A SOLUTION FOR REDUCING THE TEMPERATURE AND HUMIDITY EFFECTS ON THE ACCURACY OF TGS 2602 SENSOR IN MEASURING NH_3 GAS CONCENTRATION

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Abstract: *This paper presents a solution using artificial neural networks to reduce the effects of the temperature and humidity of the environment on the results of the TGS2602 sensor in measuring NH_3 gas concentrations. The TGS2602 in particular and the MOX (Metal Oxide based sensors in general have high sensitivity, fast response, longer service life, wider operating temperature range, low cost, low power consumption but their main disadvantages are the strong affection by humidity level and the environmental temperature. This makes the problem of eliminating (or reducing) the influence factors very important. In this paper, a system with gas sensor, temperature and humidity sensors to measure the environmental conditions and MLP (Multi Layer Perceptron) networks to calibrate the sensor reading will be presented. The simulation results will show the accuracy of the proposed solution.*

Keywords*: TGS sensors, NH_3 gas concentrations, error correction effects, artificial neural network.*

Classification number**:** *2.2*

1. Introduction

Sensors always work in a particular environment. The parameters of the environment such as temperature, humidity, pressure, magnetic field or magnetic field of the large currents... can cause drifts in the measurement results. In some cases the drift may cause the sensor reading to change 4-5 times. Among the environmental factors, the temperature and humidity level have the most frequent affects on the sensor and the object [1, 2, 4]. This makes the problem of influence compensation of the temperature and humidity level on the sensor is very necessary. There are many domestic and foreign projects with different solutions [12] to eliminate the error of this factor. These are calibration solutions uses the [7, 11] filter, or uses the calibration method [1, 5, 6, 8, 9, 10, 13].

2. Study on the temperature and humidity influence on the measurement results of the gas sensor

2.1. Introduction to the TGS2602 sensor

FIRAGO's TGS2602 sensor is of the MOX (Metal Oxide) type and is based on the principle of conductivity changing due to the concentration of gas components. The sensor main material is the tin oxide (SnO_2) with low conductivity in clean air. When the sensor is powered, it will heat the spring wire wrapped inside the sensor, causing the surrounding gas to oscillate more rapidly, colliding with the SnO_2 membrane, thereby increasing the sensitivity of the sensor. The output of the sensor is based on the ration R_s/R_0, where R_s is the resistance of the sensor at the measuring time, R_0 is a nominal resistance of the sensor (measured at a specific, predefined environmental conditions and sample gas concentration). But for that reason, the output of the sensor depends on the temperature and humidity of the environment.

A typical characteristic curve of R_s/R_0 depending on gas concentration (measured in ppm – particle per mol) is given on Fig. 1 [15]. Usually, the MOX sensors are fast, high sensitive and with simple control circuits. But the disadvantages of these sensors are the dependencies on the ambient temperature and humidity, which can be seen on the Fig. 2, where typical drifts due to the temperature (from 10 to 50°C) and the humidity (at 2 levels 40%, 85%) are presented [15].

We can see that the temperature drift is very big, which may cause the ration R_s/R_0 changed from about 1.5 (at 10°C) to about 0.35 (at 50°C). The drift due to the humidity is smaller but in some cases, it could be still significant enough to cause the results unreliable.

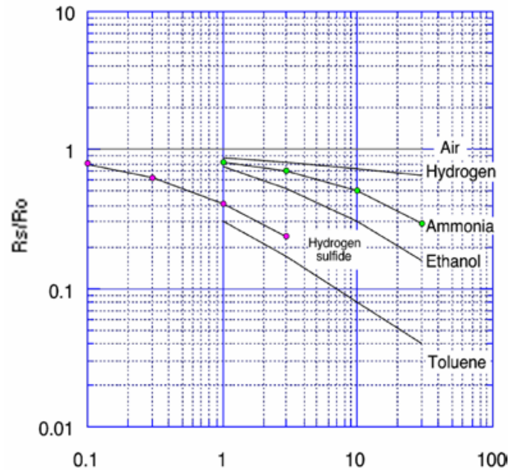


Figure 1. *The relative sensor resistance as the sensitivity characteristics [13].*

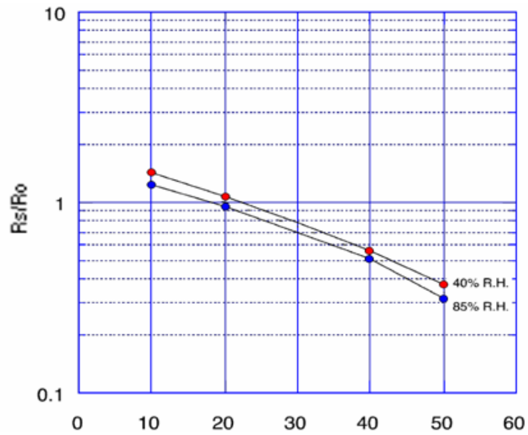


Figure 2. *The drifts due to temperature and humidity of the sensor [13]*

On fig. 3, 4 the drifts are presented in linear scales to have a bigger distances between the curves to help us better see the effects.

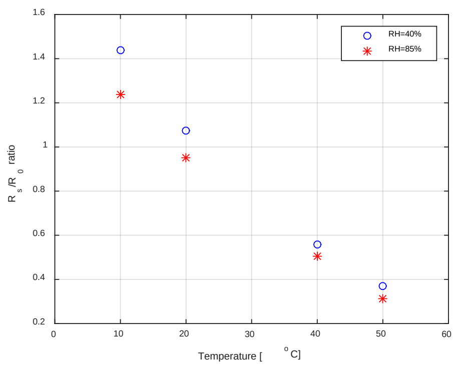


Figure 3. *The measured points from Fig.2 on linear scaled axis*

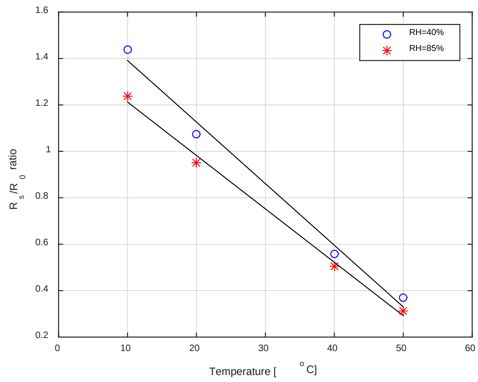


Figure 4. *The approximation of the points using least squared linear function*

2.2. Applied neural network compensates for errors caused by influencing factors

There were a number of solutions to reduce the effects of these drifts. Some producers install a temperature and humidity stabilizing circuits inside the sensors to make the working conditions more stable. But this solution requires the changes in production phase, which means the end-users cannot use them. The more frequent solutions used in practice is the application of various signal processing methods to compensate.

The classical methods include the linearization of the charateristic or the LUT (Look up Table) methods.

In this paper we propose the application of an artificial neural networks (ANN) in compensating the errors. The structural model is proposed as the figure below:

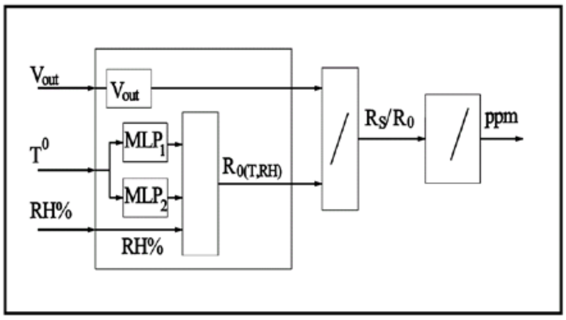


Figure 5. *The structural model is proposed.*

The general idea of temperature and humidity compensations in the sensors is following:

- Aproximation of the lower bound and the upper bound of the characteristics given in the datasheet:

• Propose a procedure to convert the output reading at an arbitrary temperature and humidity to the standardized one, in order to convert to the input ppm concentration:

For the 1st task, as in [3], we propose to use two MLP networks to perform the task, i.e.:

$$MLP_1(T^\circ) = f_{RH=40\%}(T^\circ);$$
$$MLP_2(T^\circ) = f_{RH=85\%}(T^\circ)$$

In this paper the MLP networks were trained with 4 characteristic points given on fig. 2. The Neural Network Toolbox in Matlab was used to perform the training task. The network has 1 input (for the temperature) and 1 output (for the ratio Rs/Ro). Since there are only 4 training samples, only 1 hidden layer with 1 neuron is needed. The results of using MLP networks to approximate the characteristics are presented on Fig. 6, where we can see a very good quality of approximation. The curves given by MLP networks are smooth, passing through exactly the measured points given in the datasheet. The MLPs are very simple, with just one input (the temperature), one output (corrected resistance ratio of the sensor) and 1 or 2 hidden neurons are enough for the approximation.

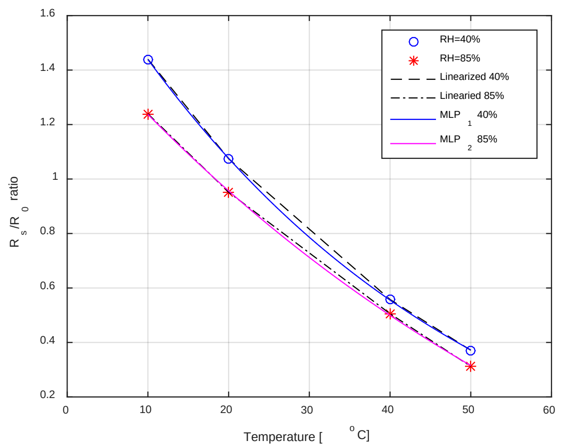


Figure 6. *The characteristic points and their approximations using piecewise linear functions and using MLP networks.*

For the 2nd task, the steps are described as follow:

1. When we have a gas mixture at concentration *X* ppm and the temperature is *T*°, the humidity level is *RH*%, the output voltage from the sensor's circuit is taken:

$$X\ ppm, T^\circ, RH\% \rightarrow V_{out}(X, T^\circ, RH\%)$$

2. From the sensor circuit, the sensor resistance is calculated from the output voltage with the formula [14] where $R_0 = 41,763k\Omega$:

$$R_s(X, T^\circ, RH\%) = \frac{100 - 20 \cdot V_{out}(X, T^\circ, RH\%)}{R_0 \cdot V_{out}(X, T^\circ, RH\%)} \quad (1)$$

3. From the characteristics on Fig. 2, we need to estimate the resistance of the sensor in fresh air at the same temperature and humidity values, it means $R_s(0, T^\circ, RH\%) \overset{def}{=} R_0(T^\circ, RH\%)$. This value we propose to calculate using the interpolation between the two curves for $RH_{low} = 40\%$ and $RH_{high} = 85\%$ on fig. 6. Theses curves are approximated using MLP networks as mentioned above.

$$R_0(T^\circ, RH\%) = \frac{MLP_2(T^\circ) - MLP_1(T^\circ)}{RH_{high} - RH_{low}}(RH\% - RH_{low}) + MLP_1(T^\circ) \quad (2)$$

4. With the values from steps 2 and 3, we calculate the sensor's resistance ratio.

$$\frac{R_s}{R_0}(X) = \frac{R_s(X, T^\circ, RH\%)}{R_0(T^\circ, RH\%)} \quad (3)$$

5. From the curve in Fig. 1, the ppm is estimated back:

$$\frac{R_s}{R_0}(X) \rightarrow X \quad (4)$$

From this we have the error compensation system consists of three inputs (V_{out}, T°, RH%). In the compensation system, two MLPs are responsible for estimating the characteristics of the temperature drifts for lower and upper levels of RH%.

The output of the system is the estimated ppm level of the gas component corrected for the given temperature and humidity level.

As the simulation test, we define a list of cases, where the gas concentration is the same, but the temperature and the humidity level varies. The cases are:

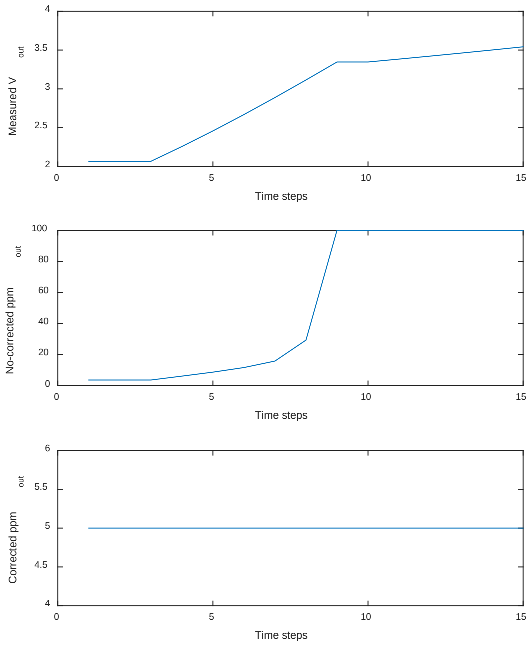
• Case 1 (and 2): Same gas, same environmental condition (the standard 20°C, 35%);

• Case 3, 4,..., 9: Same gas, same humidity

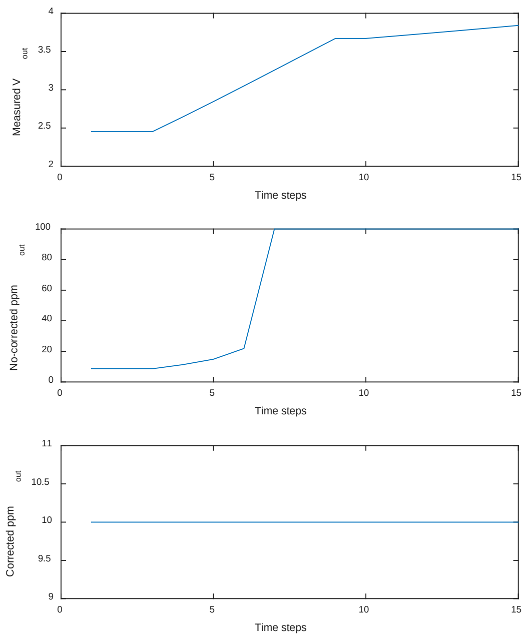
(35%), temperature increased from 20 to $50^{o}C$ (step $5^{o}C$);

• Case 10, 11,..., 15: same gas, same temperature (50oC), humidity increased from 35% to 85% (step 10% RH).

2.3. Simulation results



a)



b)

Figure 7. *The performace of the calibration method for different gas concentrations: (a) 5ppm, (b) 10ppm*

The simulation results are shown on Fig. 7, where on the left (Fig. 7a) are the results for a gas concentration of 5ppm, and on the right (Fig. 7b) are the results for a gas concentration of 10ppm. On the first row are the values of output voltage from the measuring circuit. We can see that at the same gas concentration when temperature and humidity levels are changed, the output voltage varies also. The variation range could be very big (from ~2V to 3.5V for 5ppm, from 2.5V to 3.8V for 10ppm). This will cause also big variations on the calculated ppm if no calibration procedure is performed (as we can see in the middle row). When the calibration process describe in subsection 2.2 (Fig. 5) is applied, the output is stabilized at the correct level as can be seen on the last row of the Fig. 7. This proves the quality of proposed solution.

3. Conclusions

In this paper, a solution using MLP neural networks to approximate the characteristic dependencies on temperature and humidity of a gas sensor was proposed. Base on those functions, a procedure to calibrate the sensor reading based on the temperature and humidity level informations was presented.

The simulation results showed that the quality of the method is very good. The MLPs are very simple (one input, 1-2 hidden neurons, one output) so the implementation of them on portable devices should be quite easy. This promises to have a practical application of the solution❑

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