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Detecting and diagnosing faults in dynamic stochastic distributions using a rational B-splines approximation to output PDFs

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Abstract: This paper presents a novel approach to detect and diagnose faults in the dynamic part of a class of stochastic systems. the Such a group of systems are subjected to a set of crisp inputs but the outputs considered are the measurable probability density functions (PDFs) of the system output, rather than the system output alone. A new approximation model is developed for the output probability density functions so that the dynamic part of the system is decoupled from the output probability density functions. A nonlinear adaptive observer is constructed to detect and diagnose the fault in the dynamic part of the system. Convergency analysis is performed for the error dynamics raised from the fault detection and diagnosis phase and an applicability study on the detection and diagnosis of the unexpected changes in the 2D grammage distributions in a paper forming process is included.

Keywords: Fault detection and diagnosis; Observer design; Papermaking; Stochastic systems

1 Introduction

For an improved reliability of practical stochastic control systems, the research into fault detection and diagnosis for stochastic dynamic systems has long been recognized as one of the important areas in control engineering [1]. Many methods have been developed in the past two decades. In general, those approaches can be classified into the following two groups: 1) Identification based fault detection and diagnosis for dynamic systems whose models are unknown [2]; 2) Unexpected change detection for stochastic signals [3]. The first approach uses an ARMAX model to represent the system and apply parameter identification techniques, such as least square algorithms or stochastic gradient approaches, to estimate the unexpected changes in the system. As for the unexpected change detection for stochastic signals, focus has been largely laid on either the detection of unexpected changes in the mean value and the variance of the considered random signals [3], or on the detection of unexpected parameter changes for static probability density functions of the random signal. In this case, the required fault detection and diagnosis are normally performed by applying the theory of statistical decision, where a likelihood ratio is evaluated between the hypotheses on the healthy parameters and faulty parameters using the known probability density function. As a result, the faulty parameters can be estimated by optimizing this likelihood ratio. In this context, static means that the probability density function of the considered signal does not involve any system dynamics at all. For example, when the discretised stochastic systems are considered, the current probability density function of the random signal should not be related to its probability density functions at the previous time steps. Also, in many cases it is assumed that the random signal obeys a Gaussian type of distribution.

However, the assumption that probability density functions are of general static nonlinear form is strict for many practical systems. Examples are most of the wet end control systems in papermaking, where the fibre length distribution, the pore size distribution and the flocculation size distribution in the related water systems are all subjected to dynamical changes in the system [4,5]. To describe these types of systems, a new group of stochastic models have been considered, where the system studied are subjected to a set of crisp inputs but the outputs considered are the measurable probability density functions of the system output, rather than the system output alone. For such systems, the linear B-spline approximations have been used to represent the output probability density functions and the dynamic part is expressed by a set of differential equations which link the weights of the B-spline expansions to the control input [6 ~ 9]. With such an expression, an observer based fault detection [10] has been developed for the fault detection of the stochastic systems.

In practice, there are several disadvantages in using linear B-splines. For example, when the number of the basis functions are not high, the calculated output probability density functions may become negative due to weak numerical robustness. As a result, a new nonlinear approximation model needs to be developed so as to enhance the

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numerical robustness. This forms the main purpose of the current paper where in parallel to [6,8], an observer based fault detection algorithm will be developed along with a nonlinear B-splines approximation to the measured output probability density functions. In this context, signals available to the observer are the control input and the measured output probability density functions of the system. As shown in Fig. 1, the input variables affect dynamically the shape of the probability density functions of the system output, and the task of fault detection and diagnosis is to use the system inputs $u(t)$ and the measured probability density functions of the system output $\gamma(z, u(t), F)$ to detect and diagnose the unexpected changes in F.

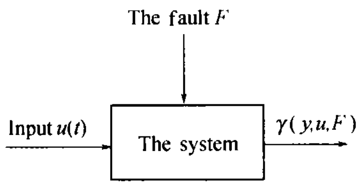

Fig. 1 Considered stochastic system.

2 Model representation

Denote $v(t) \in [a, b]$ as the output of the stochastic system and assume that $[a, b]$ is a known interval and $v(t)$ is a continuous random variable at time t for $\forall t \in [0, +\infty)$. Then there exists a probability density function of $v(t)$ such that

$$P(a \leqslant y < \zeta) = \int_a^{\zeta} \gamma(y, u) \mathrm{d}y, \ \forall u, \quad (1)$$

where $P(a \leqslant y < \zeta)$ represents the occurrence of the event that $\{a \leqslant y < \zeta\}$ and $u = u(t)$ is the input to the system. For such a probability density function, the following approximation is applied to give

$$\gamma(y, u) = \frac{\sum_{i=1}^{n} w_i(u) B_i(y)}{\sum_{i=1}^{n} w_i(u) b_i}, \ \forall y \in [a, b], \quad (2)$$

where $B_i(y) \geqslant 0$ are the pre-specified basis functions, w_i are the weights of the approximation which are only related to the control input $u(t)$, n is the number of basis functions. In this approximation, it has been denoted that

$$b_i = \int_a^b B_i(y) \mathrm{d}y > 0, \ i = 1, \cdots, n. \quad (3)$$

It can be seen that this approximation function automatically satisfies

$$\int_a^b \gamma(y, u) \mathrm{d}y = \int_a^b \frac{\sum_{i=1}^{n} w_i(u) B_i(y)}{\sum_{i=1}^{n} w_i(u) b_i} \mathrm{d}y = 1. \quad (4)$$

A preliminary study has shown that such a bounded approximation can be used to model the output probability density functions to a desired accuracy [10]. In terms of the dynamic system, the weights are related dynamically to the input. In this case, if we define

$$V(t) = (w_1(t), w_2(t), \cdots, w_n(t))^{\mathrm{T}} \in \mathbb{R}^n \quad (5)$$

as the state vector, and another two vectors

$$C(y) = (B_1(y), B_2(y), \cdots, B_n(y))^{\mathrm{T}} \in \mathbb{R}^n, \quad (6)$$

$$b_0 = (b_1, b_2, \cdots, b_n)^{\mathrm{T}} \in \mathbb{R}^n; \ y \in [a, b], \quad (7)$$

then such a dynamic relationship can be represented as

$$\dot{V}(t) = AV(t) + Bu(t) + EF,$$
$$\gamma(y, u(t), F) = \frac{C^{\mathrm{T}}(y) V(t)}{b_0^{\mathrm{T}} V(t)}, \quad (8)$$

where $\{A, B, E\}$ are the known healthy parameter matrices which have appropriate dimensions in accordance with the input and the weights vector $V(t)$, F is an additive term representing the fault in the system. For this model, the first equation presents a general linear dynamical relationship between $V(t)$, $u(t)$ and F, whilst the second equation stands for the modified B-spline expression of the probability density function of the system output.

3 Fault detection

In this section, the observer-based fault detection will be discussed, where the faults of the system are regarded as any unexpected changes of an additive term in the state space equation (8). In order to detect such a fault, let us construct the following observer

$$\dot{\hat{V}}(t) = A\hat{V}(t) + Bu(t) + K(t)\varepsilon(t),$$
$$\varepsilon(t) = \int_a^b \sigma(y)(\gamma(y, u(t), F) - \hat{\gamma}(y, u(t))) \mathrm{d}y,$$
$$\hat{\gamma}(y, u) = \frac{C^{\mathrm{T}}(y) \hat{V}(t)}{b_0^{\mathrm{T}} \hat{V}(t)}, \quad (9)$$

where $K(t)$ is an adaptive gain to be designed for the observer and $\sigma(y) \in \mathbb{R}^1$ is a pre-specified weighting vector defined on $[a, b]$. The construction of a "classical" observer would have led to $\varepsilon_1(t) = \int_a^b (\gamma(y, u(t), F) - \hat{\gamma}((y, u(t))) \mathrm{d}y$. However, $\varepsilon_1(t)$ cannot be used in this case as both $\gamma(y, u(t), F)$ and $\hat{\gamma}(y, u(t))$ are probability density functions and their direct integrations are always equal to 1.0. This means that $\varepsilon_1(t) = 0$ for any F. As such, $\varepsilon_1(t)$ is not a proper residual signal for FDI [11 ~ 14] and the involvement of a $\sigma(y) \neq 1$ is necessary here. By defining

$$e(t) = \hat{V}(t) - V(t), \quad (10)$$

and using equations (8) and (9), it can be formulated that

$$\dot{e} = A\hat{V}(t) + Bu(t) + K(t)\varepsilon(t) - AV(t) - Bu(t) - EF. \quad (11)$$

Since it can be shown that

$$\varepsilon(t) = \int_a^b \sigma(y) C^{\mathrm{T}}(y) \left(\frac{\hat{V}}{b_0^{\mathrm{T}} \hat{V}} - \frac{V}{b_0^{\mathrm{T}} V}\right) \mathrm{d}y$$

$$= \int_a^b \sigma(y) C^T(y) dy \left(\frac{\hat{V}}{b_0^T \hat{V}} - \frac{V}{b_0^T V} \right), \quad (12)$$

by denoting

$$\Sigma = \int_a^b \sigma(y) C^T(y) dy \in \mathbb{R}^{1 \times n}, \quad (13)$$

it can be further obtained that

$$\varepsilon(t) = \Sigma \left(\frac{e(t)}{b_0^T \hat{V}} + V \left(\frac{1}{b_0^T \hat{V}} - \frac{1}{b_0^T V} \right) \right). \quad (14)$$

By substituting this form of residual signal into the error dynamics in equation (11), it can be shown that

$$\dot{e}(t) = Ae(t) + K(t) \Sigma \frac{e(t)}{b_0^T \hat{V}} + K(t) \Sigma V \left(\frac{1}{b_0^T \hat{V}} - \frac{1}{b_0^T V} \right) - EF. \quad (15)$$

Since $b_0^T \hat{V}$ is a scaler number, by using the following adaptive gain

$$K(t) = L b_0^T \hat{V}(t), \quad (16)$$

it can be further obtained that

$$\dot{e}(t) = (A + L\Sigma) e(t) + L \Sigma V \left(1 - \frac{b_0^T \hat{V}}{b_0^T V} \right) - EF. \quad (17)$$

To perform the required fault detection, it is important that the error dynamics represented by equation (17) is stable when no fault occurs (i.e., $F = 0$). This means that we need to establish certain conditions under which

$$\lim_{t \to +\infty} e(t) = 0 \quad (18)$$

for $F = 0$. For this purpose, let us assume that $G = A + L\Sigma$ and that there exist a matrix L and the weighting function $\sigma(y)$ such that G is stable. This means that there exist two positive definite matrices, P and Q, such that

$$G^T P + PG = -Q. \quad (19)$$

In this context, let us select the following Lyapunov function

$$\pi = \frac{1}{2} e^T P e. \quad (20)$$

Then, it can be shown that

$$\dot{\pi} = -e^T Q e - e^T PL\, b_0^T e \left(\frac{\Sigma V}{b_0^T V} \right). \quad (21)$$

Denote $\lambda_Q = \lambda_{\min}(Q)$ as the minimum eigenvalue of matrix Q and assume that

$$0 < \sigma(y) < 1, \ \forall y \in [a, b], \quad (22)$$

then the following inequality can be obtained

$$\dot{\pi} \leqslant -[\lambda_Q - \| PL\, b_0^T \|] \| e \|^2. \quad (23)$$

As a result, the following theorem can be readily established.

Theorem 1 (Main result) Suppose that 1) the weighting vector $\sigma(y) \in \mathbb{R}^1$, the matrix L and $C(y)$ have been selected so that

① $G = A + L\Sigma$ is stable;

② there are positive definite matrices $P^T = P$ and $Q^T = Q$ such that equation (19) and the following inequality

$$\lambda_Q - \| PL\, b_0^T \| > 0 \quad (24)$$

are satisfied, then when $F = 0$, we have $\lim_{t \to +\infty} e(t) = 0$.

This means that the fault can be detected through the following mechanism

$$\| \varepsilon(t) \| > \lambda \rightarrow \text{a fault has occurred}, \quad (25)$$

where $\lambda > 0$ is a pre-specified threshold.

4 Fault diagnosis

Once the fault is detected through (25), the fault diagnosis needs to be carried out in order to estimate the size of the fault. For this purpose, let us construct the following adaptive observer

$$\dot{V}_m(t) = AV_m(t) + Bu(t) + K(t)\varepsilon(t) + E\hat{F},$$

$$\varepsilon(t) = \int_a^b \sigma(y)(\gamma(y, u(t), F) - \hat{\gamma}(y, u(t))) dy,$$

$$\hat{\gamma}(y, u) = \frac{C^T(y) V_m(t)}{b_0^T V_m(t)}, \quad (26)$$

where $\hat{F}$ is the estimate of F. In this case, the error dynamics becomes

$$\dot{e} = Ge + L\Sigma V \left(1 - \frac{b_0^T V_m}{b_0^T V} \right) + E(\hat{F} - F), \quad (27)$$

where $e = V_m - V$. By selecting the following Lyapunov function

$$\pi = \frac{1}{2} e^T P e + \frac{1}{2} \tilde{F}^T \tilde{F}, \quad (28)$$

where $\tilde{F} = \hat{F} - F$, then it can be shown that the first order derivative of π is

$$\dot{\pi} = -e^T Q e - e^T PL\, b_0^T e \left(\frac{\Sigma V}{b_0^T V} \right) + e^T PE\tilde{F} + \tilde{F}^T \dot{\hat{F}}. \quad (29)$$

To realize $\dot{\pi} \leqslant 0$, we select the following simple adaptive rule

$$\frac{d\hat{F}}{dt} = -\Gamma b_0^T V_m(t) \varepsilon(t), \quad (30)$$

where $\Gamma > 0$ is a pre-specified learning vector. Denote $\bar{P} = E^T P - \Gamma\Sigma$, then it can be formulated that

$$\begin{aligned}\dot{\pi} &= -e^T Q e - e^T PL\, b_0^T e \left(\frac{\Sigma V}{b_0^T V} \right) + \tilde{F}^T \bar{P}_e - \tilde{F}^T b_0^T e \left(\frac{\Gamma \Sigma V}{b_0^T V} \right) \\ &\leqslant -[\lambda_Q - \| PL\, b_0^T \|] \| e \|^2 + \| \tilde{F} \| (\| \bar{P} \| + \| \Gamma \| \| b_0 \|) \| e \| \\ &= -\delta_1 \| e \|^2 + \delta_2 \| \tilde{F} \| \| e \|, \end{aligned} \quad (31)$$

where

$$\delta_1 = \lambda_Q - \| PL\, b_0^T \|, \quad (32)$$

$$\delta_2 = \| \bar{P} \| + \| \Gamma \| \| b_0 \|. \quad (33)$$

Assume that the upper bound of the fault size is M (i.e, $\| F \| \leqslant \frac{M}{2}$), and that the adaptive rule (30) has been selected such that the $\|\hat{F}\| \leqslant \frac{M}{2}$, then it can be seen that

$$\dot{\pi} \leqslant -\delta_1(\|e\| - \frac{\delta_2 M}{2\delta_1})^2 + \frac{\delta_2^2 M^2}{4\delta_1} < 0, \quad (34)$$

when $\|e\| \geqslant \frac{\delta_2 M(\delta_1 + \sqrt{\delta_1})}{2\delta_1}$. This leads to the following theorem.

Theorem 2 (Convergency properties) Suppose that $\|F\| \leqslant \frac{M}{2}$ and $\|\hat{F}\| \leqslant \frac{M}{2}$, then the adaptive tuning rule (30) can guarantee that the observation error satisfies

$$\lim_{t \to +\infty} \|e\| \leqslant \frac{\delta_2 M(\delta_1 + \sqrt{\delta_1})}{2\delta_1}. \quad (35)$$

5 Applicability study

The wet end of a paper machine can be sketched as in Fig. 2. This part of paper machines consists of headbox approach systems, head box and wire table. The forming process takes place in the wire section, where the diluted fibres and other additives (5 percent solids and 95 percent water) are injected and the paper web is formed during the drainage process on the wire. During the forming phase, bonds between fibres and other additives are formed and the best performance required is to achieve, as uniform as possible, a total solid distribution. As discussed in [5], a group of chemicals, known as retention aids, can help to control such a solid distribution. This means that the input to the system is the flow rates of these chemicals and the output is a 2D probability density function of the solids distribution. By assuming a single fibre as a rod, then when a large population of such type of fibres are projected onto the wire table, they will form a random 2D fibre network as shown in Fig. 3. Since the fibre network is randomly formed, the solids density is also random and should obey a stochastic distribution.

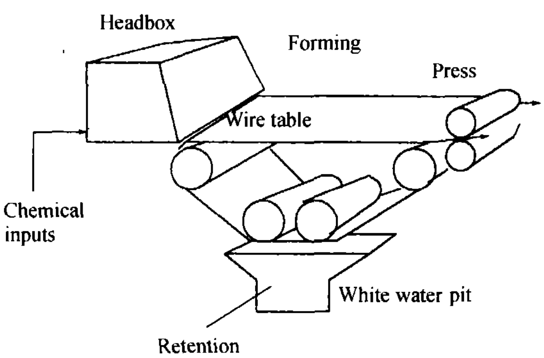

Fig. 2 A paper machine wet end.

Experimentally, it has been found that the local area density can be approximated by the following truncated Γ-distribution [4].

$$\gamma(y, \mu, \beta) = \left(\frac{\beta}{\mu}\right)^{\beta} \frac{y^{\beta-1}}{\Gamma(\beta)} e^{-y\beta/\mu} \ \forall y \in [a, b], \quad (36)$$

where $y \in [a, b]$, a and b are the minimum and maximum density, respectively. In practice, a and b can be determined experimentally [5] and $\Gamma(\beta)$ stands for the well known Gamma function.

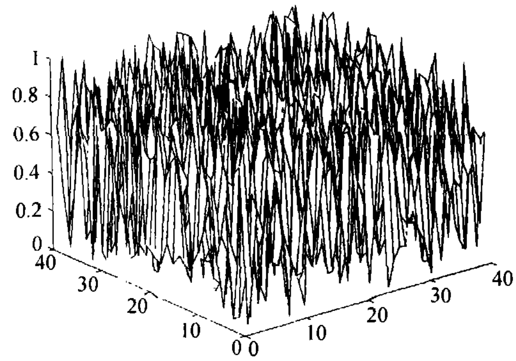

Fig. 3 The 2D solids distributions on the wire table.

6 Simulation results

In order to show the applicability of the method proposed in this paper, let us consider the following system

$$\gamma(y, u(t)) = \frac{B_1(y)w_1 + B_2(y)w_2 + B_3(y)w_3}{b_1 W_1 + b_2 W_2 + b_3 W_3}, \quad (37)$$

where a and b are set to be -3 and $+2$ (10^{-1}mm), respectively, and

$$\begin{aligned} B_1(y) &= [y^2+6y+9]I_1+[-y^2-3y-1]I_2+[y^2]I_3, \\ B_2(y) &= [y^2+4y+4]I_2+[-y^2-1y+1]I_3 \\ &\quad + [y^2 - 2y + 1]I_4, \\ B_3(y) &= [y^2 + 2y + 1]I_3 + [-y^2 + 1y + 1]I_4 \\ &\quad + [y^2 - 4y + 4]I_5. \end{aligned} \quad (38)$$

For this system, I_i are the interval functions and defined as follows

$$I_i(y) = \begin{cases} 1 & y \in [\lambda_i, \lambda_{i+1}), \\ & \lambda_i = i - 4 \ (i = 1,2,3,4,5), \\ 0 & \text{elsewhere}. \end{cases} \quad (39)$$

and the dynamic part is represented by

$$\dot{V} = \begin{bmatrix} -1 & 0.9 & 0 \\ 0.3 & -2 & 0 \\ 0 & 0.1 & -3 \end{bmatrix} V + \begin{bmatrix} 0 \\ 0.5 \\ 1 \end{bmatrix} u + \begin{bmatrix} 1 \\ 0.3 \\ -0.2 \end{bmatrix} F. \quad (40)$$

In this case, F stands for the unexpected changes of the shear forces caused by the fluid dynamics in the head box approach system. As such, $F = 0$ represents a healthy wet end operation for the web forming process. In Fig. 4, the selected basis functions are given and the response of the fault is $F = 1.0$ after 2.5 s. The result of the 3D mesh plot of the output probability density functions is shown in Fig. 5 and the related residual signal is shown in Fig. 6 (corresponding to time scale $[0,5]$ s). In Fig. 5, the 3D mesh plot along time axis is made with an increased sampling of 0.1 second so as to show the sufficient time span for the response and in the real simulation, the sampling interval is selected as 0.01 s.

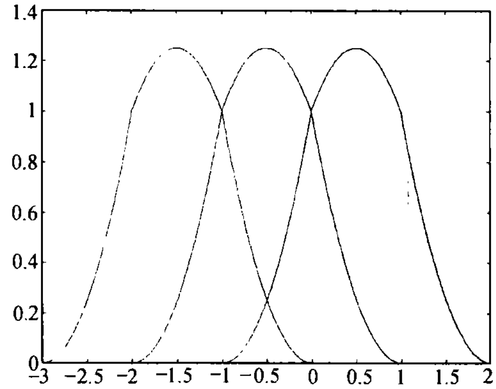

Fig. 4 The selected basis functions B_1, B_2 and B_3.

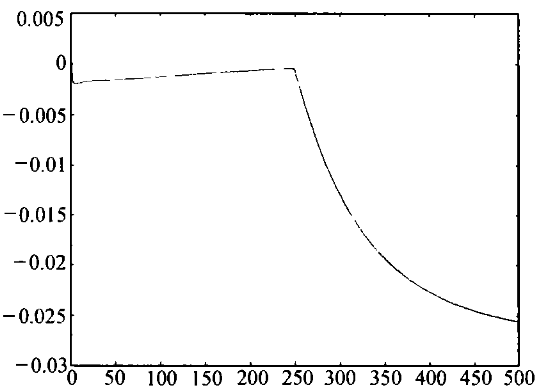

Fig. 6 The response of $\varepsilon(t)$.

From these figures it can be concluded that desired fault detection results have been obtained. The fault diagnosis results are shown in Fig. 7, where $\hat{F}$ is plotted for a longer time interval $[0, 1200]$ (corresponding to $[0,12]$ s in real time) in order to see the convergence result.

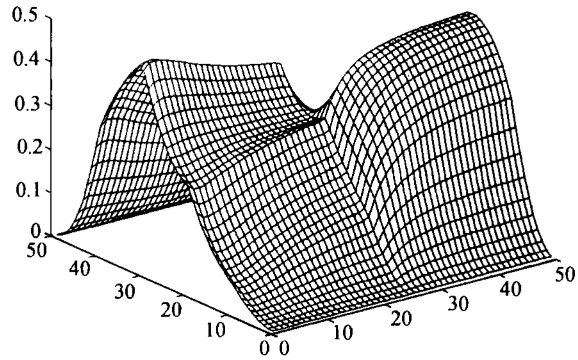

Fig. 5 The 3D response of $\gamma(y, u(t), F)$.

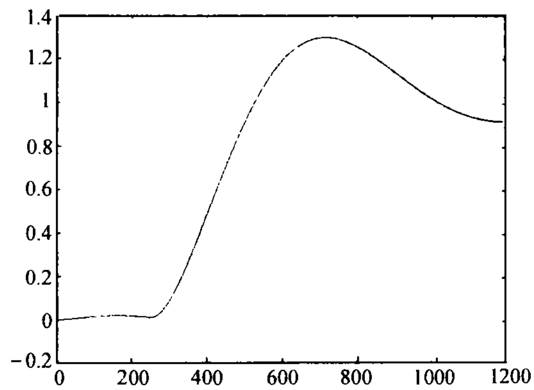

Fig. 7 The response of $\hat{F}(t)$.

7 Discussions plus residual entropy

In this paper a fault detection and diagnosis algorithm has been presented for general stochastic systems whose output probability density function is control by a crisp input. The rational model of the system is used and the fault appears in the dynamic part of the system. Under certain conditions, we have shown that the fault is detectable and its estimation is convergent in the sense that the residual signals are always bounded. Future work should be concentrated on the general stochastic dynamic systems which are subjected to explicit random input

$$y_k = f(y_{k-1}, \cdots, y_{k-n}, u_k, \cdots, u_{k-m}, F, \omega_k), \quad (41)$$

where ω_k is a known arbitrary bounded random input and F is the fault. For such a system, the residual signal has a probability density function $\gamma_\varepsilon(x, \phi(k), \hat{F})$, where $\phi(k) = [y_{k-1}, \cdots, y_{k-n}, u_k, \cdots, u_{k-m}]$. In this case, the best estimation $\hat{F}$ at sample instance k should be solved by minimizing the mean values of the residual and its entropy

$$J(\hat{F}) = -\int_a^b \gamma_\varepsilon(x, \phi(k), \hat{F}) \ln(\gamma_\varepsilon(x, \phi(k), \hat{F}))\mathrm{d}x + \int_a^b x\gamma_\varepsilon(x, \phi(k), \hat{F})\mathrm{d}x, \quad (42)$$

where the first term is the residual entropy [15, 16]. This is simply because that a good fault estimation should have a very small mean value of its residual, and at the same time the uncertainty of the residual signal should be made as small as possible. Since the entropy is a more general measure than just variance of uncertainty (randomness) for non-Gaussian distributions, it is used here for the selection of the estimated fault. To minimize $J(\hat{F})$, one can simply use the following gradient learning rule

$$\hat{F}(k) = \hat{F}(k-1) - \Gamma \frac{\partial J}{\partial F} \mid_{F = \hat{F}(k-1)}. \quad (43)$$

Similar formulations can also be obtained for continuous-time systems represented by the following Ito differential equation

$$\dot{x} = f(x, u, F)\mathrm{d}t + \sigma(x, u, F)\mathrm{d}w, \quad (44)$$

where x is a state vector and w is a stochastic process.

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