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RESEARCH ARTICLE

Distributed Fault Diagnosis of Plantwide Process for Fuel Cell Power System

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The monitoring of the plant-wide process has attracted much attention in the academic research and industry application. This paper addresses a novel combination of model-based fault detection architecture and data-based learning method to achieve the fault detection and location of the series connected process. First, the serially connected system is analyzed to obtain the partition method of the whole system and provide the conditions to construct that subsystems. Then the distributed Principle component analysis which can extract the information from the real measurement of the subsystems is carried out for the modeling of the TS type of fuzzy inference. A two dimensional Bayesian based fuzzy model is firstly introduced to achieve nonlinear identification techniques in the fault diagnosis area. The constructional residuals is generated by comparing output signals of the TS models and the real measurements of each subsystem. The evaluation of the residuals examines the fault occurrence with the location information. Finally, the feasibility and efficiency of the method are evaluated by the Solid Oxide Fuel Cells (SOFC), a New-Energy Power system.

Keywords: Serially Connected Process, Distributed PCA, TS Fuzzy Model, SOFC.

1. INTRODUCTION

With the development of the modern industry, the demand of the assurance of the safety during the productive process is growing while the structure of the plate is becoming complex. The early fault detection, diagnosis and location could make the plate robust to avoid accidents of the production line in practice which may cause a great economic loss. For plant-wide process monitoring, the traditional concentrated monitoring strategy manages the whole production data by the dimensionality reduction and feature extraction.[1–3] However, the plate-wide data reduction may reduce the location information of the system and can only judge out the fault without the fault location. Besides, the relationships among different parts of the plant-wide process are also difficult to characterize.[4] Thus, how to develop efficient monitoring methods for plant-wide processes has been a significant challenges in this area.

In fault diagnosis area, there exist two primary methods: the model-based method and the data-based method. The model-based method is based on exact process models, e.g., the first-principle of physical/chemical relationships between different variables. As a result, they tend to give more accurate results than the other two methods as long as the system model is reliable.[5–12] In model-based FDI scheme, there are two stages: (i) the models of the system are obtained offline. (ii) The residuals are obtained online and evaluated for each time instant. The residual which is based on a system model represents our expectation of the system's behaviour, and this property can be used to determine whether or not faults have occurred. Some examples of residual generators based on the analytical redundancy scheme are referring to the Kalman filter,[11, 12] Luenberger observers, state and output observers[13, 14] and parity relations, among others.

Since Data-based process monitoring methods have no requirement on the process model and the associated expert knowledge, they can be applied even when the models and expert knowledge of some complex industrial processes/systems are difficult to build and obtain in practice. Thus they have become more and more popular in recent years. Those data contain the major process information and then can be used for modeling, monitoring, and control. In the past years, a significant progress has been made in the data-mining and processing area, which can provide new technologies for the utilization of process monitoring. The traditional multivariate statistical-based method such as the principal component analysis (PCA),[14–18] independent component analysis (ICA) methods,[19–23] and the

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combination of the ICA-PCA[24, 25] has several inherent limitations since it can be carried out only by collecting a lot of data. Recently, a well known one-class classification method support vector data description (SVDD) has been introduced for process monitoring.[26–28] From the analysis above, it can be seen that although a large quantity of data-based process monitoring methods have been developed in existing works, each of these methods has its own advantages and disadvantages. A method that works well under one process condition might not provide a satisfactory monitoring performance under another process condition because the efficiency of each process monitoring method may depend on the fault and the data characteristic of specific process. Particularly, most of the methods are verified by the TE process or other kinds of known processes,[15–28] very few methods can be carried out in other chemical systems. Recently, several pieces of research works have already been carried out on experts systems, such as support vector machine (SVM),[29] artificial neural network (ANN),[29, 30] Fuzzy mathematics,[31] and so on. The TS model is widely applied in the fault diagnosis area because it has fast calculation and the ability to handle nonlinear systems.

As a benchmark simulation, the Tennessee Eastman (TE) process was considered as a representative plant-wide process,[11–24] which has been widely used to test the performance of various monitoring approaches. However, as a representative new energy resources and the new field of chemical industry, the Fuel Cell system has not been reported in existing works. Therefore, this article takes the Solid Oxide Fuel Cell (SOFC) to provide a reference to investigate connected systems which are serially connected and have more variables than TE.

The remainder of this paper is organized as follows. In Section 2, the serially connected system is introduced and the sufficient condition of a serially connected subsystem is provided. In Section 3, the distributed PCA method is employed to substract the principle information of the subsystem. Then, in Section 4, the two dimensional Bayesian based fuzzy model is deduced for system identification and modeling method. Section 5 provides the fault detection and diagnosis technique. At last, in Section 6, the monitoring method is verified by the Solid Oxide Fuel Cells system. Finally, conclusions and some discussions are made.

2. SERIALLY CONNECTED SYSTEM

In industry production line, such as chemical engineering, petrochemical engineering, electric power industry, there always exists the series connected structure In Figure 1, The serially connected system is composed of n subsystems. This class of cascade processes are composed of many subprocesses placed one after another, in such a way that each subprocess is connected with dynamic control input coupling between its neighbour subprocesses. The system information such as energy, substance transmit from the entrance to the exit through each subsystem and pass the output information to the next until end of the overall system. In each subsystem, the inputs consist of not only the outputs information from former subsystem but also the new input quantity which just enters the system from that position. As a consequence, if the malfunction happens from one subsystem all the downstream subsystems would out of order. Therefore, specialities of the serially connected system can be utilized to detect and locate the fault at the same time.

The model of the system can be describe as:

$$\begin{cases} x(k+1) = A(k)x(k) + B(k)u(k) \\ y(k) = C(k)x(k) \end{cases} \tag{1}$$

$$\begin{cases} x_i(k+1) = A_{ii}(k)x_i(k) + B_{ii}(k)u_i(k) \\ \qquad\qquad + \sum\limits_{\substack{j=1 \\ j\neq i}}^{n} A_{ij}(k)x_j(k) \\ y_i(k) = C_{ii}(k)x_i(k) + \sum\limits_{\substack{j=1 \\ j\neq i}} C_{ij}(k)x_i(k) \end{cases} \tag{2}$$

The process system can be divide into several subsystems based on the location or logical and treat all the correlation between the different subsystems as new inputs or disturbance. If the correlation between two subsystem is much that the self-correlation in one single system, then that two subsystems should be treated as one subsystem. When the correlation of the subsystem is particularly weak or the impact of the other subparts with a large time delay, that kind of subsystems could be handled separately.

The determining rule of the subsystem is:

$$\frac{\|\sum_{\substack{j=1 \\ j\neq i}}^{n} A_{ij}(k)x_j(k)\|}{\|x_i(k)\|} < 1 - \hat{\lambda}(\hat{A}(k)) \tag{3}$$

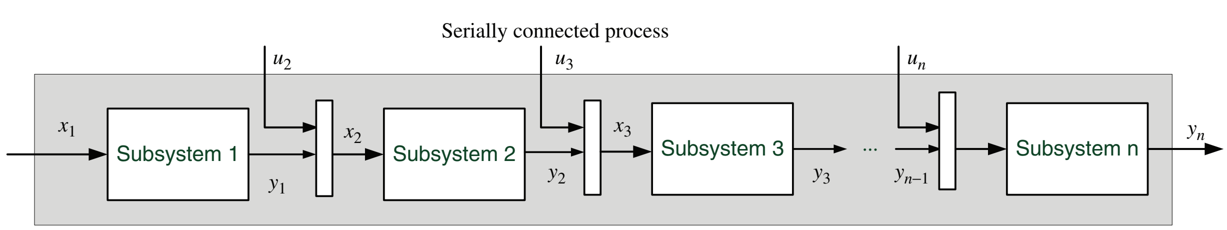

Fig. 1. Serially connected process.

If all the relationship of the $A(k)$ satisfies the rule, then the subpart i system can be treated as a independent subsystem. Otherwise, all the inputs of the whole that disobey the rule should be regarded as one subsystem logically.

$$\|x_i(k)\|_2 > \left\| \sum_{\substack{j=1 \\ j\neq i}}^{n} A_{ij}(k)x_j(k) \right\|_2 \tag{4}$$

In that way, many weakly coupled plantwide control system can be regarded as the open-loop control system.

3. DISTRIBUTED PCA METHOD

In this section a part dimension reduction method is proposed to obtain the sub-feature space of each subsystem. The main critical data characteristics in the process industrial are analyzed in the PCA method. The series connected structure of industrial system is quite common in the plant-wide process. The conventional PCA method can diagnose the fault occurrence, based on the feature extraction of the system states. The initial PCA decomposition carried out upon the whole process variables can decrease the dimension of the system, but the information of the whole process is also reduced. To identify the different patterns in the training database, the traditional PCA is modified to obtain the feature space of the model data. Instead of reducing the whole $\boldsymbol{X}$ of the system, the new method reduces the subsystem inputs to get the feature space of each subsystem. The improved PCA based method is named part dimensionality reduction, which conserves the location information of the connected subsystem.

The original variables can be divided as follow:

$$\boldsymbol{X} = [\boldsymbol{X}_1\ \boldsymbol{X}_2 \ldots \boldsymbol{X}_n] \tag{5}$$

A traditional PCA data decomposition is given as follows:

$$\boldsymbol{X} = \boldsymbol{T}\boldsymbol{P}^T + \boldsymbol{E} \tag{6}$$

where $\boldsymbol{T}$ is score matrix, $\boldsymbol{P}$ is loading matrix, and $\boldsymbol{E}$ is the residual matrix after the analysis of PCA. In the subsystem, n PCA method is carried out to reduce dimensionality and extract information.

$$\boldsymbol{X}_i = \boldsymbol{T}_i\boldsymbol{P}_i^T + \boldsymbol{E}_i \tag{7}$$

After all of the n sub-models have been built, the extracted principal components in each sub-block are arranged as follows:

$$\boldsymbol{T} = [\boldsymbol{T}_1\ \boldsymbol{T}_2\ \ldots\ \boldsymbol{T}_n] \tag{8}$$

The traditional monitoring statistic values T^2 and SPE would not be calculated. The $\boldsymbol{T}$ will be used to model the data learning model in next section.

4. TS FUZZY MODEL

Many research concerns fault detection and fault isolation by using a multiple model (MM) approach. The idea of the MM method is to approximate the considered system with a set of models. These models represent the system in a nominal fault-free working regime and in regimes corresponding to particular failures. Obtaining this set of models for complex nonlinear system is a difficult and time-consuming task. Fuzzy models of the TS type can be constructed only on the basis of input-output data and they are very good approximators for such systems. Traditional form of TS fuzzy model can be applied to modeling the nonlinear relationship between the inputs and the outputs, by combination of some linear relationship in different condition of inputs. When the TS fuzzy model recognizes the relationship of the nonlinear inputs and outputs, the residual can be generated by compare the TS outputs and the system outputs. In this section, the Two-dimensional Bayesian based fuzzy model is proposed to function two aspect of fault detection:

(i) the models of the system are obtained off line, and

(ii) residuals are obtained on line and evaluated for each time instant. Both the offline and the online TS modeling and identification method are derived.

4.1. The Traditional Form

Fuzzy modeling often follows the approach of encoding expert knowledge expressed in a verbal form in a collection of if-then rules, creating a model structure. Parameters in this structure can be adapted using input-output data. When no prior knowledge about the system is available, a fuzzy model can be constructed entirely on the basis of system measurements.

In Ref. [31], an evolving TS fuzzy model was presented whose rule-based structure is inherited and updated by adding new rules and modifying the existing rules and parameters when new data becomes available. Although the simulated results have proved its effectiveness on a nonlinear model approximation, this approach is time consuming. In order to balance the computational cost and model accuracy, we have developed the TS model by adjusting the cluster centers and the consequent parameters according to a weighted recursive least square (WRLS) method.

The contribution of the ith TS fuzzy rules to the system was expressed in the form of "If…Then" statement as follow:

$$R^i:\quad \text{If } \boldsymbol{x}_1(k) \text{ is } \boldsymbol{A}_1^i \ldots \quad \text{and} \quad \boldsymbol{x}_n(k) \text{ is } \boldsymbol{A}_n^i$$
$$\text{Then } \boldsymbol{y}^i(k+1) = p_0^i + p_1^i x_1 + \cdots + p_n^i \boldsymbol{x}_n; \quad i = 1, 2\cdots c$$

where c is the number of fuzzy rules, n is the input variables number of the TS fuzzy model, $\boldsymbol{x}_1(k)$, $\boldsymbol{x}_2(k), \ldots \boldsymbol{x}_n(k)$ are the regressive variables consisting of output and input data at the kth instance and before,

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$\boldsymbol{x}(k) = [x_1(k), x_2(k), \ldots x_n(k)]$ is the input vector of the TS fuzzy model, $\boldsymbol{A}_1^i, \boldsymbol{A}_2^i, \ldots, \boldsymbol{A}_n^i$ are the membership functions associated with the ith rule, $p_0^i, p_1^i, \ldots, p_n^i$ are the consequent parameters of the submodel (fuzzy rules) i.

Denotes β_i as the fitness grade of the submodel i, thus the model output $\boldsymbol{y}(k+1)$ at the $(k+1)$th instance can be calculated by follows:[25]

First, the model of the TS can be rewritten:

$$\begin{aligned} \boldsymbol{y}(k) &= \sum_{i=1}^{c} \beta_i \boldsymbol{y}^i(k) = \sum_{i=1}^{c} \beta_i (p_0^i + \cdots + p_n^i \boldsymbol{x}_{\boldsymbol{n}}(k)) \\ &= \sum_{i=1}^{c} (p_0^i + \cdots + p_n^i)(\beta_i + \cdots + \beta_i \boldsymbol{x}_{\boldsymbol{n}}(k))^T \end{aligned} \tag{9}$$

$$\begin{cases} \boldsymbol{\Theta}(k) = [\boldsymbol{\theta}_1, \boldsymbol{\theta}_2, \ldots, \boldsymbol{\theta}_r]^T \\ \quad = [\boldsymbol{p}_{10}, \boldsymbol{p}_{20}, \ldots, \boldsymbol{p}_{c0}, \boldsymbol{p}_{11}, \boldsymbol{p}_{21}, \ldots, \boldsymbol{p}_{c1}, \ldots, \boldsymbol{p}_{cn}]^T; \\ \boldsymbol{\Phi}(k) = [\beta_1, \ldots, \beta_c, \beta_1 \boldsymbol{x}_1(k), \ldots, \beta_c \boldsymbol{x}_1(k), \ldots, \\ \quad \beta_1 \boldsymbol{x}_n(k), \ldots, \beta_c \boldsymbol{x}_n(k)]^T \end{cases} \tag{10}$$

The outputs can be written as:

$$y(k+1) = \Phi(k)^{\mathrm{T}} \cdot \Theta(k) \tag{11}$$

In that form the antecedent parameters and consequent parameters can be calculated by the least square method.

4.2. The Two-Dimensional Bayesian Based Fuzzy Model

For a TS fuzzy model, the most important thing is to acquire antecedent and consequent parameters. The consequent parameters are acquired by fuzzy cluster method based on fuzzy C mean value algorithm, and consequent parameters are obtained with least squared method.

Based on the fuzzy C mean value algorithm the initial of the cluster center $V(1) = [v_1(1), v_2(1), \ldots v_n(1)]$ can be obtained by offline identification based on experimental data. The membership degree of $x(k)$ can also be estimated.

Calculate the distance between the input variable $x(k)$ and each $(k-1)$th instant cluster center from the following equation:

$$d_i' = \sqrt{\sum_{j=1}^{n} [x_j(k) - v_{ij}(k-1)]^2}; \quad i = 1, 2, \ldots, c \tag{12}$$

Estimate the membership degree of $x(k)$ according to each cluster center

$$u_i' = \left[\sum_{j=1}^{c} \left(\frac{d_i'(k)}{d_j'(k)} \right) \right]^{((m-1)/2)}, \quad i = 1, 2, \ldots, c \tag{13}$$

The above two parameters of the model can be calculated by the fuzzy C mean value algorithm and the one dimensional Bayesian based fuzzy model. However, if the data cluster is not equal distributed in the data cluster, a simple sum of the membership degree will not reflect the physical truth. The the data cluster center with the smallest amount of data will play the same role with the largest data cluster center. To overcome that inherent defect of the one dimensional Bayesian inference, the fitness of the cluster center is employed. The comparison of the one and two dimensional Bayesian inference is indicated in the Figure 2.

When the input equals $\boldsymbol{x}(k)$, the fitness of the ith regulation to the system output can be calculated by.

$$\beta_i = \sum_{j=1}^{c} \left(\frac{u_i}{u_j} \right), \quad i = 1, 2, \ldots, c \tag{14}$$

Its vector can be calculated by:

$$\begin{aligned} \boldsymbol{\Phi}(k) = [&\beta_1, \ldots, \beta_c, \beta_1 x_1(k), \ldots, \beta_c x_1(k), \ldots, \\ &\beta_1 x_n(k), \ldots, \beta_c x_n(k)]^T \end{aligned} \tag{15}$$

As $y(k+1)$ and $\Phi(k)$ are both known quantities, according to formula $\boldsymbol{y}(k+1) = \Phi(k)\Theta(k)$, we can get

$$\boldsymbol{\Theta}(k) = (\boldsymbol{\Phi}^T \boldsymbol{\Phi})^{-1} \boldsymbol{\Phi}^T \cdot \boldsymbol{y}(k+1) \tag{16}$$

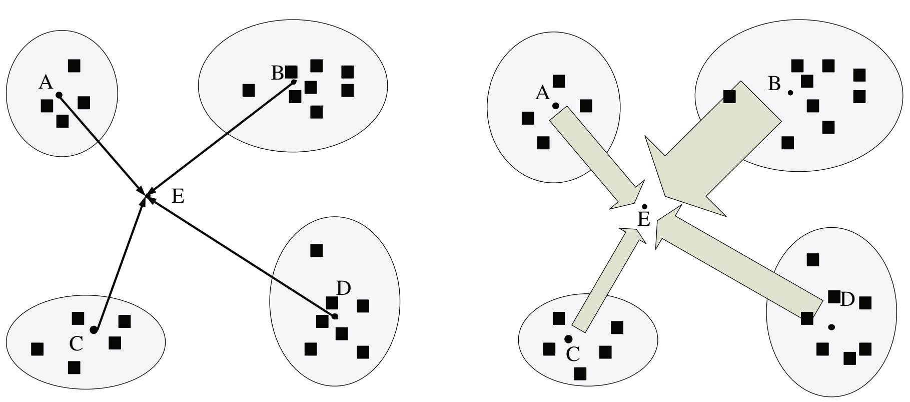

Fig. 2. The comparison of the one and two dimensional Bayesian inference.

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5. MONITORING METHODOLOGY

5.1. Residual Generation

The conventional fault diagnosis method traditionally constructs the $\boldsymbol{X}$ by put the inputs and the outputs in one single vector, then dimensionality reduction method PCA is employed. After the dimensionality reduction, the feature space is acquired, then the analysis of the feature space could judge out the fault state. This kinds of methods could realize fault detection, but the dimensionality reduction also decreases the fault information especially the fault location information contained in the $\boldsymbol{X}$. As a consequence, a novelty fault contain matrix is defined not only to detect the fault occurrence but also the position where it take place.

We define the $\boldsymbol{Y}$ as the fault contain matrix:

$$Y = [y_1, y_2, \dots y_n] \tag{17}$$

Where, $y_1, y_2, \dots, y_n$ are outputs of the subsystems. The $\boldsymbol{Y}$ consists of all the states of the subsystems, while traditional methods treat the subsystems' outputs as intermediate states.

5.2. Distributed Fault Detection

At the time fault occur in the series connected system, all the states from where the error occurred to the end of the system show to deviate from the normal working position. As a matter of fact, probably only one malfunction takes place. As a consequence, located the malfunction place is of vital importance to recover the wrong running.

In the series connected system, the fault phenomenon is quite special that the former subsystems fault would cause the system breakdown along the later subsystems. Although a series continuous subsystem could be detected breakdown, the condition is that there may only one subsystem failure. As a consequence, located the fault position is of vital important. The structure of the fault detection and location system is shown in Figure 3. First, the distributed PCA method of each subsystem is applied to decrease the dimensionality of the sub-feature space. Then, the outputs of the all the subsystem is encoded to a fault-contain matrix. After that the TS fuzzy model is employed to construct the learning machine of the all the outputs of the subsystem. The fault information could be detected by the comparison of the system outputs and the TS fuzzy model. If the information of the subsystems is accord with learning system, then it could judge that the system is working in a normal condition. In the contrast, it indicates some malfunction occur in the system. Consequently, the fault location strategy should work to judge the situation of the subsystem. The fault location strategy will be described in the follow section.

5.3. Residual Evaluation

From the above section the residual is obtained, then the evaluation should be carried out. After the fault has be detected, the next important step is fault diagnosis, which is determine the root causes of the detected fault. These variables are measured signals with estimated values, generated by a TS fuzzy model system. When the system is in normal operation the residual should be close to zero, and when the fault occurs the residual should be larger than zero. This property of residuals is used to determine whether or not faults have occurred. The analysis of each

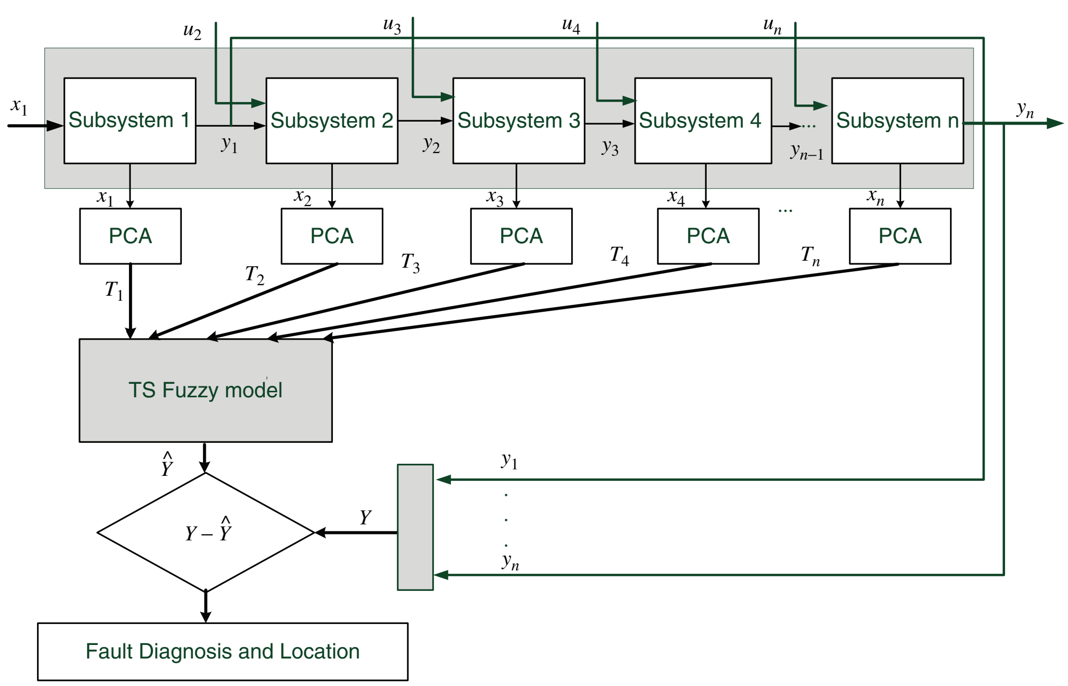

Fig. 3. Fault diagnosis of the series connected system.

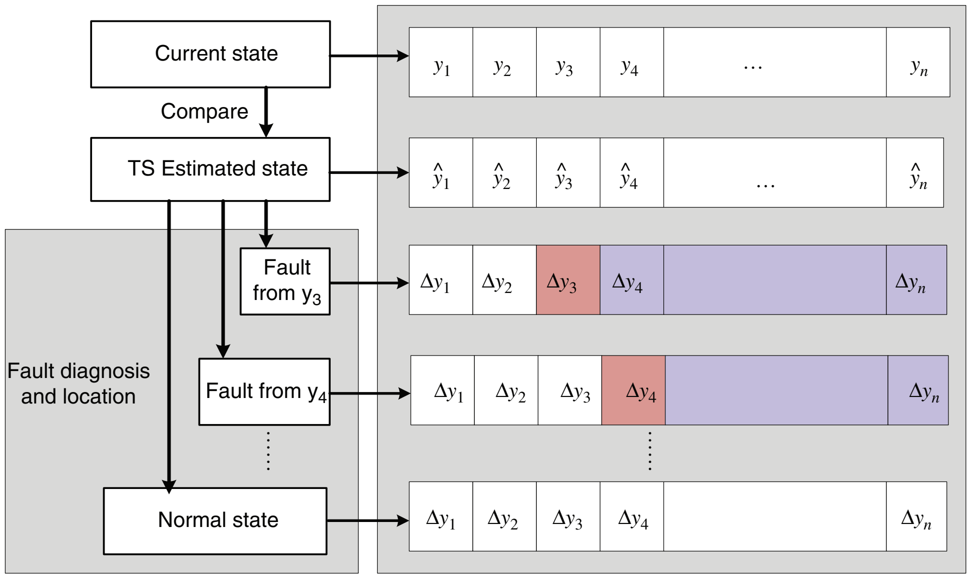

Fig. 4. Fault diagnosis and location.

residual, once the threshold is exceeded, leads to the fault isolation.

When the system is working, the TS fuzzy model calculate the outputs at the same time. Each sampling period the TS fuzzy model output the model-calculated state of each subsystem and compare with the real system, shown in Figure 4.

$$\begin{aligned} Y-\hat{Y} &= [y_1, y_2, \ldots y_n]-[\hat{y}_1, \hat{y}_2, \ldots \hat{y}_n] \\ &= [\Delta y_1, \Delta y_2, \ldots, \Delta y_n] \end{aligned} \tag{18}$$

The $[\Delta y_1, \Delta y_2, \ldots, \Delta y_n]$ would obey the normal distribution $N(0, \sigma_1)$ to $N(0, \sigma_n)$ if the fault are not occurred. If some of the variables in the $[\Delta y_1, \Delta y_2, \ldots, \Delta y_n]$ distribute outside of the 3σ. Then, the fault is take place from where the first deviation happen. In that way, the location of the fault is determined. The monitoring data information belonging to each subsystem is defined as $\boldsymbol{R}_i^2$, i is the number of the subsystem.

$$R_i^2 = (\Delta y_i)(\Delta y_i)^T \tag{19}$$

To evaluate the plant-wide performance, all subsystem monitoring results are aggregated as follows:

$$R^2 = \{R^2(1), R^2(2), \ldots R^2(n)\} \tag{20}$$

Where $\boldsymbol{R}_i^2$ represent the monitoring result of residuals in each subsystem.

5.4. The Smoothing Filter

To determine the change trend of the outputs, the residual of each subsystems need to be handled. The means of the newest data reflect the variation tendency and contain outliers. The M is the mean value of the newest c data, as the time going the newest data will replace the oldest one.

$$M_k = \frac{y_{k-m+1}+y_{k-m+2}\cdots y_k}{m} \tag{21}$$

where, the M is the mean value of the newest data, m is the number chose to reflect the variation trend. The M is the variable trend insensitive to the sharp change and could avoid the false alarm. The recursive smoothing filter is

$$M_k = M_{k-1}+\frac{y_m-y_{k-m}}{m} \tag{22}$$

The recursive smoothing filter can effectively reduce the effects of measurement noise. The larger the number of data m would cause the better ability to resist noise in the system, but at the same time the delay problem is exist and the real-time effect is bad. As a result, the m is very important to impact the noise immunity.

6. CASE STUDY

6.1. SOFC System and Model

Solid Oxide Fuel Cells (SOFC) is a new kind of power device, recently attracts the attention both in academy and industry. Solid oxide fuel cells (SOFC) convert chemical energy directly into electrical energy with a great deal of advantages, such as fuel flexibility, quiet operation, low emissions, and high efficiency, over traditional power generation systems. These benign features render SOFC generation systems are emerging as an attractive alternative in power applications for domestic, commercial, and industrial sectors. The system structure of the SOFC is in neighborhood to neighborhood the topology structure. Over recent decades, the solid oxide fuel cell (SOFC) has attracted considerable attention because of its unique characteristics including high efficiency, fuel flexibility and its environmentally friendly properties, when adopting a steam reformer to produce hydrogen at high conversion ratio. However, to our best knowledge the research of fault diagnosis based on data-driven method of the SOFC system have not been reported.

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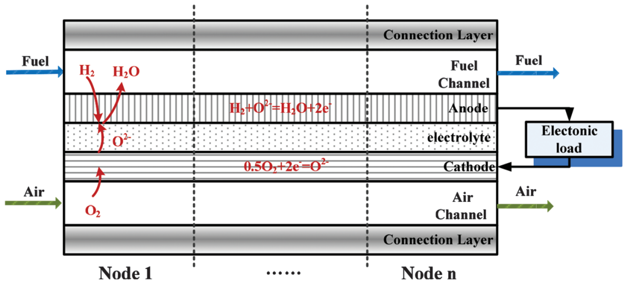

Fig. 5. Reaction mechanism.

The system consists of five different units:[32] gas supply system, heat exchanger 1, heat exchanger 2, SOFC electrical stack and burner. The system supply electric power by chemical reaction of fuel gas and oxygen under high temperature condition. The high temperature is provided by tail burner take advantage of the excess fuel gas. The system maintain the balance of heat and power to constantly supply electric energy. The system model is developed in MATLAB/Simulink platform using a modularity-based method. The models of the system components are first developed, and then they are linked together to represent the entire system. Since the system model is used for control oriented analysis and design. The reaction mechanism is shown in Figure 5. The system structure is shown in Figure 6.

6.2. Linear Series Structure and Fault Diagnosis

This system has some unique characteristic: First the outputs of the whole system, the power and the voltage of the fuel cell, is not located in the end of series. Then, the main information transmitted through the system are the energy, the pressure and the temperature which have no direct relationship with the electrical signal. Thirdly, the serially connected isolated structures of the system make the subpart of the system independent of each other in some degree. It is a combination of heat transfer process and electricity generation process.

The system can working in two condition: the constant power condition and the time variant power condition. The constant power condition indicates that the power termination working in a singe power rating. The SOFC system just supply a constant power, until the needs is end. The time variant power condition is more complex than the former one, it means the power provides by the Fuel Cell is non-constant, as a consequence, the fault detection would be very difficult. In this article, we diagnosis the fault happen both in the power constant condition and time variant power condition, and provides the TS fuzzy learn of the SOFC states of the time variant power condition not the fault.

From the Figure 6 of the SOFC system, although some pipe connected each other make it seem to be a feedback loop in the system, such as the pipeline between the Burner and the Heat Exchanger 2. As a matter of fact, the valve embedded in the pipeline control the pressure and the energy flow into the Heat Exchanger 2 depend on the demand. Therefore, the pipeline to the EX1 and the EX2 should be treat as a inputs of that subparts and the SOFC system is a series connected structure, shown in the Figure 7.

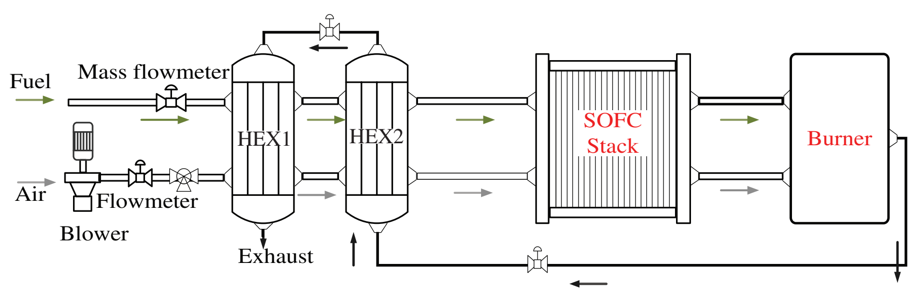

Fig. 6. Structure of the SOFC system.

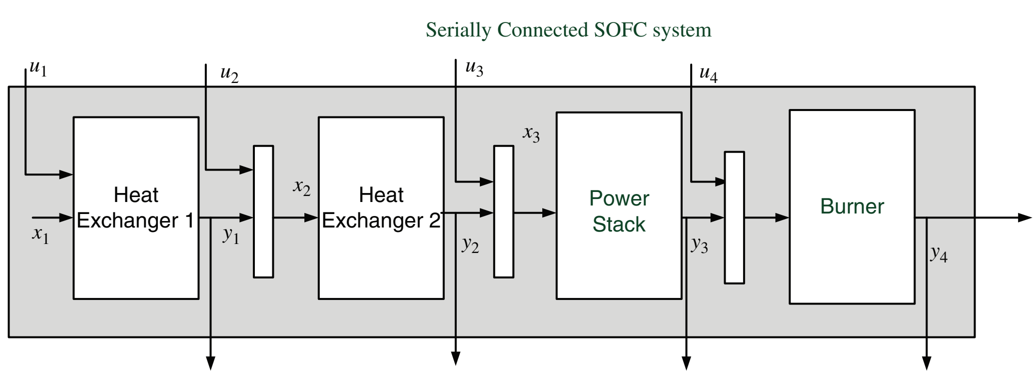

Fig. 7. Series connected system of SOFC.

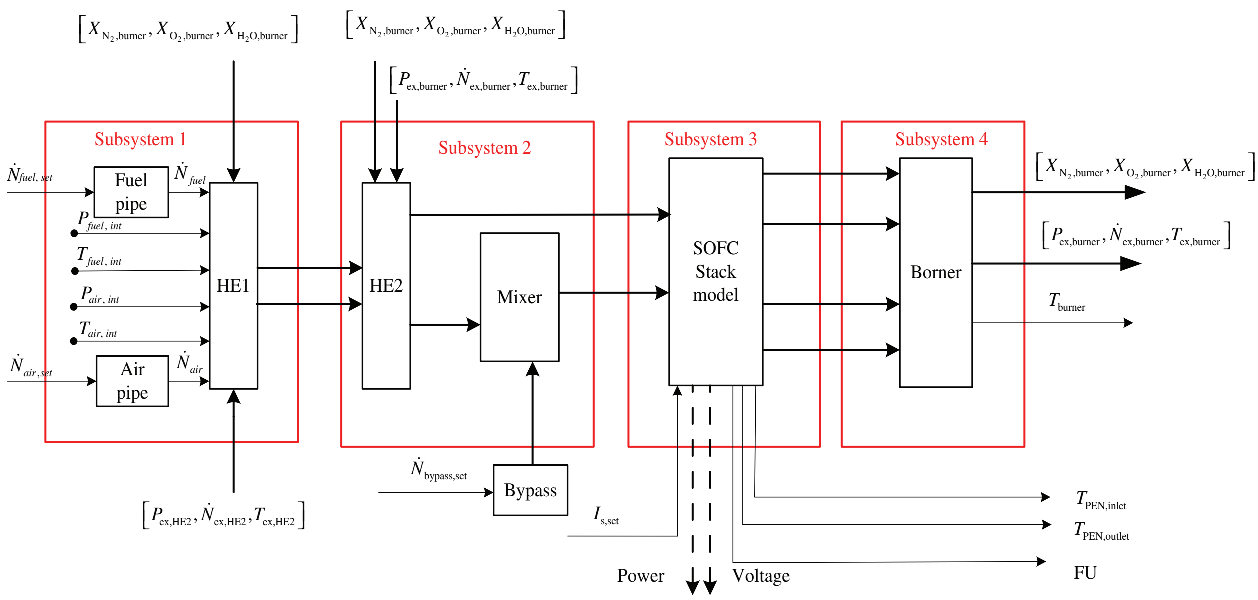

Fig. 8. Subsystems in SOFC.

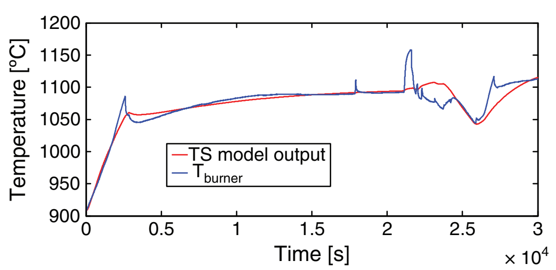

Fig. 9. Comparison of the TS and the mechanism model.

The SOFC system is separate into 4 subsystems: the heat exchanger 1 (HEX1), the heat exchanger 2 (HEX2), the power stack and the burner. In particular, the first part consists of not only the HEX1 but also the gas supply system. The second subsystem contains the HEX2 and the temperature control equipment. In that way, the series connected system is construct and the fault detection and diagnosis method can be carried out. The Figure 8 shows the variables in each subsystems.

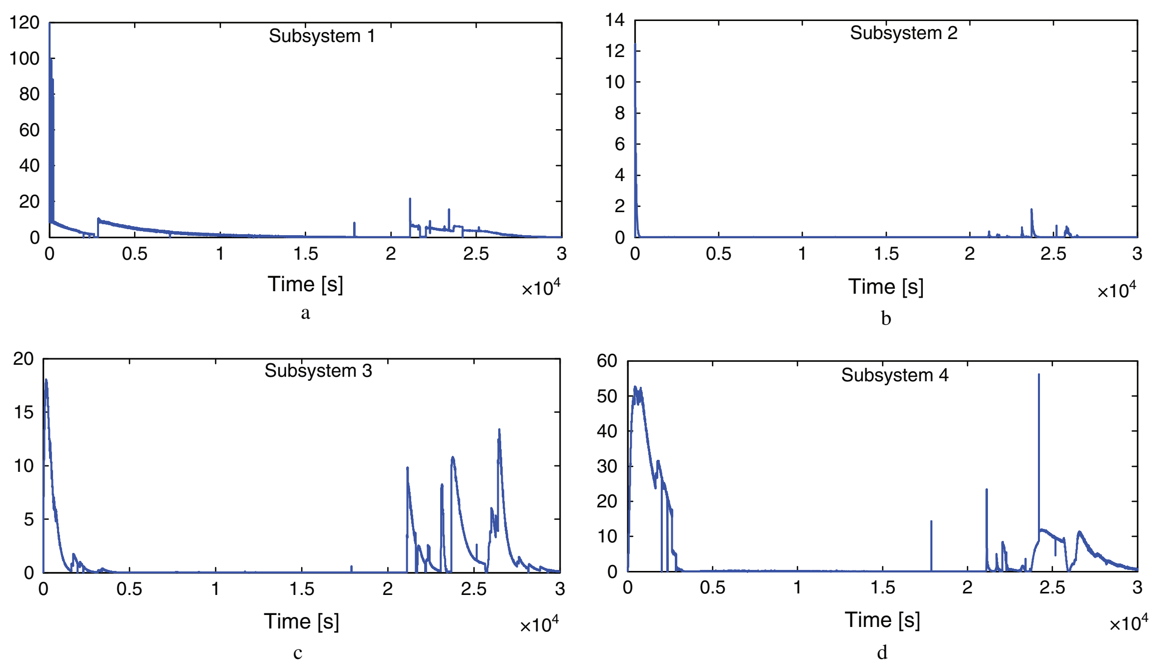

Fig. 10. Residuals of the subsystems.

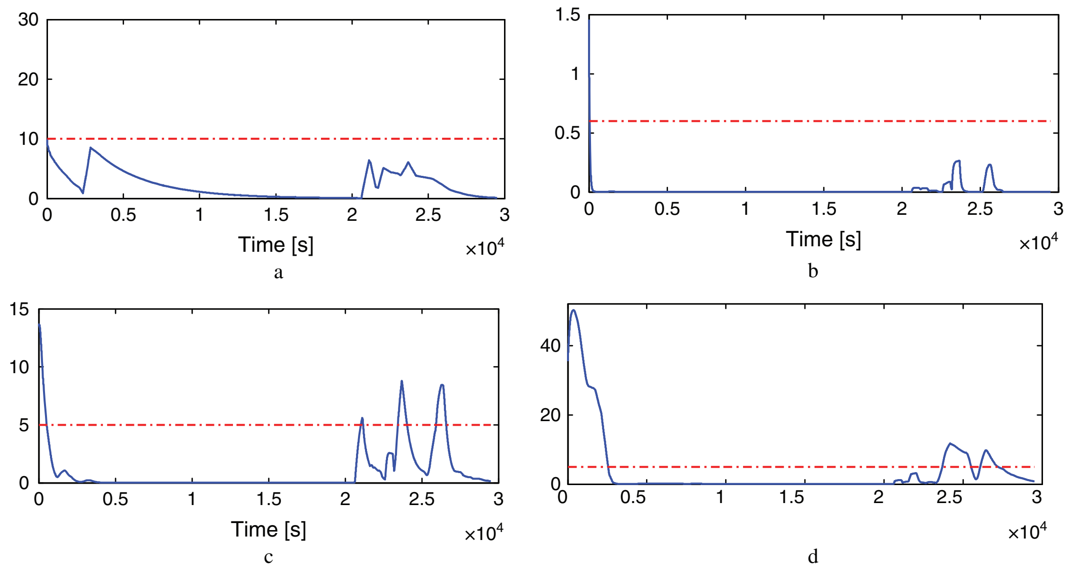

Fig. 11. Residuals after smooth filter.

The simulation is put into effect in the MATLAB/simulink condition with a computer 3 GHz and 12 G memory. The results show in Figures 9–11. The Figure 9 shows the outputs of burner temperature which is the system last outputs. The TS fuzzy model trace the temperature when the variable is normal operation. When the system deviate from the normal working condition, the TS output and the system output are not running at the same trajectory. The Figure 10 shows the $\boldsymbol{R}_i^2$ in each subsystems. In the first 4000 s, the TS fuzzy model adjust its parameters and the learning error appear. After the training period, the TS model could follow the trajectory of the system. Figure 11 shows the $\boldsymbol{R}_i^2$ results after the smooth filter. It is indicated that the first two subsystems is working in a normal condition shown in Figures 11(a) and (b) while the last two subsystems deviate normal operation condition. From the above section, it indicates the fault happens in the subsystem 3 which is the SOFC stack. In that way, the fault of the whole system can be detected while the location of the fault is obtained.

7. CONCLUSION

In this work, a fault detection and location method is present by distributed PCA and dimensional Bayesian based fuzzy model and the SOFC system is employed to verify the method. This method is a combination of model-based fault detection architecture and data-based learning method, to achieve fault detection and location of the series connected process. The serially connected system is analyzed to obtained the partition method of the whole system and provide the conditions to construct that subsystems. Then the distributed Principle component analysis is carried to extract information from the real measurement of the subsystems for modeling of the TS type of fuzzy inference. The two dimensional Bayesian based fuzzy model is firstly introduced to achieve nonlinear identification techniques in the fault diagnosis area. Both the offline and online data identification and modeling techniques are proposed. The constructional residuals is generated by comparing output signals of the TS models and the real measurements of each subsystem. The evaluation of the residuals examines the fault occurrence with the location information. Finally, the SOFC system is introduced and the simulation model is built and the series connected subsystem is construct in the system. The simulation results shows this method can diagnosis the system fault and the location of the fault can be determined.

For our future work, there are several important issues that should be noted. First, the fault recovery of the series connected system could be carried out after fault location. Second, for the SOFC system if the fault occurrence in a short time or a long time, the model would not efficient to diagnosis the fault. As a result, multimodel diagnosis method should be introduced.

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