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Monitoring reliability of sensors in an array by neural networks

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Abstract

The correlation between the responses of five semiconductor thin films sensors to $CO-NO_2$ mixtures is exploited to detect a possible malfunctioning of one of the sensors during operation. To this end, at every time instant, the current flowing in each single sensor is estimated as a function of the current flowing in the remaining ones. With multiple linear regression, we obtain, in the case of the worst sensor, a regression coefficient of 0.89. The estimation is then accomplished using the regression ability of five artificial neural networks (ANN), one for each sensor, obtaining at worst a mean estimation error on the test set of 6×10^{-3} μA^2, the signal being of the order of the microampere (μA). In the case of a simulated transient malfunctioning, we show how it is possible to detect on-line which is the sensor that is not working properly. Further, after a fault has been detected, the estimation replaces the damaged sensor response. In this way, the concentration prediction — performed by other ANNs that need the responses of all the sensors — can proceed until the damaged sensor has been replaced.

Keywords: Fault detection; Error compensation; Neural networks; Thin films

1. Introduction

Sensor arrays together with pattern recognition techniques have been shown to distinguish between different gases, both individually [1–4] and in a mixture [5–8]. Moreover, even in the case of mixtures, it has been possible to predict the components' concentrations. A chief application of this capability is to environmental monitoring.

In the cited papers, it is assumed that sensors operate correctly. For on-line application of sensor arrays in real world problems, however, it is of great interest to be able to check whether sensors do function correctly (fault detection) and, in case of malfunctioning, to compensate this malfunctioning until the damaged sensor is substituted.

In Refs. [9,10], we compared two neural network based approaches to the estimation of NO_2 and CO concentrations in mixtures with humid air. By studying the prediction ability of a five-sensor array, we found out that the estimation error on the test set increased only slightly using four sensors (while the increase with three sensors was sensible). This is due to the correlation between the sensors (see Section 3.1).

In the present contribution, we show how the correlation between different sensors can be used for fault detection and compensation. In this way, in spite of trying to minimize the number of sensors for prediction purposes by eliminating, e.g., sensors that have a low (or equal) loading on the first principal components, we exploit the redundancy present in the different responses. The technique we propose exploits the concept of a virtual sensor (see e.g., Ref. [11]) with the aim of increasing the system reliability. To our knowledge no similar approach has been proposed in the chemical sensor field.

The structure of the paper is as follows. In the next section, we give details on the sensors array and on its characterization in the quantitative measurement of component concentration in a gas mixture. In Section 3.1, we analyze the correlation among sensors, and we show the characteristics of neural cross-estimators of their conductance. The system for reliability control of a sensor array

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based on these cross-estimators is presented in Section 3.2. Experimental results on our sensor array are presented and discussed in Section 4. Conclusions are drawn in Section 5.

2. Experimental

An array of five tin oxide thin films have been deposited through the RGTO technique over alumina substrates [12]. A Pt thin film was deposited on the back of the substrate as a heater and temperature sensor. In order to enhance the array selectivity, ultra-thin films of metal catalysts (Au and Pt) were deposited over the sensor surface. The change of conductance has been monitored by a volt–amperometric technique at constant bias [13]. The array conductance response to nitrogen dioxide (0.2, 0.6, 2, 4 ppm) and carbon monoxide (0, 25, 50, 100, 200 ppm) mixtures was examined. These values are close to the alarm levels for environmental protection in many European countries. During the characterization relative humidity was set to rh = 30% at $T = 20°C$. Two runs of measurements — each constituted by 20 different concentration mixtures — were completed in order to verify the reproducibility of the array performance. Moreover, since tin oxide sensitivity to NO_2 is enhanced at lower temperature while the sensitivity to CO is enhanced at higher temperature, the local operating temperature of two sensors was kept equal to 600 K (Pt, Au), while the others were operated at 700 K (bare, Pt, Au).

3. Method

3.1. Estimation of sensors output

We would like to correlate the sensor responses by estimating the functional dependencies (for every time instant):

$$i_A = f_A(i_D, i_E, i_G, i_H)$$
$$i_D = f_D(i_A, i_E, i_G, i_H)$$
$$i_E = f_E(i_A, i_D, i_G, i_H)$$
$$i_G = f_G(i_A, i_D, i_E, i_H)$$
$$i_H = f_H(i_A, i_D, i_E, i_G)$$

In order to evaluate the correlation among the sensors' conductance, we began by assuming a linear dependence. A multiple linear regression analysis shows that the multiple linear correlation coefficients are all greater than 0.89. We subsequently tried to estimate the real non-linear functional dependence with neural networks. In this application, we use the ability of MLPs to behave as universal function approximators [14].

Every neural network has four inputs, eight hidden neurons and one output neuron; the units of the hidden and output layers have a sigmoid-shaped activation function, while the input units do not perform any calculation. The training was performed by pattern using the standard back-propagation algorithm with learning rate $\eta = 0.1$ and a momentum term $\alpha = 0.9$. To avoid misleading effects due to the particular sequence of measurements, the presentation order of the patterns was randomized. The networks were trained using the first sequence of measurements as training set and the second one, which was obtained 2 days after the first, as test set. Although the gas mixtures are the same as in the first measurement series, the sensors' responses after 2 days present a temporal drift because the sensors had not been aged previously.

As shown in Table 1, the obtained current estimation is good for every sensor. In Fig. 1 we show in graphical form the high quality result obtained on the test set for sensor A. The predicted and the measured curves are very often superimposed on each other. Similarly, in Fig. 2 the result for sensor H is shown as the scatter plot of the pairs (predicted current, measured current): this shows that the approximation is very good, because all the points lay very near to the ideal case represented by the function $y = x$, with a small variance and no noticeable bias.

3.2. Modular MLP system

The result in the preceding section suggests a viable approach to monitoring the working state and to detecting possible malfunctioning of sensors. This can be done by using five MLP networks, each of them estimating the current flowing in one sensor as non-linear function of the currents flowing in the other ones at the same time. As sketched in Fig. 3, each estimator has four inputs and one output; e.g., Estim A has D, E, G, H as inputs and estimates the current flowing in A.

In order to control the reliability of the array of sensors we can continuously compare the current flowing in each sensor (Fig. 3, left) and its estimate provided by the neural networks array (Fig. 3, right) with appropriate testing units (Fig. 3, bottom). In these units we can implement various criteria in order to detect different kind of faults. For example, by simply considering the difference between predicted output and actual output (estimation error) as a signature of the correct working state of sensors, we can

Table 1
Mean error of neural estimators (μA^2)

Sensor	Training set	Test set
A	8×10^{-5}	1×10^{-4}
D	4×10^{-3}	6×10^{-3}
E	1×10^{-5}	4×10^{-5}
G	6×10^{-4}	4×10^{-4}
H	2×10^{-4}	6×10^{-4}

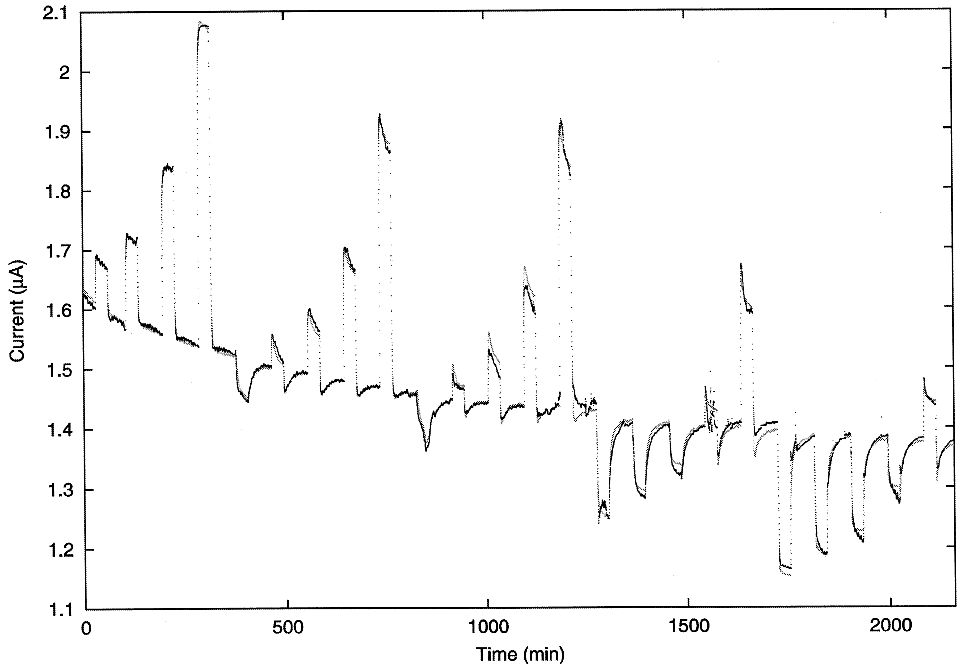

Fig. 1. Sensor A: Temporal plot of measured (gray) and estimated currents (black) for the test set (sensor A).

detect transient faults. Further, long time drifts can be detected checking if the estimation errors are normal distributed.

4. Simulation and discussion

We show now the effect of a simulated transient malfunctioning in sensor H obtained by changing the measured current at three time points (see Fig. 4).

As a first step of the fault detection algorithm, using the already trained MLPs, we compute

$$\hat{i}_A = \hat{f}_A(i_D, i_E, i_G, i_H)$$
$$\hat{i}_D = \hat{f}_D(i_A, i_E, i_G, i_H)$$
$$\hat{i}_E = \hat{f}_E(i_A, i_D, i_G, i_H)$$
$$\hat{i}_G = \hat{f}_G(i_A, i_D, i_E, i_H)$$
$$\hat{i}_H = \hat{f}_H(i_A, i_D, i_E, i_G)$$

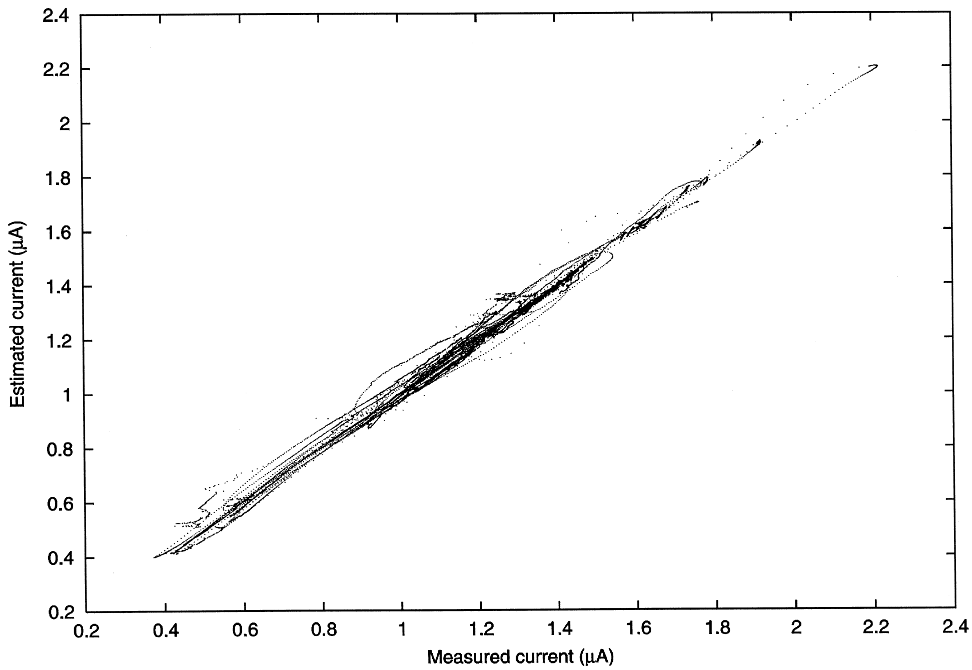

Fig. 2. Sensor H: Scatter of measured and estimated currents for the test set (sensor H).

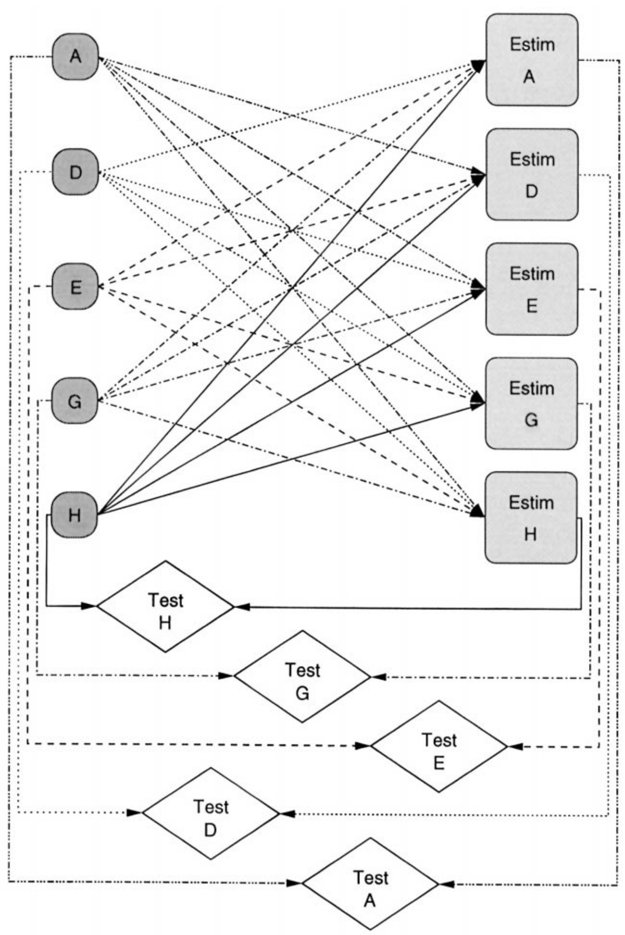

Fig. 3. Scheme of the MLP-based reliability control system.

where i_A, i_D, i_G, i_E and i_H are the measured values of the currents and $\hat{i}_A$, $\hat{i}_D$, $\hat{i}_G$, $\hat{i}_E$ and $\hat{i}_H$ the estimated ones.

Comparing i_A with $\hat{i}_A$, i_D with $\hat{i}_D$ and so on, we find unusual differences between the estimated and measured values at three points (Fig. 5). This behavior has two different sources:

- in cases A, D, E and G, the estimated output is incorrect because the input corresponding to sensor H is wrong;
- on the other hand, estimation H gives a correct value, that is a value that H would have if it worked correctly. The estimation error is unusually high due to the transient fault in i_H.

A priori all we can conclude is that (at least) one of the sensors is not working as expected, but we cannot yet say which one it is. To find out which is the malfunctioning sensor we adopt a simple strategy. We substitute one of the sensors in turn with its neural model: beginning with sensor A, we compute $\hat{i}_A = f_A(i_D, i_E, i_G, i_H)$ and then, using this value,

$$\hat{\hat{i}}_{D,A} = \hat{f}_D(\hat{i}_A, i_E, i_G, i_H)$$

$$\hat{\hat{i}}_{E,A} = \hat{f}_E(\hat{i}_A, i_D, i_G, i_H)$$

$$\hat{\hat{i}}_{G,A} = \hat{f}_G(\hat{i}_A, i_D, i_E, i_H)$$

$$\hat{\hat{i}}_{H,A} = \hat{f}_H(\hat{i}_A, i_D, i_E, i_G)$$

where e.g., $\hat{\hat{i}}_{D,A}$ means the prediction for sensor D obtained by replacing i_A with $\hat{i}_A$ as inputs of $\hat{f}_D$.

The errors $\hat{i} - i$ do not change significantly with respect to $\hat{i} - i$ until we substitute H with its model. Think for example at the prediction of the output of the sensor D: the

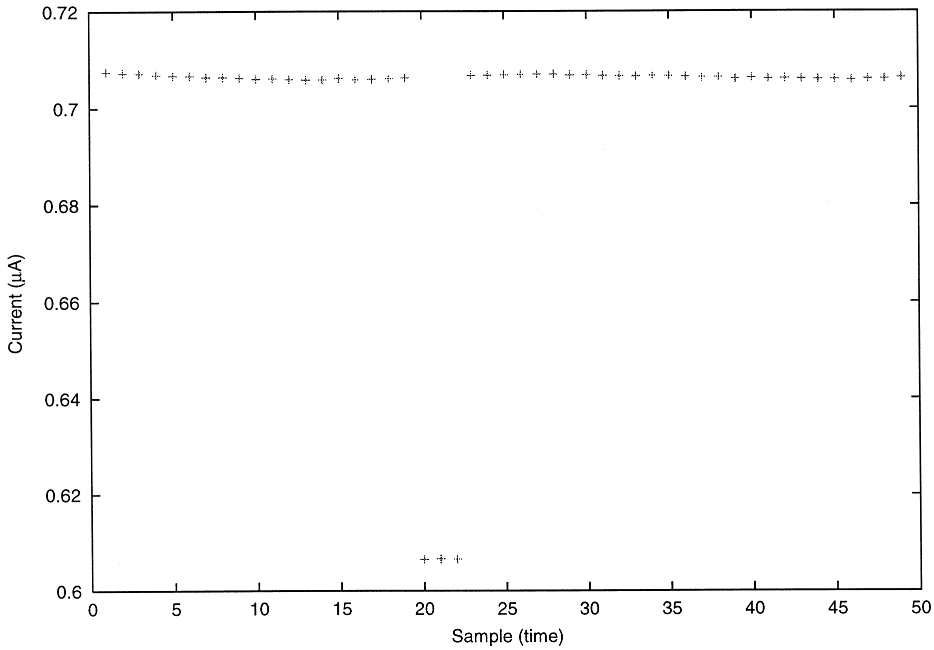

Fig. 4. The simulated malfunctioning of sensor H (points 19, 20, 21).

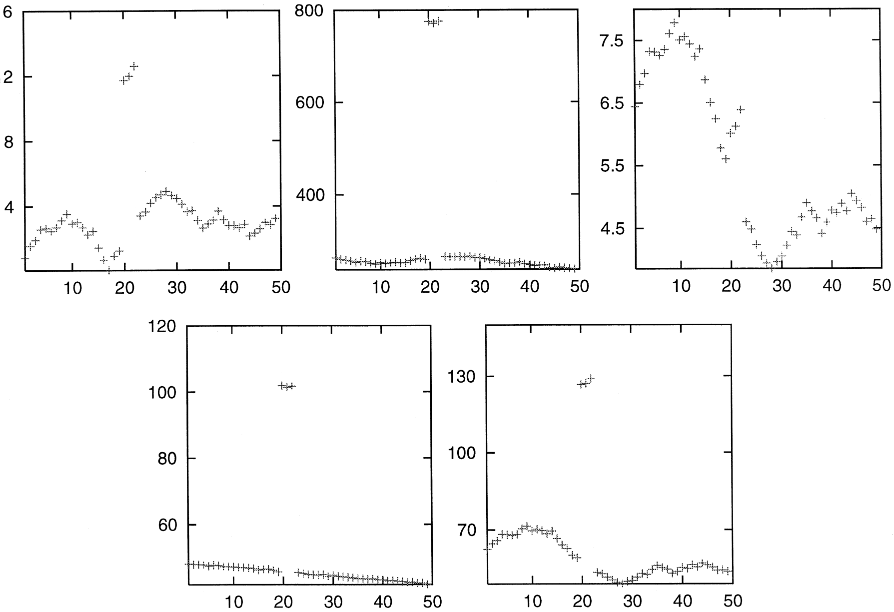

Fig. 5. Differences in nanoampere (nA) between the measured and estimated current. From top left clockwise: $|i_A - \hat{i}_A|$, $|i_D - \hat{i}_D|$, $|i_E - \hat{i}_E|$, $|i_H - \hat{i}_H|$, $|i_G - \hat{i}_G|$.

prediction for the current flowing in D is wrong both if only the input i_H (case $\hat{i}_D$) and if the inputs i_H and $\hat{i}_A$ are wrong (case $\hat{\hat{i}}_{D,A}$).

However, when we substitute H with its model the high estimation errors for the good working sensors A, D, E and G disappear (Fig. 6). This is because, e.g., $\hat{\hat{i}}_{D,H}$ now correctly estimates i_D because the input arguments of $\hat{\hat{i}}_{D,H}$ are all correct, including $\hat{i}_H$.

Having determined the malfunctioning sensor, the next step is to compensate for the error until the sensor is substituted. In fact, the neural network that had been previously trained for the prediction of the gas components' concentration needs five inputs and it surely will give wrong predictions if one input is incorrect. In our approach, we simply use the estimate $\hat{i}$ given by the other sensors to substitute the damaged one. Because of the sensors' correlation, in this way the concentration predictions are only slightly affected.

5. Conclusions

The proposed approach to reliability control exploits the strong correlation of the sensors' array conductance. It uses five MLP networks, each of them estimating the current flowing in one sensor as a non-linear function of the currents flowing in the other ones. For the worst estimated sensor we obtained a mean relative error on the test set of the order of 10^{-1}. In case a fault has been detected, the estimation replaces the response of the damaged sensor so that the subsequent phase of concentration prediction does not have to be interrupted.

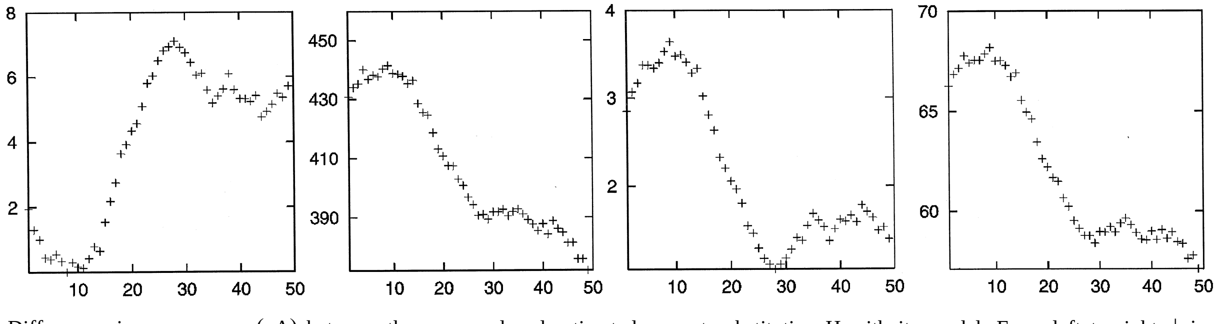

Fig. 6. Differences in nanoampere (nA) between the measured and estimated current substituting H with its model. From left to right: $|i_A - \hat{\hat{i}}_{A,H}|$, $|i_D - \hat{\hat{i}}_{D,H}|$, $|i_E - \hat{\hat{i}}_{E,H}|$, $|i_H - \hat{\hat{i}}_{G,H}|$.

On the basis of this neural cross-monitoring of the sensors' working state, various criteria can be implemented in order to detect different kind of faults. The reported experimental results are related to a transient fault detection by considering the actual estimated error levels as a signature of the correct working state of sensors. As a further application, long time drifts can be detected by checking whether the estimation errors are normal distributed.

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