STUDY OF A COPPER CAPACITIVE MEMS AS A SENSOR FOR AUTOMOTIVE FUEL EVALUATION

Lucas G. Dias Mendonça, lucas.mendonca@usp.br
Bruno Barazani, bruno.bara@usp.br
Bruno Butilhão Chaves, bruno.chaves@usp.br
Delson Torikai, delson.torikai@poli.usp.br
Ricardo Curi Ibrahim, rci@usp.br
Escola Politécnica da Universidade de São Paulo, Av. Prof. Mello Moraes, 2231

Maria Helena de Oliveira Piazzeta, nena@lnls.br
Angelo Luiz Gobbi, gobbi@lnls.br
Rua Giuseppe Máximo Scolfaro, 10.000 Pólo II de Alta Tecnologia - Campinas – SP

Teo Susnjak, teo.susnjak.1@uni.massey.ac.nz
Andre L. C. Barczak, a.l.barczak@massey.ac.nz
Massey University, Private Bag 102904, North Shore City, Auckland – New Zealand

Abstract. *In this work we report the study of a copper capacitive MEMS (Micro-Electro-Mechanical Systems) as a sensor to analyze the quality of automotive fuel such as hydrated ethanol and gasoline used in Brazil. Fuel adulteration is a frequent problem in some countries, including Brazil. The standard Brazilian gasoline ranges from 20 to 25% of dehydrated ethanol in its composition to improve octane rating of the fuel. The most common adulteration for gasoline is the ethanol over-rated concentration. Ethanol fuel has been used in large scale with small amount of water (6.2 to 7.4% m/m) as an alternative to gasoline. In this case, the typical adulteration is over-rated water, usually non-distilled water that causes many problems to the engine. The proposed microsensor has interdigitated electrodes format and its capacitance changes when it is submerged in different dielectric fluids making it capable of detecting adulterated fuel. Printed circuit boards covered with copper were used as the base material, and the electrodes were obtained by etching the copper layer. The gap between sensors electrodes has dimensions around 100µm. Another interdigitated MEMS sensor with Nickel electrodes was also been used in the measurements for comparisson. Three different prepared fuel mixtures were measured by the microsensor with temperatures ranging from 5°C up to 25°C. To improve the data analysis, an artificial intelligence algorithm, called AdaBoost, that is famous for its flexibility and simple implementation, was employed. The data obtained from the sensors was used to calibrate the AdaBoost algorithm which was applied to classify unknown fuel mixtures. The system showed good performance in the detection of adulterated and non-adulterated ethanol fuel samples in relation to distillation or water addition, with sensitivity of the order of 1% in the values of alcoholic concentration. The results show that the use of artificial intelligence combined with sensors was accurate and efficient for the analysis of ethanol fuel. The method can also be applied to Brazilian type C gasoline.*

Keywords*: MEMS, Fabrication process, AdaBoost, Fuel adulteration, Fuel sensor.*

1. INTRODUCTION

Ethanol fuel started to be used in Brazil in the 1970s, when the Brazilian government encouraged the reduction of the gasoline consumption due to the global oil crises. At the time, the vehicles adapted to utilize ethanol could not use gasoline and the consumers were not confident about the stability of ethanol supply. Consumer confidence improved when the flex fuel vehicles arrived in Brazil in the beginning of the 2000's. Nowadays, the majority of automobiles sold in the country have this option (they can use ethanol or gasoline).

The ethanol that replaces the gasoline is called AEHC (Portuguese acronym that means hydrated alcohol fuel). It must have alcoholic content between 92.6 and 93.8° INPM as regulated by ANP (Agência Nacional do Petróleo, Gás Natural e Biocombustíveis - the Brazilian agency that regulates fuels).

Another type of ethanol fuel used in Brazil is the AEAC (Portuguese acronym to dehydrated ethanol). The production of this fuel needs one more distillation process in order to obtain alcoholic content of 99.3° INPM. This high alcoholic content is necessary because this ethanol is added to all gasoline consumed in the country. The addition of AEAC reduces the gasoline consumption, works as oxidant, increases the octane number and reduces emission of carbon monoxide and non-burned hydrocarbons (Lee *et. al.*, 2007). The content of ethanol in gasoline varies from 20% to 25%. It depends on the seasonal availability of ethanol in the market.

Today, the consumption of both types of ethanol is high in Brazil and the fuel became more susceptible to fraud as it already happened with gasoline (Dias *et al*, 2007).

One of the most common ways of adulterating ethanol fuel is to add water. AEAC is only taxed after it is mixed with gasoline and because of that, the transgressors buy AEAC without paying taxes and put water in it to sell as AEHC. This irregular mixture causes damage to the car engine and other parts because the water is not distilled. Another commonly practiced fraud is the addiction of water in AEHC in order to increases its volume. It reduces the alcoholic content and can causes damage to the vehicle too.

The concern about fuel adulteration in an environment where flex fuel vehicles are common shows the necessity of the development of fuel sensors. Fuel sensors are already aim of study of several researchers. Some of these sensors are based on impedance measurement method (Rocha and Simões-Moreira, 2005; Santos, 2003), others use optical fiber (Falate, 2003a, 2005b; Roy, 1999). Others are base on photothermic effect (Lima *et. al.*, 2004). And also there are sensors of electrochemical cell type (Paixão *et. al.*, 2007). Hoffman *et. al.* (1996a, 1997b) proposed a sensor with interdigitated electrodes that among other liquids can analyze gasoline-methanol mixtures.

In this work the authors propose a new sensor of reduced dimensions made on a substrate. Two types of sensors were fabricated and characterized. One type of sensors was fabricated on printed circuit board, PCB, substrate and has copper electrodes. Another type, used for comparison, was fabricated on alumina substrate and has nickel electrodes (Mendonça *et. al.*, 2010). The reduced dimensions of the sensor award some advantages to it over other sensor that have the same objective. The proposed sensor is portable, light, and low energy consumption. Furthermore, this type of sensor allows for automation of the analysis by using an integrated circuit.

The main sensor function is to analyze the fuel sample and indicate if the fuel is *conform* or *non-conform* according to ANP. In order to improve the calibration of the sensor the obtained data were analyzed using techniques of machine learning. Pattern recognition algorithms became popular due to accuracy and speed. The algorithm used in this work was AdaBoost (Adaptive Boosting). There is a brief description of how this algorithm works in section 3.

The set of proposed sensor and the proposed computational method present good potential to be used in vehicles and gas stations pumps in order to evaluate the fuel quality in real-time.

2. PROPOSED SENSOR

The proposed microsensor is a capacitive with the form of interdigitated copper electrodes and works immerse in the fuel. Once the fuel fill space between the electrodes, it works as the capacitor dielectric. The electric field lines travel from one electrode to another through the fuel, than the relative permittivity of the fuel influences the capacitance of the sensor. Therefore, if a fuel is a mixture of two different compounds, different contents of the compounds result in different capacitances.

Ethanol has relative dielectric constant of 24 while the relative dielectric constant of water is 79 (Weast *et al,* 1985). The sensor has a characteristic capacitance value for regular hydrated ethanol (AEHC). When ethanol is adultered with water its relative dielectric constant changes and the capacitance measured by the sensor changes as well.

In order to measure the capacitance it is used an electronic circuit with a square wave generator, a counter IC, resistors and a microcontroller to collect and send the data to a microcomputer. The period of the wave is proportional to capacitance that is proportional to water content in ethanol.

3. ADABOOST

3.1. Principle

Researches on Artificial Intelligence and its techniques have been resulted in great advances in many technologic fields. Nowadays there are many studies with the aim of improving known techniques as Neural Networks and Decision Trees and good results have been achieved by using the boosting technique. Among all algorithms based on this technique the Adaptive Boosting, also known as AdaBoost, is one of the most promissory algorithms due to its potential, flexibility and simplicity to be applied in different scenarios. Great results have been achieved in a number of applications by using AdaBoost and sensor field can also get some benefit of this algorithm.

According to Freund and Shapire, Boosting can be defined as a general method to improve the performance of any learning algorithm (Freund; Schapire, 1996). Therefore, this technique works combined with other algorithms as Neural Networks and Decision Trees and in this case they are called weak learner. The principle of the Boosting method is to combine all the classifiers generated by the weak learner. It is based on the assumption that the output classifier combination provides better results than a single predictor. The AdaBoost algorithm takes as input a training set with the format: (X_1, Y_1), …, (X_N, Y_N); where each x_i belongs to some domain X and each label y_i is in some label set Y. AdaBoost calls a given weak learner repeatedly in a series of rounds t. A set of weights in maintained over the training set since the beginning when all training set have the same weight. However, these weights are changed in each round t according to the classification suggested by the weak learner. The weight associated to wrong classified examples is increased with the purpose of focusing on wrong classifications on the next round (Oza, 2001). Figure 1 resumes the algorithm.

Given: $(x_1, y_1), \ldots, (x_m, y_m)$ where $x_i \in X$, $y_i \in Y = \{-1, +1\}$
Initialize $D_1(i) = 1/m$.
For $t = 1, \ldots, T$:

- Train weak learner using distribution D_t.
- Get weak hypothesis $h_t : X \to \{-1, +1\}$ with error

$$\epsilon_t = \Pr_{i \sim D_t}\left[h_t(x_i) \neq y_i\right].$$

- Choose $\alpha_t = \frac{1}{2} \ln\left(\frac{1-\epsilon_t}{\epsilon_t}\right)$.
- Update:

$$\begin{aligned} D_{t+1}(i) &= \frac{D_t(i)}{Z_t} \times \begin{cases} e^{-\alpha_t} & \text{if } h_t(x_i) = y_i \\ e^{\alpha_t} & \text{if } h_t(x_i) \neq y_i \end{cases} \\ &= \frac{D_t(i) \exp(-\alpha_t y_i h_t(x_i))}{Z_t} \end{aligned}$$

where Z_t is a normalization factor (chosen so that D_{t+1} will be a distribution)

Output the final hypothesis:

$$H(x) = \operatorname{sign}\left(\sum_{t=1}^{T} \alpha_t h_t(x)\right).$$

Figure 1. AdaBoost Algorithm (Freund and Schapire, 1999).

4. MATERIALS AND METHOD

4.1. Sensor fabrication

The capacitive microsensor was developed at Polytechnic school of University of São Paulo and fabricated at LNLS (Synchrotron Light Laboratory). Fabrication involves microfabrication techniques. Photomasks of acetate were used to transfer the pattern to photoresist.

Two types of sensors were fabricated. One of them has electrodes of copper and its substrate is a PCB plate made of fiberglass. The other type is fabricated on substrate of alumina and its electrodes are made of nickel.

4.1.1. Copper sensors

In order to fabricate copper sensors, the copper PCB peaces were cut in desired sizes and cleaned. The photolithography process was performed and the copper was selectively etched by a chemical corrosion as illustrated in the Fig. 2 (a).

4.1.2. Nickel sensor

Nickel sensor were fabricated on an alumina substrate. On the substrate is deposited a layer of titanium and on it is deposited a new layer of gold. Then a layer of photoresist is deposited and developed to create a mold of the sensor. Then the nickel electrodes are grown by electroplating in the mold of photoresist. Then the photoresist and the layers of gold and titanium are selectively removed. Fig. 2 (b) illustrates this process.

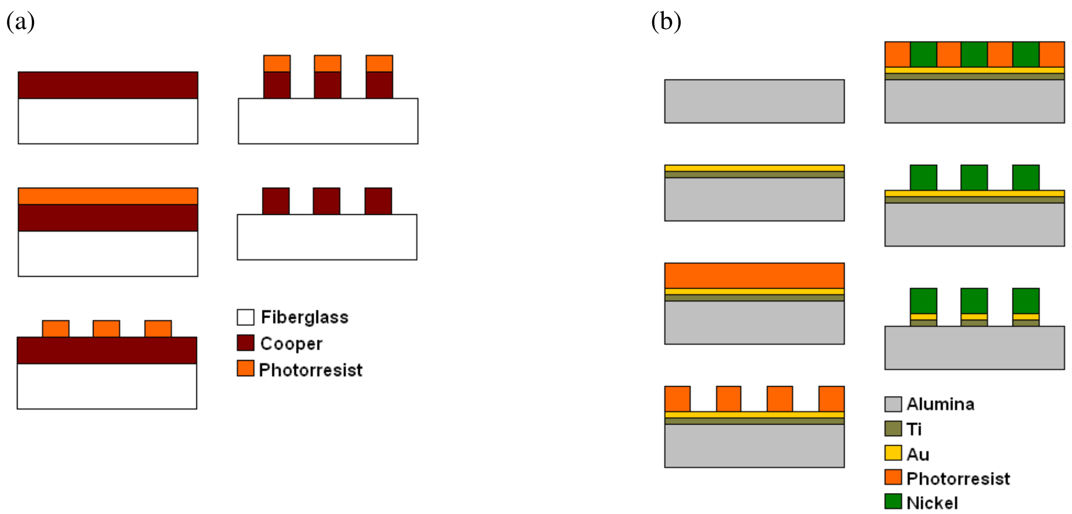

Figure 2. Microfabrication processes for: (a) Copper sensors, (b) Nickel sensors.

Two MEMS capacitive sensors were fabricated on a copper PCB and used in this study. The copper sensor data were analyzed and compared to the data from a nickel electrode sensor (Mendonça *et. al.*, 2010). Configuration of the copper and nickel sensors are shown in the pictures of Figs. 3 and 4 respectively. The Table 1 shows some features and specification of the tree sensors used in the experiments.

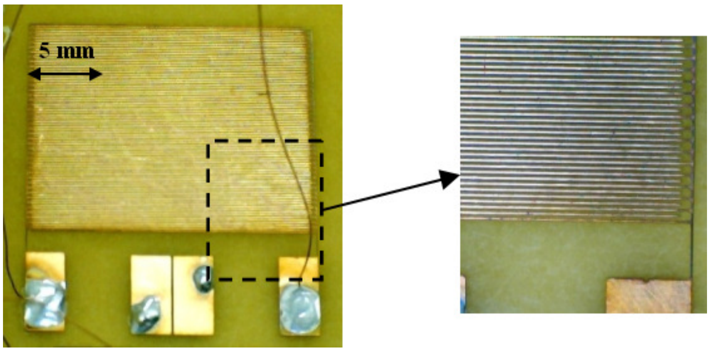

Figure 3. Detail of the copper sensor 1.

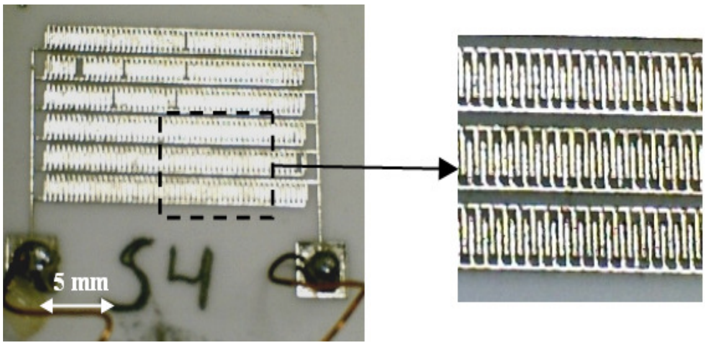

Figure 4. Detail of the nickel sensor.

Table 1. Features of the MEMS capacity sensors.

	Electrode width (µm)	Gap between electrodes (µm)	Capacitance on air (pF)
Copper 1	70	90	30,61
Copper 2	30	100	16,1
Nickel	105	55	44,79

4.2. Fluid preparation and experimental steps

Mixtures of different concentration of water in the ethanol were prepared with two burettes with capacity of 100 ml and 10 ml, with 1ml and 0.05 ml of resolution respectively. 100 ml of anhydrous ethanol were mixed with different quantities of deionized water (Tab. 2) so that it was obtained tree testing fluids, two of them considered adulterated ethanol fuel and the other regular ethanol fuel.

Table 2. Quantities and proportion of ethanol and water in the testing fluids.

Testing fluids	Amount of ethanol (ml)	Amount of water (ml)	Proportion of water (% v/v)	Fuel conformity
Mixture 1	100	4.7	4.5	No
Mixture 2	100	5.8	5.5	Yes
Mixture 3	100	6.9	6.5	No

The testing fluid was prepared in a transparent plastic container where the MEMS sensors and two temperature sensors were placed. After closing the container and performing the electrical connections between sensors and the electronic circuit, the recipient was placed in a styrofoam box which contained ice and water. When the two sensors indicated a temperature close to 5°C, an electrical resistance was used to heat the water until the testing fluid temperature reaches around 25°C. A mechanical shaker kept the water temperature homogeneous. Figures 5 and 6 show, respectively, the flowchart and the scheme of the conducted experimental procedure.

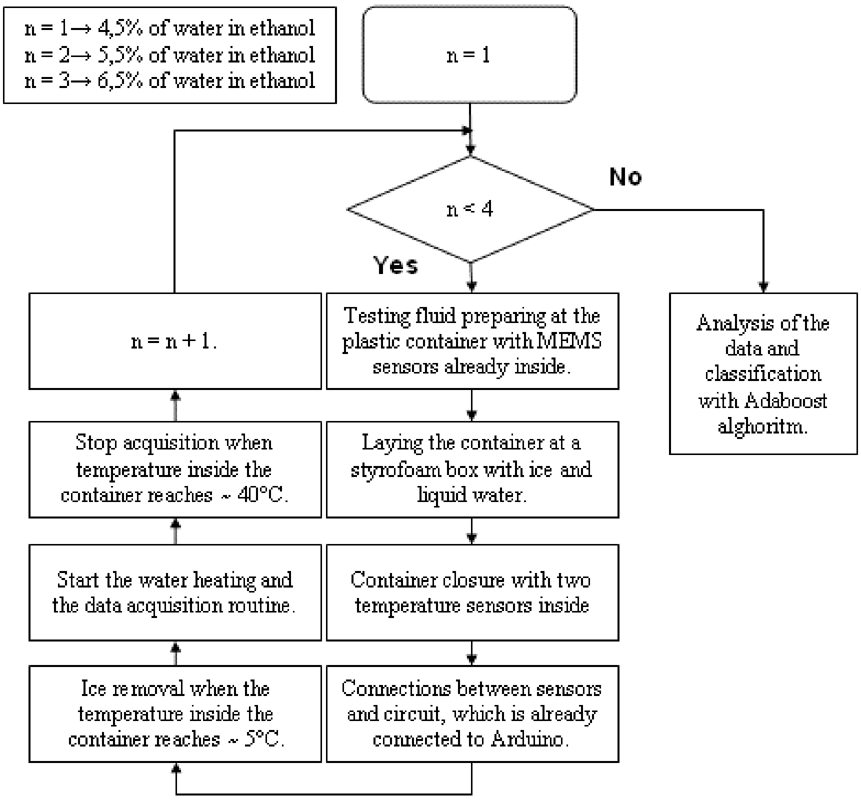

Figure 5. Flowchart of the experimental procedure.

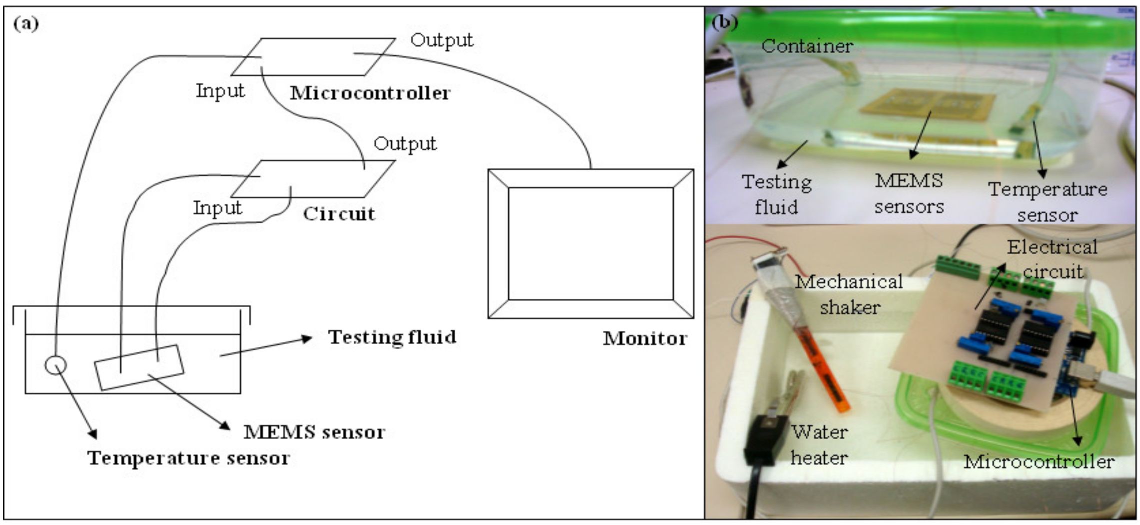

Figure 6. Scheme of experimental arrangement (a) and pictures of the system configuration (b).

4.3 Electrical circuit and data acquisition

The electrical circuit used in this study generates a square wave output signal with period ‘P’ proportional to the capacitance ‘C’ measured (Eq. 1). During the experiments the MEMS capacitive sensors were connected to this circuit which has its output linked to the microcontroller input - it was used the Arduino microcontroller. Once the sensors work independently, the circuit was replicated tree times, one for each sensor.

$$P = 2R_1C[0.405R_2/(R_1+R_2)+0.693] \tag{1}$$

During the measurements, an acquisition routine embedded at Arduino microcontroller printed the data - time, temperature and the period calculated for each sensor - on the computer screen where the microcontroller was connected. The temperature was acquired once per second and the data for each sensor was calculated once per 3 seconds. For higher precision, the square wave period was calculated as an average of 20 consecutive waves.

4.4 Fluid classification

A database with a total of 1445 examples was built by measuring samples of ethanol fuel with different concentrations of water. Five different features were used during this experiment. Two temperature values, acquired by two temperature sensors, and three capacitance values acquired by three distinct capacitive sensors. For this study we chose a binary approach. Each example is classified as either adulterated or non-adulterated. The criteria used to determine the class is in accordance with the Brazilian ANP fuel regulations.

Firstly, the data was randomly split into two sets. One of them was used as a test set and contains 755 examples. The remaining samples were used to build the training sets. Secondly, seven training sets were created by randomly collecting different number of samples: 50, 100, 200, 300, 400, 500 and 700. After that, each training set was used to train a classifier with the AdaBoost algorithm. The number of iterations during the training step was one of the parameters for each training set. The number of iterations, which corresponds to the number of weak classifiers in this case, varied between 10 and 2000.

Two different AdaBoost structures were used for comparison. Initially, the monolithic structure was tested by using the software WEKA (Witten and Frank, 2005) to run these experiments with algorithm Adaboost.M1. The second type of AdaBoost used our own implementation of a cascaded structure (Viola, Jones, 2001; Barczak, Johnson, Messom, 2008). In both cases Decision Stump was used as the weak classifier.

5. RESULTS AND DISCUSSIONS

5.1 Microsensor response

The three sensors suggested that the capacitance decreases with the increasing of the temperature as it can be seen for one of the copper sensors in the graphic of Fig. 7. The decreasing of the output wave period indicates also the decreasing of the capacitance once the two parameters are proportional to each other. The curve points in those graphics represent the mean period every 5 measures.

The fitting of first degree polynomial curves on the Period/Temperature points for the copper sensor 1 are plotted in Fig. 7, and the linear correlation coefficient between temperature and period values (Table 3) indicated that the relation among these parameters can be approximated by a straight line with little error, since the coefficient value is much close to '-1' for all measures performed.

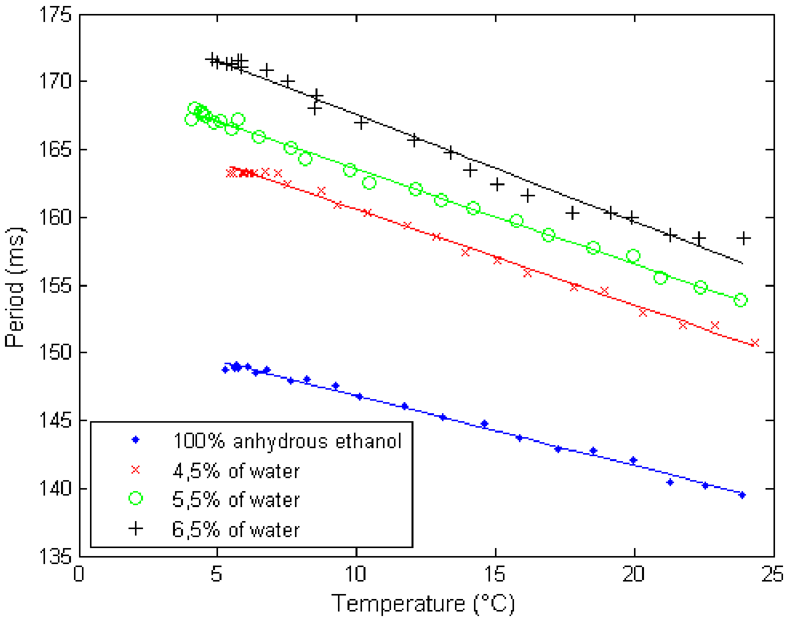

Figure 7. Copper sensor 1: output signal period as a function of temperature.

Table 3. Linear correlation coefficient among temperature and period for each sensor and concentrations of water.

Water concentration (%)	Linear correlation coefficient for Copper sensor 1	Linear correlation coefficient for Copper sensor 2	Linear correlation coefficient for Nickel sensor
0	-0.9969	-0.9928	-0.9975
4,5	-0.9971	-0.9955	-0.9870
5,5	-0.9977	-0.9878	-0.9903
6,5	-0.9905	-0.9957	-0.9896

The slope of the curve Period/Temperature was different for each sensor, but once fixed the sensor, different testing fluids compositions showed similar slope values. The Table 4 presents the slope angle of the curves obtained for different concentration for each sensor.

Table 4. Slope angles of the fit curves for each sensor and concentrations of water.

Water concentration (%)	Slope angle of Copper sensor 1	Slope angle of Copper sensor 2	Slope angle of Nickel sensor
0	-27.3	-16.6	-30.2
4.5	-35.1	-20.4	-33.4
5.5	-35.5	-21.2	-32.6
6.5	-38.3	-28.3	-26.0
Mean	-34.5	-21.6	-30.5

Despite small errors, the slope angles for each sensor are approximately the same for different proportions of water in the testing fluids. A large number of experiments would serve to increase the reliability of the average slope angle.

5.2 Fluid classification with AdaBoost algorithm

We present the results exploring two aspects. Firstly, we compared the total of hit rates obtained by using the monolithic structure, training up to 2000 AdaBoost rounds, with the hit rates obtained by using cascade structure. These results are shown by using ROC curves. From this approach it is possible to visualize that monolithic structure reached around 60% of hit ratio for 8,5% of false detection (Fig. 8) and the cascade structure reached 80% of hit ratio for the same rate of false detection (Fig. 9). The Figs. also that the classifier obtained by monolithic structure converged to a certain level no more than 60% even if the false detection increases. On the other hand, with cascade structure it is possible to calibrate the correct classification rate up to about 90% to the detriment of false detection increase.

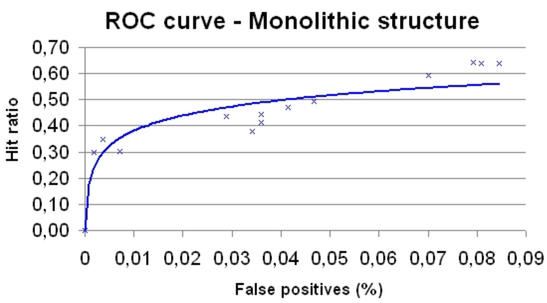

Figure 8. ROC curve obtained by Monolithic structure

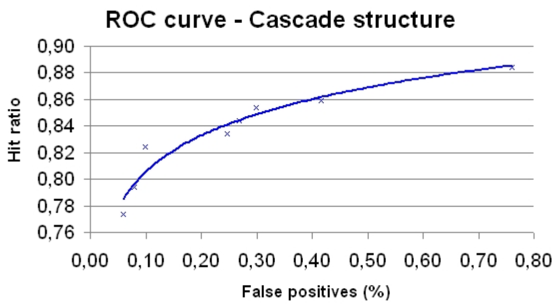

Figure 9. ROC curve obtained by Cascade structure

Secondly, we present the evolution obtained according to different rounds during the process. This gives an indication of performance as the more rounds of iteration the smaller the training error as well as test error. It is expected to converge to a certain level even if the number of rounds keeps increasing. For instance, Fig. 10 shows this analysis for the process with 700 samples on training set obtained by monolithic structure and Fig. 11 the results by using cascade structure. Over again, the results for the second one were better since the training error was eliminated and the test error dropped to level about 5%. It is also important to highlight that the number of rounds achieved by using cascade structure after run all layers was less than 650, which shows that its performance was better if compared to the first one. We have shown that this combination of algorithm and sensor network works to a reasonable accuracy.

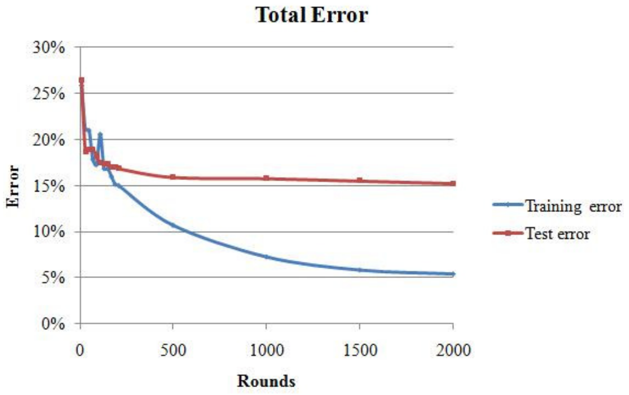

Figure 10. Total error with monolithic structure.

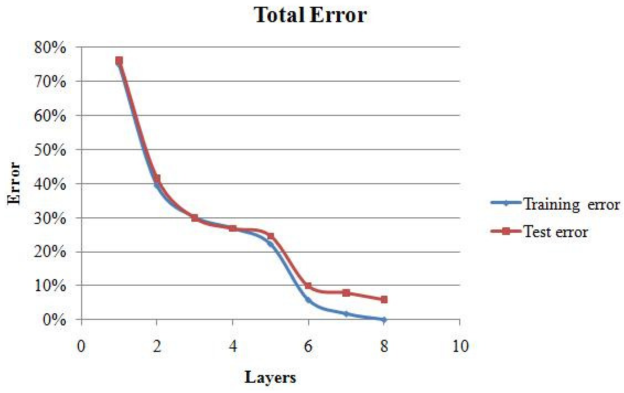

Figure 11. Total error with cascade structure.

An advantage of using AdaBoost algorithm is that it can compile information of many different sensors very fast. Moreover, it can adapt more accurately to any sensor calibration curve, even if the curve has a complex or unusual shape. For instance, the relation between temperature and period presented in section 5.1 can be approximated to a straight line. However, unusual functions can be represented more by using AdaBoost, as long as there are enough samples in its training session. These benefits can be explored to improve the sensor calibration step in future. Summing up, these results have already shown the great potential of the sensor used with AdaBoost. In future work we intend to combine the microsensors, AdaBoost classifiers and a microprocessor with the purpose of dealing with the fuel adulteration problem.

6. CONCLUSIONS

Copper and Nickel microsensors responses indicated that fluids capacitance is directly proportional to the water content and inversely proportional to the liquid temperature.

The value of the linear correlation coefficient between temperature and sensor output signal period suggested that one can be related to the other by a linear function with minor error in the range of 5 to 25°C. It was also observed that, despite a little error, the slope angles for each sensor, in a curve temperature/period, are proximally the same for different proportions of water in the testing fluids.

Finally, the use of pattern recognition combined with the proposed MEMS sensors showed good results in the analysis of ethanol fuel. The system presented 85% of correction classification analyzing the conformity or not of the prepared fluids with sensitivity of the order of 1% in the values of alcoholic concentration. The accuracy is currently limited by the number of training samples.

7. ACKNOWLEDGEMENTS

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