Fault Diagnosis of Tin Oxide Gas Sensor Using Energy Barrier and ART-2 Neural Network

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Abstract: We propose a method of fault diagnosis for tin oxide gas sensors using energy barriers at the contacting surfaces of the particles of tin oxide film and ART-2 NN (adaptive resonance theory 2 neural network) with uneven vigilance parameters. We diagnosed tin oxide gas sensors upon exposure to oil vapor, silicon vapor, and high humidity. The sensor feature for diagnosis was an energy barrier between particles extracted by temperature-simulated conductance measurement. The feature was manipulated by an ART-2 neural network and the performance was finally evaluated with real n-C_4H_{10} gas. This method proves to be helpful to diagnose a fault that was typically generated by oil vapor, silicon vapor, and high humidity.

Key words: Fault diagnosis, sensor fault, energy barrier, ART-2 neural network

1. Introduction

Reliability of the combustible gas alert system is one of the most important factors. The fault of tin oxide gas sensors fatally degrades reliability of the alert system. Unfortunately, tin oxide gas sensors have many possibilities of faults due to abnormal operating environments due to oil contamination, accidental electric shock, silicone sealants, and aging. Generally, fault diagnosis of commercial products would be conducted with standard gas sample off-line. Tin oxide gas sensors have been researched for several decades, but only a few works on the fault diagnosis have been reported [1].

Methods for FDI (fault detection and isolation) of the system fall into two major groups [2]: 1) model free methods, 2) model based methods. The model based FDI methods rely on the idea of analytic redundancy [3]. However, these methods are dependent on finding a system mathematical model that defines the relationship between the system input and output. In practice, however, the mathematical description of the relationship is not easy to obtain due to nonlinearities.

Model free methods include limit checking, expert systems and neural network-based schemes. In recent years, neural network models have been studied considerably for the optimum production and control strategy as problem-solving tools. Extensive research efforts have been devoted to the use of fault diagnosis problem [4-6]. It has been noted that neural network models consist of a suitable structure for representing the unknown nonlinear function generally. Hence this model can be used as a powerful tool for handling nonlinear problems. However, these methods are difficult to isolate new unencountered faults.

We propose herein a new method based on ART-2 NN and an energy barrier to diagnose tin oxide sensors applied to gas monitoring systems. To do this, we extracted an energy barrier between particles as a feature of the sensor and then use it as inputs of the ART-2 neural network with uneven vigilance parameters for fault isolation on-line.

2. Fabrication Process of Nano-Crystalline Tin Oxide Thin Film Sensor

Our tin oxide gas sensor was fabricated by thermal oxidation of Sn/Pt double layer. The method for high performance of Pt added SnO_2 thin film, was reported by previous research [7].

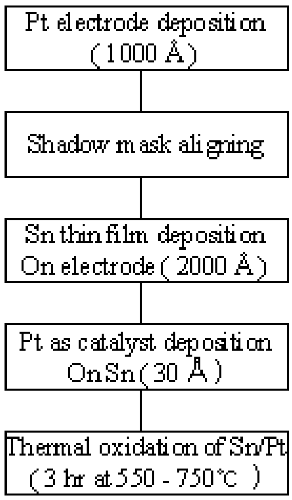
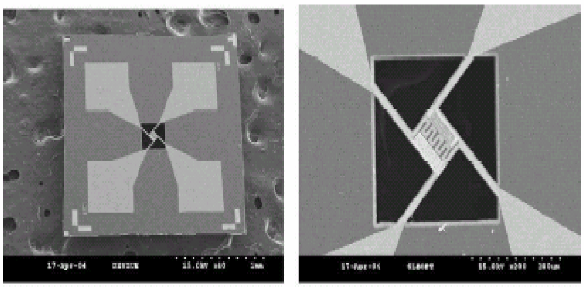


Figure 1. Flow charts for SnO_2 thin film preparation of Sn/Pt double layer oxidation.

Figure 1 shows key flow steps of a Pt-added tin oxide film prepared by thermal oxidation of Sn/Pt double layer. After the formation of 1000 Å-thick Pt electrodes on silicon micro hot plate, a 2000 Å-thick Sn film was deposited by thermal evaporation at room temperature followed by DC sputtering of 30 Å-thick Pt on the surface of Sn. Then, the double layer was oxidized at 700 for three hours in an O_2 environment. In the case of direct oxidation of the Sn/Pt multi layer, no extra Pt annealing process was required and would be much better to avoid damage of both the gas sensor and drive IC. Additionally, when compared to the conventional method, the Sn/Pt thermal oxidation method simplified the fabrication process much more by subsequent deposition and oxidation of the Sn and Pt layers, resulting in an automatic incorporation of Pt within the SnO_2 thin film.

Figure 2 shows a device fabricated on silicone micro hot plate. The detail structure was mentioned by a previous report [8].



(a) (b)

Figure 2. Device photographs of the fabricated on silicone micro hot plate

3. ART2 NN-Baesd Sensor Fault Diagnosis

Our proposed fault diagnosis method consists of data preprocessing stage by energy barrier calculation and fault classifier by an ART2 NN as shown in Figure 3. The data preprocessing stage is very important to improve the performance of the fault diagnosis. An energy barrier between particles is extracted as parameter to diagnose through pre-processing, and an ART-2 NN with uneven vigilance parameters is used for fault isolation.

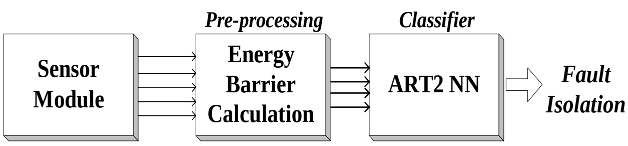


Figure3. Structure of the proposed ART2 NN-based sensor fault diagnosis method.

A. Measuring Instruments and System

The characteristics of the sensors were tested in the flowing of n-C_4H_{10} gas at the range of operating temperature, 240 to 380 .

Figure 4 shows the flow system for gas measuring. Three mass flow controllers (MFCs) are used and a dry air and a wet air are used as a carrier gas. And the flow rate of MFCs are calibrated using the gas flow meter. The electric circuit for the measurement of gas sensitivity was designed as follows: a dropping resistor (R_L) was connected in series with the sensing film along with a DC voltage supplier (Vcc) and an interfaced PC recorded the value of the output voltage (V_L) across the dropping resistor. When the voltage drop (V_L) across the dropping resistor was measured, the resistance (R_s) of a sensing film was calculated using a simple relation,

$$R_{sg} = \left(\frac{V_{CC} - V_{Lg}}{V_{Lg}} \right) \times R_L \quad (1)$$

$$R_{sa} = \left(\frac{V_{CC} - V_{La}}{V_{La}} \right) \times R_L \quad (2)$$

where R_{sa} and R_{sg} are the sensor resistances in air and in the presence of the tested gas, respectively. The sensitivity (S) of the samples to tested gas is defined as

$$S\,[\%] = \left(\frac{R_{sa} - R_{sg}}{R_{sa}} \right) \times 100 \quad (3)$$

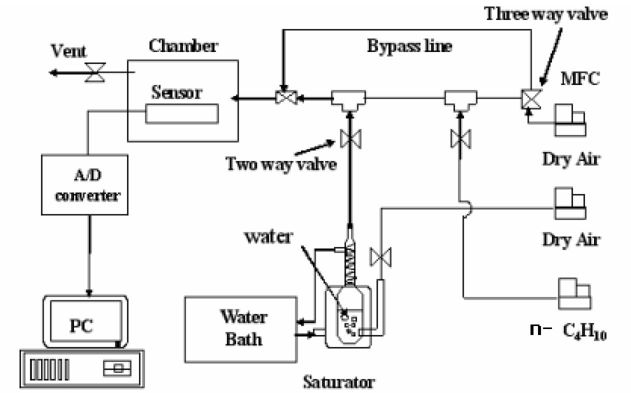


Figure 4. Schematic diagram for the automatic analysis system of gas sensor.

We conducted fault experiments of gas sensors for the following three fault types :

1) Type 1: Contaminated with cooking oil vapor
2) Type 2 : Induced by gas of silicone sealants
3) Type 3 : Exposed to humidity

Type 1: The oil in beaker is heated on a hot plate and is evaporated to the sensor as shown in figure 5(a). The sensor is exposed to evaporating oil stain for 60 minutes. After the sensor is exposed to cooking oil stain, sensitivity of the sensor drops and finally the sensor is not operating well. Additionally, we get a pattern of data from the condition of the air.

Type 2: A fault is induced by gas of silicone sealants (Figure 5(b)). Silicone sealants are well known as a major cause of fault. The sensor is stored at atmosphere of silicone sealant for 100 hours. After the sensor is exposed to gas of silicone sealant, sensitivity of the sensor drops and finally the sensor is not operating well. Additionally, we get a pattern of data from the condition of the air.

(a)

(b) (c)

Figure 5. Fault induction procedures

Type 3: The sensor is exposed to high humidity, which can affect operation of semiconductor gas sensor. After the sensor is exposed to hot vapor for 60 minutes, we get a pattern of data as same method (Figure 5(c)).

We repeated the above experiments until they resulted in breaking down. We assumed a single fault, which generated one sensor fault at that time.

B. Procedure of Extraction of Energy Barrier

We extracted an energy barrier on the basis of the barrier theory proposed by Clifford and Tuma [9]. According to Morrison equation, conductance of tin oxide film is very sensitive to the energy barrier eVs, which is related to the absorbed oxygen ions. Equation (4) shows Morrison equation [10].

$$G = G_o \exp[-eV_s / kT] \tag{4}$$

The energy barrier height versus temperature was extracted using temperature-stimulated conductance measurement [11]. The equation to extract energy barrier is as follows:

$$\ln\left(\frac{G_n}{G_i}\right) = -\frac{eV_s}{k}\left(\frac{1}{T_n} - \frac{1}{T_i}\right) \tag{5}$$

where Gi is the value of conductance at temperature (Ti) , Gn is conductance at temperature, Tn, but at the energy barrier of Ti. We calculated energy barrier eVs with Gn and Gi measured at Tn and Ti, respectively.

C. ART2 NN with Uneven Vigilance Parameters

In the proposed method, the ART2 NN with uneven vigilance parameters isolates the sensor faults using energy barrier. Architecture of the ART2 NN is shown in Figure 6. The ART2 NN with uneven vigilance parameters [12] has the same architecture of the general ART2 NN [13]. But, in the proposed network new vigilance test is used to classify the input patterns.

The distance between the input patterns and j-th output node (fault class) is computed as follows:

$$\begin{aligned} d_j &= \left\| W_j - X \right\|_\infty^E \\ &\triangleq \max_i \left| \frac{1}{\varepsilon_i}(w_{ij} - x_i) \right|, \quad j = 1, 2, \cdots, M \end{aligned} \tag{6}$$

where x_i is the input of the input node *i*, *i=1,2,…, N*, *N* is the number of input nodes, w_{ij} is the weight from output node j to input node, *M* is the number of the output nodes (created classes). And $\|\bullet\|_\infty^E$ is the weighted infinite norm, $E = diag(\frac{1}{\varepsilon_1}, \frac{1}{\varepsilon_2}, \cdots \frac{1}{\varepsilon_N})$ is the $N \times N$ diagonal weighted matrix, ε_i is the i -th vigilance parameter for i -th input node. In order to improve the classification accuracy, the vigilance parameter for the parameter with a large magnitude variation is selected large. On the other hand, the vigilance parameter for the parameter with a large magnitude variation is selected small.

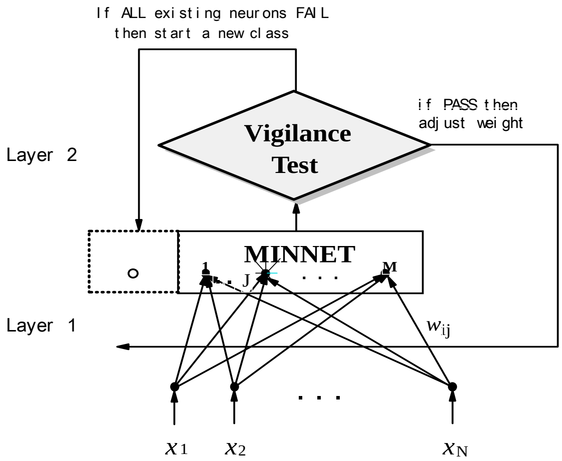


Figure 6. Architecture of the ART2 NN.

If the distance between the input patterns and the J -th output node (class) is minimum, then the class J is selected winner node. Verification is done whether input pattern X really belongs to the winner class J by performing the vigilance test as follows:

$$\textit{Vigilance test condition: } \left\| W_J - X \right\|_\infty^E < 1 \tag{7}$$

If the winner class J passes the vigilance test, adjust the weights of the class J , W_J by

$$W_J^{new} = \frac{X + W_J^{old}[class_J^{old}]}{[class_J^{old}] + 1} \tag{8}$$

where $[class_i]$ is the number of the patterns in the class i. On the other hand, if the class J fails the vigilance test, a new class (output node) is created with weight $W_{M+1} = X$.

4. Simulation Results and Discussion

Simulations are carried out to evaluate the performance of the ART2 NN-based sensor fault diagnosis system using real data obtained from the gas system. The data was collected from gas sensor and converted to digital signal patterns for fault isolation using 12bit-ADC module. We choose vigilance parameters of the ART2 NN as $\varepsilon = [0.04, 0.04, 0.1, 0.1]$.

To verify the proposed diagnosis algorithm, three types of sensor faults are introduced to the gas monitoring system at the 100-th sample number and measurement board for fault diagnosis experiment is shown in Figure 5. The faults that were introduced into the fault diagnosis experiment are summarized as follows:

Fault #1 : Contaminated with cooking oil vapor

Fault #2 : Induced by gas of silicone sealants

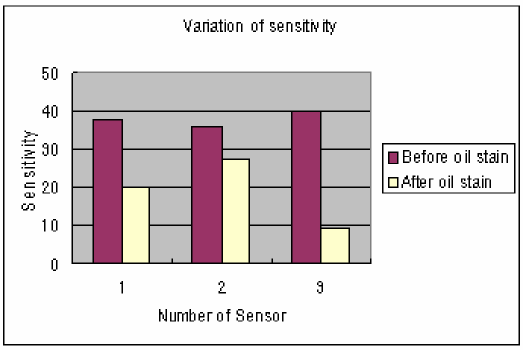
Fault #3 : Exposed to humidity

Table 1 lists the sensor energy barrier patterns for fault diagnosis. Figure 7(a), (b) and (c) show variations of gas sensitivity by fault #1, #2 and #3 respectively. The results show faults cause sensitivity to decrease.

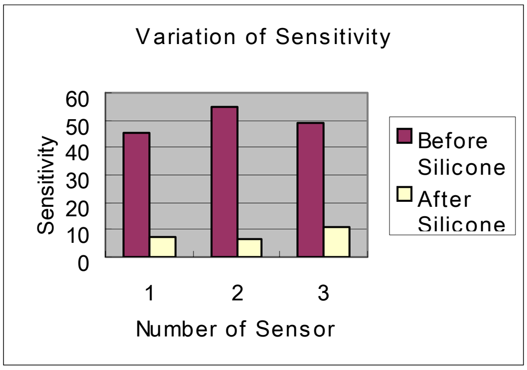
The simulation results for the fault #1, fault #2 and fault #3 are shown in Figure 8, Figure 9 and Figure 10 respectively. Figure 8 shows the output of the ART2 NN with uneven vigilance parameters. The simulation results showed that the proposed classifier successfully classifies the fault #1(P11) as new fault class 2. Also, Figure 9 and 10 show the results of fault isolation for new sensor fault #2(P21) and #3(P31) respectively. From the results, we can see that the ART2 NN creates a new fault class 3 (fault #2) and 4 (fault #3). ART2 NN with uneven vigilance parameters classifies the fault very well.

Table 1. Energy barrier patterns for fault diagnosis.

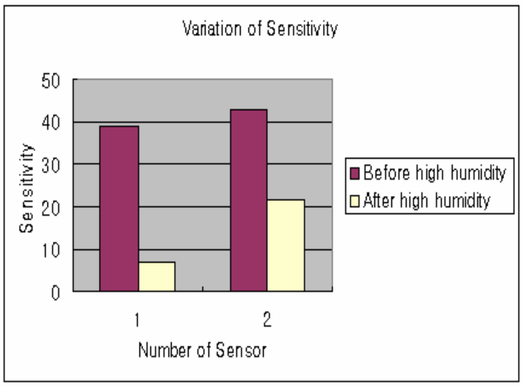
Fault	No. of patterns	Energy barrier patterns (ART2 NN inputs)
Normal	P01	0.162706977 0.06682311 0.079371199 0.012247735
Fault #1	P11	0.119768806 0.011592535 0.311628172 0.203503277
Fault #2	P21	0.085487755 0.010417576 0.659277323 0.345808442
Fault #3	P31	0.084133396 0.007053137 0.159576723 0.072001424



(a) Fault #1



(b) Fault #2



(c) Fault #3

Figure 7. Variations of sensitivity.

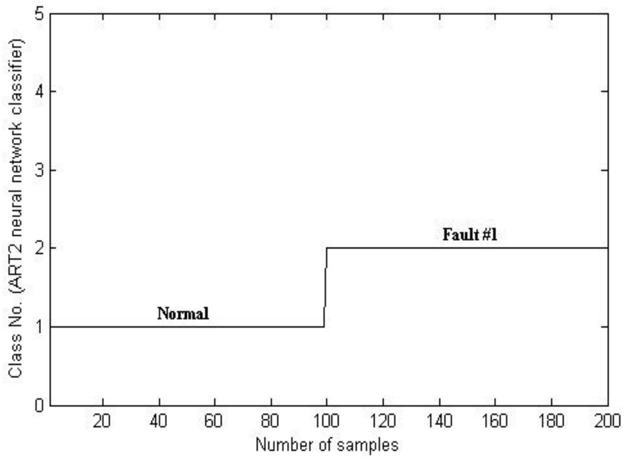


Figure 8. Result of fault diagnosis for fault #1.

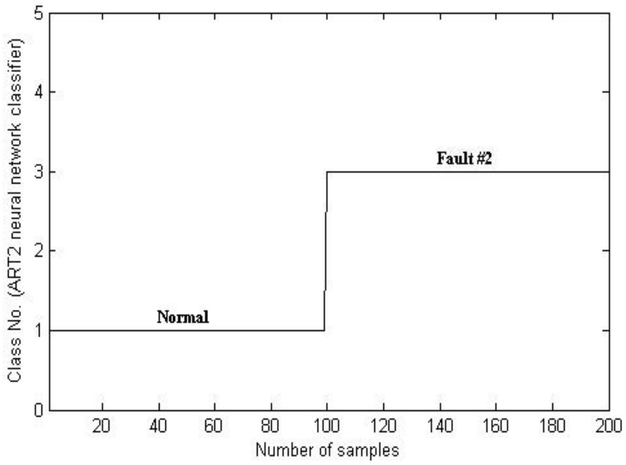


Figure 9. Result of fault diagnosis for fault #2.

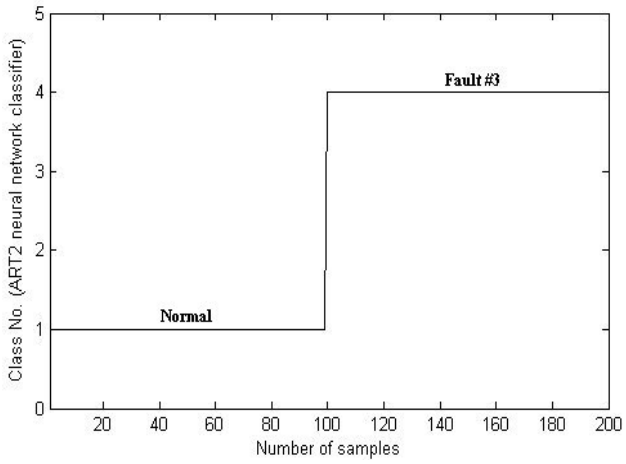


Figure 10. Result of fault diagnosis for fault #3.

5. Conclusions

In this paper, we propose an ART2 NN with uneven vigilance parameters based on a diagnostic method to determine sensor fault in gas monitoring system. In the proposed method the thermal modulation method [14] is used to extract the signal patterns from the voltage of load resistance, and energy barrier is used as parameter to diagnose. The proposed algorithm is based on ART2 NN with uneven vigilance parameters. Since the ART2 NN is an unsupervised NN it can adaptively learn and classify input patterns without a priori knowledge of classes. Therefore, the fault classifier does not require the knowledge of all possible faults to isolate the faults occurring in the system. From the simulation results using real data collected from a real system, it is verified that the proposed ART2 NN-based fault diagnosis method, was successfully applied to diagnose the problem in the gas monitoring system.

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