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Correction of gas sensor dynamic errors by means of neural networks

Abstract

The paper presents a method based on artificial neural network (ANN) technique applied for correction of dynamic error of gas concentration measuring transducer. Its response time is about 8 minutes. The results obtained in the research of this transducer were used for learning and testing ANN, which were implemented in the dynamic correction task. The described method allowed for significant reduction of the transducer's response time – the output signal was practically fixed after a time equal to one sampling period of output signal provided that the stimulus is a step function. In addition, the use of ANN allows reducing the impact of the transducer dynamic non-linearity on the correction effectiveness.

Keywords: gas sensors, artificial neural networks, dynamic correction.

1. Introduction

The response time of gas sensors to a rapid change in gas concentration is usually quite long - from a few to several minutes. This is due to two reasons: the phenomenon of chemical adsorption in a sensitive layer occurs relatively slowly [1-4] and often additional filters and screens are used e.g. for separation of undesirable substances. In many measurement applications such a long time may be unacceptable for industrial and safety systems. The possibilities of shortening the response time by a suitable design of the sensor or applying better materials of sensing layer are still being examined [e.g. 5].

Shortening the response time of the transducer is also possible by the use of a correction procedure implemented by various methods in the next section of the measuring chain, as shown in Fig. 1. The sensor can be conventionally divided into two parts. The dynamic part corresponds to a slow adsorption (or desorption) of particles on the surface of the sensitive layer, including the possible permeation through the filter, if used. The static part represents changes of an electrical parameter (e.g. conductivity) of the layer as a result of molecules adsorption. The conditioning circuit produces an output signal u, which depends on the gas concentration. Supplementing the measuring chain with an algorithm of dynamic correction, allows to obtain a corrected output signal u_c, which value is fixed after a shorter time. Because the both mentioned parts of the sensor are generally non-linear (static and dynamic) [6, 7], then the correction algorithms should take this feature into account. In the case of only dynamic correction in some cases satisfactory results can give a correction based on a simplified linear model [7].

A method of dynamic correction based on neural network is discussed in this article. Research was carried out for gas concentration measuring transducer described in [8] with solid-state resistive sensor of a SnO_2 sensitive layer (type TGS2442 Figaro).

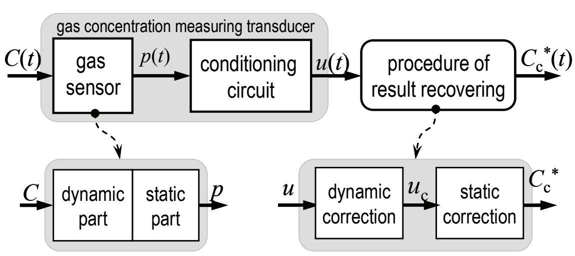


Fig. 1. Structure of the gas concentration transducer with dynamic and static correction

2. Investigation of the sensors dynamics

The analysis of dynamic properties of gas sensor, carried in a theoretical way or by a simulation method [2-4], has a significant cognitive meaning. However, in practice, it is necessary to introduce some measurement results to obtain numerical values of parameters of a model. In the case of gas sensors it is easy to perform by the step response method. Abrupt changes of the gas concentration may be obtained by rapid changes of the flow in the channel with respective constituent gases. The simplified scheme of system that was used in measurements is shown in Fig. 2. This system is more particularly described in [7].

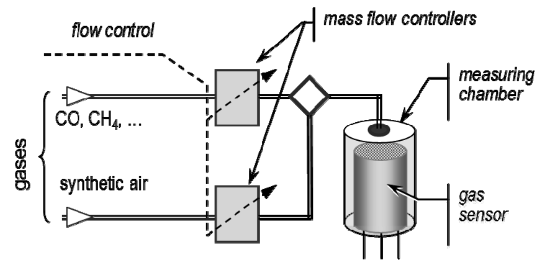


Fig. 2. Simplified diagram of the measuring system

During the tests the gas concentration was sequentially changed abruptly as shown in Fig. 3a. The resulting changes in the output signal u are shown in Fig. 3b.

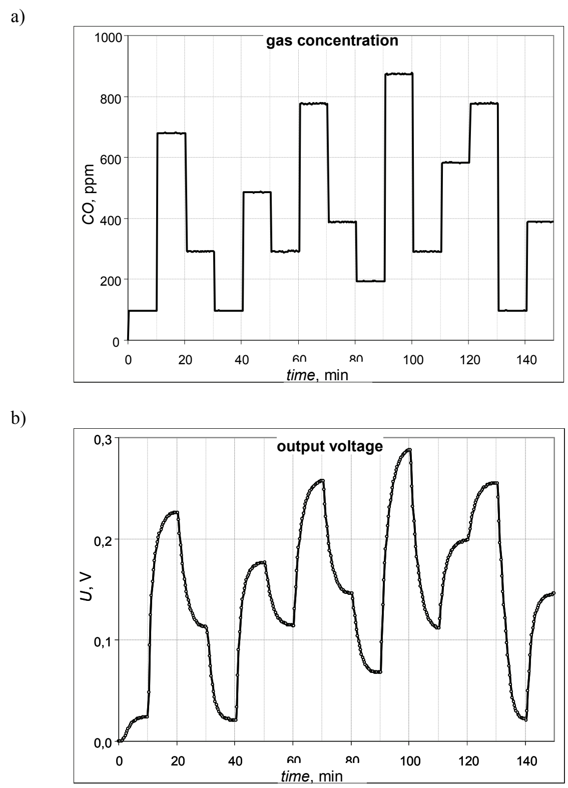


Fig. 3. a) Changes in the gas concentration, b) the corresponding changes of the transducer's output voltage

As it is visible the fixed value of output signal, corresponding to the actual constant value of gas concentration, is obtained after about ten minutes. A dynamic error of measurement may be define as: $e(t) = \hat{C}(t) - C = ku(t) - C$, where k is sensitivity of the transducer, and C is the constant value of gas concentration in particular phases. This error is a function of time and decreases to zero for the steady state. The time interval t_r from a step change in gas concentration, until the error $e(t_r)$ is less than 5% of the steady-state value, is called the response time of measuring transducer. For the investigated transducer time t_r is approximately 7-8 minutes.

3. Dynamic corrector based on artificial neural network

3.1. Correction based on dynamic model of sensor

In general, the dynamic properties of the transducers are often modeled by an n-th order linear or non-linear differential equation. The real-time dynamic correction algorithm can be achieved by numerical solving this equation due to the input quantity. The main disadvantage of such a dynamic correction algorithm is necessity to identify values of the coefficients of equation describing the dynamics model. Various methods for the identification of the dynamic model are developed in relation to the measuring transducers [e.g. 9, 10] . In the simplest case, the dynamic model of the transducer can be described by a linear first order differential equation [1, 7]:

$$T\frac{\mathrm{d}u(t)}{\mathrm{d}t} + u(t) = kC(t), \tag{1}$$

where T is called time constant, and k is sensitivity (gain) of transducer (for a linear static model).

The numerical algorithm for dynamic correction in real-time takes in this case the form [7, 9]:

$$u_c(n) = \frac{1}{\psi}\left[u(n) - \varphi u(n-1)\right], \tag{2}$$

where $u_c(n)$ represents corrected values of the voltage $u(t)$ (Fig.1) at the t_n moment of time, ($n = 0, 1, 2, \dots$) and

$$\varphi = \exp\left(-\frac{T_s}{T}\right), \qquad \psi = 1 - \exp\left(-\frac{T_s}{T}\right) = 1 - \varphi \tag{3}$$

T_s is the sampling period, T is the time constant of sensor.

As it can be seen, the designation of the coefficients φ and ψ requires the identification of parameters, in this case time constant T. This in turn requires a separate process of model identification. It can be difficult to implement a procedure, as it may be ineffective, time consuming and costly, especially for the higher order or nonlinear dynamic model of a sensor. An alternative in such situations is to use an artificial neural network (ANN) [11-14] which „performs" this type of identification in the learning process.

3.2. Neural network implementation of the real-time dynamic error correction

The equation (2) can be written in the form:

$$u_c(n) = w_1 u(n-1) + w_2 u(n). \tag{4}$$

where $w_1 = -\varphi/\psi$, and $w_2 = -1/\psi$ are the weighting factors of neuron of a simple structure shown in Fig. 4a.

In the idealized case, when the sensor is described precisely by a linear differential equation of first order (1), the corrected result is achieved after a time equal to one sampling period T_s.

For the practical verification of effectiveness of the dynamic correction implemented by a single linear neuron, the learning process was carried out. The results of the dynamic correction for the test data set are presented in the section 3.3.

As it was described in [7, 11], the linear dynamic model (1) is useful, but only as a simplified ("averaged") model. In order to take into account the dynamic non-linearity of the sensor, the neural network should be expanded by a hidden layer of neurons with sigmoidal transfer functions [15, 16]. During the research, ANNs were tested with the number of hidden neurons from 2 to 16, which has shown that in a given case four neurons in the hidden layer are sufficient, so the ANN has the 2-4-1 structure illustrated in Fig. 4b. Increasing the number of neurons in the hidden layer or increasing the number of layers did not results in a significant correction improvement.

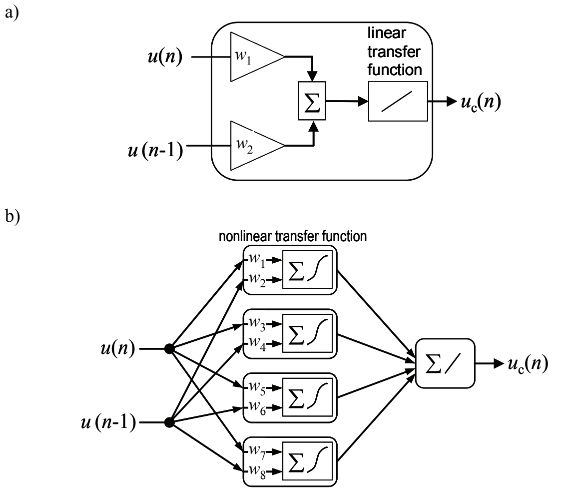


Fig. 4. Structures of ANNs realizing real-time dynamic error correction: a) linear neuron in the case of the sensor model described by first order linear differential equation (1), b) 2-4-1 structure of ANN which allows to take into account the non-linearity of the sensor's dynamic

3.3. Efficiency of the correction performed by ANN

Efficiency of the proposed correction methods was verified for sequence of step changes of gas concentration shown in Fig. 5. Both methods were compared taking into account three main aspects: the degree of shortening the response time, the impact of the sensor dynamic non-linearity and the impact of random errors.

Fig. 6 shows the results of dynamic correction implemented by a single linear neuron. There exist correction errors, resulting from the use of the simplified first order linear model to describe the dynamics of the sensor. For some phases of the test sequence overshoots occur, but in general the response time is shortened.

Furthermore, it can be noticed that random errors, resulting from the quantization process, are in this case increased by the correction algorithm. This component of dynamic error can be reduced in some degree by increasing the resolution of A/D converter and/or by decreasing the sampling period T_s. To verify this thesis further investigations should be conducted.

In turn, Fig. 7 illustrates the results of the dynamic correction implemented by the 2-4-1 ANN (Fig. 7b). It can be seen that the addition of a hidden layer improved the dynamic correction quality compared to a single linear neuron. However, the effect of random errors enhancing can still be seen.

To more detailed evaluation of effectiveness of the proposed dynamic correction methods, an dynamic error $e(t)$ has been defined as the difference between the voltage value $u_c(t)$ obtained as a result of the correction and the voltage value in a steady state, which corresponds to the measured gas concentration in the appropriate section of the test sequence. So calculated error values for the two described methods are shown in Fig. 6b and 7b, respectively.

a)

b)

c)

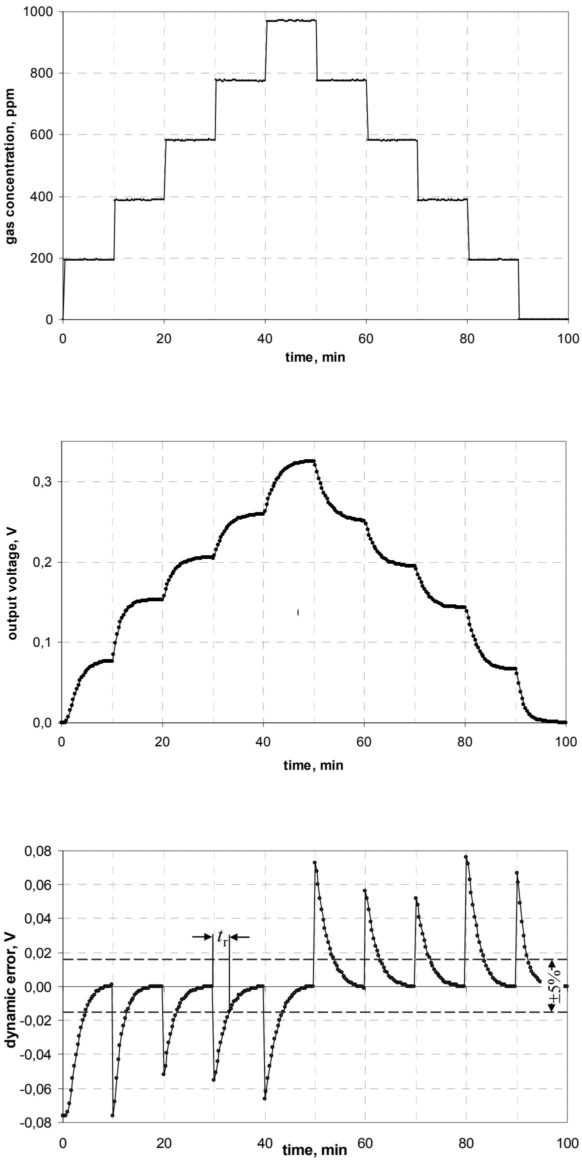
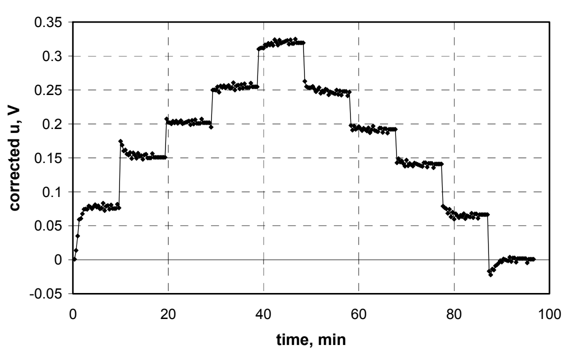


Fig. 5. a) The test sequence of step gas concentration changes used to verify the effectiveness of correction, b) the non-corrected output signal, c) the dynamic error

a)



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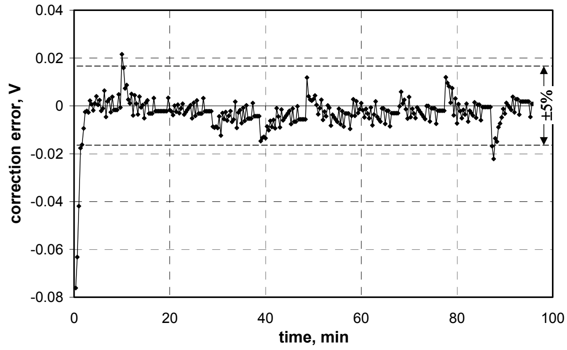

Fig. 6. Illustration of effectiveness of the real-time dynamic correction based on ANN with single linear neuron (Fig. 4a). a) The corrected output voltage u_c, b) and errors of correction

a)

b)

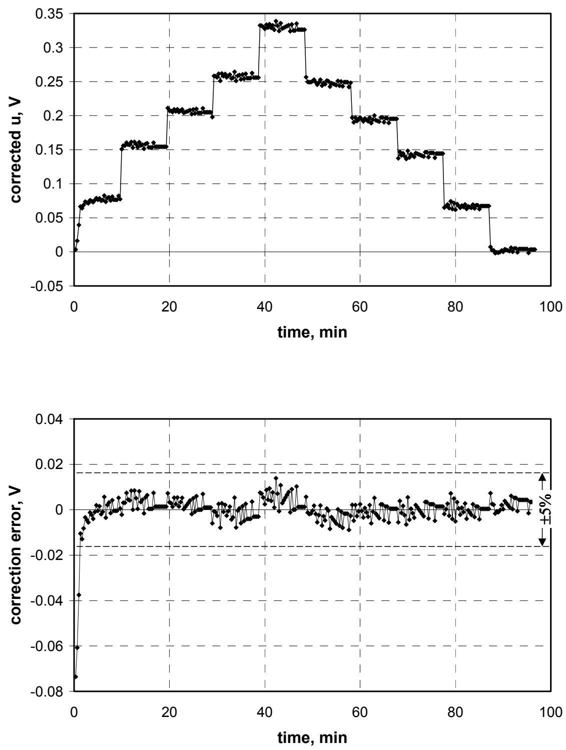

Fig. 7. Illustration of effectiveness of the real-time dynamic correction based on ANN with two layers nonlinear neurons (Fig. 4b). a) The corrected output voltage u_c, b) errors of correction

4. Conclusions

Despite the simplicity of the applied ANN, the dynamic correction algorithms based on them are very effective - the transducer response time is significantly reduced.

The transducer response time without correction is about 7-8 minutes. Both methods of dynamic correction allow shortening this time significantly. In the case of the simple structure 1, the response time does not exceeds 90 seconds, whereas in the case of structure 2, the time is equal to the sampling period (in the conducted studies: 20 seconds). The exception is the case when the concentration rise to very small values, for which the response time is more than twice as long.

As was stated above the structure 1 does not take into account the dynamic non-linearity of the sensor, due to the use of the average linear model. In this case, the degree of shortening the response time depends on the range of changes of the gas concentration and varies between 40 and 90 seconds. However, in the structure 2, the dynamic non-linearity of the sensor is, to some degree, taken into account by extending the network of hidden layer with non-linear transfer functions. The research showed that a simple 2-4-1 ANN structure allows obtaining a measurement result after time equal to the sampling period, independently of range of the concentration.

However, it should be noted that the neural real-time dynamic correction is more sensitive to the random errors of input data than the algorithm proposed in [8], which is based on dynamic model of sensor explicitly specified. In a situation when the corrected results contain random errors exceeding acceptable limit values, several actions can be taken to reduce them. The simplest way is to increase the resolution of the A/D converter. There may also be different smoothing algorithms used or the sampling period may be increased. But in both cases this leads to an extension of the time for obtaining the measurement result.

The application of ANN technique to the dynamic correction has some advantages. The most important of them is that it is not necessary to identify neither the dynamic model of the sensor nor calculation of the correction algorithm coefficients. This task is performed during the learning process of the neural network.

The verification of effectiveness of the analized correction method was based on the analysis of the step response. This allows for easy evaluation of the response time of the measuring transducer. The effectiveness of the correction for a different type of the time variation of the measured value was not examined in this case. However, studies carried out previously for other correction algorithm, described in [7], has shown that if the efficiency is confirmed by the step response method, the correction algorithm is effective for other time changes of measured value.

5. References

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