A parameter estimation method for the diagnosis of sensor or actuator abrupt faults

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A PARAMETER ESTIMATION METHOD FOR THE DIAGNOSIS OF SENSOR OR ACTUATOR ABRUPT FAULTS

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Abstract

This paper describes a method for additive abrupt fault detection and isolation. Parameter estimation is applied off line to obtain a discrete model. The contribution of sensor or actuator faults on the output error residual is analysed. Fault occurrence is detected using a Page-Hinkley algorithm. Then the parameters of several output error models of the residual are estimated. The analysis of these models allows fault isolation. As soon as a fault is diagnosed, the measurements provided to the fault detection and isolation algorithm are modified so that the detection of a consecutive fault is allowed even if the first fault is not corrected.

1 Introduction

In model-based fault diagnosis methods, the residuals are computed by the deviation between the measurements and the model computations. The basic model-based fault diagnosis methods are: parity equations [Gertler 90], [Gertler 97], state and output observers [Patton 97], identification and parameter estimation [Isermann 93].

Parameter estimation methods are based on different criteria, which are minimised in order to estimate the model parameters. These criteria can be considered as residuals. Links between these criteria and parity equations can be made [Isermann 97].

These residuals become different from zero as soon as either input or output is affected by an additive fault. Redundancy between different transfer function identification increases the number of residuals, and thus increases the fault isolation capability [Weber 98]. The isolation is only possible when the incidence matrix structure is deterministically isolable [Gertler 92]. Nevertheless in practice, the number of equations is limited by the process structure and the robustness to multiplicative fault is difficult to guarantee.

Parameter estimation is well adapted to multiplicative faults. Nevertheless, parameter estimation methods need rich excitation. A persistent excitation allowing on line diagnosis is difficult to fulfil. In addition, the parameters do not converge immediately, so the fault is not detected as fast as with parity equation methods. Moreover, additive faults disturb the estimates.

This work presents a method to avoid the increasing number of equations required for additive fault isolation; it uses a parameter estimation technique to analyse an output error residual whereas [Alcorta 96] identified observer based residuals.

The paper is organised as follows: section two presents the basic concepts of the proposed method. The implementation is detailed in section three: the fault is detected using Page Hinkley algorithm; fault isolation and identification are performed by several parameter estimation and the reset of the algorithms allows consecutive fault diagnosis. Section four presents the application to a winding system simulation, before the conclusion.

2 The proposed method

Consider small signal deviations around an operating point; the behaviour of a multiple input single output (MISO) process with m inputs can be described by a linear discrete model:

$$y(k) = \mathbf{G}(q)\cdot\mathbf{u}(k) + e(k) \qquad (1)$$

where $\mathbf{u}(k) = [u_1(k) \quad \dots \quad u_m(k)]^T$ are the inputs and $y(k)$ is the output of the process, q is the delay operator,

$\mathbf{G}(q) = [G_1(q) \quad ... \quad G_m(q)]$ represents the discrete transfer function of parallel models, each one related to one particular input and $e(k)$ represents the measurement noise.

The Output Error (OE) model is estimated off-line on fault-free data set. It is further used to compute an on-line estimation $\hat{y}(k)$ of the measured variable. Independent parallel models are fed by each actuator values:

$$\hat{y}(k) = w_1(k) + ... + w_m(k) \tag{2}$$

where $w_i(k)$ are the outputs of the independent parallel models.

The OE model is defined by:

$$\hat{y}(k) = \sum_{i=1}^{m} \left\{ \hat{G}_i(q) \cdot u_i(k) \right\} \tag{3}$$

An OE identification algorithm allows the estimation of the model parameters [Ljung 87]:

$$\hat{G}_i(q) = \frac{\hat{B}_i(q)}{\hat{F}_i(q)} \cdot q^{-d_i} \tag{4}$$

Where

$$\hat{B}_i(q) = \hat{b}_1 q^{-1} + ... + \hat{b}_{nbi} q^{-nbi} \tag{5}$$

$$\hat{F}_i(q) = 1 + \hat{f}_1 q^{-1} + ... + \hat{f}_{nfi} q^{-nfi} \tag{6}$$

d_i is the input delays, *nbi* and *nfi* are the degrees of the polynomials $\hat{B}_i(q)$ and $\hat{F}_i(q)$, $\hat{b}_l$ and $\hat{f}_l$ are the estimates.

Thus parallel model outputs are computed as:

$$w_i(k) = \hat{B}_i(q) \cdot u_i(k) + \left(1 - \hat{F}_i(q)\right) \cdot w_i(k) \tag{7}$$

Taking faults into account, $y(k)$ is rewritten as:

$$\begin{aligned} y(k) = &\sum_{i=1}^{m} \left\{ \left(\hat{G}_i(q) + \Delta\Gamma_i(q)\right) \cdot u_i(k) \right\} \\ &+ \sum_{i=1}^{m} \left\{ G_i(q) \cdot \Delta u_i(k) \right\} + \Delta y(k) + e(k) \end{aligned} \tag{8}$$

where $\Delta y(k)$ represents the sensor fault, $\Delta u_i(k)$ represents the actuator faults, and $\Delta\Gamma_i(q)$ represents the multiplicative faults and/or modelling errors.

The Output Error Residual (OER) is computed by the difference between the measurement (8) and its estimate (2):

$$\begin{aligned} r(k) = &\sum_{i=1}^{m} \left\{ \left(\Delta\Gamma_i(q)\right) \cdot u_i(k) \right\} \\ &+ \sum_{i=1}^{m} \left\{ G_i(q) \cdot \Delta u_i(k) \right\} + \Delta y(k) + e(k) \end{aligned} \tag{9}$$

The residual computed by (9) is sensitive to each fault:

- additive input faults $\Delta u_i(k)$: the actuator faults affect the residual through the transfer function $G_i(q)$;
- additive output faults $\Delta y(k)$: the sensor faults affect directly the residual;
- multiplicative faults $\Delta\Gamma_i(q)$: they affect also the residual, in the following it will be supposed that $\Delta\Gamma_i(q) = 0$.

In single fault hypothesis, the OER has the following representation:

Actuator fault on $u_i(k)$

$$r(k) = G_i(q) \cdot \Delta u_i(k) + e(k) \tag{10}$$

Sensor fault on $y(k)$

$$r(k) = \Delta y(k) + e(k) \tag{11}$$

The OER behaviour depends only on the additive faults, and the noise. When an actuator fault occurs, the residual response is the fault filtered by $G_i(q)$. Using parallel models easily separates the effects of each fault. In the case of sensor fault, the residual response is directly proportional to the fault. Thus the idea used in the following for fault isolation is to determine which model describes better the residual response.

3 Method implementation

In the proposed method, the diagnosis is performed in three steps. The first step is to detect if a fault occurred. The second step is the fault isolation and identification, in order to determine which actuator or sensor is faulty and the amplitude of the fault. This step is started only if a fault is detected. The final step is the reset of the algorithms in order to diagnose new faults even if the previous faults are not yet corrected.

3.1 Fault Detection

Considering an abrupt fault as a step signal [Isermann 97], when a fault occurs the OER mean changes. The Page-Hinkley Algorithm (PHA) detects this change. This method is simple, efficient and robust to noise [Basseville 86]. Moreover, PHA permits to define the detection sampling time k_d, more or less precisely depending on the fault and the noise. When an abrupt sensor fault occurs the OER actually follows a step (Figure 1), thus PHA is applied in the right conditions and k_d is close to the real sampling time of the fault occurrence k_f. Nevertheless, when the actuator is faulty, the residual response is the fault filtered by the process (Figure 2).

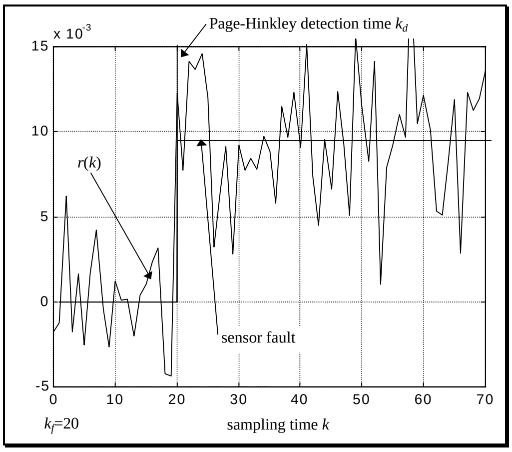

Figure 1: Page-Hinkley test for a sensor fault

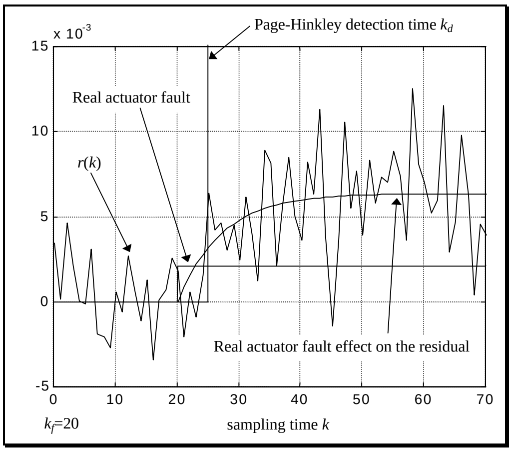

Figure 2: Page-Hinkley test for an actuator fault

Under this condition, PHA detects the fault at time k_d delayed with respect to k_f. This delay is due to the dynamic of $G_i(q)$. This method assumes the static gains of $G_i(q)$ are different from zero. In order to increase the detection ability, the OER might be filtered to guarantee that the mean of the residual changes significantly.

In conclusion, PHA allows fault detection, but the exact sampling time of the fault occurrence is uncertain due to noise and the dynamic of the process.

3.2 Fault Isolation and Identification (FII)

The FII algorithm is launched only if a fault is detected. Finding which model, (10) or (11), better explains the residual response leads to fault isolation. The first step tests the actuator fault hypothesis, and isolates the faulty input. If no actuator fault is diagnosed, then the sensor fault hypothesis is tested.

3.2.1 Actuator fault isolation and identification

The fault $\Delta u_i(k)$ is assumed to be an abrupt fault modelled by a step input, the eq (10) is written as:

$$r(k) = G_i(q) \cdot g^{\Delta u} \cdot U(k - k_f) + e(k) \tag{12}$$

where $g^{\Delta u}$ is the actuator fault amplitude and $U(k-k_f)$ is unit step input applied at time k_f. Each actuator fault hypothesis is tested successively estimating the transfer function between $r(k)$ and $\Delta u_i(k)$. If the transfer function is identical to $G_i(q)$, the hypothesis is considered valid and the i^{th} actuator is considered faulty. Successive identifications are carried until one actuator is suspected. In the following, the indices i are omitted for the sake of simplicity.

The problem here to apply a conventional identification method is that neither the amplitude $g^{\Delta u}$ nor the time k_f of application of the fault are known. These two problems are tackled in the following.

a) Amplitude estimation

Dividing (12) by the estimation $\hat{K}$ of the static gain K of $G(q)$, the following relation is obtained:

$$\frac{r(k)}{\hat{K}} = \frac{G(q) \cdot g^{\Delta u}}{\hat{K}} \cdot U(k - k_f) \tag{13}$$

$$\frac{r(k)}{\hat{K}} = \hat{G}^{\Delta u}(q) \cdot U(k - k_f) = \frac{\hat{B}^{\Delta u}(q)}{\hat{F}^{\Delta u}(q)} q^{-d} \cdot U(k - k_f) \tag{14}$$

Assuming $K \approx \hat{K}$, the static gain of $\hat{G}^{\Delta u}(q)$ is equal to the fault amplitude $g^{\Delta u}$.

The transfer function $\hat{G}^{\Delta u}(q)$ is estimated using the same model structure (nb, nf, d) as in $\hat{G}(q)$. $\hat{F}^{\Delta u}$ converges to $\hat{F}$ if the actuator is faulty and $g^{\Delta u}$ is estimated as:

$$\hat{g}^{\Delta u} = \frac{\sum_{l=0}^{nb} \hat{b}_l^{\Delta u}}{1 + \sum_{l=1}^{nf} \hat{f}_l^{\Delta u}} \tag{15}$$

The sensitivity to a small actuator fault is limited by the residual signal to noise ratio. The signal to noise ratio depends on the amplitude of the fault, on the static gain of $G(q)$ and on the measurement noise variance. Thus, the estimation must be robust to the noise in order to estimate small additive faults.

The OE optimisation algorithm is used over a window of L sampling times. The window length L must be greater than the time response of $G(q)$ leading to a good static gain estimation. Using a step input, the coefficients $\hat{b}_l^{\Delta u}$ may be badly estimated, but only their sum is used for computing $\hat{g}^{\Delta u}$. The time window must include l_0 sampling times before the fault occurrence for a better convergence of $\hat{F}^{\Delta u}$ [Foulard 87]. Nevertheless, the window must be as short as possible to limit the computation time, and the fault isolation delay.

b) k_f estimation

The diagnosis is achieved through the analysis of the $\hat{G}^{\Delta u}(q)$ estimated parameters, which must be close to those of $G(q)$. However, if k_d is not equal to k_f, then $\hat{F}^{\Delta u}$ may be inaccurate. Taking this uncertainty into account, several estimations $\hat{G}_j^{\Delta u}(q)$ are computed successively, using a step input shifted (Figure 3), where j is equal to the number of shifting times. When the shifting makes $k_f = k_d - j$, then the parameters are precisely estimated and $\hat{F}^{\Delta u}$ is close to $\hat{F}$.

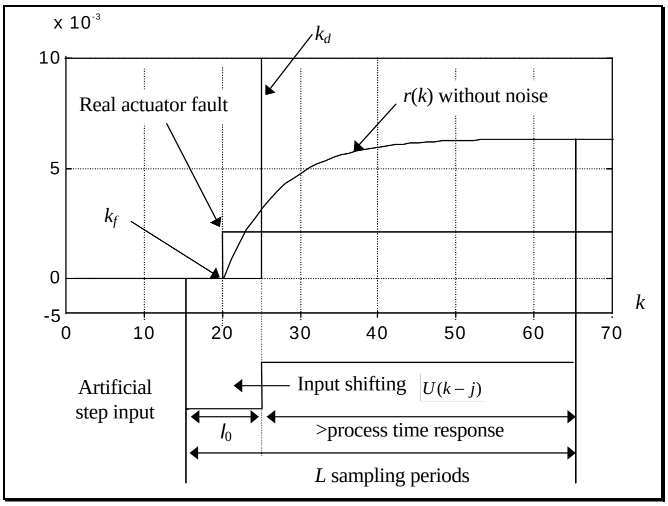

Figure 3: the fault occurrence time estimation

c) decision

The actuator is faulty if $\hat{G}^{\Delta u}(q)$ is "close to" $G(q)$. This is decided using two tests:

The parameters of $\hat{F}^{\Delta u}$ are assumed to be random variables. The OE parameter estimation results in the mean $\hat{f}_l^{\Delta u}$ and the variance $s^2(\hat{f}_l^{\Delta u})$ of each parameter. The model structure is validated if parameter variances are bounded:

$$s_{\%} = \sqrt{\frac{1}{nf}\sum_{l=1}^{l=nf}\left(\frac{s(\hat{f}_l^{\Delta u})}{\hat{f}_l^{\Delta u}}\right)^2} \le g \tag{16}$$

where g is tuned according to the noise and the desired sensitivity.

A second criterion tests if $\hat{F}^{\Delta u}$ is close to $\hat{F}$, using the normalised parameter distance:

$$\mathrm{D}(\hat{F}^{\Delta u} - \hat{F}) = \sqrt{\frac{1}{nf}\sum_{l=1}^{l=nf}\left(\frac{\hat{f}_l^{\Delta u} - \hat{f}_l}{\hat{f}_l}\right)^2} \le k \tag{17}$$

If all estimates respect these two criteria, then $\hat{F}^{\Delta u}$ ***is well estimated and close to*** $\hat{F}$. Thus the actuator is assumed to be faulty and the amplitude of the fault is $\hat{g}^{\Delta u}$. The fault occurrence sampling time is estimated as $\hat{k}_f = k_d - j$. However, several $\hat{F}^{\Delta u}$ might satisfy those criteria and the estimation minimising $D(\hat{F}^{\Delta u} - \hat{F})$ is used to determine j.

3.2.2 Sensor fault isolation and identification

This step is computed only if a fault has been detected and if no actuator fault is diagnosed. Considering the abrupt fault hypothesis, $\Delta y(k)$ is assumed to be a step input. Thus, the transfer function between $\Delta y(k)$ and $r(k)$ is a simple gain:

$$r(k) = \hat{g}^{\Delta y} \cdot U(k - k_f) + e(k) \tag{18}$$

where $\hat{g}^{\Delta y}$ is the sensor fault amplitude and $U(k)$ is a unit step input.

The window used to estimate $\hat{g}^{\Delta y}$ must be large enough to filter the noise effect. The window includes l_0 sampling times before k_d. The procedure for the sensor fault isolation and identification is the same as the actuator fault procedure. Nevertheless, the estimated structure is a simple gain, and only one criterion is tested. The criterion is based on the variance of $\hat{g}^{\Delta y}$ as defined in (16) to guarantee that $\hat{g}^{\Delta y}$ is different from zero.

Finally, if the fault is not diagnosed as an actuator or a sensor fault, then the fault is a multiplicative fault or the abrupt fault assumption is not valid.

3.3 Reset the residuals and the detection algorithm

After fault isolation PHA and OER must be reset. The fault is detected at time k_d, and $(L\text{-}l_0)$ sampling times later the fault is diagnosed. Thus the diagnosis is completed at time:

$$T = (L\text{-}l_0) + k_d \quad (19)$$

The variables $u_i(k)$ and $y(k)$ are adjusted by subtracting the estimated fault amplitudes (15) or (18). Thus, the simulation of the OE equation is calculated again from the sampling time (T-L) (i.e. before the fault occurrence). The residual $r(k)$ becomes therefore close to zero at sampling time k>T. PHA is reset to detect other residual variation. Consequently a new additive fault can be further diagnosed.

4 Application to a winding machine

This approach has been applied to the simulation of the plant represented in Figure 4. This winding process is composed by three DC-motors (M_1, M_2, M_3). Their angular velocities are represented by $\Omega_1(k)$, $\Omega_2(k)$ and $\Omega_3(k)$, which are respectively controlled by $u_1(k)$, $u_2(k)$ and $u_3(k)$. The angular velocity $\Omega_2(k)$, and the strip tensions $T_1(k)$ and $T_3(k)$ between the reels are measured. The angular velocities $\Omega_1(k)$, $\Omega_3(k)$ are not measured. The parameters are not known a priori. Identification results in three simplified input-output models defined as follows:

$$T_1(k) = G_{T1u1}(q).q^{-1}.u_1(k)+ G_{T1u2}(q).\, q^{-1}.u_2(k) \quad (20)$$

$$\Omega_2(k) = G_{\Omega 2u2}(q).\, q^{-1}.u_2(k) \quad (21)$$

$$T_3(k) = G_{T3u2}(q).q^{-1}.u_2(k)+ G_{T3u3}(q).\, q^{-1}.u_3(k) \quad (22)$$

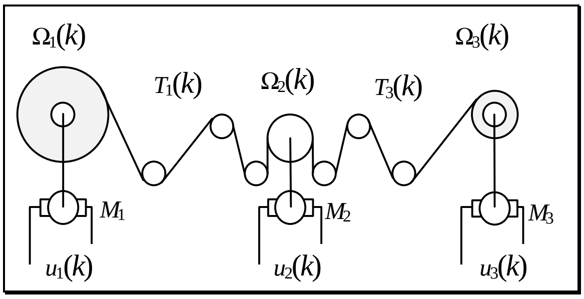

Figure 4: Winding system

Output Error Matlab algorithm estimates the model (20):

$$\hat{T}_1(k) = \frac{-0.39}{1-0.86\cdot q^{-1}}\cdot q^{-1}\cdot u_1(k) + \frac{0.229-0.217\cdot q^{-1}}{1-1.65\cdot q^{-1}+0.69\cdot q^{-2}}\cdot q^{-1}\cdot u_2(k) \quad (23)$$

The output error equation leads to $r(k)$:

$$r(k) = \hat{T}_1(k) - T_1(k) \quad (24)$$

The figures (Figure 6, Figure 8) represent a simulation of the residual $r(k)$, with sensor or actuator additive fault.

- A sensor fault is simulated at sampling time k_f=600; its amplitude is 0.0095. Figure 5 shows $T_1(k)$, $u_1(k)$ and $u_2(k)$. Figure 6 presents the residual response and the diagnosis results. The residual becomes close to zero at k=650 thanks to the reset procedure. PHA detects the fault at k_d=601, and the estimation of $\hat{k}_f$ is equal to 600 using g =0.2. The identification of the fault is $\hat{g}^{\Delta T_1} = 0.0097$, and $\hat{g}^{\Delta u_1} = \hat{g}^{\Delta u_2} = 0$ because $\hat{F}^{\Delta u_1}$ and $\hat{F}^{\Delta u_2}$ were respectively different from $\hat{F}_1$ and $\hat{F}_2$.

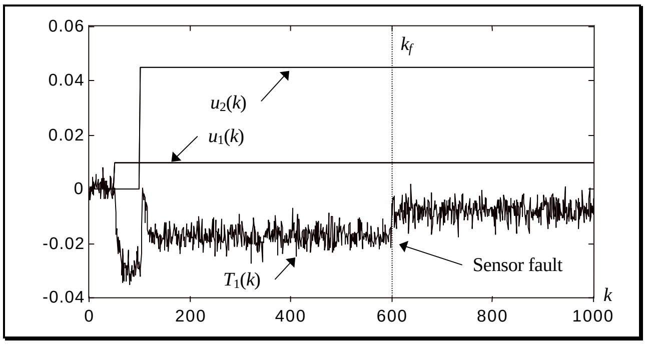

Figure 5: Inputs/output behaviour with T_1 fault

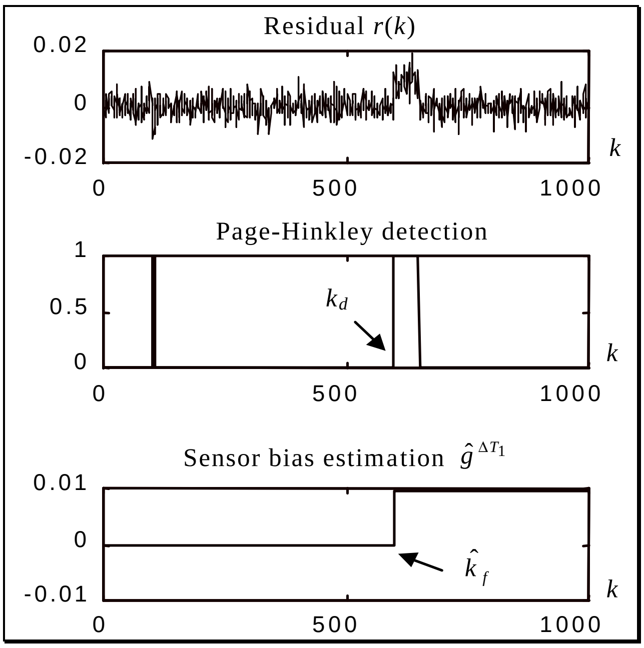

Figure 6: Residual, Detection, and Identification of T_1 fault

• An $u_1(k)$ actuator fault is simulated at time k_f=600 (Figure 7); its amplitude is 0.002 corresponding to 20% of $u_1(400)$. Figure 8 represents the residual response and diagnosis results. The residual becomes close to zero at k=655 thanks to the reset procedure. The detection sampling time is k_d=605, and $\hat{k}_f$ is estimated equal to 601 using g =0.2; k =0.1. The actuator fault amplitude is estimated to $\hat{g}^{\Delta u_1} = 2.12\times10^{-3}$ and $\hat{g}^{\Delta u_2} = \hat{g}^{\Delta T_1} = 0$.

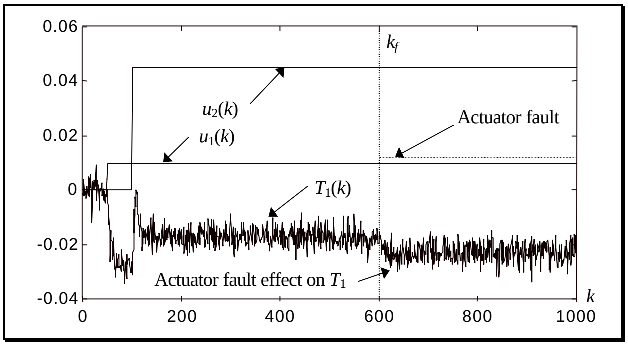

Figure 7: Inputs/output behaviour with u_1 fault

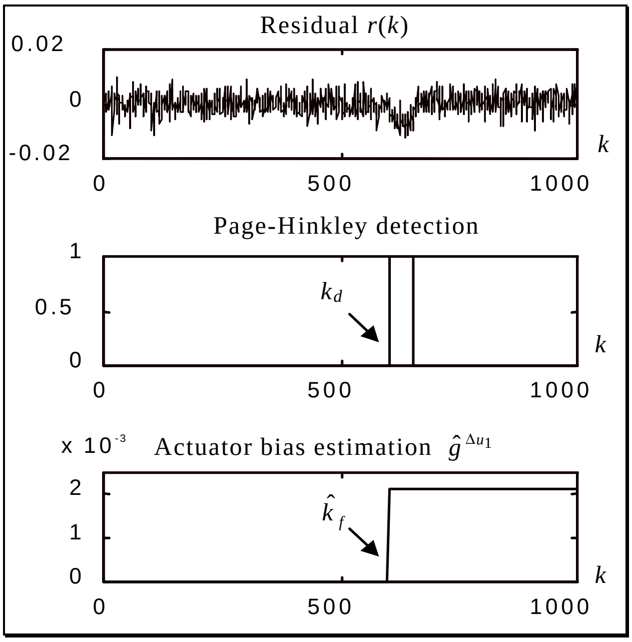

Figure 8: Residual, Detection, and Identification of u_1 fault

5 Conclusion

The diagnosis method proposed in this paper is devoted to sensor or actuator additive abrupt fault isolation. It relies on a single output error residual, obtained from the nominal model identified off-line. This residual is used for detection. Then, the residual behaviour is identified with respect to a step input. If the model is found to be a simple gain, a sensor fault is identified; otherwise, if the model is found similar to one of the transfer functions relating the inputs to the output, the corresponding actuator is suspected and the fault amplitude is identified. Because identification is applied to the residual rather than to the input-output data, the input excitation is guaranteed when the fault occurs. The isolation relies on successive estimations of simple models, with a standard algorithm. It is thus easy to implement. It has given good results on a winding machine.

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