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Dynamic response of a semiconductor gas sensor analysed with the help of fuzzy logic

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Abstract

Semiconductor gas sensors are essentially not selective to detect a single chemical species in a gaseous mixture and also the response of the sensor in most cases is influenced by the variations of ambient humidity and temperature. One of the solutions is the analysis of the dynamic response of a single sensor with modulated temperature. For the non-linear output signal the fast Fourier transform transform was calculated. The zero-order amplitude and the phases of higher harmonics were selected. These quantities served as input data for the fuzzy model of the sensor. The hybrid fuzzy sensor model, based essentially on Takagi-Sugeno-Kang (TSK) theory, comprised a two-level optimization algorithm. The authors elaborated that algorithm, utilizing conjugate gradient and genetic algorithm methods. At the output of the fuzzy model the concentrations of ethanol with minimized influence of humidity variations were obtained.

Keywords: Gas sensor; Tin oxide; Fuzzy logic

1. Introduction

Although semiconductor gas sensors are widely used, it is known that they are not selective to detect a single chemical species in a gaseous mixture. Moreover, the response of the sensor in most cases is influenced by the variations of ambient humidity and temperature. These problems are solved in different ways. One of them is based on the collection and processing of signals from arrays of partially selective sensors [1,2]. The selectivity and sensitivity of a sensor array can be greatly enhanced by developing various pattern recognition methods [3–5]. An alternative approach is the analysis of the dynamic response of a single sensor with modulated temperature [6–12]. In this case, one sensor is equivalent to an array of sensors working at different temperatures. The modulation in most cases consists in application of a pulse or sinusoidal signal to the sensor heater. The upper limit of modulation frequency depends on the sensor construction, mainly its dimensions (influencing the thermal capacity), and thermal isolation of the sensor. Sensitive layers deposited on micromachined substrates are the most promising structures [9,10,13,14]. For sensors with temperature modulated in a pulse mode the average power consumption decreases [15] and often their long-term stability improves [16].

The time dependent non-linear response of the sensor is related to the kinetics of gas molecules, i.e. adsorption, oxidation and desorption on the semiconductor surface, and is influenced by the chemical structure and concentration of the gas species. The procedure of feature extraction is usually performed by the standard method used in signal processing domain, i.e. by calculating the fast Fourier transform (FFT). Recently, wavelet analysis has been introduced to extract the features from the dynamic sensor signal [17,18].

The quantitative description of gas mixture composition using the a.m. feature extraction procedures is, however, a complicated task. Nakata et al. [19] by investigating the higher harmonics of the dynamic sensor response conclude that it is possible to determine the concentration of a gas sample in the presence of water vapour. Some authors develop neural network algorithms [2,9,20] or neural networks combined with fuzzy inference procedures [8] to perform quantitative analysis.

The authors investigated the dynamic response of the sensor consisting of ceramic LTCC structure and thin

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Fig. 1. Investigated sensor in a TO-5 package (without a cap).

SnO_2:Sb film, developing the advanced fuzzy model of the sensor for signal evaluation [21].

2. Experimental

The sensor structure suspended on thin Pt wires bonded to TO-5 header pins is shown in Fig. 1 [22]. The LTCC structure with buried heater played the role of a substrate for a sensitive layer. The small dimensions of the structure (4 mm in diameter and 0.2 mm in thickness) cause that the heat capacity of the sensor is low and hence the power consumption necessary for the adequate operation of the sensor is below 0.8 W. More details on the sensor design are given in [23]. Testing of the sensor in ethanol vapour under constant heater voltage (constant working temperature) indicates the significant influence of humidity variations on the sensor characteristics, Fig. 2. The sensitivity was defined as R_0/R_s, where R_s is the sensor resistance in a sample gas and R_0 is the sensor resistivity in air with 50% humidity. The influence of humidity on sensor resistivity, presumably caused by hydrogen atoms from the water molecule, reduces mostly the sensitivity in a certain ethanol concentration range. Generally that dependence is, however, not monotonic.

This non-linear influence restricts using of the sensor to a rather narrow humidity range. Its construction, however, made it possible to apply an alternate heater supply voltage resulting in an adequate temperature response, which enabled further elaboration of the sensor signal in view of minimization of humidity variations on the final measurement value.

By applying the sinusoidal voltage $u = 7 + 2.5 \cos 2\pi ft$ [V] where $f = 40$ mHz it was possible to obtain the sinusoidal variation of sensor temperature with the amplitude of order 100 °C, mainly due to the low heat capacity of the sensor structure. The measurement system and gas installation used in the experiment is presented in Fig. 3. As a reference for alcohol concentration a Figaro TGS2620 sensor was used. The variation of sensor temperature causes the change of kinetics of gas molecules (adsorption, desorption and oxidation) on the semiconductor surface. In effect the non-linear variations of investigated sensor resistance with time are observed (Fig. 4). The resistance values were sampled by an electrometer and recorded by the computer. Only the results for steady state conditions were taken into account. Ethanol concentration varied from 0 to 450 ppm with 30 ppm steps at selected air humidity. The measurements have been repeated for the following relative humidities: 10, 25, 50, 75 and 100%.

Gas sensor resistance values were sampled 32 times per one period of the heater voltage. Collected data contained actual values of sensor resistance, humidity and alcohol vapour concentration. During sampling the moments of alcohol concentration variation were localised. For each stage of computations a series of 128 measurements collected just before the concentration variation were selected. The starting point of the series was always at the same phase of the sinusoid.

3. Fuzzy model of the sensor

The fuzzy modelling technique consists of three stages. The first is the process of classification called *fuzzification*. The discrete values of input variables are changed to 'fuzzy value' and assigned to two or more 'fuzzy' sets. As a result one obtains for every input variable a statement, e.g.: value x_i *is element of set* A_i *in* 80% *and set* B_i *in* 25%. The second stage is data evaluation based on set of specially prepared rules. There are several models, which use different rules and methods of output evaluation. The widely known *linguistic model* (Mamdani) consists of rules of type: If

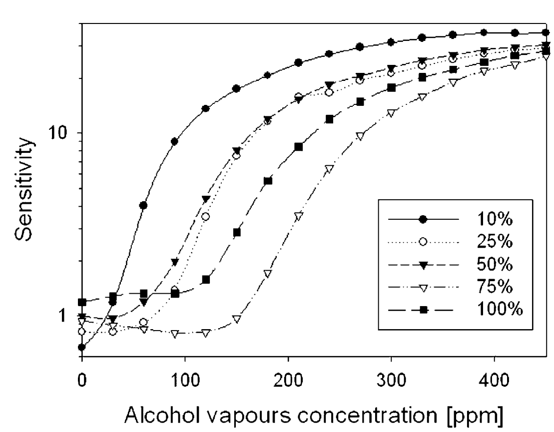

Fig. 2. Sensitivity upon ethanol concentration of investigated sensor with varying air humidity and for constant sensor working temperature.

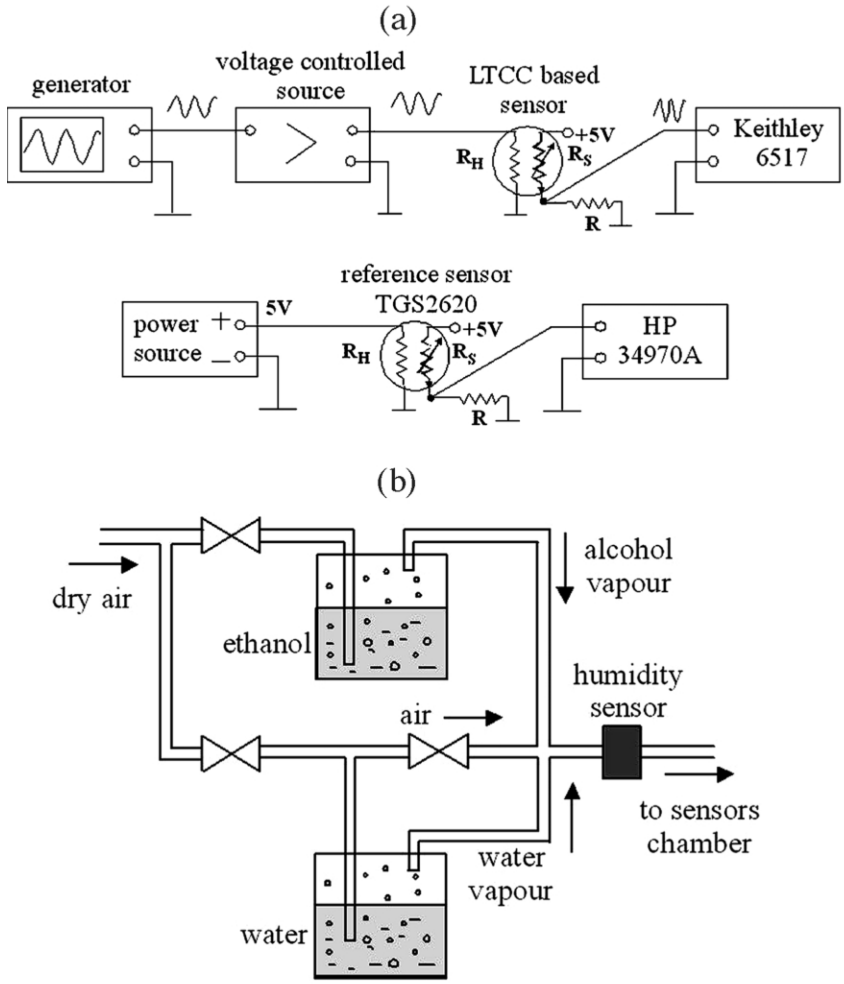

Fig. 3. The measurement system of sensor dynamic characteristics (a) and gas installation used in the experiment (b).

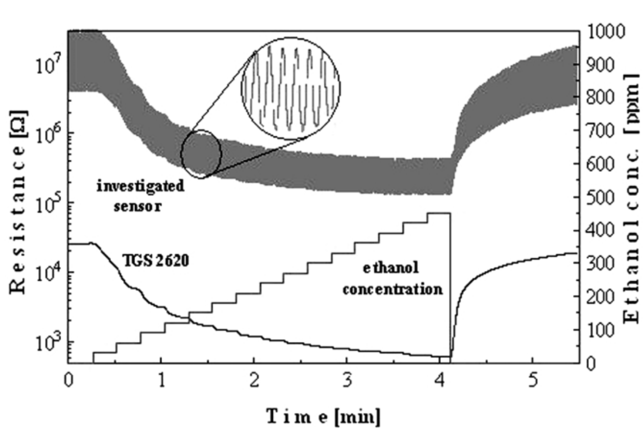

Fig. 4. Dynamic resistance vs. ethanol concentration at 10% humidity for investigated sensor in comparison to the characteristic of TGS 2620 sensor.

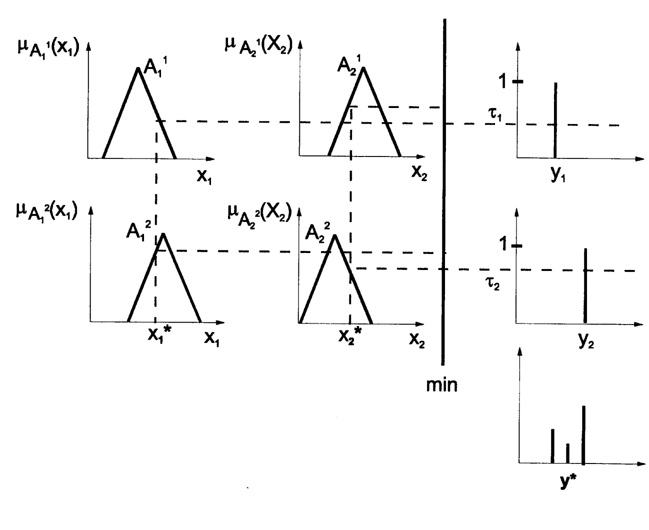

Fig. 5. An example of a TSK model for the case of two inputs x_1 and x_2.

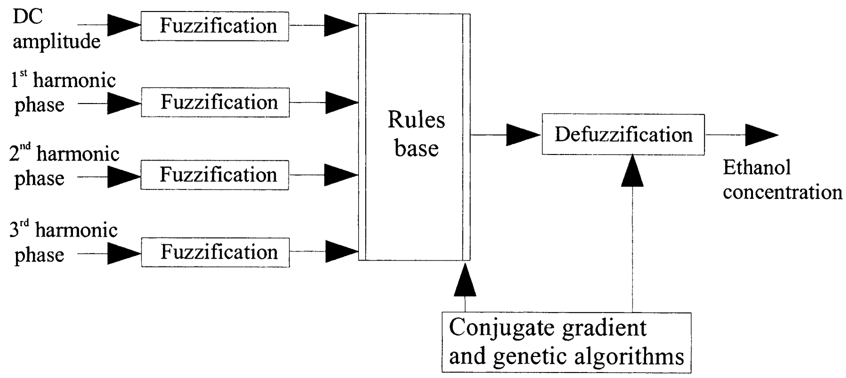

Fig. 6. The structure of hybrid fuzzy model of the investigated sensor. Genetic algorithm and conjugate gradient procedures are used in a two-level optimization of the model. Two fuzzy sets for each of four input variables give altogether 16 rules.

x_1 is small and x_2 is big then y is small. The outputs of all rules are then aggregated giving a combined fuzzy output, from which a discrete value is calculated by the procedure called *defuzzification.*

The model used in present work is based on Takagi-Sugeno-Kang (TSK) theory [24]. It combines some elements of linguistic models at the input with mathematical functions at the output and contains rules of the type: If x_1 is A_1 and x_2 is A_2 then $y = a_0 + a_{j1}\,x_1 + a_{j2}\,x_2$. The main idea of TSK theory is illustrated in Fig. 5, where x_1^* and x_2^* are the values of input variables x_1 and x_2. For these variables, we find degrees of membership to successive fuzzy sets, where $\mu_{A_1{}^1}(x_1)$ and $\mu_{A_1{}^2}(x_1)$ are the membership functions for the first input variable. Similarly, for the second variable x_2 we obtain membership functions $\mu_{A_2{}^1}(x_2)$ and $\mu_{A_2{}^2}(x_2)$. The values τ_1 and τ_2 are defined as degrees of activation of consecutive rules. In the described example τ_i is calculated as a minimum of membership functions values for every input variable. The rule condition is not always fulfilled in 100%, but usually the condition of more than one rule is fulfilled at least in a part. As a result we get two values y_1 and y_2. By *defuzzification* one obtains a discrete value y^*. That value is calculated as a weighted average of results of the successive rules, according to the formula:

$$y^* = \frac{\sum_{i=1}^{m} \tau_i y_i}{\sum_{i=1}^{m} \tau_i},$$

where τ_i are activation coefficients of the rules, y_j are output values generated by successive rules and i is the number of the rule. This method allows complicated functions to be approximated with just with a few simple rules. TSK models have the ability of limited extrapolation of training data, thus the process of building the model is easier in situation, where the set of training data is incomplete.

In real situations one uses many input variables and the TSK model complicates. In effect the hybrid fuzzy model of the sensor, comprising the two-level optimization algorithm, was elaborated [21,25], Fig. 6. The conjugate gradient and genetic algorithm methods were used for the optimisation of the model. The fuzzy model had two sets for each of four input variables. Every combination of input sets gave one rule leading to 16 rules in the used model. As a first training sample result of FFT transformation from averaged first two cycles was used. The second sample was prepared from cycles 3 and 4. For every pair 'humidity-ethanol concentration' we get two training samples, giving overall 160 training samples. Testing samples were obtained in a similar way with except that cycles 2 and 3 were selected.

4. Results and discussion

For all concentrations and humidities the FFT transforms of the output dynamic signal of the sensor were calculated. The zero-order amplitude and the phases of basic and higher order harmonics (40, 80 and 120 mHz) were selected for further considerations. The selected quantities served as input data for the fuzzy model of the sensor.

For training data a maximal error of the model was less than 20% of the full range and RMS error was lower than 5% of the range. For testing data points the RMS error was lower than 11.5% of the range. Calculated vs. real concentration of ethanol for input training data and for input testing data are shown in Fig. 7. The dependence between real and calculated concentrations is linear. The scattering of points is caused by both humidity variations and the errors introduced by the model.

5. Conclusions

The main goal of the work was elimination of the influence of humidity variations on the measurements of alcohol vapours concentration with a single semi-

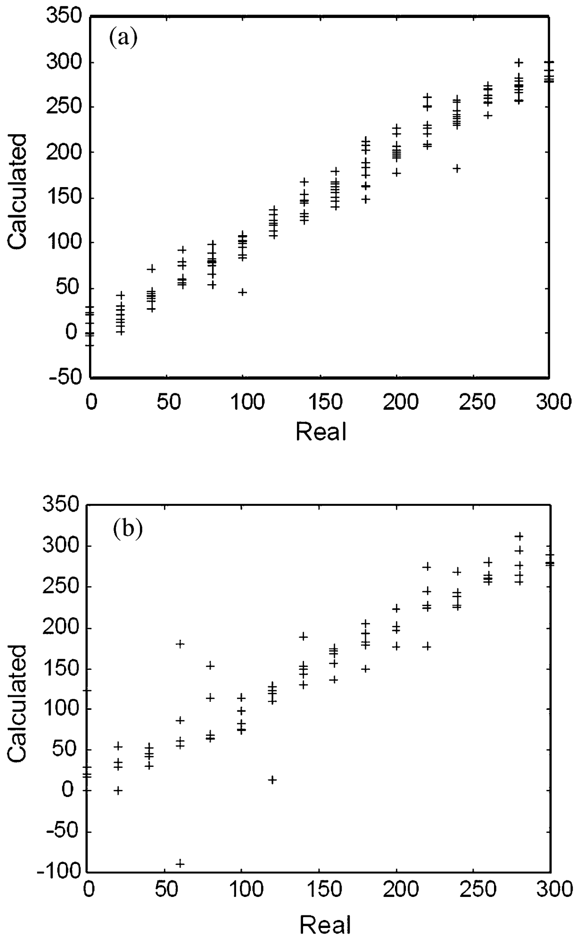

Fig. 7. Calculated vs. real concentration of ethanol (in ppm) for input training data (a) and for input testing data (b).

conductor sensor. Modulation of sensor temperature gives additional information (in our model zero-order amplitude and phases of three higher order harmonics of the FFT transform of non-linear sensor signal), which can be used as input data for the fuzzy model of the sensor. The developed fuzzy model utilizes the elements of TSK fuzzy theory in combination with optimisation algorithms enabling its tuning. The obtained results indicate that single semiconductor sensor with modulated heater temperature in connection with advanced signal processing techniques can lead to minimisation of the influence of undesirable factors.

Development of a sensor with lower heat capacity would allow for faster temperature modulation and possibly the influence of the dynamics of chemical reactions between investigated gas and semiconductor surface on the output signal could be more pronounced. To decrease errors introduced by the model, it is necessary to use large training data sets, collected in a wide range of humidity and gas concentration variations.

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References

[1] B. Yang, M.C. Carrota, G. Faglia, M. Ferroni, V. Guidi, G. Martinelli, G. Sberveglieri, Sens. Actuators B 43 (1997) 235.
[2] A. Szczurek, P.M. Szecówka, B.W. Licznerski, Sensors Actuators B 58 (1999) 427.
[3] K. Ihokura, J. Waston, The Stannic Oxide Gas Sensor – Principles and Applications, CRC Press, Boca Raton FL, 1994.
[4] A.C. Romain, J. Nicolas, V. Wiertz, J. Maternova, Ph. André, Sensors Actuators B 62 (2000) 73.
[5] S. Capone, M. Epifani, F. Quaranta, P. Siciliano, L. Vasanelli, Thin Solid Films 391 (2001) 314.
[6] W.M. Sears, K. Colbow, F. Consadori, Sensors Actuators B 19 (1989) 333.
[7] S. Nakata, S. Akakabe, M. Nakasuji, K. Yoshikawa, Anal. Chem. 68 (1996) 2067.
[8] B. Yea, T. Osaki, K. Sugakhara, R. Konishi, Sensors Actuators B41 (1997) 121.
[9] A. Heilig, N. Barsan, U. Weimar, M. Schweizer-Berberich, J.W. Gardner, W. Göpel, Sensors Actuators B43 (1997) 45.
[10] M. Jaelge, J. Wöllenstein, T. Meisinger, H. Bottner, G. Müller, T. Becker, C.Bv. Braunmuhl, Sensors Actuators B 57 (1999) 130.
[11] H. Kohler, J. Röber, N. Link, I. Bouzid, Sensors Actuators B61 (1999) 163.
[12] S. Nakata, K. Neya, K.K. Takemura, Thin Solid Films 391 (2001) 293.
[13] W.Y. Chung, J.W. Lim, D.D. Lee, N. Miura, N. Yamazoe, Sensors Actuators B64 (2000) 118.
[14] J. Cerdà, A. Cirera, A. Vilà, A. Cornet, J.R. Morante, Thin Solid Films 391 (2001) 265.
[15] G. Faglia, E. Comini, A. Cristalli, G. Sberveglieri, L. Dori, Sensors Actuators B55 (1999) 140.
[16] T. Nomura, Y. Fujimori, M. Kitora, Y. Matsuura, I. Aso, Sensors Actuators B52 (1998) 90.
[17] R. Ionescu, E. Llobet, Sensors Actuators B81 (2002) 289.
[18] E. Lobet, R. Ionescu, S. Al-Khalifa, J. Brezmes, X. Vilanova, N. Barsân, J.W. Gardner, IEEE Sensors J. 1 (2001) 207.
[19] S. Nakata, N. Ojima, Sensors Actuators B56 (1999) 79.
[20] S.J. Qin, Z.J. Wu, Sensors Actuators B80 (2001) 85.
[21] P. Potempa, Adaptation of fuzzy logic methods to the analysis of semiconductor gas sensors response, Ph.D. Thesis, University of Mining and Metallurgy, Cracow 2001 (in Polish).
[22] T. Pisarkiewicz, A. Sutor, W. Maziarz, H. Thust, T. Thelemann, Proceedings of the 24th International Conference Microelectron. Packaging Soc. – Europe, Prague June 18–20, 2000, 399.
[23] T. Pisarkiewicz, A. Sutor, P. Potempa, W. Maziarz, H. Thust, T. Thelemann (this volume).
[24] R.R. Yager, D.P. Filev, Essentials of Fuzzy Modeling and Control, John Wiley and Sons, New York, 1994.
[25] T. Pisarkiewicz, P. Potempa, Electron Technol. 33 (2000) 243.