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SCIENCE DIRECT
Sensors and Actuators B 116 (2006) 62–65
SENSORS AND ACTUATORS B CHEMICAL
www.elsevier.com/locate/snb

Committee machine for LPG calorific power classification

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Received 11 July 2005; received in revised form 17 October 2005; accepted 30 November 2005
Available online 18 April 2006

Abstract

This work shows the results of the development of a robust system as an alternative to recognize the quality of an alcohol vapor fuel sample and liquid petrol gas (LPG) calorific power in an electric nose. Two experimental methodologies were implemented to extract the features of alcohol vapor fuel and LPG gas patterns. The first approach used the multi-layer perceptron (MLP) topology of artificial neural networks (ANN) to recognize alcohol vapor fuel patterns. The second approach processed data to develop an LPG calorific power recognizing system that is robust to the loss of a random sensor. Three systems were used. The first implemented an MLP to recognize all data that simulated the failure of a random sensor. This system had 97% of right responses. The second implemented seven MLPs trained with input data subsets, so that six MLPs were trained with a different failure sensor, and the seventh MLP was trained with data considering all sensors without failure. This system had 99% of right responses. The third implemented an ensemble static learning machine containing 10 parallel MLPs. This system had 97% of right responses.

Keywords: Committee machines; Electronic nose; Principal component analysis; Artificial neural networks; Pattern recognition

1. Introduction

There has been an increase in interest in electronic noses (e-nose's) systems applied to both academic and industrial fields, because of their possibility to conduct direct measures with few refinements and easy implementation [1]. An e-nose has many applications: for example, liquid and solid food smell recognition [2–4], chemical perfumes and reagents [4], lung cancer detection using the expired breath of an ill person [5], alcoholic breath measure of a driver [1], potable water quality evaluation [6], fuel pattern recognition [7], among others.

An e-nose system is usually implemented by using an artificial neural network (ANN), because of its robustness to noisy samples analyzed [8], and its generalization capability that usually promotes correct recognition of input samples that were not present in the training data set. Liquid petrol gas (LPG) calorific power recognition applications are discussed in this paper.

Traditional methods of gas calorific power measures can be divided into three categories [9]: calorimetric bomb gas sample combustion, open flame gas sample combustion, and no flame catalytic combustion. These methods usually require expensive machinery. This work aims to implement a robust system to recognize a LPG calorific power pattern even with the failure of one random sensor, or when a sensor loses its sensitivity to the target gas. Combination of MLPs will be discussed to solve this pattern recognition problem. Two approaches will be used: static ensemble committee machines [8,10], and a substitutive MLP machine containing an arrangement of seven MLPs, such that six MLPs are trained with data subsets simulating one sensor failure, and one MLP is trained using the original train data set.

2. Methodology and experimental results

Six Taguchi Tin Oxide sensors were used: TGS-2442, TGS-2600, TGS-2602, TGS-2610, TGS-2611 and TGS-2622. They were named respectively as Sensor 1, Sensor 2, Sensor 3, Sensor 4, Sensor 5 and Sensor 6. They detect several substances including carbon monoxide, ethanol, methanol, butane, among others. They were chosen in order to avoid the "tune" effect of the detected substances. Thus, they had to be sensitive by a large number of subparts of the measured substance [11]. Moreover, the selection of the substances was done in the pattern

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0925-4005/$ – see front matter
doi:10.1016/j.snb.2005.11.072

recognition stage. Therefore, the criteria to choose the quantity and types of sensors were based in diversity of analyzed samples and diversity the responses of sensors [11].

2.1. LPG experimental data processing

Two LPG patterns were used: pure LPG and a mixture of LPG and nitrogen. The second pattern simulated a lower calorific power LPG. Pure LPG volume of 0.2 ml was injected in the e-nose system. Mixture volume of 1 ml was used. This mixture was obtained using a flow gas control system. A pure LPG flow of 200 sccm was mixed with a flow of 1000 sccm of nitrogen gas. Thus, the rate of this mixture was 1 LPG part for five parts of nitrogen. About 36 pure LPG and 43 mixture experimental samples were obtained. This mixture simulated a lower calorific power LPG than the first pure LPG pattern. Experimental data were processed in MATLAB software to extract the input attributes for MLP training step. Fig. 1 shows these experimental data samples.

The third sensor was the least sensitive of the sensor matrix because it detects ethanol, toluene and ammonia, and the LPG is composed mainly by butane and propane gases.

The final and initial resistance values of each experimental measure were used. The normalized resistance attributes extracted from sensors data were calculated by Eq. (1). The samples of each pattern were divided into training and test subsets. Validation subsets were not used because of the reduced number of experimental samples:

$$R_{\text{NORM}} = \frac{R_{\text{INITIAL}} - R_{\text{FINAL}}}{R_{\text{INITIAL}}} \qquad (1)$$

The first approach of data processing considered all sensors functioning correctly. The second approach simulated the failure of a random sensor inside the e-nose system sensor array. It was assumed that a flawed sensor loses its sensitivity. Thus, its corresponding attribute will be zero.

2.2. First experiment: single MLP to train good sensors experimental data

An MLP had been tested 100 times, to verify its generalization capability. Moreover, the MLP with the highest capable generalization feature was chosen. All sensors were considered properly functional; thus intact experimental data sets were used

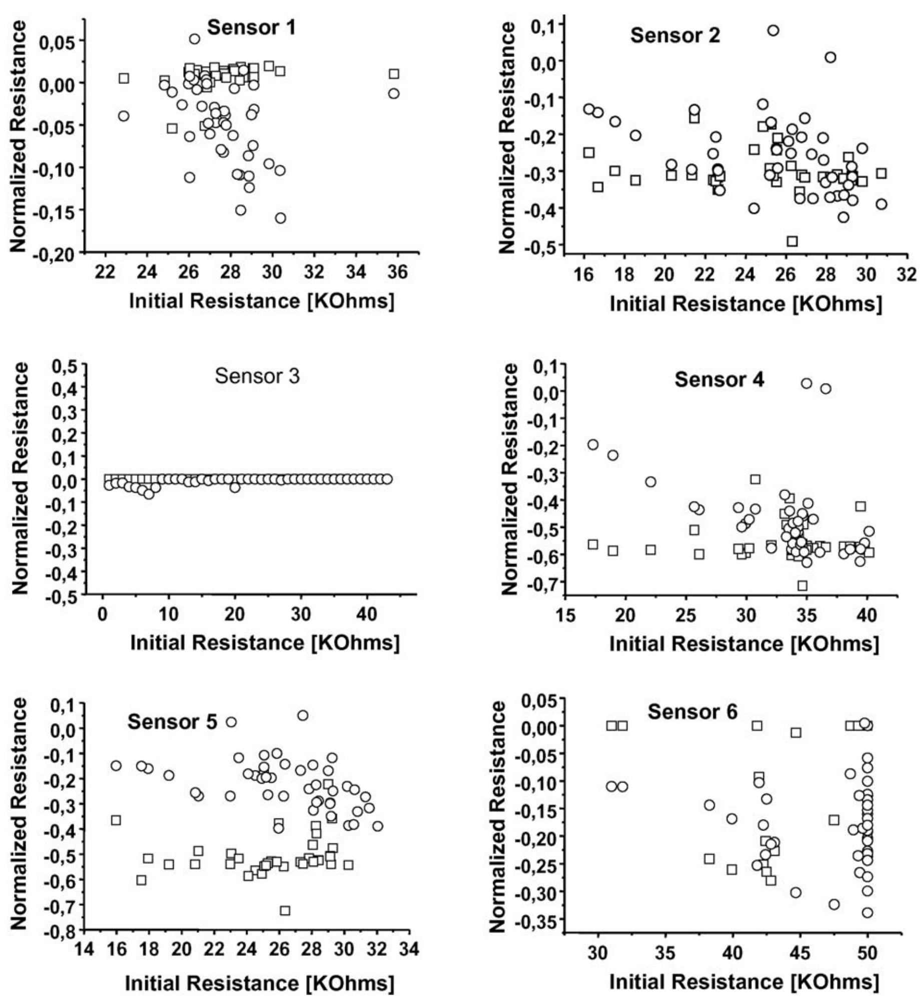

Fig. 1. Sensors responses submitted to two different LPG ambient. The square symbols correspond to sensors responses to pure LPG and circles correspond to the mixture of LPG + N_2 gas sample. In the all the cases, the sensors responses were normalized relative of their initial conditions.