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MODEL-BASED FAULT DETECTION ON A REACTION WHEEL

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Abstract: Fault detection has become an important issue in complex engineering systems, providing the requirements for fault tolerance, reliability and safety. Here, the engineering system discussed is a satellite that makes use of a reaction wheel. The objective is the fault detection in this actuator.

Keywords: Fault Detection, Parameter Estimation, Fault Diagnosis, Fault Tolerance, Hypothesis testing.

1. INTRODUCTION

The methods of fault detection and diagnosis can be used in two distinct ways: the first, in the sense to avoid faults making an early detection to improve repair and maintenance management [1]; the second, called fault tolerance, consider that faults could not be avoided and happened, in this case fault-tolerant systems are required.

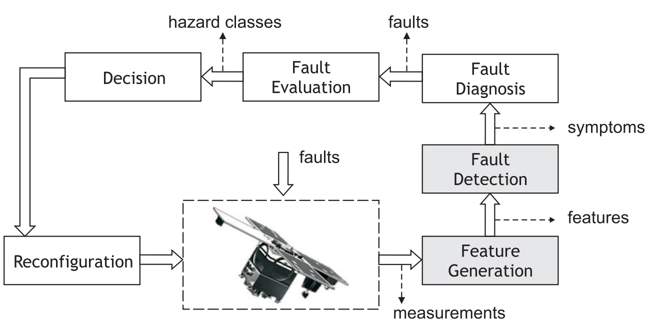

Figure 1 – Diagram showing: detection / diagnosis / reconfiguration

Here, fault detection is under second approach, and is appropriate to reconfiguration purposes. The figure 1 shows: a process (satellite) with faults, the steps executed while the fault occurrence, and the tasks related to this paper. Based on the input and output measurements, features are generated describing certain mode (normal or faulty) of the satellite. Next, methods based on process modelling and systems theory are applied to detect and obtain symptoms of possible faults. These are the two steps covered, therefore it should provide the necessary results for the rest, not treated here but present at the figure 1.

2. FAULT DETECTION BASED ON PARAMETER ESTIMATION

Fault detection methods based on models, uses relations among several measured variables to extract information of possible changes caused by faults. One tool that allows the extraction of these information is the parameter estimation. It is important to distinguish between estimated parameters and process coefficients, because the first one not always are equal to the quantities to be known in the process (process coefficients) [2].

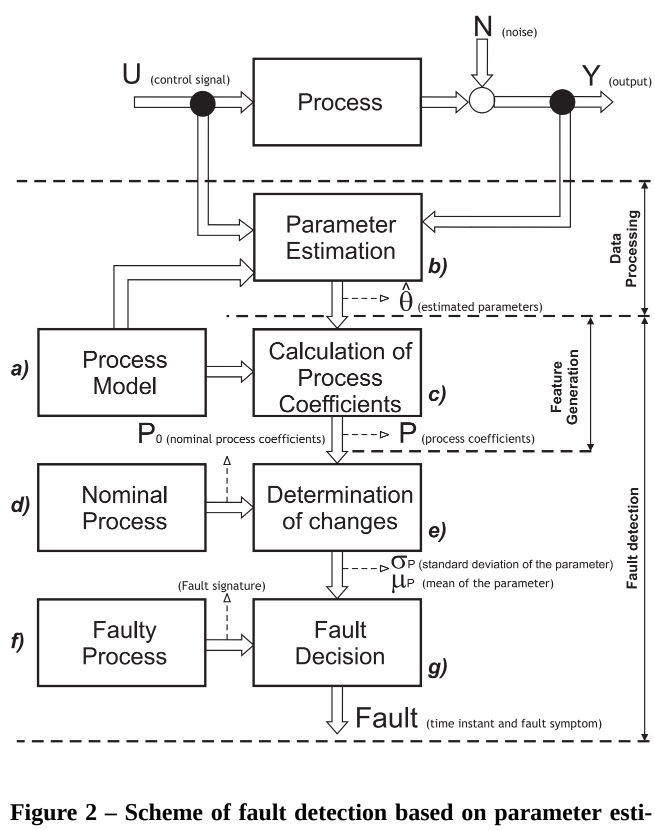

Figure 2 – Scheme of fault detection based on parameter estimation

Figure 2 shows that parameter estimation needs input measurements, output measurements and knowledge of an analytical model (figure 2a) that relates them. Thus, after applying some estimation algorithm, the estimates are provided, consequently expressing more information about the process coefficients; this phase is known as data processing (figure 2b).

Knowing the process coefficients at the current instant (figure 2c) and comparing with the nominal process (figure 2d), the changes are determined (figure 2e). Finally, the decision is taken about the fault occurrence (figure 2g); only the determination of prior changes are not sufficient for this purpose. Therefore, it is compared with the decision threshold (figure 2f).

This process results in: time of fault detection and the symptoms. The first result is the closest time of fault occurrence. And the second result is the deviation of the process coefficients.

3. THE EXPERIMENT

A reaction wheel is an attitude actuator that uses the law of conservation of angular momentum to apply torque to the body of the artificial satellite. The reaction wheel assembly is composed of: a rotating wheel over ball bearings, both encapsulated in a frame and commanded by a brushless DC motor at this same enclosure.

The motor used to simulate the reaction wheel functioning is controlled by voltage applied to the armature, in a range varying from -11V to 11V. It may reach 2000rpm. The measured signals are: armature voltage, armature current and velocity. The sample period is 0.02s with an 8 bit A/D converter and a butterworth digital filter [3] during 10 seconds, obtaining 500 samples. A computer (Intel Pentium III 900MHz, RAM: 256MB, acquisition board: MIC926) was connected on-line to the process, see figure 3.

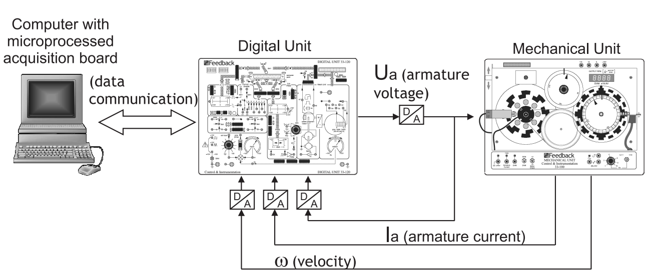

Figure 3 – Scheme of equipment

4. DATA PROCESSING AND FEATURE GENERATION

First, was obtained a model [4] such that inputs and outputs are related, and it will be applied for estimating parameters and obtaining the process coefficients. See sequence in figure 2.

The output provided by the tachometer is proportional to the motor velocity, equation 1, the armature current is related to the applied voltage as in equation 2.

$$V_T = K_T \omega(t) \quad (1)$$

$$\dot{I}_a(t) L_a + I_a(t) R_a = V_a(t) - K_b \omega(t) \quad (2)$$

Table 1 – Symbols

$V_T(t)$	Voltage generated by the tachometer
K_T	Tachometer constant
$\omega(t)$	Angular velocity of the wheel
$I_a(t)$	Armature current
L_a	Armature inductance
R_a	Armature resistance
$V_a(t)$	Voltage applied in the armature
K_b	Motor constant
$\underline{\hat{\theta}}$	Estimated parameters vector
$\underline{\gamma}(k)$	Correction factor at the instant k
$\underline{\psi}(k+1)$	Matrix relating measurement to parameters
$P(k)$	Covariance matrix
I	Identity matrix
$y(k+1)$	Vector measurement

Reorganizing the equation 2, knowing the constant of tachometer (2.5V/1000rpm) from [5], the equation 3 as a model relating input and output measurements is obtained.

$$I_a(t) = \hat{\theta}_1 V_a(t) - \hat{\theta}_2 \dot{I}_a(t) - \hat{\theta}_3 \omega(t) \quad (3)$$

With this model, the parameters $\hat{\theta}_i$ can be estimated. For this purpose, the recursive least squares algorithm is employed, [6]. Equations 4 to 6 correspond to this algorithm, indicated at figure 2b:

$$\underline{\gamma} = \frac{1}{\underline{\psi}^T(k+1) P(k) \underline{\psi}(k+1) + 1} P(k) \underline{\psi}(k+1) \quad (4)$$

$$P(k+1) = [I - \underline{\gamma}(k) \underline{\psi}^T(k+1)] P(k) \quad (5)$$

$$\underline{\hat{\theta}}(k+1) = \underline{\hat{\theta}}(k) + \underline{\gamma}(k)[y(k+1) - \underline{\psi}^T(k+1) \underline{\hat{\theta}}(k)] \quad (6)$$

The symbols used until here, are explained at table 1. The results, after 400 trials, of the parameter estimation are stated at the figure 4.

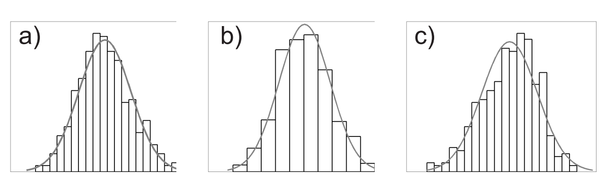

Figure 4 – Resultados: a) $R_a = 2.249 \pm 0.0549\Omega$ **b)** $L_a = 0.00767 \pm 0.00337H$ **c)** $K_b = 0.0267 \pm 0.0023 \frac{Nm}{A}$

5. FAULT DETECTION

The results obtained for the nominal operation mode, gives the information represented at figure 2d, the process coefficients are always calculated, figure 2c, and compared with their nominal values for the changes determination, through the algorithm described in equations 7 to 9.

$$\hat{\mu}_{p_i}(k) = \frac{1}{N}\sum_{j=1}^{N} p_i(k-j) \tag{7}$$

$$\hat{\sigma}^2_{p_i I}(k) = \frac{1}{N}\sum_{j=1}^{N} [p_i(k-j) - \hat{\mu}_{p_i o}]^2 \tag{8}$$

$$\hat{\sigma}^2_{p_i II}(k) = \frac{1}{N}\sum_{j=1}^{N} [p_i(k-j) - \hat{\mu}_{p_i}]^2 \tag{9}$$

Where p_i is the process coefficient, $\hat{\mu_i}$ is the mean of the process coefficient and $\hat{\sigma_i}$ is the standard deviation of the process coefficient.

These are the results which has shown at the figure 2e. Now, the fault decision about the faulty process has to be made.

A fault decision is simply to assume one of the two hypothesis: H_0 (nominal process or null hypothesis) and H_1 (faulty process or alternative hypothesis). At each time instant a decision is made, and assuming that either hypothesis can be true or false, this is a binary hypothesis testing problem. Thus, four possible cases can occur.

In two cases the decision is correct (no fault $\longrightarrow H_0 = 1$ and fault $\longrightarrow H_1 = 1$), and in other two, incorrect (no fault $\longrightarrow H_0 = 0$ and fault $\longrightarrow H_1 = 0$). The last ones are respectively called by: false alarm and miss alarm. Obviously, by reasons of safety, the consequences of an incorrect decision are not the same of a correct decision; with this reasoning, each situation have a different cost and the objective of the bayesian decision criterion is precisely to minimize the mean of the total cost (risk function). The decision rule resulting of the Bayes criterion is in equation 10, [1].

$$d_i(k) = \frac{\hat{\sigma}^2_{p_i I}(k)}{\hat{\sigma}^2_{p_i o}} - \ln\frac{\hat{\sigma}^2_{p_i II}(k)}{\hat{\sigma}^2_{p_i o}} - 1 \tag{10}$$

Using the Bayes criterion, the probabilities of hypothesis occurrence is assumed to be known. These probabilities, $P(H_0)$ e $P(H_1)$, can be estimated if a sufficient amount of data exists [6]. Here, it is assumed that these two a-priori probabilities are equal and known ($P_0 = 0.5$). It is of major influence in the threshold value at the likelihood ratio test (equation 11), [1]. In a fault case $d_i > w_i$.

$$w_i(k) = \ln\frac{NP_0}{1-P_0} \tag{11}$$

6. RESULTS

The first experiment introducing a fault is called experiment F1, when an asymmetric gain on the power amplifier is forced.

In figure 5a, it is shown the behavior of the variable velocity before fault occurrence and when the fault is injected, approximately at 2 seconds. Until the injection of fault, the system has a transient response of less than 1.5 seconds, where it achieves steady state behavior. When the fault is injected,

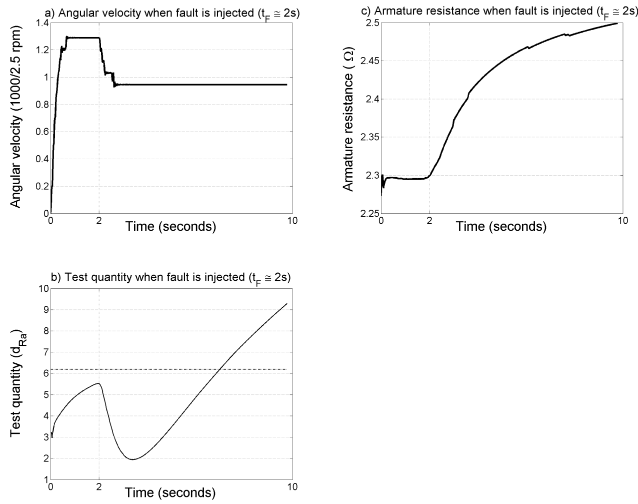

Figure 5 – Results detecting the fault 1 (F1: Asymmetric gain on the power amplifier)

around 2 seconds, the velocity behavior looks like a second transient response and achieves another steady state behavior. This system's response is due to a change in a feature of the process, not a control signal, input or disturbance.

This fault is sensed like indicated at figure 5b by the coefficient R_a, which varies as in figure 5c, increasing the mean. Note that, during the transient response, the test quantity d_{R_a} increases but never crosses the threshold, until the fault occurrence. A sluggish response of this test quantity in presence of fault F1 could be observed, perhaps, adjusting the threshold by defining its parameters according with experience or even by estimating them. The other process coefficients did not present any kind of change, neither in mean or variance.

The estimate of armature resistance, was very close to its nominal value during fault free operation. Remember that a constant voltage is applied to the armature; if for the same input, an output with smaller magnitude than before is obtained, then, a larger obstruction to the flow of current could exist. This feature was shown by the measurement model as an increasingly armature resistance.

The fault F2, is observable in all process coefficients; unlike fault F1, where only the armature resistance changes. This second fault presents a clean signature, figures 6d to 6f. It occurred approximately (this time of fault is always unknown) at 2 seconds, and is detected fairly after, figures 6a to 6c.

Figure 6a shows the response of the test quantity d_{R_a}, which immediately increases its magnitude few samples after fault occurrence. The same happens with the other two test quantities (d_{L_a} and d_K) with different magnitudes but very similar behavior. Detection by the test quantities of armature resistance and motor constant (figure 6c) is at the same time, and by the armature inductance (figure 6b) happens few samples after these.

Abrupt changes in the mean takes place in all three parameters. The magnitude at time $2s$ express this abrupt change

Table 2 – Symptoms

FAULT	R_a	L_a	K_b
F1: Asymmetric gain on the PA	+(1)		
F2: Loss of the MSB of D/A converter	+(1)	-(2)	-(1)

sensed in all output variables measured, noted too at figures 6d, 6e e 6f.

Two inserted faults (F1 and F2) could be detected, according with the Bayesian approach. Figures 5 and 6 have symptoms and time of fault, the desired results for fault the detection procedure stated at the beginning of this paper (figure 2g). But it is nothing more than working with only two hypothesis. Other task is to separate this hypothesis in different groups, in such a way to identify which situation belongs to each one of this groups. It would be the next step after fault detection.

The time in which the faults were detected, and the behavior of the process coefficients, are the results obtained to the fault diagnosis, noting that faults F1 and F2 represent different signatures.

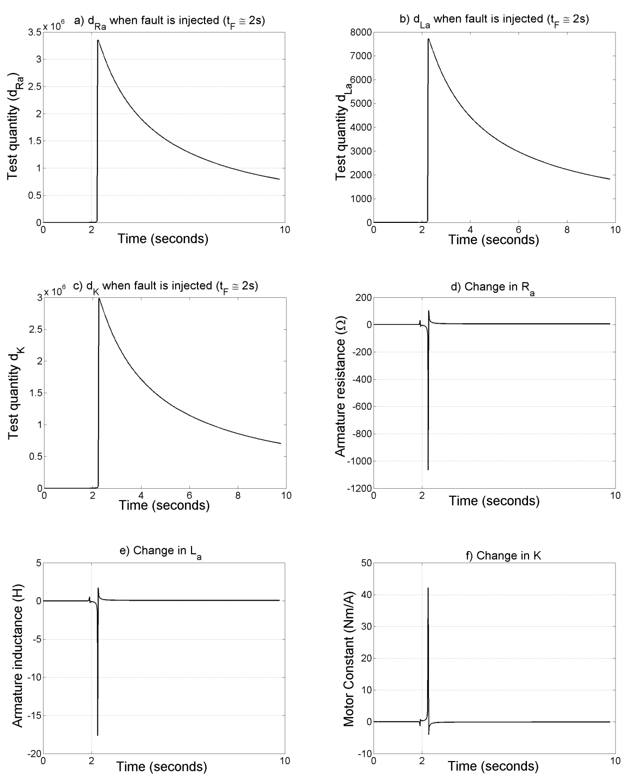

Figure 6 – Results detecting the fault 2 (F2: Loss of the most significant bit of D/A converter)

Following table 2, with fault detection results giving necessary information to perform fault diagnosis.

7. CONCLUSION

The experimental work in detecting faults based on analytical models is the beginning of the cycle described in figure 1. The steps exhibited by figure 2, were covered entirely along this work. The recursive least squares algorithm was a great tool for determining the nominal values, which were really close to a normal distribution, figure 4. Some reviews have to be made for the armature inductance, because this process coefficient has a standard deviation comparable with its nominal value. An idea to improve the results in future works, is to apply other methods or develop another measurement model for the parameter estimation.

Solely the process coefficient R_a could detect a feature change through its test quantity in fault F1. Even so, the response is too late, needing more than 150 samples to sense a faulty behavior. All the process coefficients had responses during the injection of fault F2, detected by its test quantities.

The a-priori probability of fault occurrence has an important task into fault decision, hence it is possible to move the decision threshold. For future works, the estimation of this parameter is plausible and desirable. Weighing missing and false alarms in distinct ways, more or less severe, would be also a good idea.

In general, all the results obtained were satisfactory, since detection was accomplished. Here, the concern is with testing two hypothesis (non faulty and faulty process), however the table 2 allows to go further. For example to identify other two distinct hypothesis (diagnosis); and this analysis still could be refined by evaluation of respective variances; not only the mean. Implementation in a real-time application is also of direct interest.

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