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Robust Fault Detection and Estimation for Descriptor Systems based on Multi-Models Concept

H. Hamdi[†], M. Rodrigues[‡], C. Mechmeche[†] and N. Benhadj Braiek[†]

Abstract: This paper addresses the robust fault detection and estimation problem of nonlinear descriptor system with unknown inputs observers. The considered nonlinear descriptor system is transformed into an equivalent multi-models form by using the Takagi-Sugeno (T-S) approach. Two cases are considered: the first one deals with the multi-models with measurable decision variables and the second one assumes that these decision variables are unmeasurable. Then, a residual generator based on an unknown observer is designed for fault detection and estimation. Stability analysis and gain matrices determination are performed by resolving a set of Linear Matrices Inequalities (LMIs) for both cases. The performances of the proposed fault detection and estimation method is successfully applied to an electrical circuit.

Keywords: Fault detection and estimation, descriptor multi-models, residual generation, Linear Matrices Inequalities (LMIs).

1. INTRODUCTION

It is well recognized that many practical dynamical systems are subject to various environmental changes, unknown disturbances and varying operating conditions. Thus sensors, actuators or components faults in those systems are inevitable. Since any fault in a dynamical system may lead to significant performance degradation, serious system damages and even loss of human life, it is essential to be able to detect and identify faults so that necessary protective actions can be taken in advance. Hence, fault diagnosis of dynamic systems has received more attention and significant progress has been made in recent years for model-based fault diagnosis techniques. More attention has been devoted to the development of robust fault detection methods under external disturbances for continuous time systems modeled by Ordinary Differential Equations (ODE) [15]. Differential-Algebraic Equations (DAEs), singular or descriptor systems are important in fault detection context since DAE systems appear in a large class of technical process like mechanical, electrical and chemical systems [3, 17].

With regard to state estimation or controller design, many approaches have been developed to design observers for descriptor systems. In [12], local asymptotic

observer is obtained for general nonlinear descriptor systems by means of a coordinate transformation. [6] studies observer issued for continuous nonlinear descriptor systems via a convex optimization. In addition in [10], a robust extended strictly positive real (ESPR) analysis and control for continuous-time descriptor systems with norm-bounded uncertainty was studied.

Until now, the design of fault diagnosis algorithm is a crucial problem for several physical process that are modeled by nonlinear DAEs [21]. The expansion of faults diagnosis approaches of ordinary systems [14, 15] to descriptor systems, requires to resolve DAEs on line. In practice, it may not be possible to employ standard estimation schemes described by DAEs for on line health monitoring due to difficulties in solving DAEs. Therefore, it is highly desirable to develop fault diagnosis algorithms that are based on ordinary differential equations. The design of these algorithms can become very difficult even impossible according to the type and the complexity of the employed model, from where the importance to have a mathematical model of the system where it's at the same time, simple and precise. The multi-models approach is a powerful technique of modeling nonlinear systems which make it possible to get a good compromise between the precision and the complexity of the model [14]. Multi-models are recognized for their capacity to take into account the changes in the operating mode of the system and to reproduce its behavior with precision in a broad operating range. Moreover, they offer mathematical properties which can be profitable during the design of observers. More recently, a lot of works have appeared that consider fault detection and estimation problem for multi-models

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functions $h_i(\xi(t))$ check the properties of the following convex set:

$$\begin{cases} \sum_{i=1}^h h_i(\xi(t)) = 1 \\ 0 \leq h_i(\xi(t)) \leq 1 \end{cases} \quad (3)$$

The multi-models structure makes possible to provide a mean of generalization of tools developed for linear systems to nonlinear systems. The theory for the observer design is derived for singular systems under the assumption that the system has the global observability. This concept implies the observability of the algebraic part and the differential part of a descriptor system [2, 13]. Then, the observability for descriptor multi-models notion requires that all the subsystems are observable [8]. Assumptions A2 and A3 extend the observability properties to the descriptor multi-models.

Assumption A1: $\text{rank}(CR_i) = \text{rank}(R_i)$.

Assumption A2: The row vectors of the matrices C and E must be a basis of the n -dimensional vector space:

$$\text{rank} \begin{bmatrix} E \\ C \end{bmatrix} = n \quad (4)$$

Assumption A3: Each local model of the descriptor multi-models (2), has to be observable $\forall i = 1, \dots, h$.

$$\text{rank} \begin{bmatrix} sE - A_i \\ C \end{bmatrix} = n, \quad \forall s \in \mathcal{C}. \quad (5)$$

The following section is dedicated to generate an alarm signal when a fault occurs and produce an accurate estimate of the fault vector $f(t)$.

3. ROBUST FAULT DETECTION IN DESCRIPTOR MULTI-MODELS

In this section, the design of a residual generator based on unknown input observer for descriptor multi-models is developed. The global residual generator is defined by:

$$\begin{cases} \dot{z}(t) = \sum_{i=1}^h h_i(\xi(t)) [N_i z(t) + G_i u(t) + L_i y(t) + \Delta z_i] \\ \hat{x}(t) = z(t) + T_2 y(t) \\ r(t) = M_1 z(t) + M_2 y(t) \end{cases} \quad (6)$$

where $r(t)$ is the residual vector, $z(t)$ and $\hat{x}(t)$ are the state vector and the estimated state vector respectively. The residual generator design is reduced to determine the gains $N_i, G_i, \Delta z_i, L_i, M_1, T_2$ and M_2 such that the state estimation error is stable. Then, to analyze the convergence of the residual generator, let consider the estimation error from (2) and (6) such that:

$$e(t) = \hat{x}(t) - x(t)$$

$$e(t) = z(t) - (I_n - T_2 C)x(t) + T_2 G d(t) \quad (7)$$

Under Assumption A2, there exists nonsingular matrices $T_1 \in \mathbb{R}^{n \times n}$ and $T_2 \in \mathbb{R}^{n \times m}$ such that:

$$T_1 E + T_2 C = I_n \quad (8)$$

The dynamic estimation error is then described by:

$$\dot{e}(t) = \dot{z}(t) - T_1 E \dot{x}(t) + T_2 G \dot{d}(t) \quad (9)$$

which is equivalent to

$$\dot{e}(t) = \sum_{i=1}^h h_i(\xi(t)) [N_i z(t) + G_i u(t) + L_i y(t) + \Delta z_i - T_1 A_i x(t) - T_1 B_i u(t) - T_1 R_i d(t) - T_1 F_i f(t) - T_1 \Delta x_i] \quad (10)$$

The estimation error is finally given by:

$$\begin{aligned} e(t) = & \sum_{i=1}^h h_i(\xi(t)) [N_i e(t) + (N_i T_1 E + L_i C - T_1 A_i)x(t) \\ & + (G_i - T_1 B_i)u(t) + (L_i G - N_i T_2 G - T_1 R_i)d(t) \\ & - T_1 F_i f(t) + T_2 G \dot{d}(t) + \Delta z_i - T_1 \Delta x_i] \end{aligned} \quad (11)$$

From (6), the general expression of the residual vector can be written as:

$$r(t) = M_1 z(t) + M_2 y(t) \quad (12)$$

and by using the estimation error (7), it follows:

$$\begin{aligned} r(t) = & M_1 e(t) + (M_1 T_1 E + M_2 C)x(t) \\ & + (M_2 - M_1)T_2 G d(t) \end{aligned} \quad (13)$$

If the following conditions hold true $\forall i = 1, \dots, h$:

$$N_i T_1 E + L_i C - T_1 A_i = 0 \quad (14)$$

$$M_1 T_1 E + M_2 C = 0 \quad (15)$$

$$G_i - T_1 B_i = 0 \quad (16)$$

$$L_i G - N_i T_2 G - T_1 R_i = 0 \quad (17)$$

$$T_2 G = 0 \quad (18)$$

$$\Delta z_i - T_1 \Delta x_i = 0 \quad (19)$$

then, the estimated error $e(t)$ and residual $r(t)$ become:

$$\dot{e}(t) = \sum_{i=1}^h h_i(\xi(t)) [N_i e(t) - T_1 F_i f(t)] \quad (20)$$

$$r(t) = M_1 e(t) \quad (21)$$

Therefore, the design of the residual generator (6) is reduced to satisfy the constraints (14) to (19) by taking into the stability of (20). In order to establish the gains matrices of the designed residual generator, the substitution of (8) into (14) yields to:

$$T_1 A_i = N_i (I_n - T_2 C) + L_i C \quad (22)$$

$$N_i = T_1 A_i + (N_i T_2 - L_i) C \quad (23)$$

$$N_i = T_1 A_i + K_i C \quad (24)$$

where

$$K_i = N_i T_2 - L_i$$

To design matrices T_1 and T_2 , let consider equation (8) under equality (18), one can write the following relationship:

$$\begin{bmatrix} T_1 & T_2 \end{bmatrix} \begin{bmatrix} E & 0 \\ C & G \end{bmatrix} = \begin{bmatrix} I_n & 0 \end{bmatrix} \quad (25)$$

Under Assumption A1, a solution $\begin{bmatrix} T_1 & T_2 \end{bmatrix}$ exists if and only if the matrix $\begin{bmatrix} E & 0 \\ C & G \end{bmatrix}$ is a full column rank [13]. Then, a particular solution of (25) is given by using the generalized inverse matrix such that:

$$\begin{bmatrix} T_1 & T_2 \end{bmatrix} = \begin{bmatrix} I_n & 0 \end{bmatrix} \begin{bmatrix} E & 0 \\ C & G \end{bmatrix}^+ \quad (26)$$

then, by taking,

$$T = \begin{bmatrix} I_n & 0 \end{bmatrix} \begin{bmatrix} E & 0 \\ C & G \end{bmatrix}^+ \in \mathbb{R}^{n \times (n+m)}$$

we can write:

$$T = \left[\begin{array}{c|c} 1, \dots, n & n+1, \dots, n+m \\ \hline T_1 & T_2 \end{array} \right] \quad (27)$$

After, to compute matrices M_1 and M_2 , equation (15) can be rewritten as:

$$\begin{bmatrix} M_1 & M_2 \end{bmatrix} \begin{bmatrix} T_1 E \\ C \end{bmatrix} = 0 \quad (28)$$

To solve equation (28), it is equivalent to write:

$$\begin{bmatrix} T_1 E \\ C \end{bmatrix}^T \begin{bmatrix} M_1^T & M_2^T \end{bmatrix}^T = 0 \quad (29)$$

Hence, (29) admits a solution $\begin{bmatrix} M_1^T & M_2^T \end{bmatrix}^T$ in the null space of $\begin{bmatrix} T_1 E \\ C \end{bmatrix}^T$ i.e.:

$$\begin{bmatrix} M_1^T & M_2^T \end{bmatrix}^T \subseteq \text{Ker} \begin{bmatrix} T_1 E \\ C \end{bmatrix}^T \quad (30)$$

Then, a solution can be chosen as follows:

$$\begin{bmatrix} M_1^T & M_2^T \end{bmatrix}^T = \text{ker} \begin{bmatrix} T_1 E \\ C \end{bmatrix}^T \quad (31)$$

if we express

$$\Delta^T = \text{ker} \begin{bmatrix} T_1 E \\ C \end{bmatrix}^T$$

it's equivalently to,

$$\Delta^T = \begin{bmatrix} M_1^T & M_2^T \end{bmatrix}^T$$

then, one can write:

$$\Delta = \left[\begin{array}{c|c} 1, \dots, n & n+1, \dots, n+m \\ \hline M_1 & M_2 \end{array} \right] \quad (32)$$

3.1. Design and stability analysis

In this subsection, the stability problem is studied for two cases:

Case A: when the decision variable of the weighting function depends of a measured state variable.

Case B: when this variable depends of an unmeasured state variable.

Case A: Measurable decision variable

From the following dynamic state estimation error:

$$\dot{e}(t) = \sum_{i=1}^h h_i(\xi(t)) [N_i e(t) - T_1 F_i f(t)] \quad (33)$$

and by using (24), it becomes:

$$\dot{e}(t) = \sum_{i=1}^h h_i(\xi(t)) [(T_1 A_i + K_i C) e(t) - T_1 F_i f(t)] \quad (34)$$

The stability of the dynamic estimation error (34) can be verified by the following Theorem.

Theorem 1: The estimation error equation (34) is globally asymptotically stable, if the fault $f(t)$ satisfies $\|f(t)\| \leq \mu$, $\mu > 0$ and if there exists real parameters α and β , a common positive definite matrix Q and matrices $W_i = QK_i$ such that, $\forall i = 1, \dots, h$:

$$\begin{bmatrix} (T_1 A_i)^T Q + Q(T_1 A_i) + \alpha I_n + C^T W_i^T + W_i C & Q(T_1 F_i) \\ (T_1 F_i)^T Q & -\frac{1}{\beta} I_k \end{bmatrix} < 0 \quad (35)$$

s.t.

$$W_i G + Q T_1 R_i = 0 \quad (36)$$

■

Proof:

Consider the Lyapunov function with the following quadratic form:

$$V(e(t)) = e^T(t) Q e(t) > 0 \quad (37)$$

Stability condition for the estimation error yields to that the time derivative of the Lyapunov function should be negative definite over (3). The derivative of $V(e(t))$ with respect to time evaluated on the trajectories of the error equation (33) is:

$$\dot{V}(e) = \sum_{i=1}^h h_i(\xi(t)) \{ e^T(t) [N_i^T Q + Q N_i] e(t) - 2e^T(t) Q (T_1 F_i) f(t) \}$$

If $\|f(t)\| \leq \mu$, then

$$\dot{V}(e(t)) \leq \sum_{i=1}^h h_i(\xi(t)) \{ e^T(t) [N_i^T Q + Q N_i] e(t) - 2\mu \|e^T(t) Q (T_1 F_i)\| \}$$

the estimated state $\hat{x}_4(t)$ as follows:

$$h_i(\hat{x}_4(t)) = \frac{\mu_i(\hat{x}_4(t))}{\sum_{i=1}^4 \mu_i(\hat{x}_4(t))}$$

where $\mu_i(\hat{x}_4(t))$ are defined by

$$\mu_1(\hat{x}_4(t)) = \exp(-1/2(\frac{\hat{x}_4 + 2}{2})^2)$$

$$\mu_2(\hat{x}_4(t)) = \exp(-1/2(\frac{\hat{x}_4 - 2}{2})^2)$$

$$\mu_3(\hat{x}_4(t)) = \exp(-1/2(\frac{\hat{x}_4 + 3}{2})^2)$$

$$\mu_4(\hat{x}_4(t)) = \exp(-1/2(\frac{\hat{x}_4 - 3}{2})^2)$$

For $u(t) = 10\sin(0,2\pi t)$ and $d(t)$ a gaussian signal of variance 1 and zero average, the characterization of the global behavior of the nonlinear system by the multi-models is obtained after the estimation of the state vector to reconstruct the weighting functions. The outputs of the nonlinear system and the multi-models are shown in the following Figures (2-4).

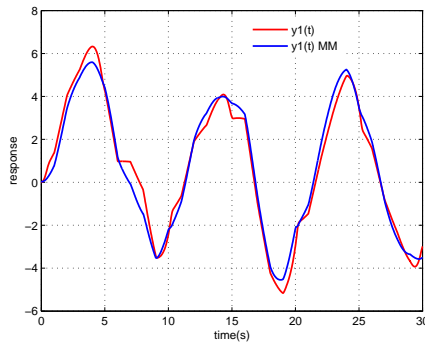


Fig 2: Nonlinear and multi-models outputs

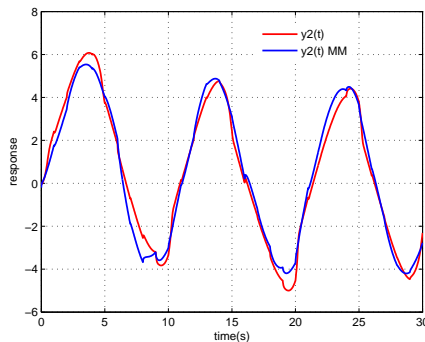


Fig 3: Nonlinear and multi-models outputs

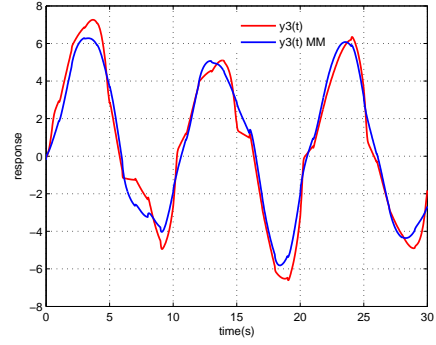


Fig 4: Nonlinear and multi-models outputs

These figures consider the multi-models form with the nonlinear system. They illustrate the superposition of the nonlinear outputs with those coming from the multi-models representation. We can see that the multi-models well approximate the nonlinear dynamic behavior.

5.2. Fault detection

In this paragraph, the main task of fault detection is to generate a residual signal which is insensitive to the system disturbances. To detect the fault, the residual has to be sensitive to this fault. According to the study in section (3.), the descriptor multi-models (70) with unknown input and fault can be described as:

$$\begin{cases} E\dot{x}(t) = \sum_{i=1}^4 h_i(\hat{x}_4(t)) [A_i x(t) + B_i u(t) + R_i d(t) + F_i f(t) + \Delta x_i + w(t)] \\ y(t) = Cx(t) + Gd(t) \end{cases} \quad (71)$$

where $F_i = F = [0 \ 0 \ 0 \ 1]^T$ is the fault vector and $w(t)$ is defined as (45). The system is subjected of fault $f(t)$ of the following form:

$$f(t) = (4 - 4\exp(-0,2(t - 20)))\varepsilon(t)$$

where

$$\begin{cases} \varepsilon(t) = 1 & \text{for } 20 \leq t \leq 25 \\ \varepsilon(t) = 0 & \text{elsewhere} \end{cases}$$

and the unknown input $d(t)$ is a white Gaussian noise with variance 0.01 and zero average.

Second, to design the residual generator (6), it can be shown that conditions (4) and (5) are satisfied. Using (26), one can obtain matrices T_1 and T_2 and the LMIs (47) can be efficiently solved under constraints (48) via numerical approach within the LMI toolbox in order to compute the gains matrices. Therefore, these inequalities are fulfilled with:

$$K_1 = \begin{bmatrix} -0.9402 & 1.0634 & 0 \\ -0.0036 & 0.0022 & -177.4767 \\ 1.1739 & -2.0024 & 0 \\ 0 & 0 & -0.0072 \end{bmatrix}$$

$$K_2 = \begin{bmatrix} -0.9144 & 1.0595 & -0.0002 \\ 0.0680 & -0.0425 & -177.4767 \\ 1.1050 & -1.9920 & -0.0001 \\ 0 & 0 & -0.0072 \end{bmatrix}$$

$$K_3 = \begin{bmatrix} -0.8985 & 1.0506 & -0.0001 \\ 0.0174 & -0.0109 & -177.4767 \\ 1.0628 & -1.9681 & 0 \\ 0 & 0 & -0.0072 \end{bmatrix}$$

$$K_4 = \begin{bmatrix} -0.9043 & 1.0385 & 0 \\ -0.0046 & 0.0029 & -177.4767 \\ 1.0781 & -1.9359 & 0 \\ 0 & 0 & -0.0072 \end{bmatrix}$$

The result of the residual signal response is shown in the following figure.

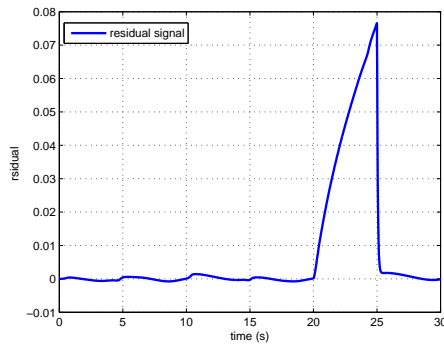


Fig 5: The residual signal $r(t)$

It's clear from the above figure (5) that the residual is almost zero throughout the time simulation run for fault-free residuals despite noisy environment and increase in magnitude considerably, when fault occurs between time $t = 20s$ and $t = 25s$.

5.3. Fault estimation

The occurred fault can be approximated by a polynomial function as follows:

$$f(t) = (0.8(t - 20) - 0.08(t - 20)^2)\varepsilon(t)$$

Let us construct the augmented descriptor multi-models as defined in (57) with $l = 2$ and solving the LMIs (67) under constraints (68), one can obtain:

$$\bar{K}_1 = \begin{bmatrix} 2.1808 & 10.4296 & 0 \\ 0 & 0 & -9.5122 \\ -8.0280 & -25.1471 & 0 \\ 0 & 0 & -0.2532 \\ 19.6191 & 71.1435 & 0 \\ 12.6064 & 47.1630 & 0 \end{bmatrix}$$

$$\bar{K}_2 = \begin{bmatrix} 2.2019 & 10.4594 & 0 \\ 0 & 0 & -9.5122 \\ -8.0821 & -25.2203 & 0 \\ 0 & 0 & -0.2532 \\ 19.6683 & 71.0525 & 0 \\ 12.6376 & 47.1054 & 0 \end{bmatrix}$$

$$\bar{K}_3 = \begin{bmatrix} 2.2065 & 10.4582 & 0 \\ 0 & 0 & -9.5122 \\ -8.0946 & -25.2202 & 0 \\ 0 & 0 & -0.2532 \\ 19.6051 & 71.0872 & 0 \\ 12.5975 & 47.1274 & 0 \end{bmatrix}$$

$$\bar{K}_4 = \begin{bmatrix} 2.1852 & 10.4133 & 0 \\ 0 & 0 & -9.5122 \\ -8.0417 & -25.1155 & 0 \\ 0 & 0 & -0.2532 \\ 19.4099 & 71.2857 & 0 \\ 12.4738 & 47.2531 & 0 \end{bmatrix}$$

These gains matrices are used to determine the remaining matrices of the augmented multi-observer. The estimated fault is then, given by the following figure (6).

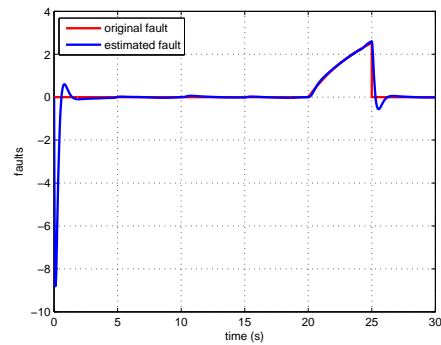


Fig 6: The original fault and its estimated

From the above simulation results, it has been shown that the fault reconstruction algorithm is effective in estimating the fault behavior, for a descriptor system subject to a large class of fault signals such as time-invariant and time-varying signals.

6. CONCLUSION

For nonlinear descriptor systems that can be represented by a set of sub-models, a multi-models residual generation is designed. This concept is used for fault detection and estimation problems for descriptor multi-models. To estimate the fault, an augmented residual generator is designed for an augmented descriptor multi-models. Sufficient conditions for the existence of residual generator have been established and the analysis of the stability have been also designed for two cases. One case is dedicated when the decision

variable of the weighting function do not depend on the unmeasured state variables. The other case is dedicated when the decision variable depends on the unmeasured state variables. The method has been successfully applied to experimental data coming from an electrical circuit with an ideal voltage source and three nonlinear components.

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