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Faults diagnosis for PEM fuel cell system based on multi-sensor signals and principle component analysis method

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ABSTRACT

Fuel cell vehicles are becoming more popular and attracting more attention from industries, but stability and reliability of the fuel cell system (FCS) are still problems for its commercial progress. Therefore, a fault diagnosis system is essential for a reliable and long working lifetime FCS. In this work, a fault diagnosis method based on multi-sensor signals and principle component analysis (PCA) is proposed to improve FCS performance. By using this method, the correlation among different sensor signals are analyzed based on multi-sensor signals, and a simplified statistic index for fault diagnosis is deduced based on the PCA. The FCS operation conditions are monitored online, and faults in sensor and system levels are diagnosed. Experimental results show that, two typical fault scenarios, i.e., a single sensor fault and a serious system failure, can be successfully diagnosed and distinguished. For the single sensor fault, the sensor signal is reconstructed immediately to ensure that fuel cell vehicles operate normally. For the system failure, the fault can be detected in 17 s and the fault source signals can be located in 31 s, so the fuel cell stack can be protected timely. The main contribution of this work is to deduce a simplified statistic index for fault diagnosis based on multi-sensor signals and PCA method, and to provide an experimental study on identifying faults in sensor and system levels of a PEM fuel cell system.

Introduction

Proton Exchange Membrane Fuel Cell (PEMFC) has been regarded as a promising alternative way for an energy source [1]. Among new energy vehicles, fuel cell vehicles have many advantages, such as zero emission, fast hydrogen filling and long range [2]. However, fuel cell vehicles still have complex structure, short service life and high cost, which are problems for its volume production [3–5].

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To ensure the stability, reliability and safety of the PEMFC system, many fault diagnosis and fault-tolerant control methods have been proposed. These methods can be classified into two general types: model-based method [6] and data-driven method [7]. The model-based method normally need system physical models and large calculation work, so it is not suitable for online diagnosis [8–10]. While data-driven method could be simpler and has been proved to be powerful. Common data-driven methods, such as neural network [11,12], fuzzy logic [13], component principle analysis [14,15], and Bayesian network [16,17] methods are used.

Among the data-driven methods, principle component analysis (PCA) method has been widely used in many engineering areas and has shown good performance and efficient results. Du et al. [18] developed three PCA models combined with joint angle plot and expert rules, to timely detect and isolate the single sensor fault in heating, ventilation and air conditioning systems. And they also built system-level PCA model and local-level PCA model to detect the system abnormal and faults, and Fisher discriminant analysis has been used to determine the fault source [19]. In recent years, the PCA method has been introduced into fuel cell area. Placca et al. [14] adopted PCA method to analyze the experiment data offline for 2.5 kW fuel cell stack and describe the correlation and features among the FCS parameters. Hua et al. [15] utilized PCA method to implement the single sensor fault diagnosis and fault signal reconstruction in the fuel cell bus, and proved this method is suitable for online diagnosis.

However, little work has been done to consider both the sensor fault and system failure for the FCS. System failure is a serious fault for the FCS, because it could introduce the irreversible damage to the fuel cell stack, which is the most expensive component in fuel cell vehicles.

In this paper, the diagnosis method based on PCA is further studied, and a simplified statistics index considering both the sensor fault and system failure is proposed. The diagnosis method of this study is implemented under MATLAB/Simulink environment. Section 2 describes the fuel cell system structure in the city bus. Principle components analysis presents the PCA method modeling process, diagnosis indexes, and signal reconstruction method of the FCS. Experimental results presents diagnosis results of two fault scenarios: sensor fault and system failure. Finally, the conclusions are presented in Section 5.

Table 1 – Configurations information for the bus and systems.

	Parameter	Value
Bus	Length	12 m
	Weight	18 ton
Fuel cell stack	Max power	30 × 2 kW
	Rated power	25 × 2 kW
	Cell number	135 × 2
	Monolithic active area	276 cm^2
Power battery	Capacity	60 Ah/34 kWh
	Rated voltage	607 V

Fuel cell system structure in the city bus

The plug-in fuel cell city bus has a distributed components layout, with fuel cell system in the rear end, radiators and hydrogen cylinders on the bus roof, and power battery under the middle floor. The configurations for the bus, fuel cell stack and power battery have been listed in Table 1.

The detailed structure of PEMFC system has been shown in Fig. 1, and it includes hydrogen subsystem, air subsystem, cooling subsystem and stack subsystem. The air subsystem consists air compressor, membrane humidifier, water separator, throttle valve and water pump; the hydrogen subsystem consists hydrogen cylinder, pressure relief valve, and other valves; the cooling subsystem includes cooling fans, water tank, membrane humidifier, heater exchanger and water pumps. The power output is controlled by the DC/DC converter. Fig. 1 also shows the installation positions and types of

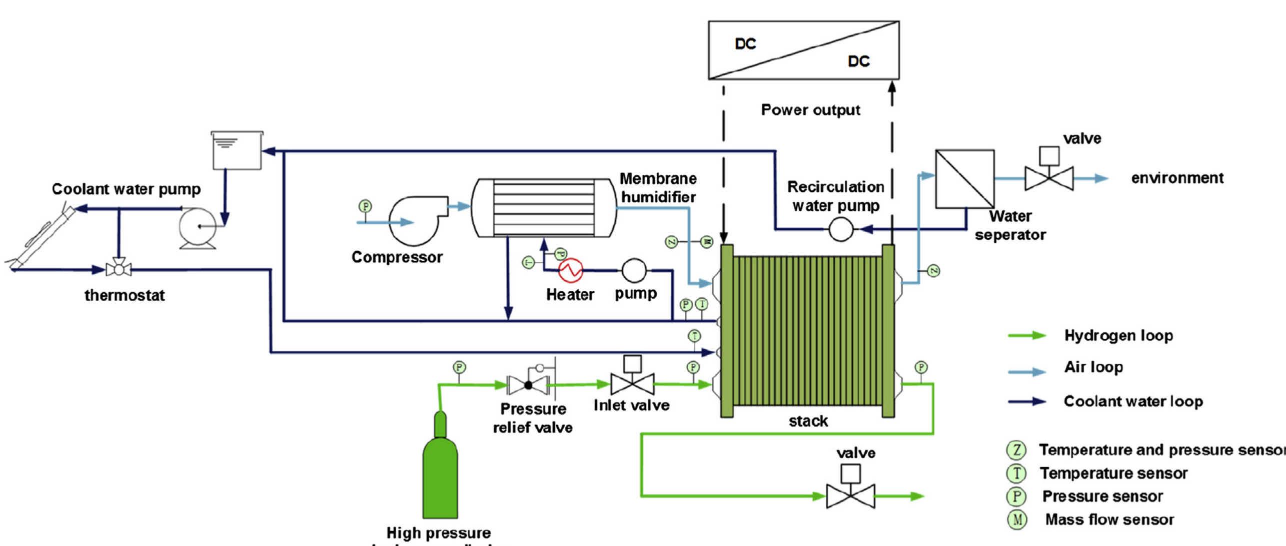


Fig. 1 – PEMFC system structure in the fuel cell city bus.

some important sensors. These sensors can detect the pressure, temperature, humidity and mass flow rate of the PEMFC system.

Principle components analysis (PCA)

Modeling process for PCA

PCA method has been widely used in the diagnosis area for lots of systems. It uses a certain number of principle components to approximately represent the system, in guarantee of as less loss of system information as possible. In this way, it extracts the basic correlation among the original variables and reduces the system dimensions.

Normally, normalized $n \times m$ dimensions sample data matrix $\mathbf{X}$ could be wrote as:

$$\mathbf{X} = \widehat{\mathbf{X}} + \mathbf{E} \tag{1}$$

$\widehat{\mathbf{X}}$ represents Principle Component Subspace (PCS), including the correlation among the original variables; $\mathbf{E}$ represents Residual Subspace (RS), describing the modeling error and noise.

To build the data matrix, in this paper, 14 important signals regarding all the subsystems of FCS have been chosen. They are all detected by different sensors. Sample data from normal operating status has been used for data training. In the data matrix X, each column represents one parameter, in total 14 parameters; each row represents one sample data, in total 12,600 samples used for correlation analysis. The symbol description of 14 parameters has been listed in Table 2.

The modeling process for PCA method has been shown in Fig. 2.

To determine the optimal number of PCs, the principle accumulative method [20] has been used, and the accumulative contribution rate has been shown in Fig. 3:

The accumulative contribution rate of the first three components is 94.03%, which means they are enough to represent the correlation among the original variables [21]. So three principle components would be chosen for the PCS.

Table 2 – FCS variables.

Symbol	Description
$P_{air\ in}$	Stack inlet air pressure
$P_{air\ out}$	Stack outlet air pressure
$P_{Hsk\ in}$	Stack inlet hydrogen pressure
$P_{Hsk\ out}$	Stack outlet hydrogen pressure
I_{total}	Stack total current
V_{total}	Stack total voltage
V_{av}	Average single cell voltage
V_m	Minimum single cell voltage
V_{cp}	Compressor control voltage
S_{cp}	Compressor speed
F_{cp}	Compressor mass flow rate
$T_{air\ in}$	Stack inlet air temperature
$T_{water\ out}$	Stack outlet coolant water temperature
$T_{water\ in}$	Stack inlet coolant water temperature

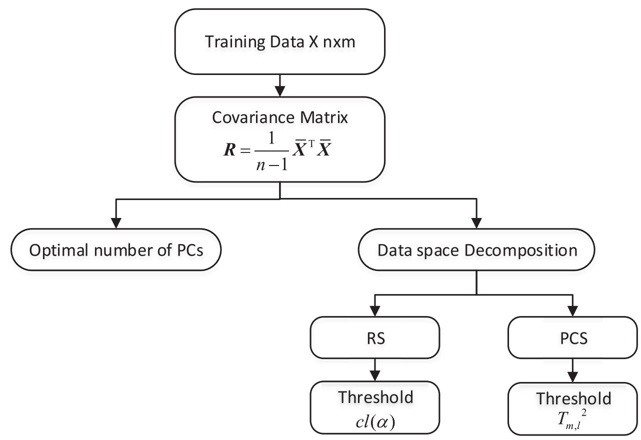


Fig. 2 – Modeling process for PCA.

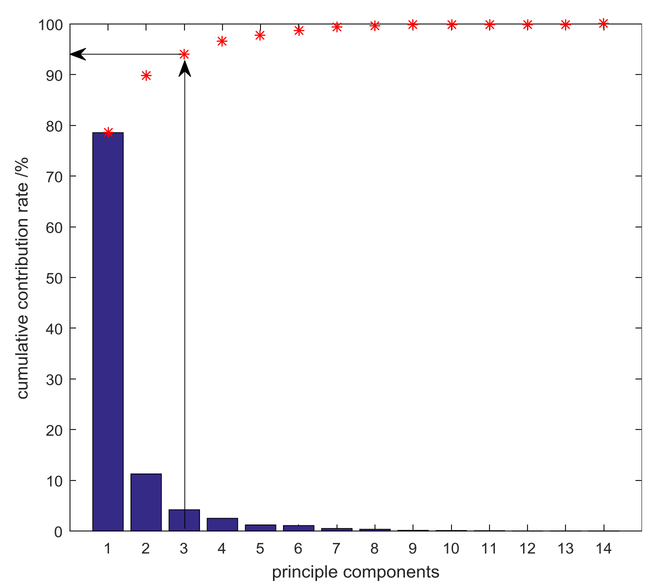


Fig. 3 – Principle components accumulative rates (star shows the cumulative contribution rates of the principle components and bar shows the contribution rate of each principle component).

For each new sample data, it would be decomposed into PCS and RS as:

$$x = \hat{x} + \tilde{x} \tag{2}$$

Fault diagnosis index

To diagnose the faults, two statistics indexes T^2 and SPE are used to monitor the PCS and RS, respectively.

T^2 monitors the variables correlation and system operation status [22–24], and if the operation status turns to be abnormal, the correlation would be destroyed, then T^2 index would exceed the threshold [25]. The definition of T^2 is:

$$T^2 = \sum_{i=1}^{l} \frac{t_i^2}{\lambda_i} \tag{3}$$

The threshold is given by F distribution, calculated using PCS information:

$$T^2_{m,l} = \frac{l(m^2-1)}{m(m-l)} F_\alpha(l, m-l) \tag{4}$$

But T^2 index is insensitive to single parameter faults, because it won't influence the correlation among the variables. To improve the diagnosis performance, SPE index has also been used in this paper.

The SPE definition is:

$$\mathrm{SPE} = \boldsymbol{e}^{\mathrm{T}}\boldsymbol{e} = \|\boldsymbol{e}\|^2 = \boldsymbol{x}^{\mathrm{T}}(\boldsymbol{I} - \boldsymbol{PP}^{\mathrm{T}})\boldsymbol{x} \tag{5}$$

Literature [25] points out the determination rule of SPE, and when the SPE value satisfies this equation, it means that fault has been found in the system.

$$\mathrm{SPE} \geq cl(\alpha) \tag{6}$$

To improve the diagnosis performance for SPE index, Exponentially Weighted Moving Average (EWMA) method has been introduced [24].

$$\begin{bmatrix} \bar{e} \\ \overline{\mathrm{SPE}} \end{bmatrix}_k = \begin{bmatrix} (I\text{-}\Lambda) & 0 \\ 0 & (1-\lambda) \end{bmatrix} \begin{bmatrix} \bar{e} \\ \overline{\mathrm{SPE}} \end{bmatrix}_{k-1} + \begin{bmatrix} \Lambda & 0 \\ 0 & \lambda \end{bmatrix} \begin{bmatrix} \bar{e} \\ \mathrm{SPE} \end{bmatrix}_k \tag{7}$$

After the fault has been detected, fault sources should be determined as soon as possible. In the literature [15], the effective index η_i was used, but this index is not qualified for the system failure diagnosis. Because once lots of signals are influenced by system failure and turn to be abnormal, the corresponding indexes for each signal would all turn to be very large. This case cannot be distinguished from the system normal status.

$$\eta_i^2 = 1 - \frac{\bar{e}_i^2}{(1-c_{ii})\sum_{j=1}^{m} \bar{e}_j^2} \tag{8}$$

So one comprehensive index [15] based on it has been proposed:

$$\chi_i = \overline{\mathrm{SPE}} \cdot (1-\eta_i) \tag{9}$$

And the thresholds are given by:

$$\chi_{\lim} = cl(\alpha) \cdot E\left(\sqrt{1-\eta_i^2}\right) \tag{10}$$

Signal reconstruction

Signal reconstruction is based on the correlation among the original variables. When reconstructing the sensor signal, the approximate value should be iterated, and the equation finally converge to:

$$\hat{x}_i = \frac{[x_1, x_2, \ldots, x_{i-1}, 0, x_{i+1}, \ldots, x_m]\mathbf{c}_i}{1-c_{ii}} \tag{11}$$

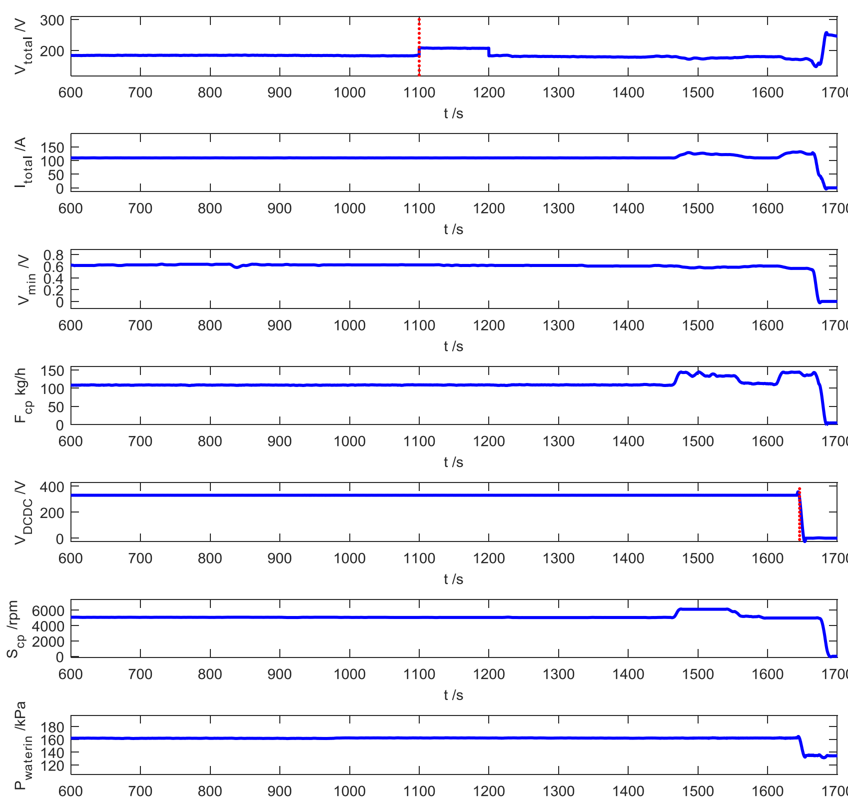


Fig. 4 – Fuel cell vehicle operation parameters (red line shows the fault start time). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Experimental results

Fault scenarios

There are different kinds of faults in a PEMFC system, such as sensor/actuator failures, stack failures, air compressor/water pump failures. From a viewpoint of system engineering, they can be roughly classified into two kinds, sensor level faults and system level faults. A sensor fault is a failure in a single or multi sensor(s) itself. Such a fault will cause no damage to the fuel cell stack directly, but it may result in mistakes in control strategies, which lead to indirect damage to the fuel cell stack. For this kind of fault, it is necessary to identify the sensor failures in time, and to reconstruct a new signal value to replace the old one. A system level fault is a failure in the PEM fuel cell system level. It is usually caused by the actuators or the fuel cell stacks, and reflects in several sensor signals. In this case, all the sensors function well but the whole system works in an abnormal status. For this kind of fault, it is not only necessary to identify the failures in time, but also to reduce the output power or even shut down the system in a proper way.

Fig. 4 illustrates the major operation conditions of a fuel cell vehicle in an experiment, which lasted for 1679 s. At the 1100th second, an error occurred in the stack voltage sensor and caused a 10% drift in the voltage value. This error was diagnosed by the proposed strategy at the 1100.5th second, and the signal was reconstructed at the same time. At the 1648th second, an error occurred in the DCDC converter for the water pump, and caused abnormal values in signals such as single cell voltage, cooling water pressure, voltage of the DCDC converter. This error was detected by the strategy at the 1668th seconds, and meanwhile the output power of the FCS was lowered down. The fault occurred at the 1100th second is a sensor-level fault, and the one happened at the 1648th second is a system-level fault. The two scenarios are explained in details in following paragraphs.

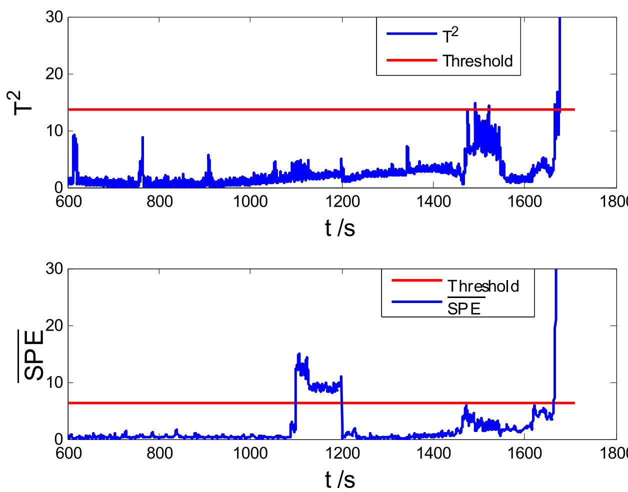


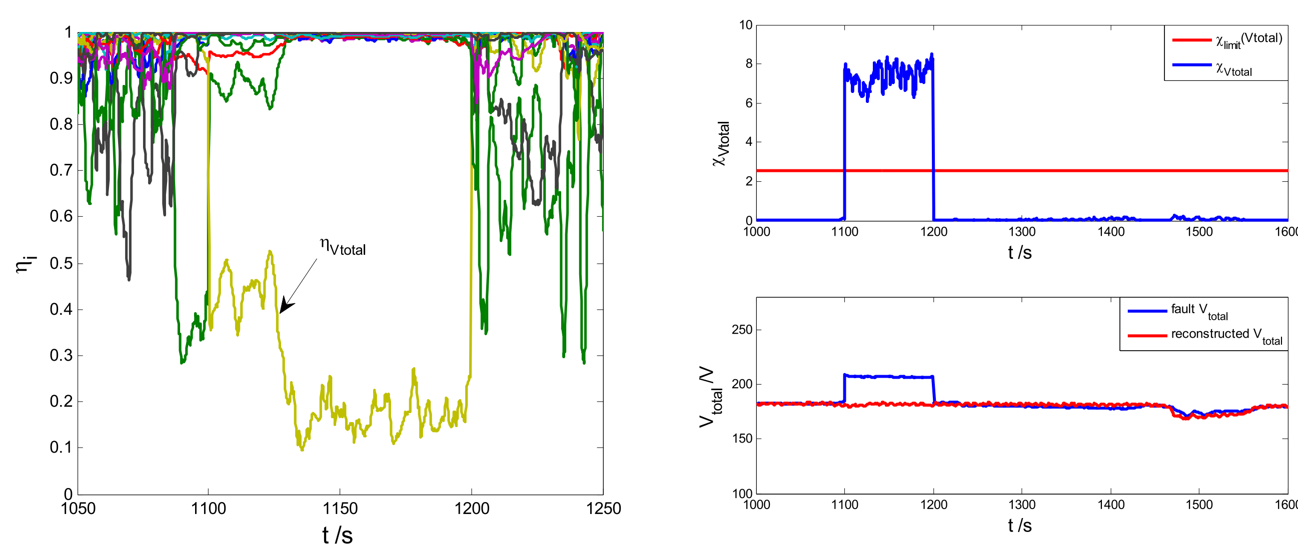
Fig. 5 – Diagnosis indexes curves.

Diagnosis process

Fig. 5 shows the curves of the indexes in the whole process time. Based on the definition of these two indexes, T^2 reflects the correlation among the original variables, and $\overline{SPE}$ normally indicates the residual error. When T^2 remains to be normal, it means that the correlation among different sensors remains unchanged and the system functions well. When $\overline{SPE}$ exceeds the threshold, it means that one or several parameters are abnormal.

Diagnosis process for fault scenario 1

At the 1100th second, $\overline{SPE}$ exceeded the threshold and T^2 remained normal. Based on the above analysis, it can be concluded that the FCS operation status remained normal, but a sensor-level fault happened. In order to identify the malfunctioned sensor, an effective index η_i was calculated for



(a) (b)

Fig. 6 – (a) The effective index; (b) the comprehensive index and the comparison of the reconstruction and original signal.

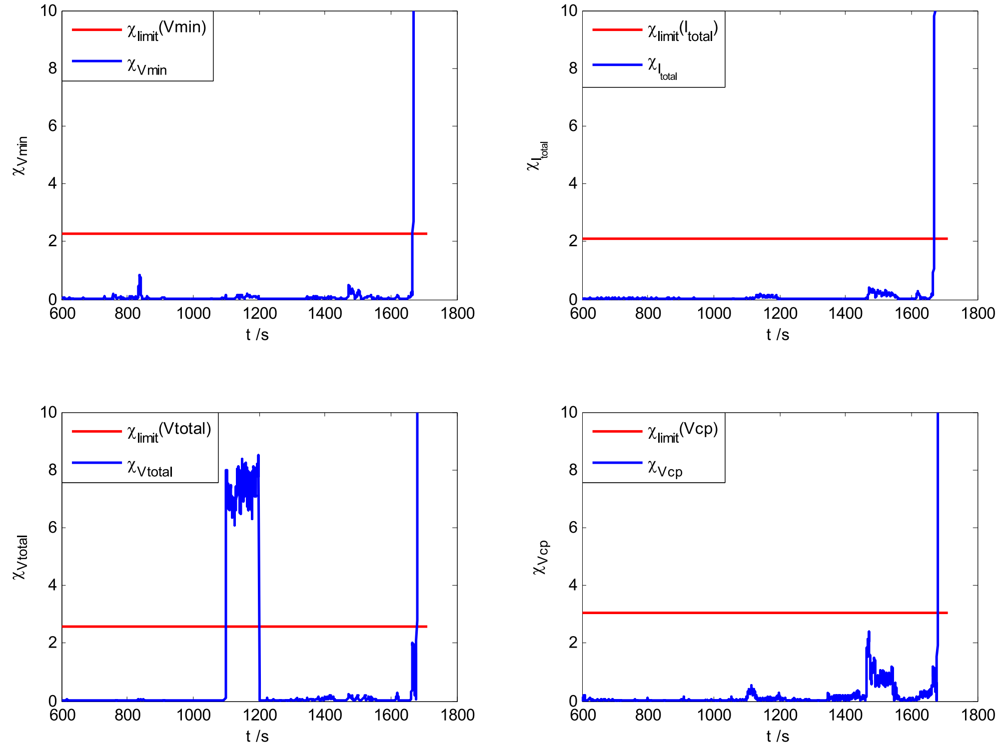


Fig. 7 – Comprehensive indexes curves for minimum single cell voltage, total current, compressor voltage and total voltage respectively.

each sensor signal, which is shown in Fig. 6(a). The effective index of the stack voltage, η_{Vtotal}, deviated from other values at the 1100th second, meaning that the stack voltage sensor was the fault source. The value of χ_{Vtotal} exceeded its threshold value at this moment in Fig. 6(b), which also proved that the stack voltage sensor was the fault source. Therefore, the signal was reconstructed based on Equation (11), and is illustrated in the lower sub-figure of Fig. 6(b).

Diagnosis process for fault scenario 2

At the 1665th second, both of T^2 and $\overline{SPE}$ exceeded the thresholds, as in Fig. 5. From the analysis above, it can be concluded that the FCS's status was abnormal, and a system failure may happen. In order to determine the fault category and to find the fault sources, the comprehensive index χ_i corresponding to each signal was calculated. All of the comprehensive indexes χ_i exceeded their thresholds, and it can be concluded that a system-level fault occurred. Four of them are shown in Fig. 7, and the timings for detecting the system-level fault and determining the fault source are listed in Table 3.

Being presented in Fig. 4, at the 1648th second, the DCDC converter for the water pump had technical problems and didn't work well. This malfunction caused abnormal values in sensor signals. By using the PCA algorithm, a system-level fault was detected at the 1665th second (17 s later than the malfunction), and all the fault source signals were detected at the 1679th second (31 s later than the malfunction).

From Table 3, we can see that the minimum cell voltage (V_{min}), stack current (I_{total}) and compressor speed (S_{cp}) were affected by the system-level fault firstly. The first parameter, i.e., V_{min}, is important for the FCS. If it is lower than 0.3 V and the air compressor keeps working at the meantime, the polymer electrolyte membrane will be dehydrated and be damaged seriously. An active tolerant control strategy is designed for the FCS to avoid this situation. When a system-level fault is detected, the stack current (I_{total}) and air compressor speed (S_{cp}) will decease synchronously to let the air compressor stop before the minimal cell voltage decreases below 0.3 V, and then the FCS is shut down. Fig. 8 presents the profiles of the DCDC voltage, the V_{min}, the stack inlet water

Table 3 – The timing for detecting a system-level fault and determining the fault source.

Detecting system-level fault by using $\overline{SPE}$ and T^2	Signals	Determining the fault source by using χ_i
1665 s	Minimum single cell voltage	1667 s
	Total current	1668 s
	Total voltage	1679 s
	Compressor speed	1666 s
	Compressor control voltage	1679 s
	Compressor mass flow	1671 s
	Stack inlet hydrogen pressure	1672 s
	Stack inlet air pressure	1673 s

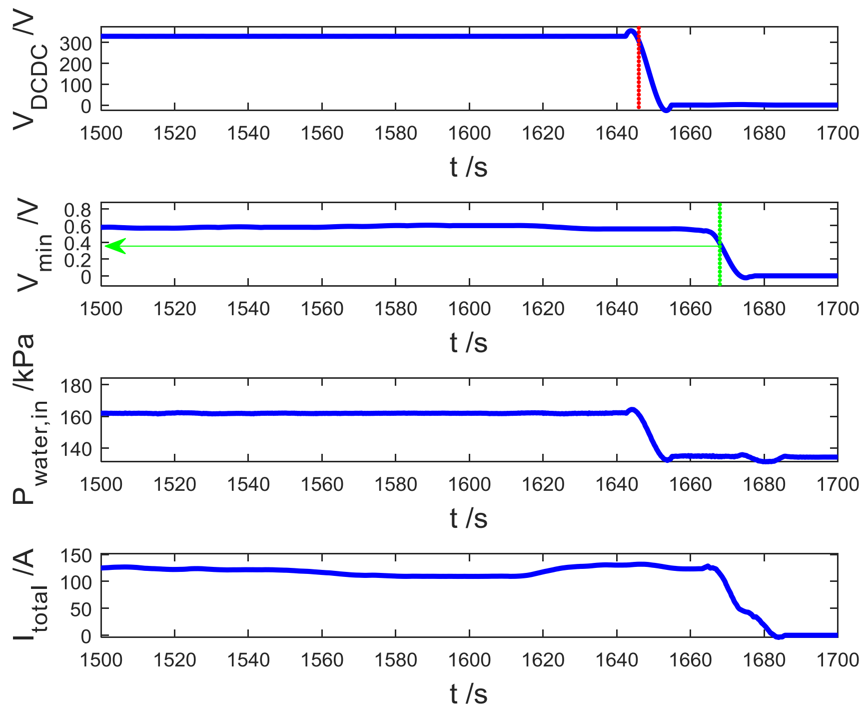


Fig. 8 – DC/DC voltage, minimum single cell voltage, stack inlet water pressure, and total current (red line indicates the fault start time (1648 s), green line indicates the fault source determined time of signal V_{min} (1667 s)). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

pressure and total stack current. It shows that, 1) the fault source of V_{min} was determined 19 s after the DCDC converter fault happened; 2) $V_{min} = 0.37$ V when it was recognized as an abnormal signal. At that moment, the active tolerant control strategy started to work to avoid further damage to the stack. A detailed discussion on the active tolerant control strategy will be conducted later in our studies.

Conclusion

To ensure the stability and reliability of the FCS in the commercial fuel cell vehicles, one diagnosis method based on PCA is proposed and designed for the fuel cell city bus. This method includes two stages. Firstly, the correlations among the sensor signals are extracted by training sufficient sample data. Secondly, the online fault diagnosis is designed based on the simplified comprehensive index. From a viewpoint of system engineering, two kinds of faults are dealt with. A sensor fault is a failure in a single itself. Such a fault will cause no damage to the fuel cell stack directly, but it may result in mistakes in control strategies, which may lead to an indirect damage to the fuel cell stack. A system level fault is a failure in the PEM fuel cell system level. It is usually caused by several actuators or the fuel cell stacks, and reflects in several sensor signals at the same time. In this case, all the sensors function well but have abnormal values, and the whole system works in an abnormal status.

An experiment was carried out to verify the proposed method. During this experiment, a stack voltage sensor fault and a system-level fault were detected and dealt with. For the stack voltage sensor fault, the strategy can immediately reconstruct the signal value after the fault source was determined by the comprehensive index, so fuel cell vehicles' safety can be ensured. For the system-level fault, the fault can be detected in 17 s and the fault source signals can be located in 31 s. The strategy can diagnose and distinguish the fault timely by the simplified comprehensive index, so the fuel cell stack can be protected.

In the future work, a complete fault diagnosis and tolerant control system will be studied and tested based on data- and model-driven algorithms.

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