Available online at www.sciencedirect.com
ScienceDirect
journal homepage: www.elsevier.com/locate/he

Fuzzy observer-based fault tolerant control against sensor faults for proton exchange membrane fuel cells[☆]

Elkhatib Kamal [a,*], *Abdel Aitouche* [b]

[a] *Department of Industrial Electronics and Control Engineering, Faculty of Electronic Engineering, Menoufia University, Menouf, 32952, Menoufia, Egypt*
[b] *CRIStAL UMR CNRS 9189, HEI-Lille, Lille, France*

ARTICLE INFO

Article history:
Received 25 July 2018
Received in revised form
2 October 2018
Accepted 9 October 2018
Available online xxx

Keywords:
Proton Exchange Membrane Fuel Cells (PEMFC)
Fault estimation
TS fuzzy system
Unknown input observer
Fuel cells
Sensor faults

ABSTRACT

In this paper, robust fault diagnosis problem of Proton Exchange Membrane Fuel Cells (PEMFC) is presented based on Takagi-Sugeno (TS) Fuzzy Unknown Input Observer (FUIO). TS FUIO based on Linear Matrix Equalities (LMEs) and the Linear Matrix Inequalities (LMIs) are design. Firstly, the nonlinear PEMFC system with sensor faults and disturbance is represented by TS fuzzy model. Then, a FUIO and sensor fault estimation algorithm is developed and then a model based Fuzzy Fault Tolerant Controller design uses the concept of Parallel Distributed Compensation (PDC). Sufficient stability conditions are studied based on LMIs and LMEs. In order to verify the proposed approach, a PEMFC system with return manifold pressure and hydrogen mass sensors fault and disturbance was tested to illustrate the effectiveness of the proposed strategy.

Introduction

In the last years, major efforts to reduce greenhouse effects and pollution have increased the demand for environmentally friendlier energy sources [1,2]. With the increasing capacity and complexity of the Proton Exchange Membrane Fuel Cells (PEMFC), the reliability and safety of the system become more and more important. PEMFC are nonlinear systems with many auxiliary subsystems, which is characterized by multiple variables and a strong coupling with profound dynamics. Therefore, it is difficult to apply control theory methods. For this reason, several publications of dynamic fuel cell system models have been developed in the literature [3–8]. In Ref. [3], dynamic model of the PEMFC based on physical principles is built, in the form of a nonlinear state space model is

☆ This work is partially supported by the National Natural Science Foundation of China (61304077), by International Science & Technology Cooperation Program of China (2015DFA01710), by the Natural Science Foundation of Jiangsu Province (BK20170094), and by Campus France.

* *Corresponding author.*
E-mail addresses: elkhateb.ibrahim@el-eng.menofia.edu.eg, elkateb.kamal@gmail.com (E. Kamal), abdel.aitouche@hei.fr (A. Aitouche).

https://doi.org/10.1016/j.ijhydene.2018.10.070

presented. Ref. [4] have developed a PEMFC dynamic model based on bond-graph modeling in order to be used it in diagnosis [5]. A mathematical modeling and control study of PEMFC based on Fuzzy Logic Controller (FLC) is presented in Ref. [6]. A coolant circuit mathematical model is developed in Ref. [7], which includes a PEMFC thermal, a water reservoir, a water pump, a bypass valve, a heat exchanger models and a PEMFC electrochemical model. Ref. [8] presents a MATLAB/Simulink model based on adopted mathematical models that describe the fuel cell's operational voltage, which is simulates the behavior of a PEMFC. However, the dynamic PEMFC model is characterized by multiple variables and a strong coupling with profound dynamics, which may be easily affected by sensor or component faults [9]. To be suitable for control and diagnosis, a Takagi-Sugeno (TS) model can be used in order to represent nonlinear dynamical systems. Many control strategies for PEMFC have been studied [10–22]. Fixed-order multivariable robust control strategies based on H_∞ for PEMFC system are given [10]. Advanced control of the motocompressor group for PEMFC is addressed in Ref. [11]. Robust controllers and fuzzy controllers based on proportional-integral-derivative (PID) for a PEMFC system are presented in Refs. [12–17]. Optimal control and model predictive control for PEMFC are given in Refs. [18,19]. Sliding mode control for PEMFC are presented in Refs. [20–22].

Recently, the research community of PEMFC has shown a considerable interest for Fault Detection and Diagnostic (FDD) and Fault Tolerant Control (FTC) in order to ensure safety, security, when faults occur. These faults must be detected early and some time estimated and accommodated. Therefore, several researchers have exploited a FDD and FTC for PEMFC [23–30]. In Ref. [23], fault diagnosis of PEMFC is reviewed with a special emphasis on model-based methods. Ref. [24] focuses on developing a reliable fault identification and localisation tool for PEMFC. In Ref. [25], the problem of robust fault diagnosis of PEMFC is addressed based one TS interval observers that consider uncertainty in a bounded context. Ref. [26] presents the basics of the fault diagnosis of PEMFC to improve its durability and reliability which are crucial issues to be widely commercialized. In Ref. [27], a fault diagnosis method based on multi-sensor signals and principle component analysis is proposed to improve PEMFC performance. The portability of an innovative data driven approach dedicated to PEMFC diagnosis, named singularity analysis is presented in Ref. [28]. Once the fault has been detected, a FTC must be used. FTC is a highly developed topic in safety critical applications such as transports, aircrafts, spacecrafts and PEMFC plants. Usually, FTC methods can be classified into two types: passive [29] and active [30]. In the active FTC approaches, the observer and its corresponding algorithm play a very important role to estimate fault signals which are compensated by FTC. Recently, several researchers have exploited a TS fuzzy observer to deal with nonlinearity in FDD and FTC problems [31–35]. The main principle is to use the TS fuzzy models to represent nonlinear dynamic systems by local linear models. Based on the idea of TS fuzzy models and Linear Matrix Inequalities (LMIs), the fuzzy observer is designed to estimate the faults. FDI and controlling based on the TS fuzzy model description for PEMFC systems are presented in Refs. [36,37]. In Ref. [38], considering the unmeasurable premise variables in the fuel cell system, a PI observer with an additional corrective sliding term based on TS fuzzy model is introduced. In Ref. [39], an adaptive second-order sliding mode observer is developed to estimate and reconstruct the actuator fault for PEMFC. In Ref. [40], a quasi-Linear Parameter Varying (qLPV) virtual actuator approach by using a reference model is presented for PEMFC. In Ref. [41], considering a fault scenario of sudden air leak in the air supply manifold, a modified suppertwisting sliding mode observer is designed.

Thus, this paper will consider TS models and Fuzzy Unknown Input Observer (FUIO) to estimate the sensor faults in PEMFC with disturbance. The main contribution of this paper is to address the problem of fuzzy FTC strategy of PEMFC based on TS FUIO to estimate the sensor faults. This approach is an extension of the work proposed in Ref. [42]. Furthermore, based on the information from online fault estimation, an observer-based fuzzy FTC is designed to compensate the effect of faults by stabilizing the closed-loop system. Sufficient conditions for the existence of both FUIO and fuzzy FTC are given in terms of Linear Matrix Equalities (LMEs) and the LMIs. The contributions of this paper is the estimation of time varying process faults and composite fuzzy FTC which compensates the effects of faults by stabilizing the closed-loop system in the presence of faults. Simulation results from a PEMFC are presented to illustrate the effectiveness of the proposed method.

The structure of this paper is organized as follows. Section TS fuzzy plant model, fuzzy unknown input observer and fault estimation and convergence analysis presents the TS fuzzy plant model, FUIO and fault estimation analysis. Robust fault estimation and convergence analysis is given in sections Robust fault estimation of the fuio and convergence analysis, Modeling of pemfc system based on ts fuzzy model shows modeling for PEMFC system based on TS fuzzy model. In section Simulation studies, a PEMFC system with return manifold pressure and hydrogen mass sensor faults are tested to verify the performance of the proposed method. Finally, conclusions are given in section Conclusion.

TS fuzzy plant model, Fuzzy Unknown Input Observer and fault estimation and convergence analysis

In this section, the TS fuzzy plant model subject to sensor faults and disturbance are given. The main objective is to design the fuzzy FTC for the PEMFC.

A. TS fuzzy model with faults and disturbance

The fuzzy dynamic model proposed by TS fuzzy model [43] is often used to represent a nonlinear PEMFC system subject to sensor fault [42].

$$\begin{aligned}&\text{Plant Rule } i: \text{If } q_1(t) \text{ is } h_{i1} \text{ and} \ldots \text{and } q_\psi(t) \text{ is } h_{i\psi}(t), \text{then}\\ &\dot{x}(t) = A_i x(t) + B_i u(t) + D_i d(t)\\ &y(t) = C_i x(t) + F_i f(t) \quad i = 1, 2, \ldots, p\end{aligned} \tag{1}$$

where $x(t)\in\Re^{n\times 1}$, $y(t)\in\Re^{g\times 1}$ and $u(t)\in\Re^{m\times 1}$ are the state, the output and the input vectors, respectively, $C_i\in\Re^{g\times n}$ is the system output matrix, $A_i\in\Re^{n\times n}$ and $B_i\in\Re^{n\times m}$ are the system matrix and input matrix, respectively, h_{ij} $(i = 1, 2, \ldots, p; j = 1, 2, \ldots, \psi)$ are the premise variables and the fuzzy sets that are characterized by the membership function, p is the number of TS fuzzy model rules, $d(t)$, $f(t)$,D_i and F_i are the disturbance and the sensor fault vector and matrices, respectively. The global TS fuzzy mode is given by Ref. [44]:

$$\begin{aligned} \dot{x}(t) &= \sum_{i=1}^{p} \mu_i(q(t))[A_i x(t) + B_i u(t) + D_i d(t)] \\ y(t) &= \sum_{i=1}^{p} \mu_i(q(t))[C_i x(t) + F_i f(t)] \end{aligned} \tag{2}$$

where: $\mu_i(q(t)) = \frac{SS_i(q(t))}{\sum_{i=1}^{p} SS_i(q(t))}$, $SS_i(q(t)) = \prod_{j=1}^{\psi} h_{ij}(q_j(t))$, $SS_i(q(t)) \geq 0$, $i = 1,2,\ldots,p$, $\mu_i(q(t)) \geq 0$, $\sum_{i=1}^{p} \mu_i(q(t)) = 1$, in which $h_{ij}(q_j(t))$ is the grade of membership of $q_j(t)$ in h_{ij}.

Considering the measure noise of the sensor, a first-order filter is taken and the model is given as [45] is given by:

$$\begin{aligned} \dot{W}(t) &= \sum_{i=1}^{p} \mu_i(q(t))[-A_{wi} w(t) + A_{wi} y(t)] \\ y_{wi}(t) &= \sum_{i=1}^{p} \mu_i(q(t)) C_{oi} W(t) \end{aligned} \tag{3}$$

where $A_{wi} \in \Re^{r \times r}$ and C_{oi} are the first order filer matrices, substituting from (2) into (3), we obtain

$$\begin{aligned} \dot{W}(t) &= \sum_{i=1}^{p} \mu_i(q(t))[-A_{wi} w(t) + A_{wi} C_i x(t) + A_{wi} F_i f(t)] \\ y_{wi}(t) &= \sum_{i=1}^{p} \mu_i(q(t)) C_{oi} W(t) \end{aligned} \tag{4}$$

From (2) and (4), we are obtained,

$$\begin{aligned} \dot{X}(t) &= \sum_{i=1}^{p} \mu_i(q(t)) [\overline{A}_i X(t) + \overline{B}_i U(t) + \overline{D}_i d(t) + \overline{F}_i f(t)] \\ Y(t) &= \sum_{i=1}^{p} \mu_i(q(t)) \overline{C}_i X(t) \end{aligned} \tag{5}$$

where $X(t) = [x(t) \quad W(t)]^T$, $Y(t) = [y(t) \quad W(t)]^T$, $U(t) = [u(t) \quad 0]^T$, $\overline{A}_i = \begin{bmatrix} A_i & 0 \\ A_{wi} C_i & -A_{wi} \end{bmatrix}$, $\overline{B}_i = \begin{bmatrix} B_i \\ 0 \end{bmatrix}$, $\overline{C}_i = [0 \quad C_{oi}]$. $\overline{F}_i = \begin{bmatrix} 0 \\ A_{wi} F_i \end{bmatrix}$, $\overline{D}_i = \begin{bmatrix} D_i \\ 0 \end{bmatrix}$, where C_{oi} is an identity matrix with appropriate dimensions.

Notice that system (2) with sensor fault is converted into a new system with actuator faults. The main objective of the observer becomes the estimation of these faults. Firstly, some assumptions are given as following.

1) $(\overline{A}_i, \overline{C}_i)$ are observable;
2) The disturbance $d(t)$ and fault $f(t)$ are bounded, i.e., $\|f(t)\| \leq f_m, \|d(t)\| \leq d_0$, where $0 < f_m, d_0 < \infty$.

B. TS fuzzy model unknown input observer and fault estimation

FUIO is proposed based on [31,46], to estimate the state,

$$\begin{aligned} \dot{z}(t) &= \sum_{i=1}^{p} \mu_i(q(t)) \left[N_i z(t) + G_i u(t) + L_i Y(t) + T_i \hat{f}(t)\right] \\ \hat{X}(t) &= z(t) - EY(t) = z(t) - \sum_{i=1}^{p} \mu_i(q(t)) E_i \overline{C}_i X(t) \end{aligned} \tag{6}$$

and the estimated algorithm of fault is selected as

$$\begin{aligned} \hat{f}(t) &= \sum_{i=1}^{p} \mu_i(q(t)) \left[\Gamma S_i((Y(t) - \hat{Y}(t)) + \sigma \int (Y(t) - \hat{Y}(t)) dt\right] \\ &= \sum_{i=1}^{p} \mu_i(q(t)) \left[\Gamma S_i((Y(t) - \overline{C}_i \hat{X}(t)) + \sigma \int (Y(t) - \overline{C}_i \hat{X}(t)) dt\right] \\ &= \sum_{i=1}^{p} \mu_i(q(t)) \left[\Gamma S_i \overline{C}_i \left(e(t) + \sigma \int e(t) dt\right)\right] \end{aligned} \tag{7}$$

where $\hat{X}(t)$, $\hat{f}(t)$ are the observer states, fault estimation $f(t)$, respectively, $N_i \in \Re^{(n+m)\times(n+m)}$, $L_i \in \Re^{(n+m)\times m}$, $G_i \in \Re^{(n+m)\times p}$, $T_i \in \Re^{(n+m)\times(p+q)}$, $E \in \Re^{(n+m)\times m)}$, Γ, S_i are the observer gains with appropriate dimensions. They satisfy the following conditions:

$$\begin{aligned} M\overline{A}_i - N_i M - L_i \overline{C}_i &= 0 \\ M\overline{B}_i - G_i &= 0 \\ M\overline{D}_i &= 0 \\ M\overline{F}_i - T_i &= 0 \end{aligned} \tag{8}$$

Let,

$$\begin{aligned} e(t) &= X(t) - \hat{X}(t) = MX(t) - z(t) \\ \tilde{f}(t) &= f(t) - \hat{f}(t) \end{aligned} \tag{9}$$

we can obtain,

$$e(t) = \sum_{i=1}^{p} \mu_i(q(t))(I + E_i \overline{C}_i) X(t) - z(t) = MX(t) - z(t) \tag{10}$$

where $M = \sum_{i=1}^{p} \mu_i(q(t))(I + E_i \overline{C}_i)$, I is an identity matrix of appropriate dimensions. From (10), the derivative of the error is given by,

$$\begin{aligned} \dot{e}(t) &= M\dot{X}(t) - \dot{z}(t) \\ &= \sum_{i=1}^{p} \mu_i \Big[N_i e(t) + (M\overline{A}_i - N_i M - L_i \overline{C}) X(t) \\ &\quad + (M\overline{B}_i - G_i) U(t) + M\overline{D}_i d(t) + M\overline{F}_i \tilde{f}(t) \\ &\quad + (M\overline{F}_i - T_i) \hat{f}(t)\Big] \end{aligned} \tag{11}$$

Based on (8), the derivative of the error is given by,

$$\dot{e}(t) = \sum_{i=1}^{p} \mu_i \left[N_i e(t) + M\overline{F}_i \tilde{f}(t)\right] \tag{12}$$

Note that the error dynamic state is related to the $\tilde{f}(t)$. If the matrix N_i is stable and the fault estimation error tends to zero, the estimation error will converge. If conditions (8) are not satisfied, the proposed observer in Eq. (6) will be unsuitable. Stability condition of the FUIO is analyzed as the following.

Robust fault estimation of the FUIO and convergence analysis

In this section, stability conditions are derived for the PEMFC subject to sensor faults and disturbance.

A. Stability and convergence analysis of the FUIO

The results of this subsection can be summarized by the Theorem and Lemma 1 [46].

Lemma 1 [46]: The following inequality is satisfied:

$$2x^Ty \le \frac{1}{\mu}x^TP_{1o}x + \rho y^TP_{1o}^{-1}y \quad x, y \in R^n \tag{13}$$

where $\rho > 0$ is scalar and P_{1o} is a symmetric positive definite matrix.

Theorem 1. *If the following LMIs are satisfied for* $i = 1, \ldots r$

$$\begin{bmatrix} N_i^TP_o + P_oN_i & * \\ -\frac{T_i^TP_oN_i}{\sigma} & \frac{1}{\sigma\rho_1}(P_{1o} - 2\rho_1T_i^TP_oT_i) \end{bmatrix} < 0 \tag{14}$$

$$T_i^TP_o - S_i\overline{C}_i = 0 \tag{15}$$

Then the system (11) is stable, where P_o is symmetric positive definite matrices.

From (6) and (12), the derivative of the fault estimated algorithm is given by,

$$\dot{\hat{f}}(t) = \sum_{i=1}^{p}\mu_i\left[\Gamma S\overline{C}_i(\dot{e}(t) + \sigma e(t))\right]$$
$$= \sum_{i=1}^{p}\mu_i[\Gamma S\overline{C}_i((N_i + \sigma)e(t) + M\overline{F}_i)\tilde{f}(t)]$$

where σ is a positive scalar.

Proof. Let Lyapuonv function as the following

$$V(t) = e^T(t)P_oe(t) + \frac{1}{\sigma}\tilde{f}^T(t)\Gamma^{-1}\tilde{f}(t) \tag{17}$$

then we have

$$\begin{aligned} \dot{V} &= \dot{e}^TP_oe + e^TP_o\dot{e} + \frac{1}{\sigma}\dot{\tilde{f}}^T\Gamma^{-1}\tilde{f} + \frac{1}{\sigma}\tilde{f}^T\Gamma^{-1}\dot{\tilde{f}} \\ &= \dot{e}^TP_oe + e^TP_o\dot{e} + \frac{1}{\sigma}\dot{\tilde{f}}^T\Gamma^{-1}\tilde{f} + \frac{1}{\sigma}\tilde{f}^T\Gamma^{-1}\dot{\tilde{f}} \\ &= \sum_{i=1}^{p}\mu_i\left(e^T(N_i^TP_o + P_oN_i)e + 2\tilde{f}^TT_i^TP_oe\right) \\ &\quad + \frac{2}{\sigma}\tilde{f}^T\Gamma^{-1}\dot{\tilde{f}} \end{aligned} \tag{18}$$

According to Eq. (16), the derivative of estimation fault becomes

$$\begin{aligned} \dot{\tilde{f}}(t) &= \dot{f}(t) - \dot{\hat{f}}(t) \\ &= \dot{f}(t) - \sum_{i=1}^{p}\mu_i[\Gamma S\overline{C}_i((N_i + \sigma)e(t) + M\overline{F}_i)] \end{aligned} \tag{19}$$

Substituting Eqs. (18) in (19), we have

$$\begin{aligned} \dot{V} &= \sum_{i=1}^{p}\mu_i(e^T(N_i^TP_o + P_oN_i)e + 2\tilde{f}^T(T_i^TP_o - S_i\overline{C})e \\ &\quad + \frac{2}{\sigma}\tilde{f}^T\Gamma^{-1}\dot{f} - \frac{2}{\sigma}\tilde{f}^TS_i\overline{C}_iN_ie - \frac{2}{\sigma}\tilde{f}^TS_i\overline{C}_iT_i\tilde{f}\Big) \\ &= \sum_{i=1}^{p}\mu_i(e^T(N_i^TP_o + P_oN_i)e + \frac{2}{\sigma}\tilde{f}^T\Gamma^{-1}\dot{f} \\ &\quad - \frac{2}{\sigma}\tilde{f}^TS_i\overline{C}_iN_ie - \frac{2}{\sigma}\tilde{f}^TS_i\overline{C}_iT_i\tilde{f}\Big) \end{aligned} \tag{20}$$

Consider, $\left\|\dot{f}(t)\right\| \le f_m$, where $0 < f_m < \infty$. Using the Lemma 1 and considering a positive symmetric matrix $P_{1o} > 0$ and scalar $\rho_1 > 0$, we obtain

$$\begin{aligned} \frac{2}{\sigma}\tilde{f}^T\Gamma^{-1}\dot{f} &\le \frac{1}{\sigma}\left(\frac{1}{\rho_1}\tilde{f}^TP_{1o}\tilde{f} + \rho_1\dot{f}^T\Gamma^{-T}P_{1o}^{-1}\Gamma^{-1}\dot{f}\right) \\ &\le \frac{1}{\sigma\rho_1}\left(\tilde{f}^TP_{1o}\tilde{f} + \rho_1^2f_m^2\lambda_{\max}(\Gamma^{-T}P_{1o}^{-1}\Gamma^{-1})\right) \end{aligned} \tag{21}$$

Substituting Eq. (21) into (20), we have

$$\begin{aligned} \dot{V} < \sum_{i=1}^{p}\mu_i(e^T(N_i^TP_o + P_oN_i)e - \frac{2}{\sigma}\tilde{f}^TS_i\overline{C}_iN_ie \\ - \frac{2}{\sigma}\tilde{f}^TS_i\overline{C}_iT_i\tilde{f}) + \frac{1}{\sigma\rho_1}(\tilde{f}^TP_{1o}\tilde{f} \\ + \rho_1^2f_m^2\lambda_{\max}(\Gamma^{-T}P_{1o}^{-1}\Gamma^{-1})\Big) \end{aligned} \tag{22}$$

Denoting the vector $\xi = \begin{bmatrix} e & \tilde{f} \end{bmatrix}^T$, $\dot{V}$ can be rewritten as

$$\dot{V} = \sum_{i=1}^{p}\mu_i\xi^T\Psi_i\xi + \frac{\rho}{\sigma}f_m\lambda_{\max}(\Gamma^{-T}P_{1o}^{-1}\Gamma^{-1}) \tag{23}$$

where $\Psi_i = \begin{bmatrix} N_i^TP_o + P_oN_i & * \\ -\frac{1}{\sigma}S_i\overline{C}_iN_i & \frac{1}{\rho\sigma}P_{1o} - \frac{2}{\sigma}S_i\overline{C}_iT_i \end{bmatrix}$.

Using Theorem 1, if the matrix $\Psi_i < 0$ is satisfied, we have

$$\dot{V} \le -\varepsilon||\xi||^2 + \frac{\rho}{\sigma}f_m\lambda_{\max}(\Gamma^{-T}P_{1o}^{-1}\Gamma^{-1}) \tag{24}$$

where $\varepsilon = ||\lambda_{\min}(\Psi_i)||_{\min}$. Then $\dot{V} < 0$, for $\varepsilon||\xi||^2 > \frac{\rho}{\sigma}f_m\lambda_{\max}(\Gamma^{-T}P_{1o}^{-1}\Gamma^{-1})$.

B. FUIO gains calculation

In this subsection, FUIO gains are obtained. Since C_i and D_i are of full column rank according the assumption (1), the pseudo inverse matrix of the matrix $H \triangleq \begin{bmatrix} I & \overline{D}_1 & \cdots & \overline{D}_r \\ -\overline{C}_i & 0 & \cdots & 0 \end{bmatrix}$ exist and the solution of the matrices M, E_i can be obtained by multiplication with the pseudo inverse matrix

$$[M \quad E_i] = [I \quad 0 \quad \cdots \quad 0]\begin{bmatrix} I & \overline{D}_1 & \cdots & \overline{D}_r \\ -\overline{C}_i & 0 & \cdots & 0 \end{bmatrix}^{\dagger} \tag{25}$$

where $(\bullet)^{\dagger}$ denotes pseudo inverse matrix. If the rank of the matrices C_i and D_i are not of full column, the proposed method will be not appropriate.

Substituting Eq. (25) in (8) and denoting the matrix $K_i = L_i + N_iE_i$, the gains of the observer can be obtained as

$$\begin{aligned} N_i &= M\overline{A}_i - K_i\overline{C} \\ L_i &= K_i(I + \overline{C}_iE_i) - M\overline{A}_iE_i \\ T_i &= M\overline{F}_i \end{aligned} \tag{26}$$

Now the matrix N_i in Eq. (14) can be replaced by Eq. (26), it becomes

$$\begin{bmatrix} \Lambda_{11} & \Lambda_{21}^T \\ \Lambda_{21} & \Lambda_{22} \end{bmatrix} < 0 \tag{27}$$

where $\Lambda_{11} = (M\overline{A}_i - K_i\overline{C}_i)^TP_o + P_o(M\overline{A}_i - K_i\overline{C}_i)$, $\Lambda_{21} = -\frac{T_i^TP_o(M\overline{A}_i - K_i\overline{C}_i)}{\sigma}$, $\Lambda_{22} = \frac{1}{\sigma\rho_1}(P_{1o} - 2\rho_1T_i^TP_oT_i)$.

If we denote the matrix $\overline{K}_i \triangleq P_oK_i$ in (27), the solutions of the LMIs can be obtained easily. Then, we have the matrix $K_i = P_o^{-1}\overline{K}_i$.

FUIO gains are calculated based on the following steps:

Step 1: Calculate the matrices M, E_i from Eq. (25), and G_i from Eq. (8);
Step 2: Replace N_i with $N_i = M\overline{A}_i - K_i\overline{C}_i$ and compute the matrices P_o and K_i from Eq. (27);
Step 3: Calculate the matrices N_i, L_i, T_i from Eq. (26).

C. Proposed fuzzy FTC algorithm design and stability analysis

After we design the FUIO gains in the previous section, the fuzzy FTC is developed. based on PDC [42]. For simplicity, let $\overline{F}_j = \overline{B}_j K_{2j}$, where K_{2j} are known matrices. The final output of the fuzzy FTC based on [44] is given as the following,

$$U(t) = \sum_{j=1}^{p} \mu_j \left[K_{1j}\widehat{X}(t) - K_{2j}\widehat{f}(t)\right] \tag{28}$$

where K_{1j} are the controller gains. The main results are summarized by the following Theorem 2.

Theorem 2. If the following LMIs are satisfied,

$$O\overline{A}_i^T + \overline{A}_i O - \left(\overline{B}_i^T Q_j\right)^T - \left(\overline{B}_i^T Q_j\right)^T < 0 \tag{29}$$

Then (5) is stable, $P > 0$ is the symmetric and positive definite matrix, $P = diag(P_1, P_2)$, $O = P_1^{-1}$, $K_{1j} = Q_j O^{-1}$.

Proof. From (28) and (2), we obtain,

$$\begin{aligned}\dot{X}(t) &= \sum_{i=1}^{p} \mu_i \left[\overline{A}_i X(t) + \overline{F}_i f(t) + \overline{D}_i d(t)\right] \\ &+ \sum_{i=1}^{p} \mu_i \overline{B}_i \left\{ \sum_{j=1}^{p} \mu_j \left[K_{1j}\widehat{X}(t) - K_{2j}\widehat{f}(t)\right] \right\}\end{aligned} \tag{30}$$

From (30) and (9), we have,

$$\begin{aligned}\dot{X}(t) &= \sum_{i=1}^{p}\sum_{j=1}^{p} \mu_i\mu_j \left[A_i + \overline{B}_i K_{2j}\right] X(t) \\ &+ \sum_{i=1}^{p} \mu_i \left[\overline{F}_i f(t) + \overline{D}_i d(t)\right] \\ &- \sum_{i=1}^{p}\sum_{j=1}^{p} \mu_i\mu_j \overline{B}_i K_{1j} e(t) - \sum_{i=1}^{p} \mu_j \overline{B}_i K_{2j} \widehat{f}(t)\end{aligned} \tag{31}$$

From (9) and (31), we obtain the following:

$$\begin{aligned}\dot{X}(t) = \textstyle\sum_{i=1}^{p}\sum_{j=1}^{p} \mu_i\mu_j &\left[\left(\overline{A}_i + \overline{B}_i K_{1j}\right) X(t) \right.\\ &\left. -\overline{B}_i K_{1j} e(t) + \overline{F}_i \tilde{f}(t) + \overline{D}_i d(t)\right]\end{aligned} \tag{32}$$

The augmented fuzzy system is obtained based on (11), (19) and (32).

$$\begin{aligned}\tilde{X}(t) &= \sum_{i=1}^{p} \mu_i\mu_j \left[\tilde{A}_{tij}\tilde{X}(t) + \tilde{F}_i F(t)\right] \\ \tilde{Y}(t) &= \sum_{i=1}^{p} \mu_i \tilde{C}_i \tilde{X}(t)\end{aligned} \tag{33}$$

with $\tilde{X}(t) = \begin{bmatrix} X(t) \\ e(t) \\ \tilde{f}(t) \end{bmatrix}$, $F(t) = \begin{bmatrix} d(t) \\ \dot{f}(t) \end{bmatrix}$, $\tilde{F}_i = \begin{bmatrix} \overline{D}_i & 0 \\ 0 & 0 \\ 0 & I \end{bmatrix}$,

$$\tilde{A}_{tij} = \begin{bmatrix} \left(\overline{A}_i + \overline{B}_i K_{1j}\right) & -\overline{B}_i K_{1j} & \overline{F}_i \\ 0 & N_i & M\overline{F}_i \\ 0 & -\Gamma S_i \overline{C}_i (N_i + \sigma) & -\Gamma S_i \overline{C}_i M \overline{F}_i \end{bmatrix},$$

$$\tilde{C}_i = \left[\overline{C}_i \quad 0 \quad 0\right]$$

The matrices $\tilde{A}_{tij}$, $\tilde{F}_i$ and $\tilde{C}_i$ can be expressed as:

$$\tilde{A}_{tij} = \begin{bmatrix} \left(\overline{A}_i + \overline{B}_i K_{1j}\right) & A_{t1ij} \\ 0_{2x1} & A_{t2ij} \end{bmatrix}$$

$$A_{t1ij} = \left[-\overline{B}_i K_{1j} \quad \overline{F}_i\right], \tilde{C}_i = \begin{bmatrix} \overline{C}_i \\ 0 \end{bmatrix}^T,$$

$$A_{t2ij} = \begin{bmatrix} N & M\overline{F}_i \\ \Gamma_{1i} & \Gamma_{2i} \end{bmatrix}$$

where $\Gamma_{1i} = -\Gamma S_i \overline{C}_i (N_i + \sigma)$ and $\Gamma_{2i} = -\Gamma S_i \overline{C}_i M \overline{F}_i$. Let Lyapunov candidate function $V(t)$ as the following:

$$V(t) = \tilde{X}(t)^T P \tilde{X}(t) \tag{34}$$

where P is a common positive definite matrix, when $F(t) = 0$, we obtain

$$\tilde{X}(t) = \sum_{i=1}^{p} \mu_i \tilde{A}_{ti} \tilde{X}(t) \tag{35}$$

By the time derivative of $V(t)$ and substituting (35), one obtains

$$\dot{V}(t) = \frac{1}{2}\tilde{X}(t)^T \sum_{i=1}^{p} \mu_i \left(\tilde{A}_{tij}^T P + P\tilde{A}_{tij}\right)\tilde{X}(t) \tag{36}$$

From (36), the time derivative of (34) is uniformly negative if the following inequality is satisfied

$$P\tilde{A}_{tij} + \tilde{A}_{tij}{}^T P < 0 \ \forall i,j \tag{37}$$

Let $P = \begin{bmatrix} P_1 & 0 \\ 0 & P_2 \end{bmatrix}$. Therefore, the inequality (37) will be rewritten as:

$$P_1\left(\overline{A}_i + \overline{B}_i K_{1j}\right) + \left(A_i + B_i K_{1j}\right)^T P_1 < 0 \ \forall i,j \tag{38}$$

By multiplying (38) from left and right by $O = P_1^{-1}$, and applying the change of variables $O = P_1^{-1}$, $Q_j = K_{1j}O$, LMI (29) is obtained.

Modeling of PEMFC system based on TS fuzzy model

The non-linear model of the PEMFC and TS fuzzy model are presented in this section.

A. Non-linear model of the PEMFC system

The non-linear model of the PEMFC (cf. Fig. 1) [3–5,47–49] is given by the following,

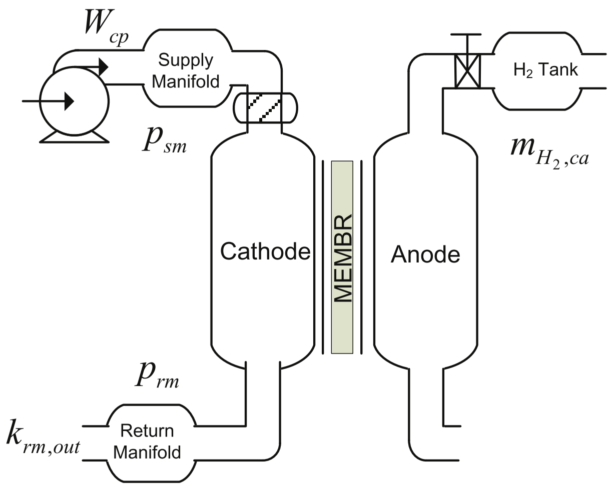

Fig. 1 – PEMFC system.

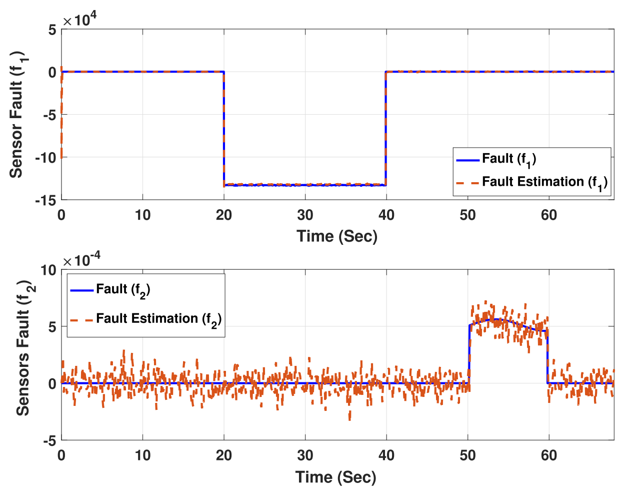

Fig. 2 – Fault and its estimation, f_1 and f_2 are the pressure supply manifold (Pascal) and –Hydrogen mass sensors fault.

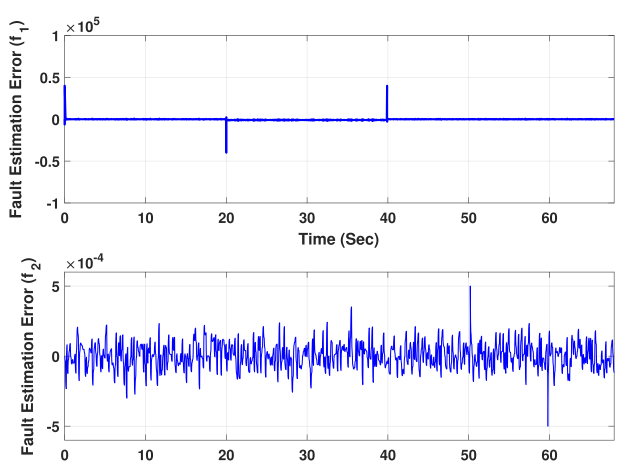

Fig. 3 – Fault estimation error, f_1 and f_2 are the pressure supply manifold and –Hydrogen mass (kg/s) sensors fault.

$$\dot{p}_{sm} = \frac{\gamma R_a}{V_{sm}}\left(T_{atm} W_{cp}\left(1+\frac{1}{\eta_{cp}}\right)\left(\frac{p_{sm}}{p_{atm}}\right)^{\frac{\gamma-1}{\gamma}} + k_{sm,out} \times \left(p_{sm} - \frac{m_{O_2,ca} R_{O_2} T_{st}}{V_{ca}} T_{sm}\right)\right) \tag{39}$$

$$\dot{p}_{rm} = \frac{R_a T_{rm}}{V_{rm}}\left(k_{ca,out}\left(\frac{m_{O_2,ca} R_{O_2} T_{st}}{V_{ca}} - p_{rm}\right) - k_{rm,out}(p_{rm} - p_{atm})\right) \tag{40}$$

$$\dot{m}_{O_2,ca} = k_{sm,out} p_{sm} - \frac{m_{O_2,ca} R_{O_2} T_{st}}{V_{ca}}(k_{sm,out} + k_{ca,out}) + k_{ca,out} p_{rm} - \frac{n I_{st}}{4F} M_{O_2} \tag{41}$$

$$\dot{m}_{H_2,an} = K_1\left(K_2 p_{sm} - \frac{m_{H_2,an} R_{H_2} T_{st}}{V_{an}}\right) - \frac{n I_{st}}{2F} M_{H_2} \tag{42}$$

where p_{sm} is supply manifold pressure dynamic, p_{rm} is return manifold pressure dynamic, $m_{O_2,ca}$ is the oxygen mass flow state and $m_{H_2,an}$ is the hydrogen mass flow state. PEMFC system parameters are presented in Table 1 [3–5].

The state vector $x(t)$, input vector $u(t)$, output vector $y(t)$ and the disturbance $d(t)$ are defined as

$$x(t) = [p_{sm} \quad p_{rm} \quad m_{H_2,an} \quad m_{O_2,ca}],$$
$$y(t) = [p_{sm} \quad p_{rm} \quad m_{H_2,ca}]^T,\ u(t) = [W_{cp} \quad k_{rm,out}]^T,\ d(t) = I_{st}$$

The state space equations of the PEMFC can be obtained as

$$\begin{aligned} \dot{x}(t) &= Ax(t) + B(x)u(t) + Dd(t) \\ y(t) &= Cx(t) \end{aligned} \tag{43}$$

where

$$A = \begin{bmatrix} -\frac{\gamma R_a k_{sm,out} T_{sm}}{V_{sm}} & 0 & 0 & a_{14} \\ 0 & -\frac{R_a T_{rm} K_{ca,out}}{V_{rm}} & 0 & a_{24} \\ K_1 K_2 & 0 & -\frac{K_1 R_{H_2} T_{st}}{V_{an}} & 0 \\ k_{sm,out} & k_{ca,out} & 0 & a_{44} \end{bmatrix},$$

$$B(x) = \begin{bmatrix} b_{11}(p_{sm}) & 0 \\ 0 & b_{22}(p_{rm}) \\ 0 & 0 \\ 0 & 0 \end{bmatrix}, C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}, D = \begin{bmatrix} 0 \\ 0 \\ -\frac{nM_{H_2}}{2F} \\ -\frac{nM_{O_2}}{4F} \end{bmatrix}$$

with

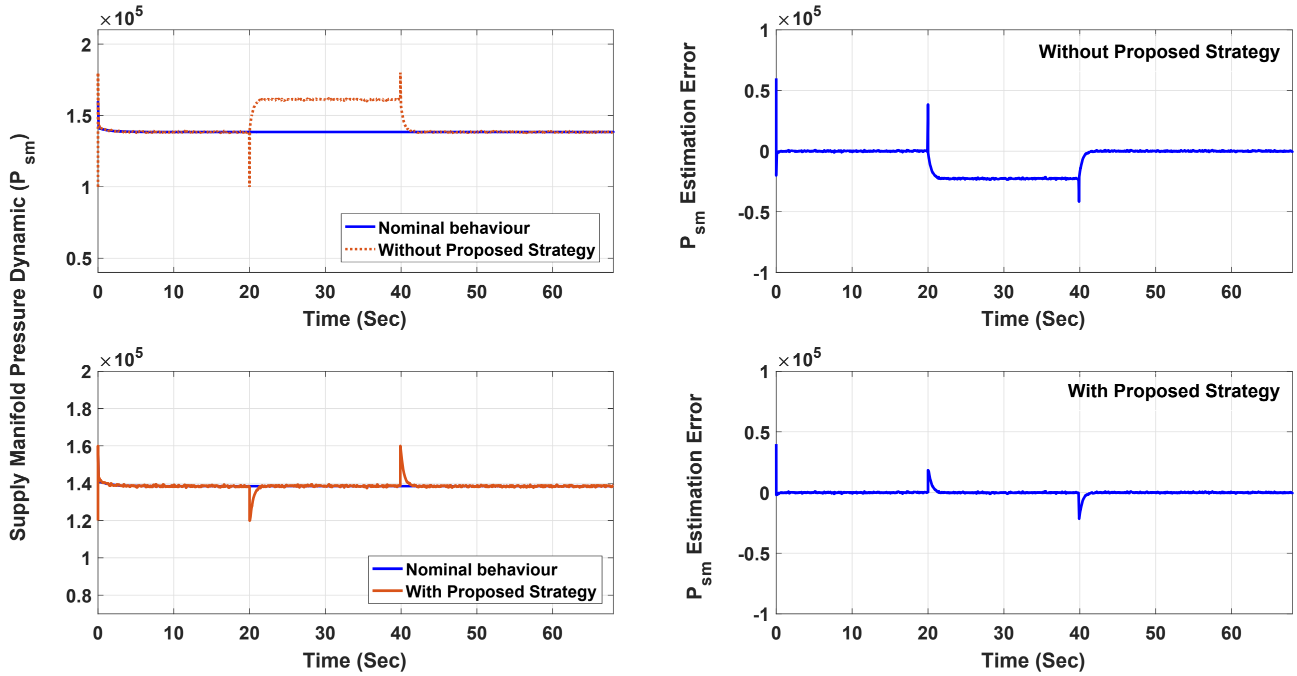

Fig. 4 — Trajectories of the supply manifold pressure dynamic (p_{sm}) and its estimation and estimation error without and with proposed strategy.

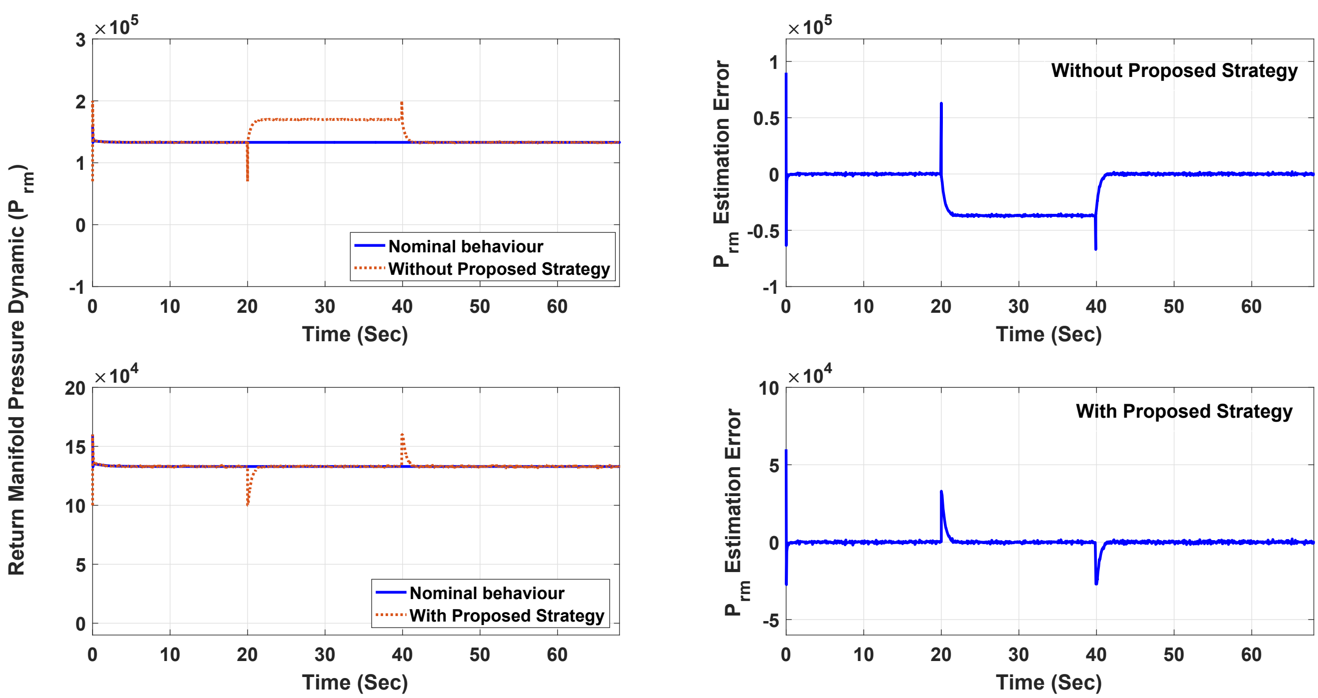

Fig. 5 — Trajectories of the return manifold pressure dynamic (p_{rm}) and its estimation and estimation error without and with proposed strategy.

Please cite this article as: Kamal E, Aitouche A, Fuzzy observer-based fault tolerant control against sensor faults for proton exchange membrane fuel cells, International Journal of Hydrogen Energy, https://doi.org/10.1016/j.ijhydene.2018.10.070

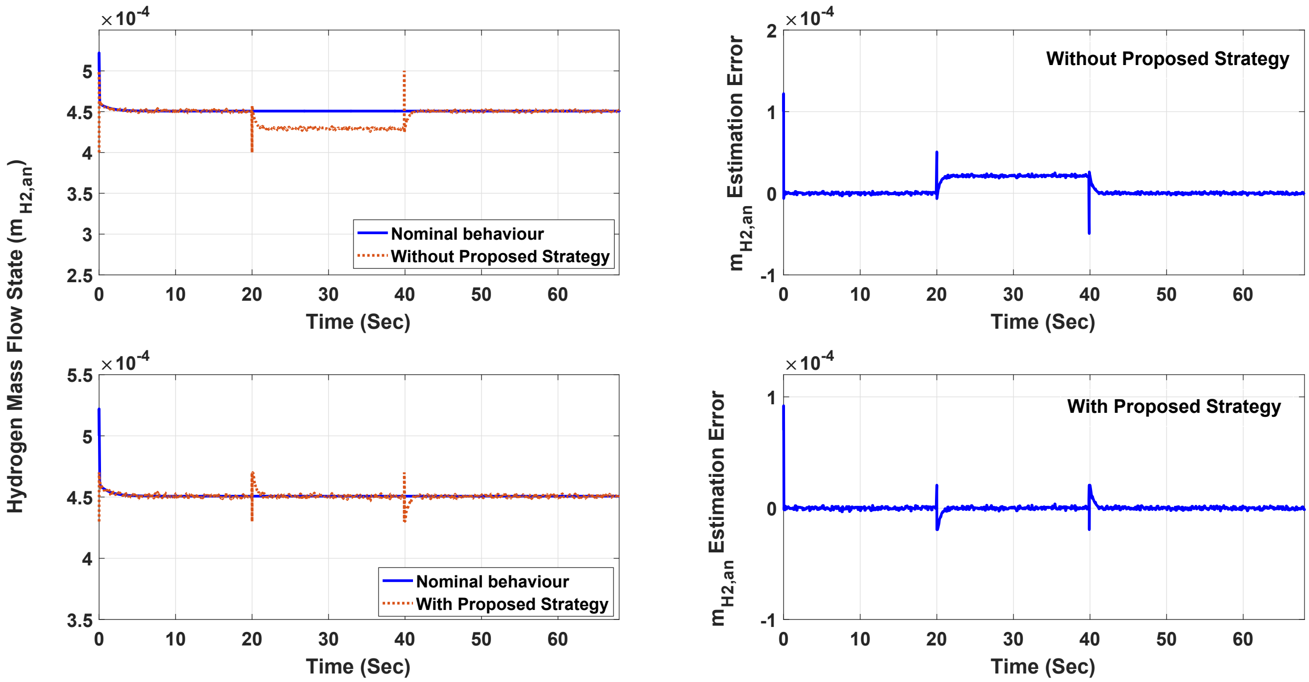

Fig. 6 – Trajectories of the hydrogen mass flow state ($m_{H_2,an}$) and its estimation and estimation error without and with proposed strategy.

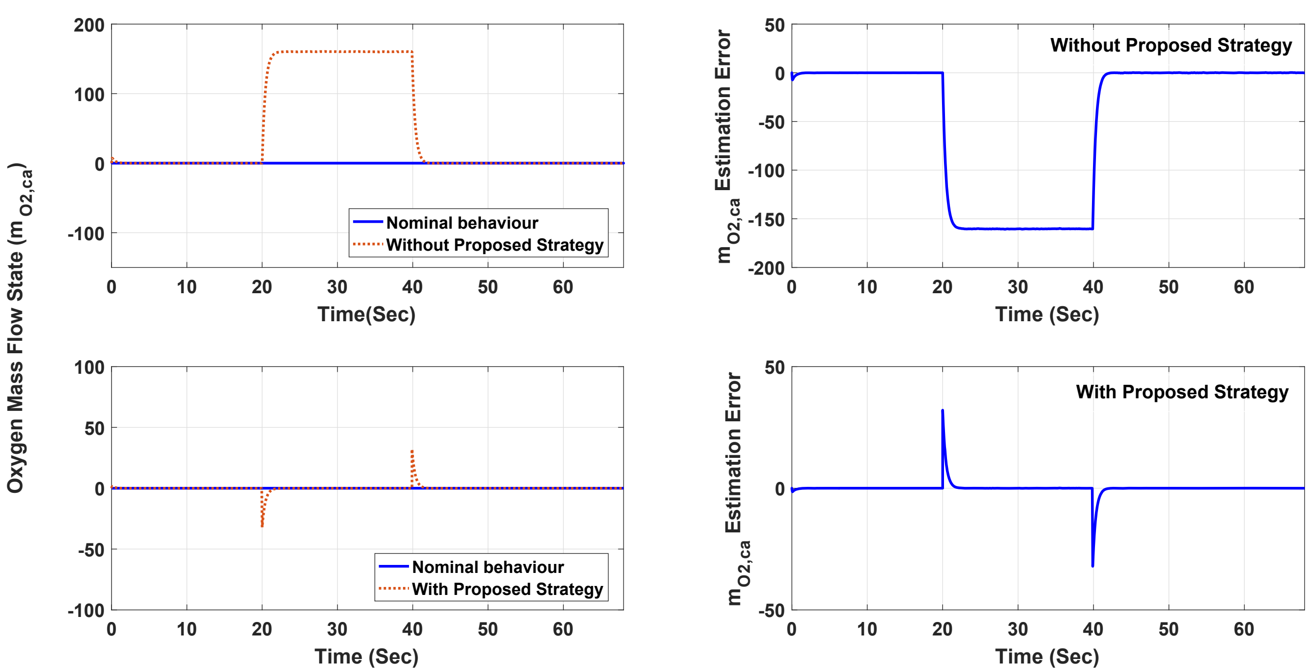

Fig. 7 – Trajectories of the oxygen mass flow state ($m_{O_2,ca}$) and its estimation and estimation error without and with proposed strategy.

$$
\begin{aligned}
a_{14} &= \frac{\gamma R_a k_{sm,out} R_{O_2} T_{st} T_{sm}}{V_{ca} V_{sm}},\\
a_{24} &= \frac{R_a T_{rm} k_{ca,out} R_{O_2} T_{st}}{V_{rm} V_{ca}},\\
a_{44} &= -\frac{(k_{sm,out} + k_{ca,out}) R_{O_2} T_{st}}{V_{ca}},\\
b_{11}(p_{sm}) &= \frac{\gamma R_a T_{atm}\left(\eta_{cp}+1\right)}{V_{sm}\eta_{cp}}\left(\left(\frac{p_{sm}}{p_{atm}}\right)^{\frac{\gamma-1}{\gamma}} - 1\right),\\
b_{22}(p_{rm}) &= -\frac{R_a T_{rm}}{V_{rm}}(p_{rm} - p_{atm}).
\end{aligned}
$$

Note that the matrix B is a function of the (p_{rm}, p_{sm}).

B. TS fuzzy PEMFC description

TS Fuzzy PEMFC system subject to faults and disturbance is obtained. Considering the range of the supply and return manifold pressures, $[p_{sm_{min}}, p_{sm_{max}}]$ and $[p_{rm_{min}}, p_{rm_{max}}]$, the membership function can be selected as

$$
\begin{aligned}
\rho_1(p_{sm}, p_{rm}) &= \frac{p_{sm_{max}} - p_{sm}}{p_{sm_{max}} - p_{sm_{min}}} \times \frac{p_{rm_{max}} - p_{rm}}{p_{rm_{max}} - p_{rm_{min}}}\\
\rho_2(p_{sm}, p_{rm}) &= \frac{p_{sm_{max}} - p_{sm}}{p_{sm_{max}} - p_{sm_{min}}} \times \frac{p_{rm} - p_{rm_{min}}}{p_{rm_{max}} - p_{rm_{min}}}\\
\rho_3(p_{sm}, p_{rm}) &= \frac{p_{sm} - p_{sm_{min}}}{p_{sm_{max}} - p_{sm_{min}}} \times \frac{p_{rm_{max}} - p_{rm}}{p_{rm_{max}} - p_{rm_{min}}}\\
\rho_4(p_{sm}, p_{rm}) &= \frac{p_{sm} - p_{sm_{min}}}{p_{sm_{max}} - p_{sm_{min}}} \times \frac{p_{rm} - p_{rm_{min}}}{p_{rm_{max}} - p_{rm_{min}}}
\end{aligned}
\tag{44}
$$

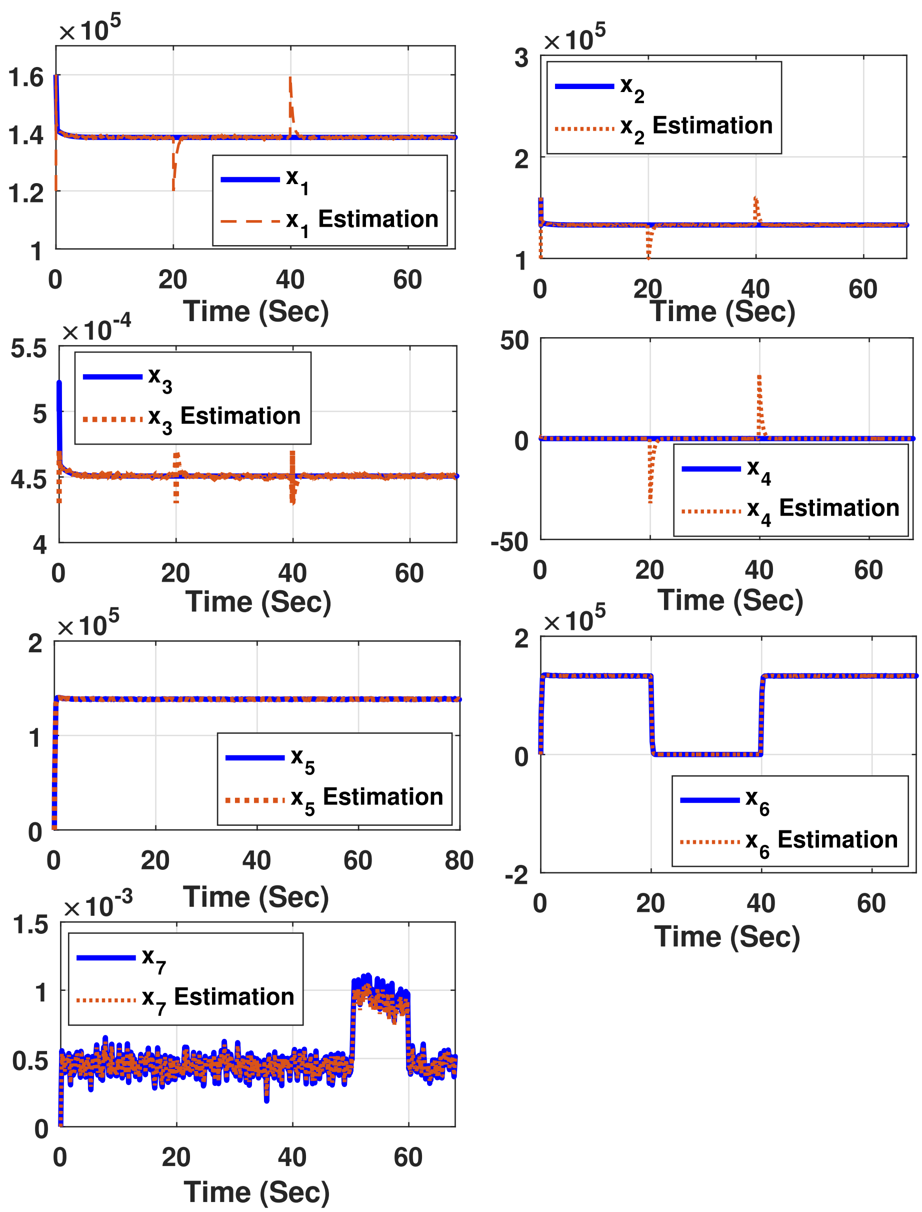

Fig. 8 – Trajectories of PEMFC system and the proposed filter states variables and their estimates.

Please cite this article as: Kamal E, Aitouche A, Fuzzy observer-based fault tolerant control against sensor faults for proton exchange membrane fuel cells, International Journal of Hydrogen Energy, https://doi.org/10.1016/j.ijhydene.2018.10.070

The matrices of the PEMFC model described in Eq. (43) can be computed and given as the following,

$$A=\begin{bmatrix} -\frac{\gamma R_a k_{sm,out} T_{sm}}{V_{sm}} & 0 & 0 & a_{14} \\ 0 & -\frac{R_a T_{rm} K_{ca,out}}{V_{rm}} & 0 & a_{24} \\ K_1 K_2 & 0 & -\frac{K_1 R_{H_2} T_{st}}{V_{an}} & 0 \\ k_{sm,out} & k_{ca,out} & 0 & a_{44} \end{bmatrix}$$

$$B_1=\begin{bmatrix} b_{11}(p_{sm_{max}}) & 0 \\ 0 & b_{22}(p_{rm_{max}}) \\ 0 & 0 \\ 0 & 0 \end{bmatrix},$$

$$B_2=\begin{bmatrix} b_{11}(p_{sm_{max}}) & 0 \\ 0 & b_{22}\left(p_{rm_{min}}\right) \\ 0 & 0 \\ 0 & 0 \end{bmatrix},$$

$$B_3=\begin{bmatrix} b_{11}\left(p_{sm_{min}}\right) & 0 \\ 0 & b_{22}(p_{rm_{max}}) \\ 0 & 0 \\ 0 & 0 \end{bmatrix},$$

$$B_4=\begin{bmatrix} b_{11}\left(p_{sm_{min}}\right) & 0 \\ 0 & b_{22}\left(p_{rm_{min}}\right) \\ 0 & 0 \\ 0 & 0 \end{bmatrix}, C=\begin{bmatrix} 1.0 & 0 & 0 & 0 \\ 0 & 1.0 & 0 & 0 \\ 0 & 0 & 1.0 & 0 \end{bmatrix}$$

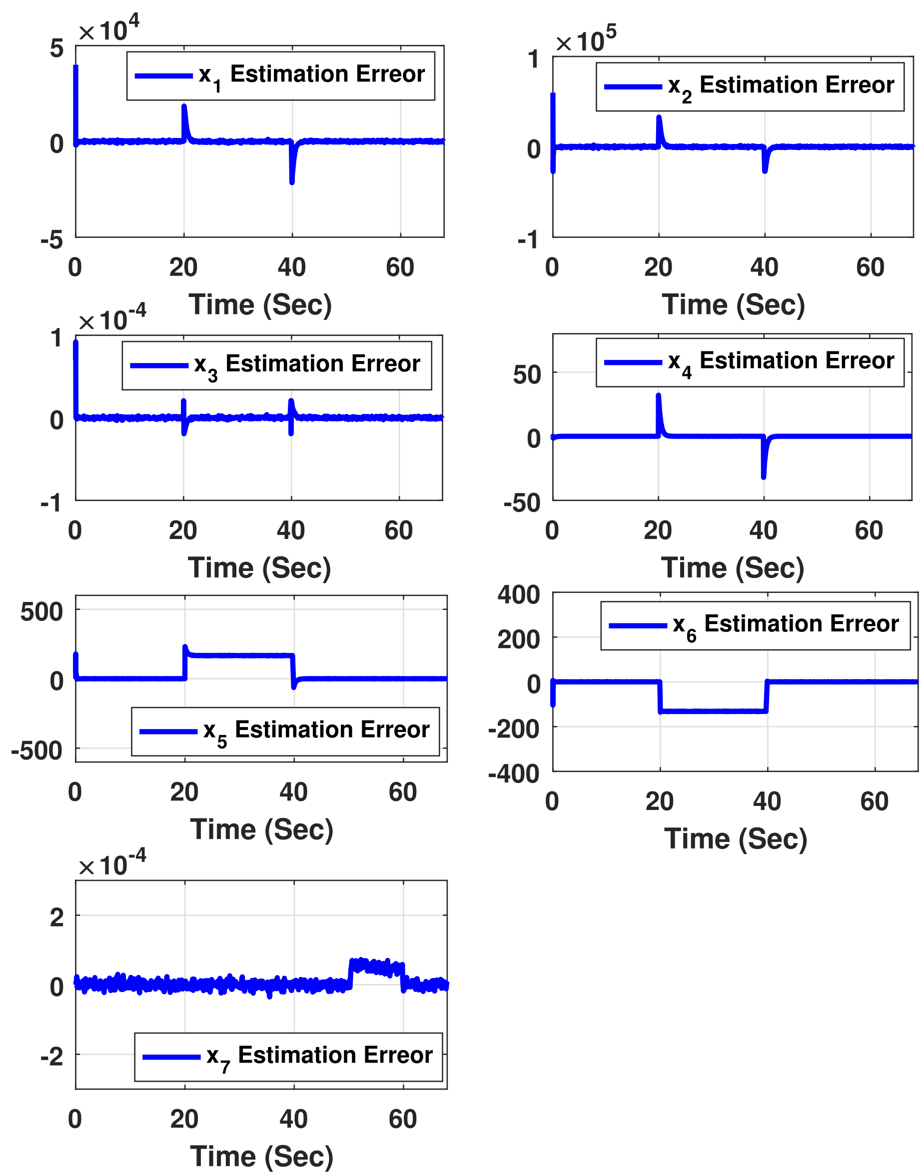

Fig. 9 – Estimates errors for trajectories of PEMFC system and the proposed filter states variables and their estimates.

Please cite this article as: Kamal E, Aitouche A, Fuzzy observer-based fault tolerant control against sensor faults for proton exchange membrane fuel cells, International Journal of Hydrogen Energy, https://doi.org/10.1016/j.ijhydene.2018.10.070

Simulation studies

To check the PEMFC model and the performances of the proposed overall control, Matlab simulation and discussions on the model proposed in section IV are presented. In the simulation, the initial state values of the PEMFC system are chosen as $x_{init0} = \begin{bmatrix} 1.6\times10^5 & 1.6\times10^5 & 5\times10^{-4} & 0.01\end{bmatrix}^T$, and we consider sensor faults given by the following;

$$f_1(t) = \begin{cases} -p_{sm}, & 20 \le t \le 30 \\ 0, & otherwise. \end{cases}$$
$$f_2(t) = \begin{cases} 0.5\times10^{-3}(\sin(0.5t)+2), & 40 \le t \le 50 \\ 0, & otherwise. \end{cases} \quad (45)$$

Figs. 2 and 3 show the faults, their estimates and the corresponding fault estimation errors, respectively. In Fig. 2, f_1 and f_2 are the supply manifold pressure and hydrogen mass sensors, respectively.

Figs. 4–7 show the result of the evolution of the supply manifold pressure dynamic (p_{sm}), return manifold pressure dynamic (p_{rm}), the oxygen ($m_{O_2,ca}$) and the hydrogen ($m_{H_2,an}$) mass flow states, their estimates and estimates errors with and without proposed strategy, respectively. Trajectories of PEMFC system and the proposed filter states variables and their estimates errors are given (cf. Figs. 8 and 9).

From the simulation results, in Figs. 4–7, such a behavior corresponds to the p_{sm}, p_{rm}, $m_{H_2,an}$ and $m_{O_2,ca}$ responses getting as near as possible to the nominal response (blue line). It can be seen that the responses when no fault tolerance mechanism acts on the PEMFC system (upper) is quite different with respect to the nominal one. The proposed strategy can compensate the fault resulting in an almost perfect matching between the response with proposed strategy (lower) and the nominal one.

In summary, we can observe that the PEMFC system is stable and the fault can be efficiently estimated with a small error. The sensor fault estimates tend to the actual values rapidly, which shows the effectiveness of the proposed strategy based on FUIO.

Conclusion

In this paper, fuzzy FTC strategy based on FUIO (Fuzzy Unknown Input Observer) is presented for nonlinear PEMFC system. First-order filter is added to build an augmented PEMFC system. For this augmented system, a FUIO is design to estimate the faults. In addition, a proposed strategy is developed for the PEMFC system subject to the sensor faults and disturbance with the state variables are unavailable. Robust stabilization sufficient conditions are formulate based on the Lyapunov stability theory, LMIs and LMEs. In order to show the effectiveness of the proposed approach, a PEMFC system with return manifold pressure and hydrogen mass sensors fault and disturbance was tested. In the future work, we will take in consideration the sensor and actuator faults with parameter uncertainties.

Nomenclature

η_{cp}	Compressor efficiency 0.8
γ	ratio of specific heats of air 1.4
R_a	Air gas constant $286.9J/(kgK)$
R_{O_2}	Oxygen gas constant $256.9J/(kgK)$
R_{H_2}	Hydrogen gas constant $4124.3J/(kgK)$
M_{H_2}	Hydrogen molar mass $2.016\times10^{-3}kg/mol$
M_{O_2}	Hydrogen molar mass $32\times10^{-3}kg/mol$
$k_{ca,out}$	cathode outlet orifice constant 0.2177×10^{-5}
$k_{sm,out}$	manifold outlet orifice constant 0.3629×10^{-5}
k_t	Compressor motor $0.0153N.m/A$
k_v	Compressor motor constant $0.0153V.(rad/s)$
K_1	proportional gain 2.1
K_2	nominal pressure drop coefficient 0.94
C_p	specific heat capacity of air $1004J/(mol.K)$
T_{atm}	atmospheric temperature 298.15 K
T_{sm}	supply manifold temperature 300 K
T_{rm}	return manifold temperature 300 K
T_{st}	stack temperature 350 K
V_{ca}	cathode volume $0.01m^3$
V_{rm}	return manifold volume $0.005m^3$
V_{an}	anode volume $0.005m^3$
n	cell number in fuel cell stack 381
F	Faraday constant 96485 coulombs
W_{cp}	compressor outlet mass flow rate $0.1kg/s$
p_{atm}	atmospheric pressure $101325Pa$

REFERENCES

[1] Yilanci A, Dince I, Ozturk H. Performance analysis of a PEM fuel cell unit in a solar-hydrogen system. Int J Hydrogen Energy 2008;33:7538–52.

[2] Daud W, Rosli R, Majlan E, Hamid S, Mohamed R, Husaini T. PEM fuel cell system control: a review. Renew Energy 2017;113:620–38.

[3] Olteanu SC, Aitouche A, Oueidat M, Jouni A. PEM fuel cell modeling and simulation via the takagi-sugeno fuzzy model. In: 2012 international conference on renewable energies for developing countries (REDEC), 28-29 Nov. 2012; 2012. p. 1–7. Beirut, Lebanon.

[4] Yang Q, Aitouche A, ould Bouamama B. Structural monitorability of fuel cell stack system based on bond graph tool, Fault Detection, supervision and safety of technical, June 30 - July 3. 2009. Barcelona, Spain.

[5] Aitouche A, Yang Q, Ould Bouamama B. Fault detection and isolation of PEM fuel cell system based on nonlinear analytical redundancy, an application via parity space approach. Eur Phys J Appl Phys 2011;54(2):1–11.

[6] Harrabi N, Souissi M, Aitouche A, Chaabane M. Modeling and control of photovoltaic and fuel cell based alternative power systems. Int J Hydrogen Energy 2018;43:11442–51.

[7] Hu P, Cao G-Y, Zhu X-J, Hu M. Coolant circuit modeling and temperature fuzzy control of proton exchange membrane fuel cells. Int J Hydrogen Energy 2010;35:9110–23.

Please cite this article as: Kamal E, Aitouche A, Fuzzy observer-based fault tolerant control against sensor faults for proton exchange membrane fuel cells, International Journal of Hydrogen Energy, https://doi.org/10.1016/j.ijhydene.2018.10.070

[8] Al-Dabbagh AW, Lu L, Mazza A. Modelling, simulation and control of a proton exchange membrane fuel cell (PEMFC) power system. Int J Hydrogen Energy 2010;35:5061–9.
[9] Zheng Z, Petrone R, Pra M-C, Hissel D, Becherif M, Pianese C, et al. A review on non-model based diagnosis methodologies for PEM fuel cell stacks and systems. Int J Hydrogen Energy 2013;38(21):89148926.
[10] Wang F-C, Chen H-T. Design and implementation of fixed-order robust controllers for a proton exchange membrane fuel cell system. Int J Hydrogen Energy 2009;34:27052717.
[11] Becherif M, Hissel D. MPPT of a PEMFC based on air supply control of the motocompressor group. Int J Hydrogen Energy 2010;35:1252112530.
[12] Wang F-C, Ko C-C. Multivariable robust PID control for a PEMFC system. Int J Hydrogen Energy 2010;35:1043710445.
[13] Ou K, Wang Y-X, Li Z-Z, Shen Y-D, Xuan D-J. Feedforward fuzzy-PID control for air flow regulation of PEM fuel cell system. Int J Hydrogen Energy 2015;40:1168611695.
[14] Baroud Z, Benmiloud M, Benalia A, Ocampo-Martinez C. Novel hybrid fuzzy-PID control scheme for air supply in PEM fuel-cell-based systems. Int J Hydrogen Energy 2017;42:1043510447.
[15] Ahmadi S, Abdi S, Kakavand M. Maximum power point tracking of a proton exchange membrane fuel cell system using PSO-PID controller. Int J Hydrogen Energy 2017;42:20430–43.
[16] Berbaoui B. Fuzzy multi-objective technique combined with VCS algorithm for unified power quality conditioner based on hybrid power source PEMFC/SC. Int J Hydrogen Energy 2018;43:62756293.
[17] Huang S-R, Linc CY, Wu C-C, Yang S-J. The application of Fuzzy controller for fuel cell generating studies. Int J Hydrogen Energy 2008;33:52055217.
[18] Niknezhadi A, Allue-Fantova M, Kunusch C, Ocampo-Martnez C. Design and implementation of LQR/LQG strategies for oxygen stoichiometry control in PEM fuel cells based systems. J Power Sources 2011;196:4277–82.
[19] Ziogou C, Papadopoulou S, Georgiadis M, Voutetakis S. Online nonlinear model predictive control of a PEM fuel cell system. J Process Contr 2013;23:483–792.
[20] Matraji I, Laghrouche S, Wack M. Pressure control in a PEM fuel cell via second order sliding mode. Int J Hydrogen Energy 2012;37:16104–16.
[21] Derbeli M, Farhat M, Barambones O, Sbita L. Control of PEM fuel cell power system using sliding mode and super-twisting algorithms. Int J Hydrogen Energy 2017;42:8833–44.
[22] Fang C, Xu L, Cheng S, Li J, Jiang H, Ouyang M. Sliding-mode-based temperature regulation of a proton exchange membrane fuel cell test bench. Int J Hydrogen Energy 2017;42:11745–57.
[23] Petrone R, Zheng Z, Hissel D, Pera M, Pianese C, Sorrentino M. A review on model-based diagnosis methodologies for PEMFCs. Int J Hydrogen Energy 2013;38(17):7077–91.
[24] Mohammadi A, Djerdir A, Steiner NY, Khaburi D. Advanced diagnosis based on temperature and current density distributions in a single PEMFC. Int J Hydrogen Energy 2015;40:15845–55.
[25] Rotondo D, Fernandez-Canti RM, Tornil-Sin S, Blesa J, Puig V. Robust fault diagnosis of proton exchange membrane fuel cells using a Takagi-Sugeno interval observer approach. Int J Hydrogen Energy 2016;41:2875–86.
[26] Benmouna A, Becherif M, Depernet D, Gustin F, Ramadan HS, Fukuhara S. fault diagnosis methods for proton exchange membrane fuel cell system. Int J Hydrogen Energy 2017;42:21534–43.
[27] Zhao X, Xu L, Li J, Fang C, Ouyang M. Faults diagnosis for PEM fuel cell system based on multi-sensor signals and principle component analysis method. Int J Hydrogen Energy 2017;42:18524–31.
[28] Benouioua D, Candusso D, Harel F, Picard P, Franois X. On the issue of the PEMFC operating fault identification: generic analysis tool based on voltage pointwise singularity strengths. Int J Hydrogen Energy 2018;43:11606–13.
[29] Lebreton C, Damour C, Benne M, Grondin-Perez B, Chabriat J-P. Passive Fault Tolerant control of PEMFC air feeding system. Int J Hydrogen Energy 2016;41:15615–21.
[30] Lebreton C, Benne M, Damour C, Yousfi-Steiner N, Grondin-Perez B, Hissel D, et al. Fault Tolerant control strategy applied to PEMFC water management. Int J Hydrogen Energy 2015;40:10636–46.
[31] Kamal E, Adouane L. Hierarchical energy optimization strategy and its integrated reliable battery fault management for hydraulic-electric hybrid vehicle. IEEE Trans Veh Technol 2018;67(5):3740–54.
[32] Kamal E, Aitouche A, Abbes D. Robust fuzzy scheduler fault tolerant control of wind energy systems subject to sensor and actuator faults. Int J Electr Power Energy Syst 2014;55(1):402–19.
[33] Kamal E, Aitouche A. Fuzzy Fault-tolerant control of wind-diesel hybrid systems subject to sensor faults. IEEE Tran. Sustainable Energy 2013;4(4):857–66.
[34] Kamal E, Aitouche A. robust fault tolerant control of DFIG wind energy systems with unknown inputs. Renew Energy 2013;56:2–15.
[35] Kamal E, Aitouche A. Fuzzy scheduler Fault Tolerant control for wind energy conversion systems. IEEE Trans Contr Syst Technol 2014;22(1).
[36] Tekin M, Hissel D, Pera M-C, Kauffmann JM. Energy management strategy for embedded fuel-cell systems using fuzzy logic. IEEE Trans Ind Electron 2007;54(1):595–603.
[37] Tao S, Si-jia Y, Guang-yi C, Xin-jian Z. Modelling and control PEMFC using fuzzy neural networks. J Zhejiang Univ - Sci 2005;6(10):1084–9.
[38] Olteanu S, Aitouche A, Belkoura L. Contribution to state and sensor fault estimation applied to PEM fuel cell systems. In: Systems and control (ICSC), 5th international conference on. IEEE; 2016. p. 217–24.
[39] Laghrouche S, Liu J, Ahmed FS, Harmouche M, Wack M. Adaptive second-order sliding mode observer-based fault reconstruction for pem fuel cell air-feed system. IEEE Trans Contr Syst Technol 2015;23(3):1098–109.
[40] Rotondo D, Puig V, Nejjari F, Romera J. A fault-hiding approach for the switching quasi-lpv fault-tolerant control of a four-wheeled omnidirectional mobile robot. IEEE Trans Ind Electron 2015;62(6):3932–44.
[41] Liu J, Luo W, Yang X, Wu L. Robust model-based fault diagnosis for PEM fuel cell air-feed system. IEEE Trans Ind Electron 2016;63(5):3261–70.
[42] Kamal E, Aitouche A. Robust scheduler fuzzy controller of DFIG wind energy systems. IEEE Trans. Sustain Energy 2013;4(3):706–15.
[43] Takagi T, Sugeno M. Fuzzy identification of systems and its applications to modeling and control. IEEE Trans Syst Man Cybern 1985;15(1):116–32.
[44] Kamal E, Aitouche A, Ghorbani R, Bayart M. Robust Fuzzy Fault tolerant control of wind energy conversion systems subject to sensor faults. IEEE Trans Sustain Energy 2012;3(2):231–41.
[45] Tan CP, Edwards C. Sliding mode observers for robust detection and reconstruction of actuator and sensor faults. Int J Robust Nonlinear Cont 2003;13(5):443–63.

Please cite this article as: Kamal E, Aitouche A, Fuzzy observer-based fault tolerant control against sensor faults for proton exchange membrane fuel cells, International Journal of Hydrogen Energy, https://doi.org/10.1016/j.ijhydene.2018.10.070

[46] Zhang K, Jiang B, Cocquempot V. Adaptive observer-based fast fault estimation. Int J Contr Autom Syst 2008;6(3):320–6.
[47] Rotondo D, Puig V, Nejjari F. Model reference gain scheduling control of a PEM fuel cell using Takagi-Sugeno modelling. In: International conference on information processing and management of uncertainty in knowledge-based systems. Springer; 2014. p. 518–27.
[48] Olteanu SC, Aitouche A, Belkoura L, Jouni A. Embedded P.E.M. Fuel cell stack nonlinear observer by means of a takagi-sugeno approach, studies in informatics and control. Stud Inf Contr 2015;24(1):61–70. ISSN 1220-1766.
[49] Pukrushpan JT, Stefanopoulou AG, Peng H. Control of fuel cell breathing. IEEE Contr Syst Mag 2004;24(2):30–46.