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FAULT DIAGNOSIS OF SOLID OXIDE FUEL CELL SYSTEM BASED ON ADABOOST ALGORITHMS

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ABSTRACT

In the existing SOFC system, because of the high temperature isolation of the hot box, it is difficult to obtain the situation of the SOFC stack accurately. Therefore, the key problem of real-time judgment of the SOFC system operation state is to develop a state diagnosis method. Therefore, this paper intends to use strong classifier to evaluate the state of SOFC system, which is consist of multi weak classifiers and called AdaBoost algorithms. The algorithms can achieves efficient classification, which provides a powerful guidance for the overall performance evaluation of the system.

Keywords: Solid oxide fuel cells (SOFC), Adaptive boosting (AdaBoost), Fault diagnosis, System analysis

NONMENCLATURE

Abbreviations	
SOFC	Solid Oxide Fuel Cell
Symbols	
N	The number of training sample
S	Data set
W	Weight value
α	Error rate
H	Classifier
D	Weight vector
I	i th component of the weight vector
P	Pressure
T	Temperature
F	fuel
A	air
In	inlet
Out	outlet

1. INTRODUCTION

Solid oxide fuel cell (SOFC) is a novel electrochemical power generation device, which shows great advantages in environmental friendliness and generation efficiency [1, 2]. SOFC energy conversion efficiency is up to 80%. It has wide application prospects in distributed regional power supply, large-scale power generation, new energy vehicles and other fields. In addition, SOFC has many advantages, such as small area, environmentally friendly and easy to integrate [3, 4].

In order to realize better the commercialization of SOFC, systematization is the only way. Under the existing system architecture, SOFC stack is integrated in the hot box, and the hotbox environment is high temperature and airtight, which brings difficulties to evaluate the real-time performance of SOFC stack. With the rapid rise of artificial intelligence, there are many intelligent fault diagnosis methods in the field of energy system, such as artificial neural network(ANN), support vector machine(SVM), fuzzy mathematics and grey system theory[5]. Because the model of single fault diagnosis method is difficult to build accurately. The selection of parameters often depend on experience, which restricts the improvement of diagnosis accuracy. Therefore, the development of a diagnosis algorithm for SOFC stack is to prevent the operation of SOFC system from deviating from the expected target and the establishment of an alarm system, which has the characteristics of pertinence and predictability. It collects data through sensors embedded in SOFC system, but there is no efficient algorithm for real-time evaluation of SOFC stack. Figure 1 is a classic SOFC system structure [6]. Therefore, the design of an algorithm to identify the stack state is of great significance to the safety of the system accurately, and helpful to provide intellectual support for making scientific decisions.

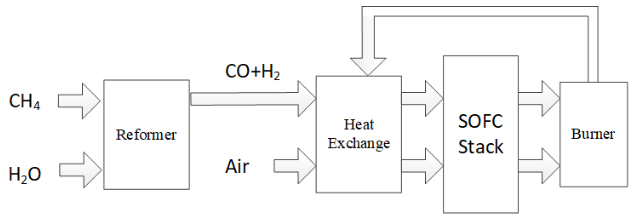

Fig. 1 SOFC system diagram

Boosting, also known as reinforcement learning or promotion method, is an important integrated learning technology. It can enhance the weak learner whose prediction accuracy is only slightly higher than that of random guess to a strong learner with high prediction accuracy. This provides a novel and effective method for the design of learning algorithm when a strong learner is very difficult to construct directly. The most successful application method is the AdaBoost algorithm, which is proposed by Yoav Freund and Robert Schapire in 1995[7, 8]. This paper will adapt this method to diagnosis SOFC system fault.

2. ADABOOST FAULT DIAGNOSIS ALGORITHMS

AdaBoost is the abbreviation of "Adaptive Boosting". This algorithms characteristic is that the weight of the misclassified sample by the former basic classifier will increase, while the weight of the correct classified sample will decrease. Then the obtained weight is used to train the next basic classifier again. At the same time, a new weak classifier added every iteration, and the strong classifier is not determined until a predetermined small error rate or a predetermined maximum number of iterations are completed. The fault diagnosis model is shown in Fig. 2.

The Adaboost algorithm is finished in following three steps [9]:

(1) Firstly, the weight distribution of training data is initialized. Assuming that there are N training samples, each training sample is set the same weight at the beginning: W1 = 1/N.

(2) Then, the weak classifier h_i is trained. Specific training process is: if a training sample point is accurately classified by weak classifier h_i, its corresponding weight will be reduced in the construction of the next training set; On the contrary, if a training sample point is misclassified, its weight should be increased. The weight of updated sample set is used to train next basic classifier, and the entire training process proceeds iteratively.

(3) Finally, the weak classifiers combined into a strong classifier. After the training process of each weak classifier finished, the weight of the weak classifier with small classification error rate will increased to play a greater decisive role in the final classification function, while the weight of the weak classifier with large classification error rate will reduced to play a smaller decisive role in the final classification function.

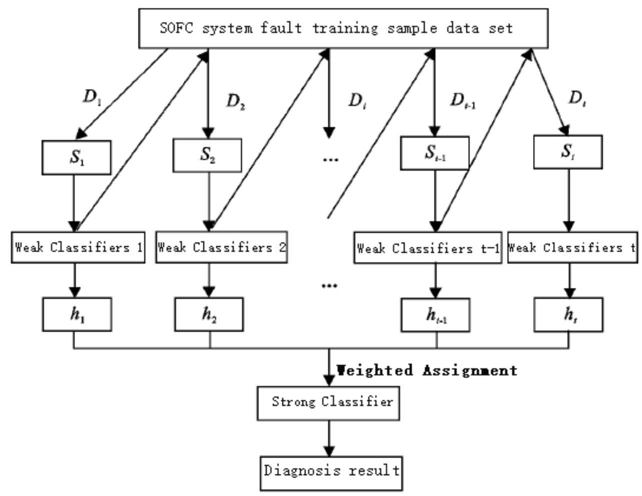

Fig. 2 Adaboost fault diagnosis model

In other words, the weak classifier with low error rate occupies a larger weight in the strong classifier. Otherwise, the weight value is a small digital.

Training Algorithms: Improving the Performance of Classifiers Based on Errors

The mentioned basic classifier or weak classifier, which means that the performance of the classifier will not be very good. It may be better than random guess. Generally speaking, in the case of second class classification, the classification error rate of weak classifier is even more than 50%, which is obviously only slightly better than random guess. However, the classification error rate of strong classifiers is much smaller than that of weak classifiers. The AdaBoost algorithm is easy to combine these weak classifiers to complete classification prediction.

The running process of AdaBoost: each sample of training data is set a weight, which constitutes the weight vector D, and the dimension is equal to the number of samples in the data set. At the beginning, these weights are equal. Firstly, some data are selected for training classifiers; the error rate of the classifier is calculated. Then the weak classifier is trained again based on the same data set. However, the weight of the samples data set is adjusted in the second training based on the error rate of the classifier. The weight of the samples correctly classified will reduced, while the score will reduced. Sample weights errors increase, but the sum of these weights remains unchanged to 1.

Furthermore, the final classifier will allocate different decision coefficients alpha based on the classification error rate of the trained weak classifiers. The classifier with low error rate will get higher decision coefficients, which will play a key role in data prediction. The α calculation is based on the error rate:

$$\alpha = 0.5 * \ln((1-\varepsilon)/\varepsilon) \quad (1)$$

Among them, ε is the ratio of the number of correctly classified samples to the total samples, and ε is used to prevent the occurrence of denominator zero due to the error rate.

After calculating alpha, the weight vectors can be updated, so that the wrong samples get higher weight, while the correct samples get lower weight. The formula for calculating D is as follows:

If a sample is correctly classified, the weight is updated to:

$$D(m+1,i) = D(m,i) * \exp(-\alpha) / sum(D) \quad (2)$$

If a sample is misclassified, the weight is updated to:

$$D(m+1,i) = D(m,i) * \exp(\alpha) / sum(D) \quad (3)$$

Among them, m is the number of iterations, *i. e*. the *m* th classifier is trained, *i* is the *i* th component of the weight vector, *I* is larger than the sample number of data sets.

After we update the weight of each sample, we can do the next iteration training. The AdaBoost algorithm repeats the training and adjusts the weight until the number of iterations is reached, or the training error rate is zero.

3. EXPERIMENTAL VERIFICATION

3.1 Experimental scheme

The above theoretical should be verified by experiments. The experimental device is the power generation equipment of SOFC system, which structure is shown in Fig. 1. Using natural gas as experimental fuel supply, pressure sensors are installed at the inlet and outlet of reactor fuel and air in SOFC system. The detail SOFC system sensor installed diagram can be seen in renference [10]. Sensor signals are obtained: P_{f_in}, P_{f_out}, P_{A_in} and P_{A_out}; voltage U and current I are drawn from the top and bottom covers of SOFC stack to the electronic load, and current signal I and voltage signal U are obtained. Temperature sensors T_{f_in}, T_{f_out}, T_{a_in} and T_{a_out} are installed at the inlet and outlet of SOFC stack, respectively. The SOFC system device can simulate normal state, transition stage, system fault state.

On the integrated detection and test equipment of SOFC system, operating states of the system are sampled. In the experiment, the sampling time is 1 hour and the sampling points are 11. The experimental data are collected according to the time series. The experimental data with a significant fault is used as the object of analysis and processing. From this, we can see that the system states reflected by the data can be divided into three categories: normal state, transition stage and fault state. Among the collected data, 2000 samples of all data are used as training samples and other data as testing samples.

3.2 Fault diagnose result

After PCA dimensionality reduction, the data dimension can be reduced to 3 dimensions [11, 12]. That is to say, the collected data remains air heat exchanger temperature, bypass airflow rate, and voltage values. The three-dimensional data is insert into Adaboost algorithm. By adjusting the number of weak classifiers, learning rate and algorithm selection to diagnosis system state, the number of weak classifiers is set to 20 and learning rate is set to 0.5. The algorithm chooses SAMME [13]. Through this classifier, fault detection is carried out, and the diagnosis results is shown in the following Fig. 3.

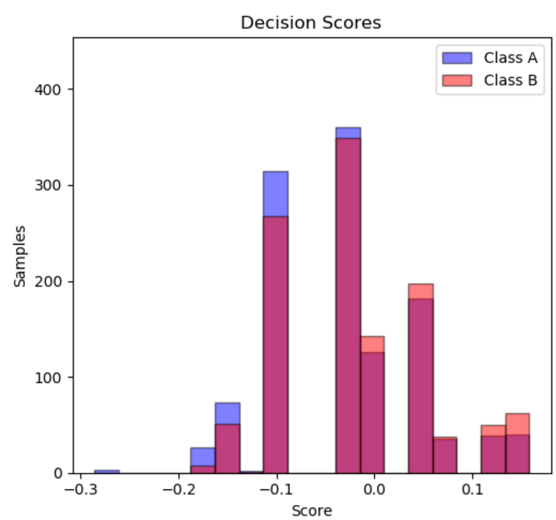

Fig. 3 Adaboost fault diagnosis result

In addition, the absolute value of strong classifier and weak classifier diagnosis results for system state are shown in Fig. 4. From Fig. 4, we can see that the effect of strong classifier is significantly better than that of weak classifier.

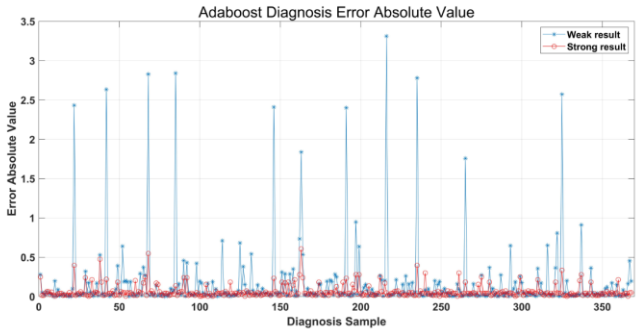

Fig. 4 Adaboost fault error

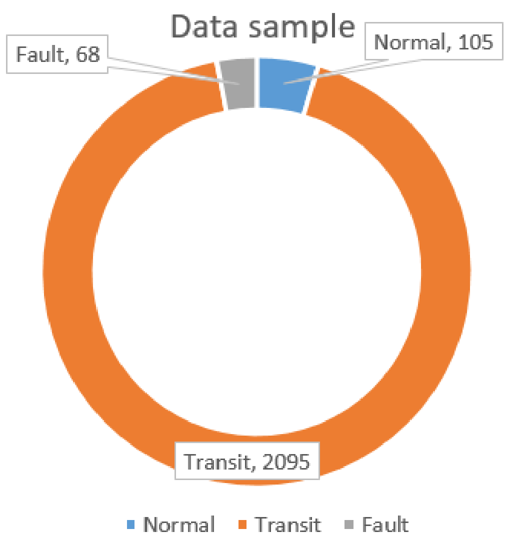

Fig. 5 Time series diagram of diagnosis result

3.3 Discussion

The Adaboost fault diagnosis result is shown in the Fig. 3. The selected data are divided into three categories: A (blue bar) is normal state, B (yellow bar) is fault condition, and red bar is transition stage data. Therefore, according to the amount of data and time series, the start time of transition stage and fault occur can be judged.

In the uncertain aspect, the original data has been processed by PCA and Adaboost algorithm, and the data retains its original characteristics, but it will inevitably cause discard of some additional attributes, so the weak classifier diagnosis results show a larger absolute error than strong classifier. This is tolerable, and the algorithm guarantees the accuracy of fault diagnosis in this system state.

From a sensitivity point of view, the result can be shown in Fig. 4. Although the weak classifier of the algorithm is sensitive to the fault performance, its diagnostic error is too large, which results in the poor accuracy of the diagnostic results. While the strong classifier is less sensitive than the weak classifier, the absolute value error of the diagnosis is significantly lower than that of the weak classifier. Therefore, it can be concluded that the diagnosis result of strong classifier is significantly stronger than that of weak classifier.

In addition, the number of A is 105 and the number of B is 68. The number of samples in the transition phase is 2095. Therefore, the obvious fault occur at 173 hours, and the warning of failure appeared in 69 hours.

4. CONCLUSION

AdaBoost algorithm is used to classify SOFC system faults, and decision tree is introduced into AdaBoost algorithm to realize the judgment and recognition of system faults, which greatly improves the automation and intelligence level of SOFC system fault diagnosis. Through experimental analysis, the intelligent fault diagnosis method has shorter classification time and higher classification accuracy. The novel fault diagnosis of SOFC system is effective. Through the Adaboost classification of the values of these three kinds of sampling points, we can obtain the time that the fault occurs, which is helpful to judge the fault accurately. In addition, there is a clear time division between the normal state and the fault state of the system, which helps to predict the fault and play a guiding role in the development of fault-tolerant control. The next work will be extended to online fault diagnosis based on offline work of this paper.

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