ON-LINE FAULT DIAGNOSIS TECHNIQUE OF THE MAGNETIC LEVITATION VEHICLE SYSTEM

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ABSTRACT

The supervision of technical processes is the subject of increased development because of the reliability and safety. The use of process computers and microcomputers permits the application of methods, which result in an earlier detection of process faults than is possible by conventional limit and trend checks. With the aid of process models, estimation and decision methods it is possible to also monitor non-measurable variables like process states, process estimation and characteristic quantities. This paper describes how recursive identification techniques can be used in order to detect the faults of the dynamic continuous systems. This approach employs a combination of operators, the system dynamic being expressed in terms of the incremental difference delta that serves to some theoretical advantages and the time delays expressed using the z operator. So, estimation of parameters of diagnose model, and the faults detection who makes to the aide of statistical methods based on the interval of confidence (χ^2 distribution, Fisher distribution and Student distribution). This technique is validated in simulation by the application on a magnetic levitation vehicle system MLV.

KEYWORDS :

Parameter estimation, fault detection and isolation, Residual generation, Residual evaluation, statistical distribution, Magnetic levitation vehicle.

1. INTRODUCTION

Faults or failures in complex automated control systems are unavoidable fact that is why quick detection, location and identification are necessary in order to eventually accommodate the system. The fault detection and isolation (FDI) idea is the investigation subject of many researchers during the last years, as Clark (1978), Ge & Fang (1988), Patton & al. (1989), Gertler (1991), Park & Rizzoni (1994). Some approaches have been proposed for linear systems, for example, the unknown input observer (Kudva & al. 1980 ; Frank & Wunnenberg, 1989 ; Hou and Muller, 1994 ; Chen & al. 1996), and recently for bilinear systems the bilinear fault detection observer (Yu & al. 1996) and a bilinear reduced-order observer (Hac, 1992 ; Yu & al. 1996). Another kind of method is the parity space method and analytic redundancy of parameters. As a result, a disadvantage of these methods is that they are not capable of isolating faults that have the same direction in the system state space [13].

The strategy of surveillance by the parameter estimation technique is based on available observation on the process state, which must provide information, which predict the origins of the faults. This approach is fundamentally based on the automatic concept and makes call to the developed techniques in identification.

The diagnosis by the parameter estimation method uses the intermediate model called « Grey box »:

Near to the knowledge model in order to preserve a trace of mechanisms explaining the working.

Near to the representation model in order to use a simple structure, adapted to calculus of reasonable complexity.

The parameter estimation method for fault diagnosis can detect and isolate faults, and may diagnose fault size, even for faults having the same direction in the state space of the model. A limitation to the parameter estimation method is that the number of physical parameters must be less than or equal to that of model parameters. This condition, however, can sometimes not satisfy in practice. In order to solve this practical problem, a combination of the system modelling and the hybrid parameter estimation method is considered in this paper.

The failure detection based on compare of the real functioning of the system with which will be under the normal functioning hypothesis. The result of the detection procedure is a significant alarm that normal functioning model is not able to describe the real function of the supervised system.

2. SYSTEM IDENTIFICATION USING DELTA OPERATOR

2.1 Model description in delta

The shift operator z is used extensively in order to describe the discrete time systems. That conducts to undesirable casualties of the physical system, which constitutes a serious constraint. On this point of view, we can suspect which a best correspondence between the continuous and discrete time, which is obtained if the shift operator z is, replaced by an operator who is more similar a derivative (d/dt). The use of an obtaining method of a continuous model with the help of delta operator can offer any advantages, respecting the model choice which is the result of compromise between its complexity and its aptitude to translate the behaviour of the studied system.

In order to study the systems in the discrete and continuous cases together, we use the unified formalism which gives hybrid representation [4, 9], which that the discrete incremental difference (or delta) operator is defined by,

$$\delta = \frac{z-1}{T} \tag{1}$$

Where z the forward shifts operator and T is the sampling interval. It can be seen that the delta operator is a form of the forward-difference formula [8],

$$\dot{f}(x) = \frac{f(x+h) - f(x)}{h} \tag{2}$$

Which is used extensively in numerical analysis for computing the derivative of a function at a point. The use of the delta operator in the field of control engineering is not entirely new, Gawthrop introduced the idea of a hybrid control strategy based on the backward difference operator in 1980 whilst Goodwin & al. demonstrated the use of the operator in a model reference adaptive controller in 1986. The operator has also been shown to exhibit improved finite word length characteristics (Middleton & Goodwin) over its discrete time counterpart.

The interest of this representation is the unified study of the continuous and discrete cases and the passage from the discrete case to the continuous case, by tending T toward zero. The choice of this representation is not only the presentation of the systems study in the continuous and discrete time, but especially the realisation of numerical treatment of quality: in fact, the systems advancing nearly always in the continuous time, their numerical treatment with the help of the shift operator z depends on sampled period T; otherwise, the delta operator permits a discrete representation near to the continuous model [1]. Consequently, more T is small, the approximation is better. The relationship between δ and z is a simple linear function, so δ offers the same flexibility of modelling of the systems as the shift operator of z.

The dynamical behaviour of the systems can be introduce by an equation between the derivative δ^i of the input u(t) and the observed output y(t) writing in the invariable linear systems cases on time,

$$\begin{aligned} &A(\delta)y(t) = B(\delta)u(t) \\ &A(\delta) = \sum_{i=0}^{n} a_i \delta^i, \ a_n = 1 \\ &B(\delta) = \sum_{i=0}^{m} b_i \delta^i \end{aligned} \tag{3}$$

The estimation method that we will study in this paper basically depend on our ability to rearrange the model so that the predicted output describable as a linear function of a parameter vector θ: that is, there exists some vector of measured variables, $\varphi(t)$, such that the model output can be expressed as,

$$y(t) = \varphi^T(t)\theta \tag{4}$$

When the generalised derivatives of y(t) and u(t) are available, then the model in (4) is immediately in the required form, where,

$$\begin{aligned} \theta^T &= \begin{bmatrix} -a_{n-1} & \cdots & -a_0 & b_m & \cdots & b_0 \end{bmatrix} \\ \varphi^T(t) &= \begin{bmatrix} \delta^{n-1}y(t) & \cdots & y(t) & \delta^m u(t) & \cdots & u(t) \end{bmatrix} \end{aligned} \tag{5}$$

Effectively, we have linear model with regard to the parameters, but impracticable because explanatory variables y(t) and u(t) are not available. The principle is correct, but a previous filtering of data is necessary in order to achieve a transformation of model under a realist form. The methodology is called chain moments of Poisson, which that consists to use a stable nth-order filter $1/E(\delta)$ [9]. In practice, we prefer use a simple structure, depending of minimum parameters. For this reason, habitually we use,

$$E(\delta) = (\delta + \eta)^n \tag{6}$$

The choice of η conditions the bias, but also the convergence of the estimation. We can choose η in manner that $E(\delta)$ approach to the better of $A(\delta)$, for example according to the criterion of bandwidth. Then, the model becomes,

$$\begin{aligned} &A(\delta)y_f(t) = B(\delta)u_f(t) \\ &y_f(t) = \frac{y(t)}{E(\delta)}\ ;\ u_f(t) = \frac{u(t)}{E(\delta)} \end{aligned} \tag{7}$$

with,

$$y(t) = \frac{E(\delta) - A(\delta)}{E(\delta)} y(t) + \frac{B(\delta)}{E(\delta)} u(t) \tag{8}$$

We obtain a linear model with regard to the parameters by a transformation of the original data to the filtered data, where an analogue relation to the equation (3), but realist because the variables $y_f(t)$, $u_f(t)$ are calculable, with,

$$y(t) = \delta^n y_f(t)$$
$$\theta^T = \begin{bmatrix} e_{n-1} - a_{n-1} & \cdots & e_0 - a_0 & b_m & \cdots & b_0 \end{bmatrix} \tag{9}$$
$$\varphi^T(t) = \begin{bmatrix} \delta^{n-1} y_f(t) & \cdots & y_f(t) & \delta^m u_f(t) & \cdots & u_f(t) \end{bmatrix}$$

It is interesting to note that the regression vector φ(t) for the proceeding two models can be readily generated via the following nth-order state space models,

$$\begin{aligned} \delta\varphi_y &= \overline{E}\varphi_y + \beta y \\ \delta\varphi_u &= \overline{E}\varphi_u + \beta u \\ \varphi_y^T &= \begin{bmatrix} \delta^{n-1} y_f & \cdots & y_f \end{bmatrix} \\ \varphi_u^T &= \begin{bmatrix} \delta^{n-1} u_f & \cdots & u_f \end{bmatrix} \\ \overline{E} &= \begin{bmatrix} -e_{n-1} & & \cdots & -e_0 \\ 1 & & & \\ & \ddots & & \vdots \\ & & 1 & 0 \end{bmatrix}, \beta = \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \end{aligned} \tag{10}$$

2.2 Hybrid parameter estimation

The estimation problem consists the parameter identification, which appears in the model by the treatment of the input/output data. We consider that θ the parameter vector, which can correctly traduce the dynamic behaviour of the process, and *φ(t)* the regression vector. The estimation consists to find a good estimate $\hat{\theta}$ of *θ*. The common measure of goodness of an estimate in the least squares cost function,

$$c(\hat{\theta}, t) = \frac{1}{2}\int_0^t (y(\tau) - \varphi^T(\tau)\hat{\theta})^2 d\tau \tag{11}$$

In this case, we can define the hybrid algorithm of the generalised least squared according to,

$$\begin{aligned} \varepsilon(t) &= y(t) - \varphi^T(t)\hat{\theta}(t-1) \\ \delta\hat{\theta}(t) &= \frac{\alpha(t)P(t)\varphi(t)\varepsilon(t)}{\Gamma(t) + T\varphi^T(t)P(t)\varphi(t)} \\ \delta P(t) &= -\frac{\alpha(t)P(t)\varphi(t)\varphi^T(t)P(t)}{\Gamma(t) + T\varphi^T(t)P(t)\varphi(t)} + \Omega(t) \end{aligned} \tag{12}$$

where,

α(t) = a (time-varying) gain, α(t)∈[0 1].

Γ(t) = a (time-varying) normalisation term, Γ(t)>0.

and where Ω(t) represents a modification to the "covariance" update, with: $\Omega(t) = \Omega^T(t) \geq 0$.

The term covariance update is used since P(t) can be correspond to a covariance matrix under suitable conditions. For the least squares with forgetting factor, we use,

$$\Omega(t) = \left(\frac{1}{1 - T\lambda}\right)\left(\lambda P(t) - \frac{TP(t)\varphi(t)\varphi^T(t)P(t)}{\Gamma + T\varphi^T(t)P(t)\varphi(t)}\right) \tag{13}$$
$$\alpha(t) = 1, \lambda \leq 1$$

3. DIAGNOSIS

The purpose of diagnosis is to determine the origin or the nature of the fault by using the knowledge of the system structure. In this paper, we have studied the statistical methods of detection based on the confidence interval. These methods generate detection test depending on confidence interval constructed on the statistical distributions of the residual. These residuals before reflect maximum information of faults. The redundancy among the measurements can be evaluated for the diagnosis with the general procedure:

Choice of the degree confidence ξ necessary to the construction of the interval confidence.

Choice of the liberty degree number of the considered statistical distribution.

Generation of residuals i.e. functions that are made oversensitive to the fault.

Decision concerning the faults and their isolation.

If the fault occurs, the redundancy relations are no longer satisfied and one residual ε differs significantly from zero. The residual is then used to form an appropriate decision function. The basic idea of the hybrid estimation approach is to estimate the system parameters from all the measurements or subsets of measurements. We use the estimation error ε in (12) as a residual for the fault detection and isolation.

To analyse these residuals, it was suggested to use a statistic test based on the transformed residual vector.

3.1 Test based on χ^2 distribution

This test rests on the comparison of an estimated value ε^2 at two threshold values delimiting the confidence interval. When the residual signal is the prediction error, this test equals to the whiteness test of the innovation. The ε^2 value constructed on innovation *e*(*k*) written as,

$$\begin{aligned} \beta_n(k) &= \sum_{i=k-n+1}^{N} e_n^2(k) \\ e_n(k) &= \frac{e^2(k)}{\sigma^2(k)} \in (0,1) \end{aligned} \tag{14}$$

And the detection test will be according to,

$$\chi_{n,-\alpha/2} \le \beta_n(k) \le \chi_{n,\alpha/2} : \text{No failure}$$

3.2 Test based on Fisher distribution

The Fisher variable results to the report of two variables of ε^2 divided by they number of freedom degrees. Consider the variances $s_1^2(k)$ and $s_2^2(k)$ of the estimated prediction error following two samples of different signal size, and normalised by their freedom degree n_1 and n_2 respectively. We obtain the following Fisher variable,

$$F(k) = \frac{s_1^2(k)}{s_2^2(k)} \tag{15}$$

And the detection test will be according to,

$$F < F_{n_1,n_2,\alpha} \text{ and } F^{-1} < F_{n_2,n_1,\alpha} : \text{No failure}$$

3.3 Test based on Student distribution

The Student variable results to the report of two variables, one according to the normal distribution, centred and reduced, and the other according to Student distribution. By considering the prediction error and his estimated variance. The Student variable is defined as follow,

$$S(k) = T^2 \frac{e(k) - \bar{e}(k)}{\sqrt{\dfrac{\sigma_e^2(k)}{\hat{\sigma}_e^2(k)}}} \tag{16}$$

And the detection test will be according to,

$$-S_{n,\alpha/2} \le S(k) \le S_{n,\alpha/2} : \text{No failure}$$

With $S_{n:\xi/2}$, the value of the Student distribution for a chosen confidence interval ξ and n, the size of the observation window.

4. DESCRIPTION OF THE MLV SYSTEM

The technology of the magnetic suspension is greatly more advanced until present; it is the international investigation subject [5]. Their application on the vehicles requires energy, elimination of the disturbances and the safety must be very important in order to contribute to the method success. The principal block diagram of MLV system is illustrated on Fig.1.

The instantaneous flux linkage between the two magnetised bodies through the airgap z(t) is Φ_m; but if the magnet winding and geometry are such that $\Phi_T \cong \Phi_m$, then the instantaneous magnet inductance may be expressed as [10],

$$L(z,i) = \frac{N}{i}\Phi_T = \frac{N}{i(t)}\frac{Ni(t)}{R_T} \tag{17}$$

Where R_T is the reluctance of the entire magnetic circuit and N the coils or turns number. If the reluctance in the magnetic core is assumed to be negligible compared with the two airgaps (total length=2z(t)), then,

$$L(z) = \frac{\mu_0 N^2 A}{2z(t)} \tag{18}$$

Where A is the magnet surface and μ_0 is the electrical permeability.

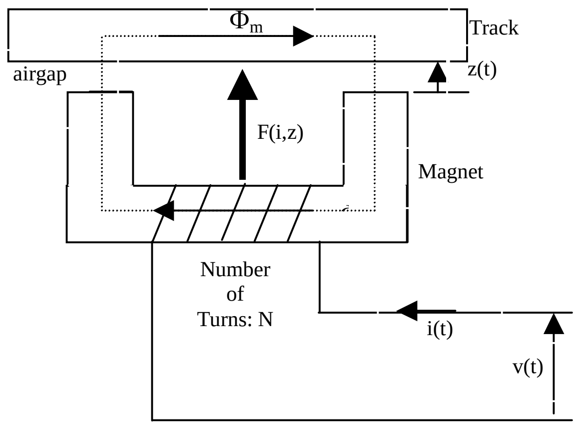

***Fig.1 :** Electromagnet-track configuration*

Also the force of attraction at any instant of time is,

$$F(i,z) = \frac{\beta^2 A}{\mu_0} = \frac{\mu_0 N^2 A}{4}\left[\frac{i(t)}{z(t)}\right]^2 \tag{19}$$

Where β is the density flux. Thus if R is the total resistance of the circuit then for an instantaneous voltage v(t) across the magnet winding, the excitation current is controlled by,

$$\begin{aligned} v(t) &= Ri(t) + \frac{d}{dt}\left[L(z,i)i(t)\right] \\ &= Ri(t) + \frac{\mu_0 N^2 A}{2}\frac{d}{dt}\left[\frac{i(t)}{z(t)}\right] \\ &= \mathrm{Ri(t)} + \frac{\mu_0 N^2 A}{2z(t)}\frac{di(t)}{dt} - \frac{\mu_0 N^2 A i(t)}{2[z(t)]^2}\frac{dz(t)}{dt} \end{aligned} \tag{20}$$

By using the notations in Fig.1, the force generated by the above excitation i(t) will control the vertical dynamics of the system, which, with reference to an absolute datum, is described by ($f_d(t)$=disturbance force input),

$$m\ddot{z}(t) = -F(i,z) + f_d(t) + mg$$
$$mg = F_0(i_0, z_0) = -\frac{\mu_0 N^2 A}{4}\left[\frac{i_0}{z_0}\right]^2 \qquad (21)$$

Where m is the mass of the suspended body and (i_0, z_0) denotes the equilibrium point.

Exact analysis of the suspension dynamics would require numerical solution of equation (21), but a reasonably accurate linear model may be obtained by using linear approximations of the attraction force for excursions around the nominal equilibrium point (i_0,z_0). The small perturbation linear equations of the system are,

$$\begin{aligned} m\Delta\ddot{z}(t) &= -\frac{\mu_0 N^2 A}{4}\left[\frac{i_0+\Delta i(t)}{z_0+\Delta z(t)}\right]^2 + f_d(t) + mg \\ &\cong -k_i\Delta i(t) + k_z\Delta z(t) + f_d(t) \end{aligned} \qquad (22)$$

with,

$$k_i = \frac{\mu_0 N^2 A i_0}{2z_0^2}, k_z = \frac{\mu_0 N^2 A i_0^2}{2z_0^3} \qquad (23)$$

and,

$$\begin{aligned} v_0 + \Delta v(t) &= R\left[i_0 + \Delta i(t)\right] + \\ &+ \frac{\mu_0 N^2 A}{2}\frac{d}{dt}\left[\frac{i_0+\Delta i(t)}{z_0+\Delta z(t)}\right] \\ &\cong Ri_0 + R\Delta i(t) + L_0\Delta\dot{i}(t) - k_i\Delta\dot{z}(t) \end{aligned} \qquad (24)$$

Where L_0 is the inductance of the magnet winding at (i_0,z_0),

$$L_0 = \frac{\mu_0 N^2 A}{2z_0} \qquad (25)$$

The block diagram of the above linear system is given in Fig.2. The transfer function of the open-loop system, with $f_d(t)=0$ is,

$$\frac{\Delta Z(s)}{\Delta V(s)} = -\frac{(k_i/mR)}{\left(1+\frac{L_0}{R}s\right)\left\{s^2 + \frac{k_i^2}{mR\left(1+\frac{L_0}{R}s\right)}s - \frac{k_z}{m}\right\}} \qquad (26)$$

If the power amplifier has a wide enough bandwidth $T_m << 1$, then an approximate form of open-loop characteristic equation is,

$$(1+T_m s)\left(s^2 + \frac{k_i^2}{mR}s - \frac{k_z}{m}\right) = 0, T_m = \frac{L_0}{R} \qquad (27)$$

To derive the transfer function of the open-loop system, the parameters of the magnet at the equilibrium point need to be calculated. The nominal equilibrium for both magnets was chosen to be i_0=2A and z_0=1.5mm. The values of magnet constants at this point are given by [4],

k_i=44N/A, k_z=58000N/m, m=3kg, R=7Ω, L_0=33mH

We can put the transfer function of the MLV system in the following form,

$$\frac{\Delta Z(s)}{\Delta V(s)} = \frac{b_0}{\left(s+\frac{1}{T_m}\right)\left(s^2 + a_1 s + a_0\right)} \qquad (28)$$

with,

$$a_0 = -\frac{k_z}{m}, a_1 = \frac{k_i^2}{mR}, b_0 = -\frac{k_i}{mL_0} \qquad (29)$$

The transfer function $\frac{\Delta Z(s)}{\Delta V(s)}$ is now in a form that enables a digital controller to be designed and implemented on a micro-controller. If however, the operator z is substituted using,

$$z = T\delta + 1 \qquad (30)$$

The following transfer function of the MLV system is obtained,

$$\frac{Z(\delta)}{V(\delta)} = \frac{b_0}{\left(\delta+\frac{1}{T_m}\right)\left(\delta^2 + a_1\delta + a_0\right)} \qquad (31)$$

We desire to estimate the parameter b_0, a_0 and a_1 of the described model by the following polynomial equation,

$$A(\delta)z(t) = B(\delta)v_1(t) \qquad (32)$$

with,

$$\begin{aligned} A(\delta) &= \delta^2 + a_1\delta + a_0 \\ B(\delta) &= b_0 \\ v_1(t) &= \frac{1}{(\delta + 1/T_m)}v(t) \end{aligned} \qquad (33)$$

For the filtering, we take η=300,

$$E(\delta) = (\delta+300)^2 = \delta^2 + e_1\delta + e_0 \qquad (34)$$

We can have the model in the following form,

$$z(t) = (e_1 - a_1)\delta z_f(t) + (e_0 - a_0)z_f(t) + b_0 v_{1f}(t) \qquad (35)$$

The equation (35) has the form,

$$z(t) = \varphi^T(t)\theta \qquad (36)$$

where,

$$\varphi^T(t) = \left[\delta z_f(t) \quad z_f(t) \quad v_{1f}(t)\right]$$
$$\theta^T = \left[e_1 - a_1 \quad e_0 - a_0 \quad b_0\right] \tag{37}$$

5. EXPERIMENTAL RESULTS

The relationships between the system physical parameters and the model parameters according to (32) and (36) are,

$$R = \frac{K_i^2}{ma_1}, L_0 = -\frac{K_i}{mb_0} \tag{38}$$

It can be seen that the number of physical parameters in equation (38) is inferior than the of the model parameters, this facilitate the isolation. It result, therefor, that the changes in the physical parameters in (38) can be identified by detecting the changes in the in the model parameters. However, with the assistance of the statistic methods which gives the fault alarm, the faults can be diagnosed by estimating the groups of the physical parameters in (38) from the system delta model in (32). The recursive least square with forgetting factor was used to estimate a_0, a_1 and b_0 on line. Furthermore, the size of a fault can be diagnosed if the estimation is precise. Let the confidence degree ξ=10%, which wants that the estimation makes with a confidence rate of 90%.

The set of faulty data simulates a change in efficient of resistance (parameter R) and a change in the efficient of inductance (parameter L_0):

$$\Delta R/R = 0.9\,, \Delta L_0/L_0 = 0.9\,, t > 200$$

Fig.3 describe the output and input measurement and the estimates of a_0, a_1 and b_0 were obtained, and are shown in Fig.4, Fig.5 and Fig.6, and they decisions functions based on the statistical distribution (χ^2, Fisher, Student) are shown in Fig.7, Fig.8 and Fig.9.

The percentage decrease on a_1 caused by ΔR is calculated as $\Delta a_1/a_1 = 0.47$ and the percentage decrease on b_0 caused by ΔL_0 is $\Delta b_0/b_0 = 0.47$ It is observed that the relative change in size of the estimated model parameter is approximately equivalent to the relative change in size of the physical parameter for both faults. Therefore, the fault size is diagnosed.

Note that the physical parameters change for all the faults, due to the convergence of the estimates of the model parameters. Then it is consequently necessary in diagnosis to know the pertinent parameters precision; but more than the absolute precision, it is the relative precision between different parameters which allows to have a decision about the effective pertinence or about the manner to improving this precision, in particular, thanks to sensibilisants inputs. It is usually recommended to use a pseudo-random binary sequence (rich in information) in order to excite the system: this input assures the condition of persistent excitation and allows sensibilising all the modes of the system thanks to the width of its spectrum.

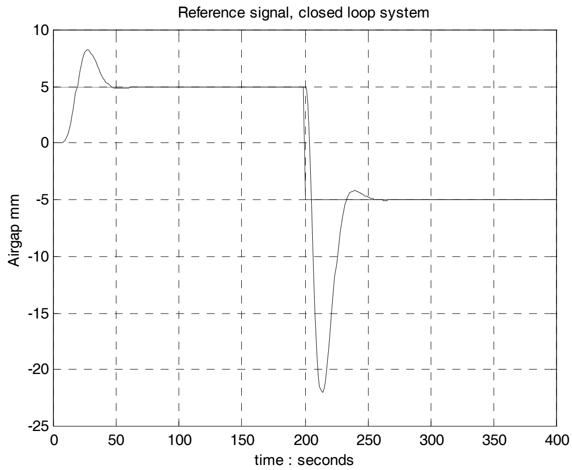

Fig.3. *Voltage input and airgap*

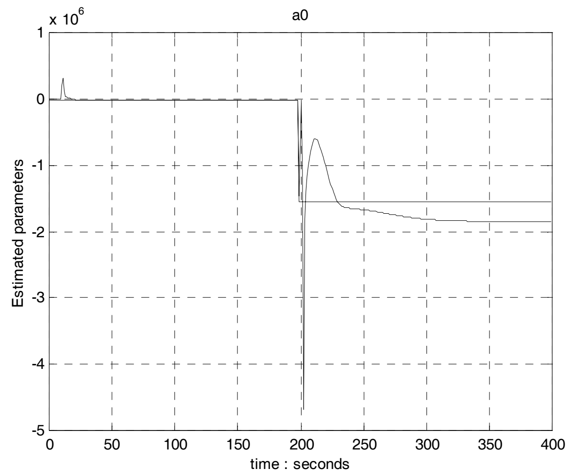

Fig.4. *Estimate of a_0 using least square algorithm with forgetting factor*

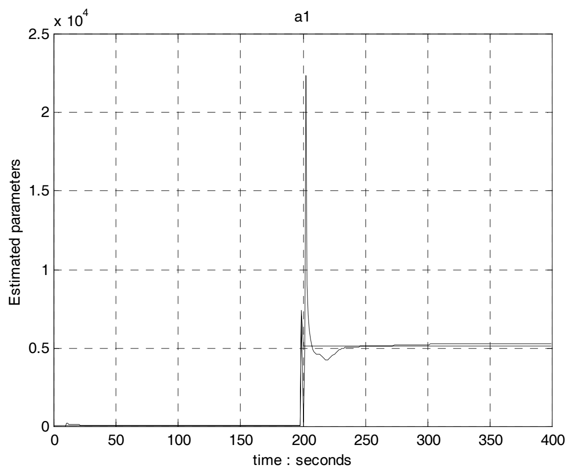

Fig.5. *Estimate of a_1 using least square algorithm with forgetting factor*

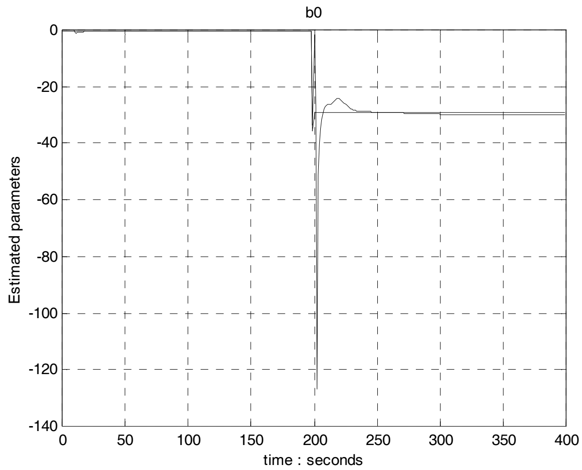

Fig.6. *Estimate of b_0 using least square algorithm with forgetting factor*

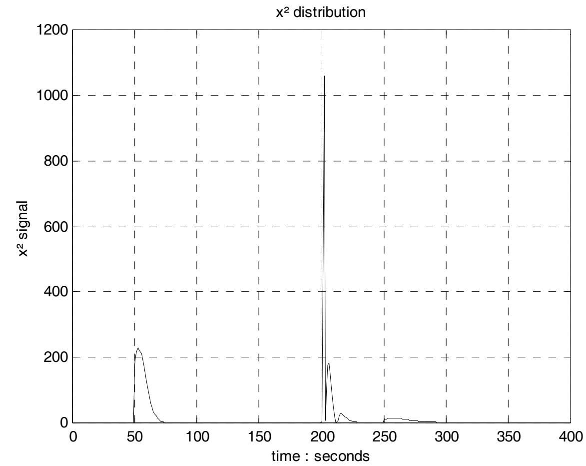

Fig.7. *Fault detection using χ^2 distribution*

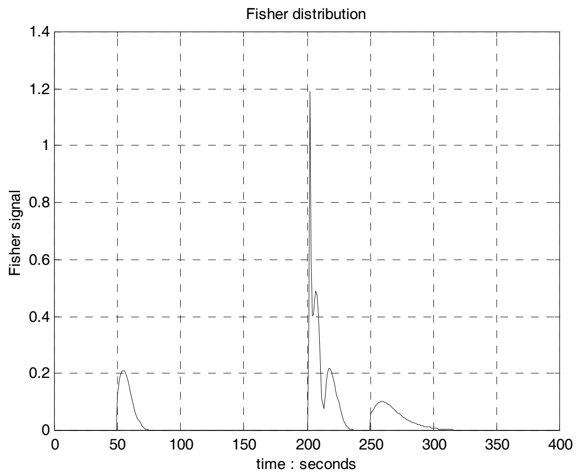

Fig.8. *Fault detection using Fisher distribution*

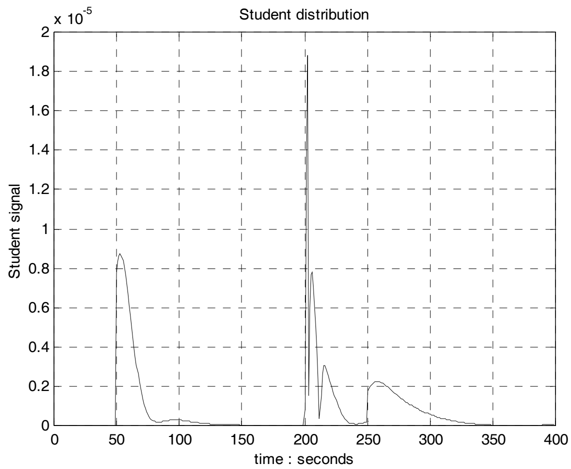

Fig.9. *Fault detection using Student distribution*

6. CONCLUSION

The hybrid parameter-estimation method is applied to a magnetic suspension system in order to detect the changes of the physical parameters by the surveillance of the model parameters. The method operates in combination with a statistical method, which gives the fault alarms. The aim of diagnosis is the surveillance, since of available information on the system, in order to detect and localise the failure, which affect the performances and security of system. Then, it is possible to generate the alarms, to providing of validated information about the system and eventually to pursuit the functioning conditions of system. Then, every failure can lead stops, where a service break and by consequence a production diminution. The simulation study suggests that the combination of different methods will be more efficient for fault diagnosis in real industrial systems.

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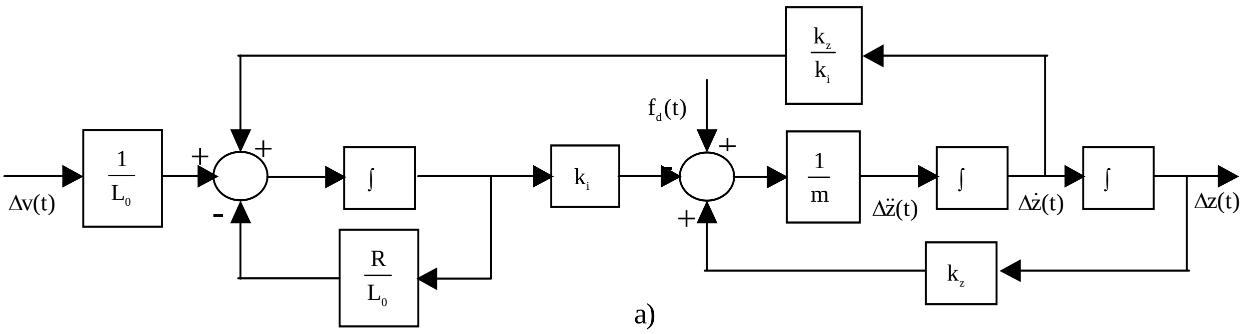

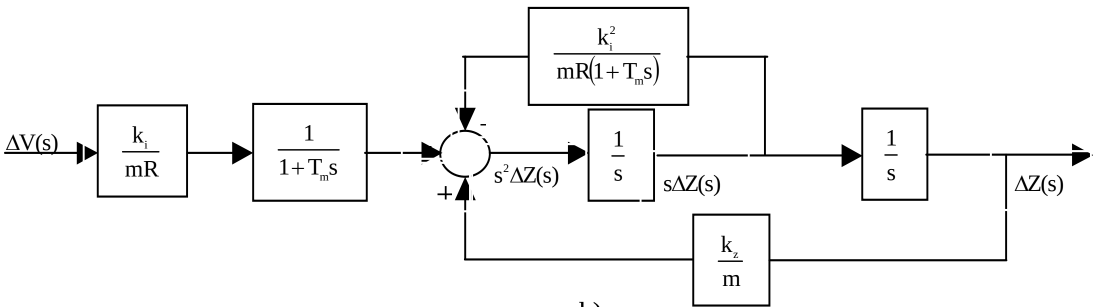

***Fig.2**. Block diagram of the open-loop system*

a) Based on linearised state equations.

b) Modified transfer function.