpoint as described in the previous example.

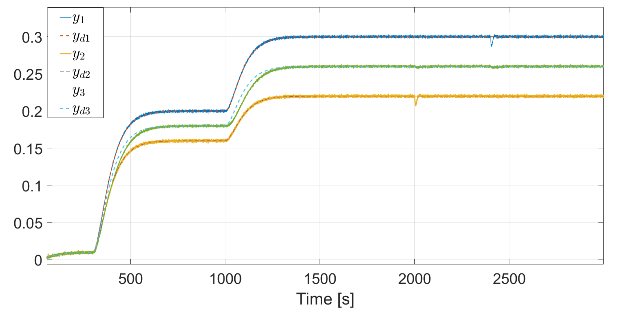

Fig. 12. y and y_d for setpoint tracking

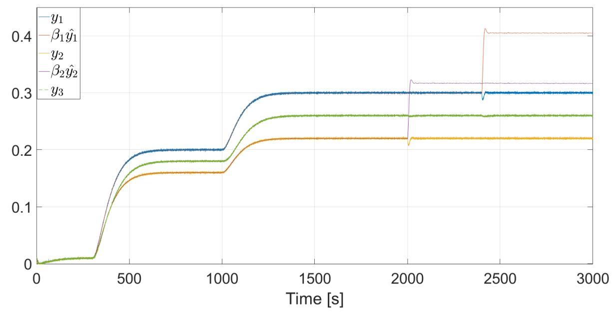

Fig. 13. Measured and estimated outputs y and $\beta\hat{y}$

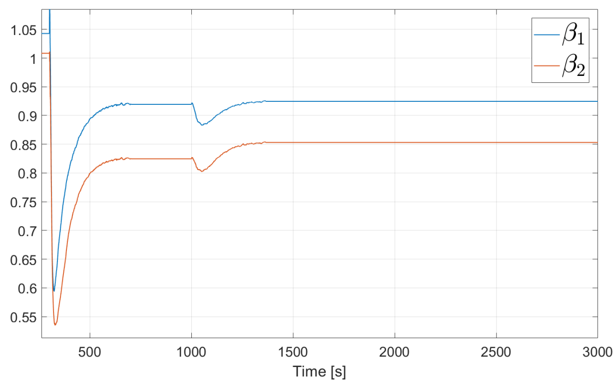

Fig. 14. β_1 and β_2

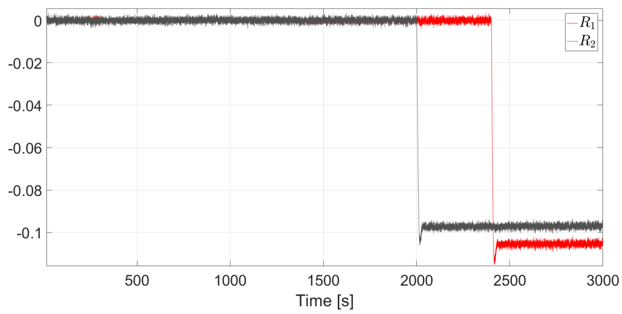

Fig. 15. Residual fault indicator

4. CONCLUSION

A new fault detection method has been presented in this paper, the proposed method is based on the ultra-local model and the model-free control. The idea is to reconstruct the output using the estimated dynamics of the system and the applied control law. Once the estimated output is obtained, it is corrected by a β parameter in order to generate a residual signal which is the indicator of the presence of a defect. This parameter is always constant for the different setpoint changes for linear systems. On the other hand, for non-linear systems, this parameter evolves during the operating points of the system. A new calculation of this parameter is mandatory when the setpoint changes. Simulation results show that the proposed method is able to detect an actuator fault for linear, nonlinear and nonlinear multivariable systems. The fault detection is done online by generating a residual signal.

The proposed approach seems very promising for the diagnosis of complex systems where no knowledge of the precise mathematical model of the system is required. In addition, the ease of on-line implementation with low computational cost are the main advantages. However, there are some aspects that need to be addressed to make the MFFD more effective. Among these aspects, it is necessary to distinguish between disturbances that can affect the system and defects. Concerning non-linear systems, the fault cannot be detected during setpoint changes. For this purpose, our research focuses on the enhancement of an alternative way to determine the β parameter which is very important in the proposed method. An experimental application is also planned to test the proposed method on-line.

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