



# Robust Residuals Generation for Faults Detection in Electric Powered Wheelchair

S. Tahraoui<sup>1</sup> (✉), M. Z. Baba Ahmed<sup>1</sup>, F. Benbekhti<sup>2</sup>, and H. Habiba<sup>3</sup>

<sup>1</sup> Department of Electronic Engineering, Universit Hassiba Benbouali de Chlef, Ouled Fares, Chlef, Algeria

s.tahraoui@univ-chlef.dz, zaki.babaahmed@gmail.com

<sup>2</sup> Technology Department, Faculty of Sciences and Technology, Djilali Bounaama Khemis Miliana University, Khemis Miliana, Algeria

f\_benbekhti@yahoo.fr

<sup>3</sup> Faculty of Technology, Abou Bekr Belkaid University, B.P 230 Chetouane, Tlemcen, Algeria

houari\_habiba@yahoo.fr

**Abstract.** A diagnostic approach for generation robust residuals to the dynamic model of an electric wheel chair is proposed in this paper. The method formulated here uses the observer presented in this work in order to design a residual generator that allows the detection of faults. The unknown input observer with perfect decoupling allows assessing these faults, which leads to their localization and detection. The present study focuses on faults arising from actuators for linear systems. Finally, the application of the observer algorithm is presented to study the performances of this observer.

**Keywords:** Electric powered wheelchair · Diagnosis · Robust residual · Detection fault · Observer

## 1 Introduction

Electric wheelchairs (EWC) belong to the category of under-actuated systems, which have fewer control inputs than the available degrees of freedom. The first electric wheelchair (EWC) was developed in Canada in the early 20th century, but it was not until the 1960s, with the advanced technological discoveries, such as the microprocessors, that it became reliable and was therefore ready to be used. Electric wheelchairs in this category are powered by motors and can be used indoors or outdoors. There are three different categories of chairs, namely the electric wheelchairs with fixed chassis, the electric wheelchairs with a folding chassis and the adjustable electrical wheelchairs [1–3]. In this article, a model-based diagnostic method is proposed for the detection and estimation of faults that can occur in an electric wheelchair (EWC); this system can be considered as a prototype for studying autonomous vehicles. Indeed, the issues raised by the electric wheelchair (EWC) constitute a subject of study in their own right; they provide an excellent basis for the study of more complex mobile systems. Our approach, which is based on the unknown input observer (UIO) with perfect decoupling, aims at designing a residual generator that allows detecting, localizing and

identifying faults. This operation aims at generating structured residuals in order to locate faults and minimize false alarms. The unknown input observer (UIO) makes it possible to estimate these alarms, and also helps to detect and locate them. This study focuses on the defects of actuators in a linear system. The problem of estimating the state of a system is of considerable practical importance, whether for the implementation of a control law or for the elaboration of a diagnostic strategy. The basic principle of generating residuals, using observers, consists in carrying out an estimation of the outputs of the system from the quantities accessible to measurement, namely the inputs and the outputs. Then, the residual vector may be constructed as the difference between the estimated output and the measured output; this can be achieved by assessing the error on the output. When modeling a system, it is common to use inputs that are not measurable. The term unknown inputs is therefore used to designate such inputs, and the reconstruction of the state of such systems can only be achieved under certain conditions. The observers are then called unknown input observers (UIO) [4]. Therefore, the principle of constructing an observer with unknown inputs is to make the estimation error independent of non-measurable perturbations. Consider a system to be monitored, in which the observer with unknown inputs (UIO) can solve the problem of sensitivity to the various faults and perturbations by introducing their state matrices into the synthesis equations of the observer-based residual generation. In this case, the decision-making requires comparing the fault indicator with the threshold that is obtained empirically or theoretically Chen et al. [5] were first to introduce the usage of unknown input observers (UIOs) in the detection of faults. In this context, the generation of residuals in systems based on linear models has been the subject of several research works using the state observer. Researchers such as Kiyak et al. [6], Sun [7], Khan and Ding [8], Cristofaro and Johansen [9], were particularly interested in this subject. For example, authors like Bagherpour et al. [10], Tahraoui et al. [11] have widely used the unknown input observer (UIO) in the diagnosis of failures in industrial processes and installations. This paper focuses on the problem of diagnosing defects of actuators in an electric wheelchair (EWC) using the unknown input observer (UIO) with a perfect decoupling between unknown inputs.

## 2 Unknown Input Observer (UIO) with Perfect Decoupling

The principle of the unknown input observer (UIO) consists in generating an estimation error (of the state vector) which tends asymptotically towards zero even in the presence of perturbations. Thus, the generated residual is decoupled from the perturbations because it depends on the estimation error. The unknown input observer (UIO) theory with perfect decoupling consists in making the estimation error independent of the unmeasurable perturbations. This is the theory of the generation of robust residuals. The synthesis of this type of observers is possible for models of systems admitting the form that is properly described by the following state representation:

$$\begin{cases} \dot{\mathbf{x}}(t) = \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{u}(t) + \mathbf{F}_x\mathbf{f}(t) + \mathbf{D}_x\mathbf{d}(t) \\ \mathbf{y}(t) = \mathbf{C}\mathbf{x}(t) + \mathbf{F}_y\mathbf{f}(t) \end{cases} \quad (1)$$

### 2.1 Observer Structure

The model of the observer with perfect decoupling is given by:

$$\begin{cases} \dot{z}(t) = Mz(t) + Nu(t) + Py(t) \\ \hat{x} = z(t) - L_y y(t) \end{cases} \quad (2)$$

Where  $\hat{x} \in R^n$  and  $z \in R^n$  are the estimated state vector and the observer state vector, respectively. The matrices M, N, P, Ly are determined so as to obtain a residual r(t). These matrices are determined in such a way that the estimate  $\hat{x}(t)$  converges asymptotically towards the real state x(t) of the system, in spite of the influence of the perturbations.

### 2.2 Observer Synthesis Algorithm

The observer synthesis algorithm can be summarized as follows:

- Rank  $CD_x = nd$ .
- Calculation of  $L_y = -D_x[(CD_x)^T(CD_x)]^{-1}(CD_x)^T$ .
- Calculation of  $E = I + L_y C$ .
- Calculation of  $N = EB$ .
- Impose M as a Hurwit matrix. For this purpose, one may choose M as a diagonal matrix which shows the eigenvalues that are sought for the observer.

Calculation of  $PC = EA - ME$ .

Remark: Decoupling is only possible if the rank of the matrix CDx is equal to the number of inputs to be decoupled.

Theoretical calculation of residuals Calculating the transfer matrix linking the defects to the estimation error at the output.

Let:  $F = ML_y F_y + P F_y - E F_x, \dot{F} = -L_y F_y$

The residual vector is:

$$\begin{cases} e_y(s) = [C(sI - M)^{-1}(F + s\dot{F}) - F_y]f(s) \\ F = ML_y F_y + P F_y - E F_x \\ \dot{F} = -L_y F_y \end{cases} \quad (3)$$

The error transfer function is:

$$G_f(s) = C(SI - M)^{-1}(F + SF') - F_y \quad (4)$$

The purpose is not only to make the residual generator insensitive to unknown inputs but also to make it as sensitive as possible to faults.

Q(s) Allows structure the residuals in order to facilitate faults location.

Let Q(s) be a proper and stable transfer matrix. Let's generate a residual vector r(s) such that r(s):

$$r(s) = Q(s)e_y(s) = Q(s)G_f(s)f(s) \tag{5}$$

Q(s) makes it possible to structure the residuals in order to be able to localize the defects. This allows generating the signature table which presents the impact of the defects on each residual [12].

### 3 State Representation of the Electric Wheelchair

The present study was carried out on the dynamic model of the electric wheelchair, which was developed by Boubekeur et al. [13]. The state representation of for the electric wheelchair takes the following form (3):

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) + D_x d(t) \\ y(t) = Cx(t) \end{cases} \tag{6}$$

This is the nominal form where the disturbances are taken into consideration. The following state representation is therefore obtained:

$$\begin{cases} \dot{x} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & l_1 & 0 & l_2 \\ 0 & 0 & 0 & 1 \\ 0 & l_3 & 0 & l_4 \end{bmatrix} x + \begin{bmatrix} 0 & 0 \\ y_1 & y_3 \\ 0 & 0 \\ y_2 & y_4 \end{bmatrix} u + \begin{bmatrix} 0 \\ 1 \\ 0 \\ 1 \end{bmatrix} T \\ y = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} x \end{cases} \tag{7}$$

Where:  $l_1 = l_4 = -\frac{ac}{a^2-b^2}$ ,  $l_2 = l_3 = \frac{ac}{a^2-b^2}$ ,  $y_1 = y_4 = \frac{aR}{a^2-b^2}$ ,  $y_2 = y_3 = -\frac{aR}{a^2-b^2}$ .

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## 4 Modeling and Generating the Unknown Input Observer (UIO) of the System

### 4.1 Modeling the System in the Presence of Faults

The model of the system to be monitored is correctly described by the previous state representation (1). The present study assumes that the system is subjected to two actuator defects and one perturbation, in addition to the perturbation that is supposed to be due to the inclined plane. The corresponding state representation has the following form:

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) + F_x f(t) + D_x d(t) \\ y(t) = Cx(t) \end{cases} \quad (8)$$

Such that:

$$A = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & l_1 & 0 & l_2 \\ 0 & 0 & 0 & 1 \\ 0 & l_3 & 0 & l_4 \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & -1.0537 & 0 & 0.0175 \\ 0 & 0 & 0 & 1 \\ 0 & 0.0175 & 0 & -1.0537 \end{bmatrix}, B = \begin{bmatrix} 0 & 0 \\ y_1 & y_3 \\ 0 & 0 \\ y_2 & y_4 \end{bmatrix} \begin{bmatrix} 0 & 0 \\ 0.9837 & -0.0163 \\ 0 & 0 \\ -0.0163 & 0.9837 \end{bmatrix}$$

$$C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}; D = 0, F_x = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix}; D_x = \begin{bmatrix} 0 \\ 1 \\ 0 \\ 1 \end{bmatrix}; F_y = 0; D_y = 0$$

And:

$F_x$ : Action matrix of actuator faults  $f(t)$  to be detected

$D_x$ : Action matrix of disturbances  $d(t)$ , resistant torque  $T$

$v_i(t)$ : Measurement noise vector.

The new state representation is:

$$\left\{ \begin{aligned} \begin{bmatrix} \dot{x}_1(t) \\ \dot{x}_2(t) \\ \dot{x}_3(t) \\ \dot{x}_4(t) \end{bmatrix} &= \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & -1.0537 & 0 & 0.0175 \\ 0 & 0 & 0 & 1 \\ 0 & 0.0175 & 0 & -1.0537 \end{bmatrix} \begin{bmatrix} x_1(t) \\ x_2(t) \\ x_3(t) \\ x_4(t) \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 0.9837 & -0.0163 \\ 0 & 0 \\ -0.0163 & 0.9837 \end{bmatrix} \begin{bmatrix} c_r \\ c_l \end{bmatrix} \\ &+ \begin{bmatrix} 1 & 0 \\ 0 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} f_1(t) \\ f_2(t) \end{bmatrix} + \begin{bmatrix} 0 \\ 1.0220 \\ 0 \\ 1.0220 \end{bmatrix} d(t) \\ \begin{bmatrix} S_r \\ \dot{S}_r \\ S_l \\ \dot{S}_l \end{bmatrix} &= \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_1(t) \\ x_2(t) \\ x_3(t) \\ x_4(t) \end{bmatrix} + \begin{bmatrix} v_1(t) \\ v_2(t) \\ v_3(t) \\ v_4(t) \end{bmatrix} \end{aligned} \right. \quad (9)$$

## 5 Residual Generator Synthesis Based on an Unknown Input Observer (UIO) with Perfect Decoupling

Step 1: Rank  $CD_x = nd$

It is first checked whether the system allows obtaining a perfect decoupling; then the rank of  $CD_x$  is determined. The rank of  $CD_x = 1$  is equal to the number of inputs to

decouple  $d(t)$ . It is possible to construct a fault-sensitive and non-disturbance-sensitive residual generator. The observer with perfect decoupling is given by:

$$\begin{cases} \dot{\hat{x}}(t) = Mz(t) + Nu(t) + Py(t) \\ \hat{x} = z(t) - L_y y(t) \end{cases}$$

Remember that the present work aims to determine the matrices  $M, N, P, L_y$  such that the estimate  $\hat{x}(t)$  converges asymptotically towards the real state  $x(t)$  of the system, despite the influence of the perturbations, while checking the following constraints:

$M$  is a Hurwitz matrix (stable).

$$ME + PC = EA$$

$$N = EB$$

$$ED_x = 0$$

$$ML_y F_y + P F_y - E F_x \neq 0$$

$$L_y F_y \neq 0$$

The observer synthesis algorithm is applied.

Step 2: Calculation of  $L_y = -D_x [(CD_x)^T (CD_x)]^{-1} (CD_x)^T, L_y = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & -0.5 & 0 & -0.5 \\ 0 & 0 & 0 & 0 \\ 0 & -0.5 & 0 & -0.5 \end{bmatrix}$

Step 3: Calculation of  $E = I + L_y C, E = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0.5 & 0 & -0.5 \\ 0 & 0 & 1 & 0 \\ 0 & -0.5 & 0 & 0.5 \end{bmatrix}$

Step 4: Calculation of  $N = EB, N = \begin{bmatrix} 0 & 0 \\ \frac{y_1 - y_3}{2} & \frac{y_2 - y_4}{2} \\ 0 & 0 \\ \frac{y_3 - y_1}{2} & \frac{y_4 - y_2}{2} \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ 0.5 & -0.5 \\ 0 & 0 \\ -0.5 & 0.5 \end{bmatrix}$

Step 5: Impose  $M$  as a Hurwitz matrix. In this case, it is possible to choose  $M$  as a diagonal matrix that shows the eigenvalues that are desired for the observer.

The diagonal matrix  $M$  and its eigenvalues are:  $\lambda_1 = -1, \lambda_2 = -2, \lambda_3 = -2, \lambda_4 = -1$

$$M = \begin{bmatrix} -1 & 0 & 0 & 0 \\ 0 & -2 & 0 & 0 \\ 0 & 0 & -2 & 0 \\ 0 & 0 & 0 & -1 \end{bmatrix}$$

Step 6: Calculation of  $PC = EA - ME, C$ : identité

$$P = \begin{bmatrix} 1 & 1 & 0 & 0 \\ 0 & \frac{l_1-l_3}{2} + 1 & 0 & \frac{l_2-l_4}{2} - 1 \\ 0 & 0 & 2 & 1 \\ 0 & \frac{l_3-l_1}{2} - \frac{1}{2} & 0 & \frac{l_4-l_2}{2} + \frac{1}{2} \end{bmatrix} = \begin{bmatrix} 1 & 1 & 0 & 0 \\ 0 & 0.4644 & 0 & -0.4644 \\ 0 & 0 & 2 & 1 \\ 0 & 0.0356 & 0 & -0.0356 \end{bmatrix}$$

The unknown-input reconstructor and the output estimation error are obtained as follows:

$$\left\{ \begin{array}{l} \begin{bmatrix} \dot{z}_1(t) \\ \dot{z}_2(t) \\ \dot{z}_3(t) \\ \dot{z}_4(t) \end{bmatrix} = \begin{bmatrix} -1 & 0 & 0 & 0 \\ 0 & -2 & 0 & 0 \\ 0 & 0 & -2 & 0 \\ 0 & 0 & 0 & -1 \end{bmatrix} \begin{bmatrix} z_1(t) \\ z_2(t) \\ z_3(t) \\ z_4(t) \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 0.5 & -0.5 \\ 0 & 0 \\ -0.5 & 0.5 \end{bmatrix} \begin{bmatrix} c_r \\ c_l \end{bmatrix} \\ \\ \begin{bmatrix} 1 & 1 & 0 & 0 \\ 0 & 0.4644 & 0 & -0.4644 \\ 0 & 0 & 2 & 1 \\ 0 & 0.0356 & 0 & -0.0356 \end{bmatrix} \begin{bmatrix} S_r \\ \dot{S}_r \\ S_l \\ \dot{S}_l \end{bmatrix} \\ \\ \begin{bmatrix} e_{S_r} \\ e_{\dot{S}_r} \\ e_{S_l} \\ e_{\dot{S}_l} \end{bmatrix} = \begin{bmatrix} S_r \\ \dot{S}_r \\ S_l \\ \dot{S}_l \end{bmatrix} - C \begin{bmatrix} z_1 \\ z_2 + \frac{1}{2}(\dot{S}_r + \dot{S}_l) \\ z_3 \\ z_4 + \frac{1}{2}(\dot{S}_r + \dot{S}_l) \end{bmatrix} \end{array} \right.$$

## 5.1 Theoretical Calculation of Residuals

Calculation of the transfer matrix linking the defects to the output estimation error: The error transfer function is:

$$G_f(s) = C(sI - M)^{-1}(F + \dot{F}s) - F_y$$

$$F = ML_y F_y + PF_y - EF_x = \begin{bmatrix} -1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & -1 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}, \dot{F} = -L_y F_y = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

The residual vector is written as:  $r(t)$

$$r(s) = \begin{pmatrix} r_1 \\ r_2 \end{pmatrix} = \begin{pmatrix} G_{f11} & G_{f12} \\ G_{f21} & G_{f22} \end{pmatrix} \begin{pmatrix} f_{ac1}(s) \\ f_{ac2}(s) \end{pmatrix}$$

$$= \begin{pmatrix} \frac{-s^3 - 5s^2 - 8s - 4}{s^4 + 6s^3 + 13s^2 + 12s + 4} & 0 \\ 0 & \frac{-s^3 - 4s^2 - 5s - 2}{s^4 + 6s^3 + 13s^2 + 12s + 4} \end{pmatrix} \begin{pmatrix} f_{ac1}(s) \\ f_{ac2}(s) \end{pmatrix}$$

### 5.2 Table of Signature

The signature table associated with this residual generator is given in Table 1, where “1” indicates the occurrence of a defect  $f_i$  affecting the residual  $r_{ij}$  and “0” the insensitivity of that residual to the defect.

**Table 1.** Table of signatures (EWC)

	fac1	fac2
r1	1	0
r2	0	1

According to the signature table, the residuals are insensitive to the disturbances  $d(t)$ . The structure allows the complete location of the defects. In addition, it is theoretically possible to detect and locate the faulty actuator.

## 6 Simulation

The residuals generated by the unknown input observer (UIO) with perfect decoupling of the electric wheelchair are evaluated as a function of the values of the nominal parameters of the system as follows [14] (Table 2):

**Table 2.** The nominal parameters of the system EWC

$J = 16.08 \text{ kg.m}^2$	$R = 0.17 \text{ m}$
$J_a = 0.0024 \text{ kg.m}^2$	$L = 0.57 \text{ m}$
$J_w = 0.0289 \text{ kg.m}^2$	$C_a = 0.06 \text{ N.m/rad/s}$
$\sigma = 0.033$	$C_w = 0.008 \text{ N.m/rad/s}$
$M = 210.00 \text{ kg}$	$g = 9.81 \text{ m/s}^2$
$m_w = 2.00 \text{ kg}$	$J_e = \begin{bmatrix} a & b \\ b & a \end{bmatrix}, C_e = \begin{bmatrix} c & 0 \\ 0 & c \end{bmatrix},$ $a = \frac{1}{\sigma} J_a + \sigma \left\{ J_w + \left( \frac{M}{4} + m_w \right) R^2 + \left( \frac{R}{L} \right)^2 J \right\}$ $c = \frac{1}{\sigma} C_a + \sigma C_w$ $T = \sigma \left( \frac{M}{2} + m_v \right) g R \sin \psi$
$b = \sigma R^2 \left( \frac{M}{4} + \frac{1}{L^2} J \right)$	
$c = \frac{1}{\sigma} C_a + \sigma C_w$	

The simulation consists in checking the detection of faults. This operation is characterized by the appearance of the signals of the corresponding residuals through the implementation of the unknown input observer that estimates the defects  $f_{ac1}$  and  $f_{ac2}$ . Indeed, the observer reconstructs the residual r1 or the residual r2 of the system. If the output presents a defect, it will immediately be estimated. Thus, if a residual  $r(t)$  deviates from the threshold interval, a defect  $f$  will certainly occur. Therefore, with this



observer, it is possible to detect and locate the two actuator faults even if they occur simultaneously at the two outputs. In practice, it is considered that the input signal is a driving torque, and a disturbance input is a resistive torque. A measurement noise is added to the measurements  $S_r, S_l, \dot{S}_r, \dot{S}_l$  in order to simulate the normal operation. The residuals are evaluated in normal operation and in faulty operation. It is assumed that the two actuator faults are defined as follows:

$$f_{AC1} = \begin{cases} -20 & 10 \leq t \leq 25 \\ 0 & \text{elsewhere} \end{cases} \quad f_{AC2} = \begin{cases} -35 & 15 \leq t \leq 20 \\ 0 & \text{elsewhere} \end{cases}$$

Normal operation,

- (a) With perturbation

It is modeled using the resistive torque T. Figure 1 illustrates the residuals  $r1(t)$  and  $r2(t)$ . The perturbations are perfectly decoupled because of the observer with perfect decoupling. In practice, the residuals are different from zero due to the measurement noise.

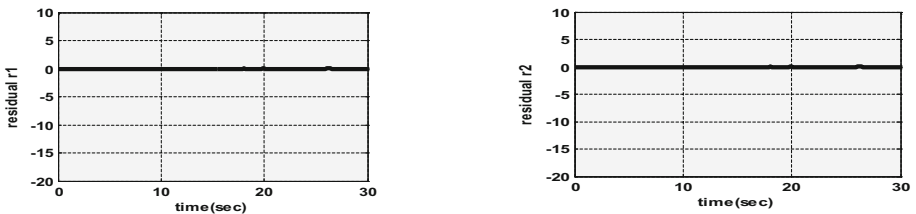


Fig. 1. Residuals  $r1(t)$  and  $r2(t)$  in the presence of perturbations

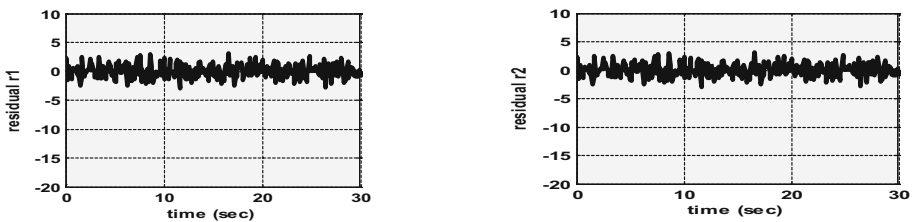


Fig. 2. Residuals  $r1(t)$  and  $r2(t)$  in the presence of disturbances, with measurement noises

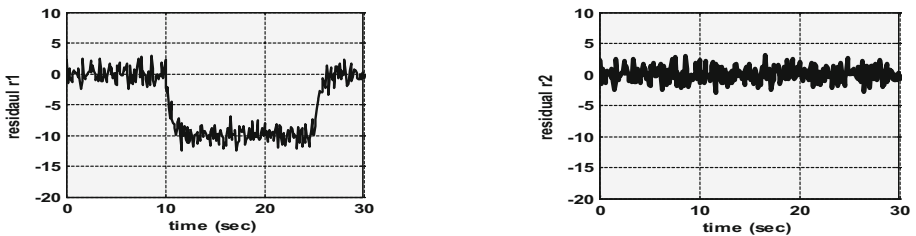
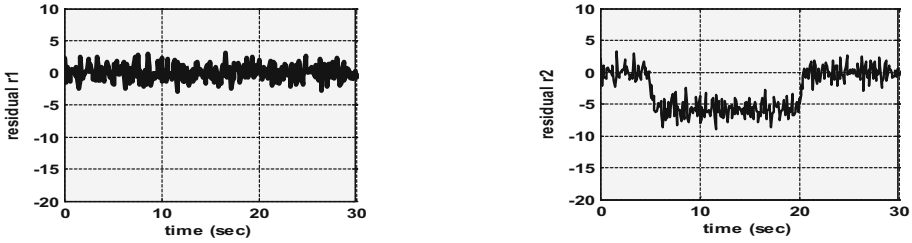


Fig. 3. Residuals  $r1(t)$ ,  $r2(t)$  with disturbances, measurement noises and fault  $f_{ac1}$



**Fig. 4.** Residuals  $r_1(t)$  and  $r_2(t)$  in with disturbances, measurement noises and fault  $fac_2$

(b) Addition of measurement noises

To get closer to reality, random signals are added to the measurements, as shown in Fig. 4.

(c) Faulty operation

The results shown in Fig. 3 are obtained by simulating an additive fault  $fac_1$  at the input, at the instant  $10 \leq t \leq 25$ . For this fault, only the residual  $r_1(t)$  is sensitive, and therefore detectable, as indicated in the signature table.

The results illustrated in Fig. 4 are obtained by simulating an additive fault  $fac_2$  at the input, at the instant  $10 \leq t \leq 25$ , and by changing the amplitude. It is clearly noted that only the residual  $r_2(t)$  is sensitive to this fault  $fac_1$  at the input, at the instant  $5 \leq t \leq 20$ . The results of the simulation, as shown in Figs. 1, 2, 3 and 4, evolve according to the previous signature table. The signature table has a localizing structure (two different signatures). The results of the simulation thus confirm the effectiveness of the suggested approach.

## 7 Conclusion

The present work focused on the detection of actuator defects in a linear system, using an unknown input observer with perfect decoupling. The developed method was applied using a dynamic model of an electric wheelchair, with unknown inputs (disturbance). The results of the residual generation by simulation, using this method, proved to be effective for all the cases considered. It would have been desirable to validate these results through an experimental manipulation on a real electric wheelchair.

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