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Anastasios D. Pouliezos
Technical University of Crete

George Stavrakakis
Technical University of Crete

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FAULT DETECTION USING PARAMETER ESTIMATION

A. POULIEZOS, G. STAVRAKAKIS AND C. LEFAS
Department of Production Engineering, Technical University of Crete, Aghiou Markov Street, 73132 Chania, Greece

SUMMARY

This paper presents a brief summary of fault-detection methods using parameter estimation techniques. An overview of the fault-detection system design methodology is first presented, followed by the principles of parameter-estimation fault-detection techniques. Applications from the field of industrial processes are given and finally a case study is described which applies the general techniques to the fault detection of D.C. motors using multiprocessor systems.

KEY WORDS Fault detection Parameter estimation Reliability

INTRODUCTION

The increasing complexity of man-made systems, such as computer and communication networks, manufacturing systems and electrical power systems, poses difficult problems to the users of these systems.

The complexity arises not only from the high dimensionality of these systems and the large volumes of the information flow, but also from the randomness of faults and failures.

Carefully constructed optimal operational strategies can easily be rendered null by an unexpected failure, hence the crucial importance of reliable and fast fault detection, location and isolation.

Benveniste[1] distinguishes three typical situations in which the need for detecting changes in dynamical systems arises:

1. Change detection is an integral part of the modelling of a signal or a system. A typical example of this is the segmentation of signals in view of pattern recognition, especially speech signals, electroencephalograms, or various geophysical signals. Applications are reported by Doerschuk *et al.*,[2] Andre-Obrecht[3] and Nikiforov and Tikhonov.[4]
2. Detection plays the part of an alarm during the monitoring of a dynamical system, the most frequent case being the detection of failures in sensors or actuators in control systems. A more difficult variant of this category is the monitoring of vibrating structures (turbines, motors, offshore platforms), where monitoring is aimed at the detection of changes in the vibrating behaviour of the structure, possibly related to the occurrence of fissures or fatigue.
3. Change detection is a tool for improving the tracking capability of an adaptive algorithm in the presence of non-stationarities in the system to be identified. In this case, detection is only one of the possible ways of adapting the gain of a recursive algorithm.

In this paper we survey a subset of the many failure detection methods available, namely those that are based on parameter estimation.

PROBLEM STATEMENT

Following Iserman,[5] a fault is defined as a non-permitted deviation of a characteristic property of a system, which leads to the inability of the system to fulfil its intended purpose. Fault monitoring or fault detection is performed by checking whether certain directly measurable or estimated variables are within specified tolerance limits.

The next step is fault diagnosis: the fault is located and the cause of it is established. This is followed by the fault evaluation, which is accompanied by an estimation of the fault's size and possibly an indication of the time instant of its occurrence, which may show how the fault will affect the process.

Faults are divided into different hazard classes according to an incident/sequence analysis or a fault tree analysis, as

(a) unsteady faults (random structural changes)
(b) steady faults (permanent structural changes)
(c) catastrophic faults (structural changes creating catastrophes)

Faults often appear in that order, and progressive deterioration may lead to catastrophes. Faults can also be classified into evolving (due to ageing) and cataleptic (random).

After the effect of the fault is evaluated, a decision on the action to be taken can be made. If the fault is tolerable, the process may continue operating; if it is conditionally tolerable, a change of operation has to be performed. If the fault is intolerable, the process must be stopped, and the fault eliminated. The above ideas are shown schematically in Figure 1.

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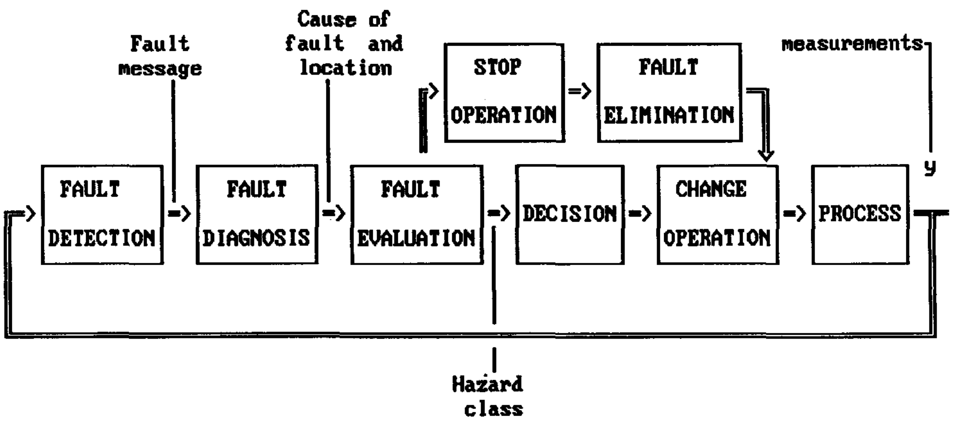

Figure 1. Supervision loop on appearance of a fault

Cataleptic fault detection is carried out as a real time task. Modelling of the wear process is performed by monitoring the evolution of evolving faults and consequently the forecasting of the risk of failure or unavailability is made practical.

The design of fault-detection systems involves the consideration of several issues. One is usually interested in designing a system that will respond rapidly when a fault occurs. This property, however, will in most cases make the system sensitive to noise, resulting in frequent false alarms triggered by noise in the fault-detection mechanism. The trade-off between these two design issues will depend on the specific application.

Fault-detection schemes are mainly parameter-estimation algorithms trying to detect unexpected variations of the monitored parameters. Since monitored signals are usually embedded in noise, any fault-detection algorithm aims at the rejection of noise.

The effectiveness of a fault-detection algorithm is qualitatively judged by the 'probability' of false alarms and the speed with which a fault is detected. A fault-detection algorithm is usually the implementation of a general-purpose estimation method to the particular monitored process.

The quality of fault detection depends mainly on two factors:

(i) the sophistication of the algorithm
(ii) the sampling rate of the system.

Unfortunately, these two factors have contradicting requirements. More sophisticated algorithms require more computations per iteration and consequently result in smaller sampling rates. A compromise has to be found between the tolerable cost of a fault monitoring system (which directly affects the computational resources that can be allocated to the fault detection system), the sophistication of the estimation algorithm and the resulting sampling rate.

The cost of computer hardware is dropping dramatically as VLSI technology advances. Modern microprocessors offer computational power unimaginable even five years ago and at the same cost. This makes the implementation of sophisticated estimation algorithms feasible in new areas not thought possible up to now. It also allows the use of other techniques for fault detection.

FAULT DETECTION METHODOLOGY

Excellent surveys of fault detection methods are given by Willsky,[6] Iserman[5] and Tzafestas.[7] An interesting survey of methods of detecting instants of change of random process properties is given by Kligene and Telksnis,[8] and Torgovitskii[9] surveys similar methods.

Recent advances in fault detection and reliability, including knowledge-based systems, robust, fault tolerant and intelligent controllers and sophisticated estimation/detection techniques, appear in References 10 and 11.

Supervision of technical processes was for a long time restricted to checking directly measurable variables for upward or downward trends. This was sometimes automated using simple limit-value monitors. Various faults in the process could then be detected, but often only after the measurable output values had been effected considerably.

The general problem of fault detection could be described as an attempt to orientate process faults with the aid of the input and output variables $\mathbf{u}(t)$ and $\mathbf{y}(t)$, as shown in Figure 2.

Mathematical models of the process and its signals,

$$\mathbf{y}(t) = \mathbf{f}\{\mathbf{u}, \mathbf{n}, \boldsymbol{\theta}, \mathbf{x}\} \quad (1)$$

can be used, where $\mathbf{n}$ represents non-measurable disturbance signals from the process and its manipulating and measuring equipment, $\boldsymbol{\theta}$ non-measurable process parameters and $\mathbf{x}$ partially measurable internal state variables. Process parameters are constant or slowly changing time-variable coefficients and state variables are time-dependent.

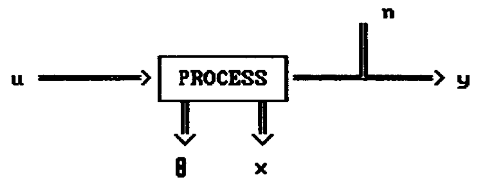

Figure 2. Representation of a process with measurable input variables **u**, measurable output variables **y**, and non-directly measurable disturbance variables **n**, process parameters **θ** and state variables **x**

MODEL-BASED PARAMETER ESTIMATION DETECTION METHODS

Fault detection via parameter estimation relies on the principle that possible faults in the process can be associated with specific parameters and states of a mathematical model of a process. However, it is necessary to have a theoretical dynamic model of the process to apply parameter estimation methods. This is derived from the basic balance equations for mass, energy and momentum, the physico-chemical state equations and the phenomenological laws for any irreversible phenomena. The models will then appear in the continuous-time domain, in the form of ordinary or partial differential equations. Their parameters θ_i are expressed in dependence on process coefficients p_j, such as storage or resistance quantities, whose changes indicate a process fault. Hence, the parameters θ_i of continuous time models have to be estimated. In this case there is a minimum number of independently measurable quantities which permit the estimation of various states and parameters. Parameter estimation is a non-linear procedure when coupled with state estimation and, consequently, linear observability theory does not apply, resulting, in some cases, in erroneous estimation.[12]

A simple dynamic process model with lumped parameters, linearized about an operating point, may be described by the differential equation

$$y(t) + \ldots + a_n y^{(n)}(t) = b_0 u(t) + b_1 u^{(1)}(t) + \ldots + b_m u^{(m)}(t)$$

The process model parameters,

$$\boldsymbol{\theta}^{\mathrm{T}} = [a_1 \ldots a_n \mid b_0 \ldots b_m] \tag{2}$$

are defined as relationships of several physical process coefficients, e.g. length, mass, speed, drag coefficient, viscosity, resistances, capacities. Faults which become noticeable in these physical process constants are therefore also expressed in the process model parameters. If the physical process coefficients, indicative of process faults, are not directly measurable, an attempt can be made to detect their changes via the changes in the process model parameters **θ**. The following procedure is therefore applied:

1. Establishment of the mathematical model of the normal process,

$$\mathbf{y}(t) = \mathbf{f}\{\mathbf{u}(t), \boldsymbol{\theta}\} \tag{3}$$

mainly from theoretical considerations. At this stage allowable tolerances for process coefficient values are also defined.
2. Determination of the relationship between the model parameters θ_i and the physical process coefficients p_j,

$$\boldsymbol{\theta} = \mathbf{f}(\mathbf{p}) \tag{4}$$

3. Estimation of the model parameters θ_i from measurements of $\mathbf{y}(t)$, $\mathbf{u}(t)$, by a suitable estimation procedure.
4. Calculation of process coefficients, via the inverse relationship,

$$\mathbf{p} = \mathbf{f}^{-1}(\boldsymbol{\theta}) \tag{5}$$

5. Decision on whether a fault has occurred, based on the changes Δp_j calculated in step 4 and tolerance limits from step 1. Decisions can be made either by simply checking against the predetermined threshold levels, or by using more sophisticated methods from the fields of statistical decision theory and pattern recognition. A fault decision should include the fault type, fault size and time of occurrence. Location and cause of the process fault will follow a positive fault decision. This may be achieved with the aid of a fault catalogue in which the relationship between process faults and changes in the coefficients Δp_j has been established.

The basis of this class of methods is the combination of theoretical modelling and parameter estimation of continuous-time models. A block diagram is given in Figure 3. Since, however, a necessary requirement of this procedure is the existence of the inverse relationship (5), it may be restricted to well-defined processes.

Having in mind these requirements the next section will briefly discuss some applications of the method and a case study, indicating the different approaches taken for each of the steps 1–5 described earlier.

APPLICATIONS

Dalla Molle and Himmelblau[13] have applied real-time parameter estimation techniques for fault detection in an evaporator. The complexities of a real evaporator have been simplified, so that the model reduces to

$$\frac{\mathrm{d}x_1}{\mathrm{d}t} = F - (wx_1 + E_c) - V \tag{6}$$

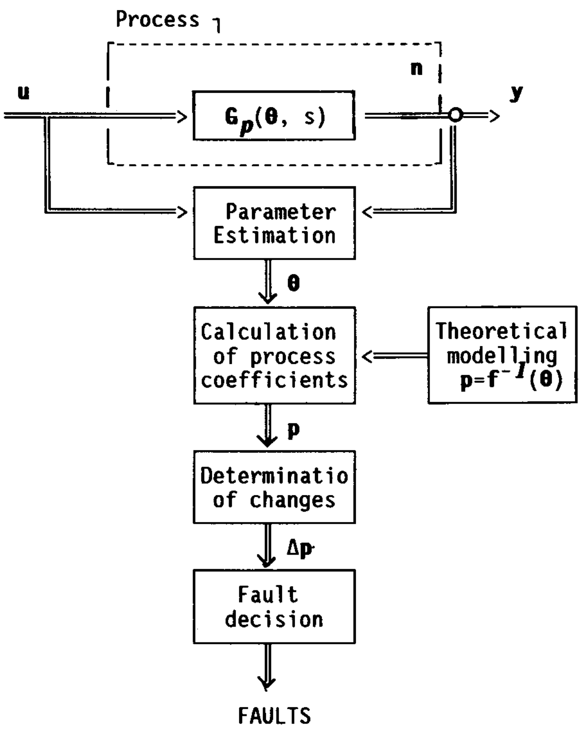

Figure 3. Fault detection based on parameter estimation and theoretical modelling

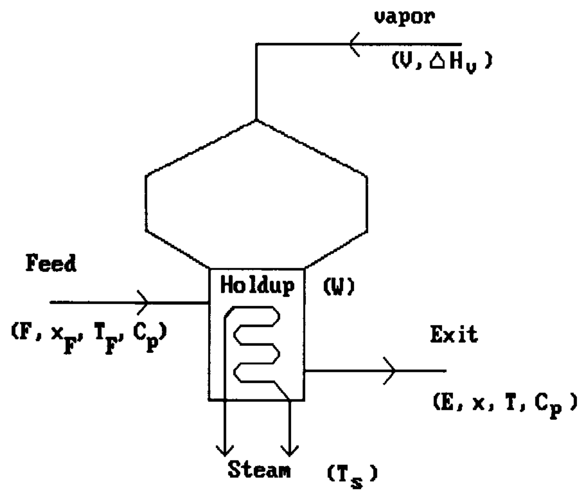

Figure 4. Evaporator configuration and flow chart

$$\frac{dx_2}{dt} = [\beta F x_F + (V-F)(x_2 - T_B)]/x_1 \qquad (7)$$

where

$$[x_1 x_2] = [W\ T]$$
$$V = [\mathrm{UA}(T_s - T) - FC_p(T - T_F) - Q_L]/\Delta H_v$$

and UA = (heat transfer coefficient) × (area of heat transfer)
T_s is the steam temperature in the steam chest, T_B is the normal boiling point of the solvent, C_p is the heat capacity of the solution, T_F is the temperature of the feed system, Q_L is the rate of heat loss to the surroundings, ΔH_V is the heat of vaporization of the solvent, Q_s is the total rate of heat trtansfer from steam, w is constant (0·6), β is the boiling point elevation per mass fraction of solute and E_c is constant (0·1).

Figure 4 shows the rest of the notation.

Here the states of the model are the holdup and temperature. Two techniques for non-linear estimation were compared, namely (a) a non-linear state observer combined with a least-squares (LS) parameter-estimation scheme and (b) an extended Kalman filter. The need for non-linear techniques is due to the fact that x_1 (holdup) appears in the denominator of the differential equation for x_2 (temperature).

Two process parameters of interest associated with process degradation or faulty operation are the heat transfer coefficient UA, which cannot be measured directly by any means, and the composition of the feed, x_F. Simulated faults on these parameters were used to compare the two fault detection methods. Results from the LS estimation scheme with a forgetting factor of 0·95 were quite satisfactory and showed that the scheme is valid in the simultaneous presence of faults. The extended Kalman filter required 15 times more computational time than the L.S.E. scheme and its simulation results showed that there was need for some heuristics in the analysis of the estimates to avoid misdiagnosing faults when more than one fault occurs at a time. Furthermore, decision rules and confidence coefficients should be selected based on filter parameters and the dynamics of the process.

Stavrakakis and Dialynas[14] used recursive least-squares estimation with forgetting factor and hypothesis-testing techniques for improving the reliability performance of power substations. Following a positive fault decision, the substation is reconfigured according to a detailed fault tree. The fault detection methodology adopted was applied to the following power substation components:

(A) Power transformers, modelled by their one-phase equivalent circuit, described by,

$$V_i = R_1 I_i + L_{1e}\frac{dI_i}{dt} - M\frac{dI_o}{dt} \qquad (8)$$

$$V_o = M\frac{dI_i}{dt} - R_2 I_o - L_{2e}\frac{dI_o}{dt} \qquad (9)$$

where V_i and V_o are the actual input (primary) and output (secondary) voltages, I_i and I_o are the actual input (primary) and output (secondary) currents, R_1 and R_2 are the primary and secondary winding resistances, L_1 and L_2 are the primary and secondary winding self-inductances, L_m is the mutual inductance between windings on the same core, and

$$M = \frac{L_m}{a}, L_{1e} = L_1 + L_m, L_{2e} = L_e + \frac{L_m}{a_2}$$

The faults that most frequently arise in practice in the power transformers, were classified as follows:

1. Failures in the magnetic circuits (cores, yokes and clamping structure).
2. Failures in the windings (coils and minor insulation and terminal gear).
3. Failures in the dielectric circuit (oil and major insulation).
4. Structural failures.

By monitoring the estimated values of R_1, R_2, L_{1e}, L_{2e}, M and performing a hypothesis testing using the likelihood ratio test, a change in these parameters can be detected, leading to a decision regarding one of the failures 1–4, described above.

(B) Substation lines and cables, modelled by their equivalent one-phase circuit which neglects entirely the susceptance and leakance, and is described by the simple first order differential equation

$$V_i = V_o + RI_i + L\frac{dI_i}{dt} \tag{10}$$

The most important failures occurring on the lines or cables of power substations are the short circuits which are generally due to insulation breakdown. By applying the previously described method on the parameters R and L of this model, short circuits can be detected and localized early, in this way avoiding further degradation of the system.

(C) Synchronous generators. The model used corresponds to an unsaturated cylindrical-rotor machine under balanced polyphase conditions, and is described by

$$E_f = V_o + r_a I_o + L_s\frac{dI_o}{dt} \tag{11}$$

where V_o is the actual value of terminal voltage, E_f is the actual value of the excitation voltage, L_s is the synchronous reactance (constant at constant frequency) and r_a i the armature resistance.

Here, deviations of L_s, r_a from their nominal values will indicate a voltage failure of the a.c. synchronous generator, which is a result of an open in the field circuit, an open in the field rheostat or a failure of the exciter generator. The loss of field excitation to a generator operating in parallel with others, causes it to lose load and overspeed. High armature current caused by the high voltage differential between the armature and the bus, and the high currents induced in the field iron and field windings by the armature current, will cause rapid heating of the apparatus. This is avoided, in the case of failure, by the fast detection which the proposed method provides.

Simulation results on a typical 400/150 kV high-voltage substation were analysed and showed that the proposed methodology is suitable for integrated power automation.

Geiger[15] uses a discrete square root filter (DSF), to monitor the operation of a d.c. motor pump system. The methodology is similar to that of the previous authors, differing only in the way that the parameters of interest are estimated. The differential equations used in the modelling are

$$L_2\frac{dI_2}{dt} + R_2\Delta I_2(t) + \Psi\Delta\Omega = \Delta U_2(t) \tag{12}$$

$$\Theta\frac{d\Omega}{dt} + c_{F1}\Delta\Omega(t) = \Psi\Delta I_2(t) \tag{13}$$

where $\Delta U_2(t)$ is the armature voltage, $\Delta I_2(t)$ is the armature current (A), $\Delta\Omega(t)$ is the speed of rotation (s^{-1}), R_2 is the armature resistance (Ω), L_2 is the armature inductance (H), Ψ is the magnetic flux linkage (Wb), Θ is the moment of inertia (kgm^2) and c_{F1} is the friction coefficient (Nms).

The required derivatives of the process input and output signals were calculated using quasi-analogue state variable filters (SVFs), realized on a digital computer. Maximum likelihood estimation was used in the decision-making process, which is able to distinguish between five different types of fault, i.e. in the resistance, inductance, magnetic flux, moment of inertia and friction coefficient.

A simulated fault of 2 per cent in the armature resistance R was successfully detected after 12 sampling intervals, verifying the speed of the method. A drawback of this method is the fact that it cannot be used for on-line detection.

A CASE STUDY

The case study describes a fast fault detection system for robotic d.c. motor drives. The detection system is implemented on a commercially available parallel processing machine.

The dynamic equations for the armature circuit and the mechanics of a d.c. motor lead to the state-space representation for the actuator of the ith robot link, given in the Appendix. Also shown in detail in the Appendix are the steps of the fault detection algorithm.

The effectiveness of the method was verified using simulated data. For this purpose the d.c. motor robotic actuator parameters were chosen as

$$R = 1{\cdot}04\,\Omega,\ L = 0{\cdot}00089\,\text{H},\ K_m = 0{\cdot}0224\,\text{Vs/rad}$$
$$J_m = 0{\cdot}00005\ \text{kgm}^2,\ \rho = 0{\cdot}005\ \text{kgm}^2/\text{s},\ N = 64$$

where R is the armature resistance, L is the armature inductance, K_m is the electromechanical constant of the motor, J_m is the moment of inertia of the drive rotor, ρ is the viscous friction coefficient and N is the gear ratio.

A 2 kHz sampling frequency is considered. The non-error statistics are calculated using $N_s = 300$ samples, whereas the detection window was $N_w = 50$. The first parameter estimate to be used by the detection procedure was taken at time $k = 70$, giving a large initial sample. The likelihood ratio fault-detection threshold value is 11·2 and $M = 10$. From sample time $k = 1$ to 130, the normal operating d.c. drive was simulated. A simulated fault occurred at $k = 131$, indicated by a 4·8 per cent change in the armature resistance R_i ($R_{if} = 1{\cdot}09$ Ω). A recursive least-squares (RLS) estimator (see Appendix) with a forgetting factor of $\lambda = 0{\cdot}95$ for estimating θ_a, and $\lambda = 0{\cdot}99$ for θ_b is used. All estimates converge quickly to their respective true values. The exact estimated values are shown in Table I.

A major factor for the success of the algorithm is the 2 kHz sampling rate. This means that the algorithm must be implemented on a computer capable of performing all the above calculations in 0·5 ms. The above procedure is, however, suitable for implementation in commercially available parallel processing machines, e.g. the INMOS transputer system. This algorithm is implemented in a system employing five transputers, as shown in Figure 5. The numbers shown in Figure 5 correspond to the tasks performed by each machine according to the task partition 1–5 described earlier. This also forms a four-stage pipeline where its first stage consists of machine 1. Its second stage consists of machines 2 and 3 and its third stage consists of machines 4 and 5. Stage 6 consists only of machine 6, which is underused by the algorithm, leaving power for suitable presentation of the results.

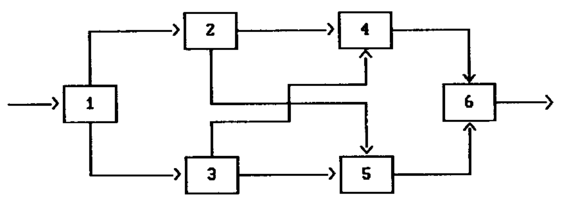

Figure 5. The INMOS transputer for the real-time computer implementation of the d.c. drive fault detection algorithm

CONCLUSIONS

An attempt has been made, based on our knowledge and experience, to review some fault-detection methods based on process model parameter estimation. These methods require a precise knowledge of the process and the application of estimation and decision-making algorithms. The failure-detection problem is an extremely complex one and the choice of an appropriate design depends heavily on the particular application. Issues such as available computational facilities and level of hardware redundancy enter in a crucial way in the design decision.

The development of failure-detection methods has passed its infancy stage. However, much work needs to be done in the development of implementable systems, complete with a variety of design tradeoffs. Work is also needed in the development of efficient techniques for failure compensation and system reorganization. In addition there is a need for the analysis of the robustness of various failure detection systems in the presence of variations in system parameters and in the presence of modelling errors and system non-linearities.

APPENDIX

Using the global dynamic model of a three degrees-of-freedom robotic manipulator derived by Tzafestas and Stavrakakis,[16] the state-space representation for the actuator of the ith link of the robot can be written as

$$\mathbf{y}^{(1)}(t) + \mathbf{A}_1\mathbf{y}^{(1)}(t) + \mathbf{A}_0\mathbf{y}(t) = \mathbf{B}_0\mathbf{u}(t) \qquad (14)$$

where

$$\mathbf{A}_1 = \mathbf{0} \in \mathbb{R}^{4\times 4}$$

$$\mathbf{A}_0 = \begin{bmatrix} \dfrac{R_i}{L_i} & \dfrac{K_{mi}N_i}{L_i} \\ -\dfrac{K_{mi}}{J_{mi}N_i} & \dfrac{\rho_i}{J_{mi}} \end{bmatrix}$$

$$\mathbf{B}_0 = \begin{bmatrix} \dfrac{1}{L_i} & 0 \\ 0 & -\dfrac{1}{J_{mi}(N_i)^2} \end{bmatrix}$$

$$\mathbf{u}^{\mathrm{T}}(t) = [V_i(t) \quad T_{Li}(t)]$$

$$\mathbf{y}^{\mathrm{T}}(t) = [\, i_i\,(t) \quad \omega_i(t)]$$

where V_i is the applied armature voltage, T_{Li} is the disturbance torque referred to the link side of the drive shaft, i_i is the armature current, ω_i is the shaft

Table I. True and estimated values for test run

	R_1	L_1	$K_{m1}N_1$	$J_{m1}(N_1)^2$	$\rho_1(N_1)^2$
True value	1·09	0·00089	1·4336	0·2048	20·48
Estimated values at sample time k=300	1·1	0·000896	1·4476	0·2038	20·82

angular velocity referred to the link side of the drive shaft, N_i is the gear ratio, J_{mi} is the moment of inertia of the drive rotor, K_{mi} is the electromechanical constant of the motor (the back-emf constant is equal to the torque constant), R_I is the armature resistance, L_i is the armature inductance, ρ_i is the viscous friction coefficient, and the subscript i denotes the ith joint of the robotic manipulator.

Define

$$\theta_1 = \frac{R_i}{L_i}, \theta_2 = \frac{K_{mi}N_i}{L_i}, \theta_3 = \frac{1}{L_i},$$

$$\theta_4 = -\frac{K_{mi}}{J_{mi}N_i}, \theta_5 = \frac{\rho_i}{J_{mi}}, \theta_6 = -\frac{1}{J_{mi}(N_i)^2} \quad (15)$$

i.e.

$$\boldsymbol{\theta}^{\mathrm{T}} = [\theta_1, \theta_2, \theta_3, \theta_4, \theta_5, \theta_6] \in \mathbb{R}^6$$

The following variables are measured for each motor:

(a) armature current
(b) angular velocity
(c) armature voltage
(d) shaft torque.

The former two are the system outputs, whereas the latter are the system inputs. Input and output signal measurements are available at discrete times $t = kT_0$, $k = 0, 1, \ldots, N, \ldots$, where T_0 is the sampling time, defined as $i_i(k)$, $\omega_i(k)$, $V_i(k)$, $T_{Li}(k)$. The fault-detection algorithm for this case consists of the following steps (tasks):

1. Measure $i_i(k)$, $\omega_i(k)$, $V_i(k)$, $T_{Li}(k)$ and compute the derivatives $i_i^{(1)}(k)$ and $\omega_i^{(1)}(k)$ by a third-order backward formula.
2. Perform one iteration of the recursive least squares (RLS) parameter estimation algorithm for parameters

$$(\boldsymbol{\theta}_a)^{\mathrm{T}} = [\theta_1\, \theta_2\, \theta_3]$$

3. Perform one iteration of the parameter estimation algorithm for parameters

$$(\boldsymbol{\theta}_b)^{\mathrm{T}} = [\theta_4\, \theta_5\, \theta_6]$$

4. (a) Calculate the physical parameters $p_i(k)$, $i = 1, 2, 3$ from the previously computed estimates θ_a and θ_b, using

$$p_1(k) = R_i = \frac{\theta_1(k)}{\theta_3(k)}$$

$$p_2(k) = L_i = \frac{1}{\theta_3}(k) \quad (16)$$

$$p_3(k) = N_iK_{mi} = \frac{\theta_2(k)}{\theta_3(k)}$$

The case of a fault occurrence in the gear box is considered as an event with probability 0.

(b) Redefine the data window by accepting the new estimates $p_i(k)$, $i = 1, 2, 3$, dropping the oldest estimates $p_i(k-N_w-1)$ and recalculating the real-time parameter mean and variance estimates (i.e. the parameter statistics are estimated over the $N_w + 1$ most recent parameter estimates).

(c) Compute the likelihood ratio for the hypothesis-detection problem.

(d) Decide on whether a fault condition exists. The decision is taken by comparing the likelihood ratio obtained in stage 4(c), against a predefined threshold. To avoid false alarms, the fault condition is signalled if the threshold is exceeded at M consecutive instants. The optimal threshold value and M are best chosen by trial and error using simulation.

5. Perform steps 4(a) to 4(d) for parameters $p_4(k)$, $p_5(k)$, using

$$p_4(k) = (N_i)^2 J_{mi} = -\frac{\theta_2(k)}{\theta_3(k)\theta_4(k)} \quad (17)$$

$$p_5(k) = (N_i)^2 \rho_i = -\frac{\theta_2(k)\theta_5(k)}{\theta_3(k)\theta_4(k)}$$

The above procedure assumes that the algorithm is run initially on a fault-free d.c. motor. From this run the non-error statistics are obtained and are used subsequently in steps 4(b), 4(c), 5(b), 5(c).

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Authors' biographies:

A. Pouliezos was born in Athens, Greece in 1951. He received his MSc. in Control Systems from Imperial College, London, in 1977 and his Phd. from Brunel University in 1980. He has worked in the field of electronic phototypesetting, and for the past four years has been Adjunct Professor at the Technical University of Crete. His research interests include fault detection in dynamical systems, decision support systems and control systems software.

C. Lefas was born in Athens in 1953. He received his first degree in Physics from the University of Patras in 1977, an MSc. in Automatic Control Theory and Practice from UMIST in 1978 and his Ph.d. from UMIST in 1981. He has worked in many fields of control engineering including aircraft control, industrial microprocessor systems and greenhouse climate control. He has been a researcher at the research centre 'Democritus' in Athens and is currently assistant Professor in the Department of Electronic Engineering at the Technical University of Crete. His research interests include microprocessor control, solar and wind energy and aircraft monitoring.

G. Stavrakakis was born in Crete in 1956. He received his first degree in Electrical Engineering from EMP, Athens, in 1980, his D.E.A. in Automatic Control and Systems Analysis from I.N.S.A., Toulouse, in 1981 and his Docteur Ingenieur from Paul Sabatier University, Toulouse in 1984. He has worked as a research assistant in the Robotics Laboratory of EMP, Athens, and as an Adjunct Professor at the Polytechnic of Crete. He is currently at the ISPRA research centre, Italy. His research interests include robotics, solar and wind energy engineering and fault detection in technological systems.