Integrated Electrical System Based AD5933 Impedance analyzer: Towards Multi-Selective Detection of Complex Gas Mixtures

Louis routier ¹, Alexandre westrelin ¹, Anthyme cerveaux ¹, Gaël Louis ¹, Thomas Holach ¹, Pierre Foulon ¹, Kamal Lmimouni ¹, Sébastien Pecqueur ¹, and Bilel Hafsi ²

¹Affiliation not available
²ICAM School engineering

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Abstract

In this work, we present the development of miniaturized, multiplexed, and connected platform for impedance spectroscopy. Designed for online measurements and adapted to wireless network architectures, our platform has been tested and optimized to be used for multi-selective chemical organic sensor nodes. Our designed circuit is built from low cost and low power consumption microelectronics components that achieve long duration operability without compromising on sensor measurement accuracy and precision. We used the well-known impedance network analyzer AD5933 (Analog Devices, Norwood, MA, USA) chip which can measure a spectrum of impedances in the range 5 Hz to 100 kHz. The proposed system is based on ESP32-C3 Microcontroller to manage the AD5933 through its I2C interface and two multiplexer components CD74HC4067 used for calibration process and data feedback. Our platform is able to interface up to 15 conductimetric sensors with real time acquisition (less than 90 ms per acquisition) and the possibility to relay the information through the network for data analysis and storage. The paper describes the microelectronics design, the impedance response over time, the measurement’s sensitivity and accuracy and the testing of the platform with embedded chemical sensors for environmental classification and recognition.
Integrated Electrical System Based AD5933 Impedance analyzer: Towards Multi-Selective Detection of Complex Gas Mixtures

L. Routier, A. Westrelin, A. Cerveaux, G. Louis, T. Horlac'h, P. Foulon, K. Lmimouni, S. Pecqueur, B. Hafsi*

Abstract—Advances on System-On-Chip and organic sensors allows the development of miniaturized impedance measurement hardware for environmental monitoring in IoT. In this work, we present the development of miniaturized, multiplexed, and connected platform for impedance spectroscopy. Designed for online measurements and adapted to wireless network architectures, our platform has been tested and optimized to be used for multi-selective chemical organic sensor nodes. Our designed circuit is built from low cost and low power consumption microelectronics components that achieve long duration operability without compromising on sensor measurement accuracy and precision. We used the well-known impedance network analyzer AD5933 (Analog Devices, Norwood, MA, USA) chip which can measure a spectrum of impedances in the range 5 Hz to 100 kHz. The proposed system is based on ESP32-C3 Microcontroller to manage the AD5933 through its I²C interface and two multiplexer components CD74HC4067 used for calibration process and data feedback. Our platform is able to interface up to 15 conductimetric sensors with real time acquisition (less than 90 ms per acquisition) and the possibility to relay the information through the network for data analysis and storage. The paper describes the microelectronics design, the impedance response over time, the measurement’s sensitivity and accuracy and the testing of the platform with embedded chemical sensors for environmental classification and recognition.

Index Terms—Polymer sensors, impedance measurements, AD5933, environmental monitoring

I. Introduction

Air pollution is a major public health issue. The European Environment Agency's recent report reveals that most of European cities suffer from low air quality [1]. In fact, the concentrations of harmful pollutants such as nitrogen oxides (NOx), volatile organic compounds (VOCs) and ozone (O₃), continue to have significant impacts on the state of health of European citizens, which inevitably leads to the aggravation of certain chronic pathologies such as cardiovascular and respiratory diseases, cancer [2], etc. Therefore, the environment quality control requires the measurement of different species of gases and particles which have proven to be of great constitutive complexity. Thus, the design of chemical detection platforms with a high number of specific sensors is crucial to identify these pollutants. Electrochemical biosensors are becoming increasingly popular as rapid, specific, and cost-effective detection devices. Despite their quite remarkable development over the past few years in various fields such as environmental monitoring [3][4], the food industry [5], health [6], public and industrial safety [7], and the potential of integrating them in microsystems as part of the Internet of Things remain underused. Generally, most of the Electro-Impedance Spectroscopy (EIS) studies are performed in laboratory condition, with voluminous and expensive measuring bench system-based impedance spectrometers [8][9].

One of the major challenges is the creation of ultra-sensitive arrays of organic conductivity microsensors and the development of hardware that can perform impedance measurements, which can be integrated into microchips. This research enables the merging of both the fundamental studies of the biochemical interactions between target species and selective materials, and the practical application of developing usable field detection systems for pollution, chemical weapons, or biomarkers [10].

Our study aims to create a smart and self-sufficient tool capable of providing initial solutions for detecting and recognizing molecular issues where current solutions are lacking, such as the detection of organic pollutants like (alcohol, acetone …). Besides producing and evaluating sensors, we will also address signal processing and data

(*)Corresponding author: Dr. Bilel HAFSI, Department of Electrical, Institut Catholique d’arts et Métiers (ICAM), Lille, 59800 France (e-mail: bilel.hafsi@icam.fr).
collection, storage, transfer, and retrieval using embedded systems based on microcontrollers that have the ability to integrate a secure communication solution. We will also address signal processing and data collection, storage, transfer, and retrieval using embedded systems based on microcontrollers that have the ability to integrate a secure communication solution.

Commonly used in various applications such as in bio-impedance analysis, sensing, and electrochemistry, the AD5933 is a highly integrated and low-cost solution for portable applications. Developed by Analog Devices [11], this integrated circuit can perform frequency-domain impedance measurements and can operate in the frequency range of 10 Hz to 100 kHz.

AD5933-based systems have been used in a variety of applications, including biomedical [12] [13], agriculture [14], and textile-enabled [15] applications, as well as for the characterization such as the study of metal corrosion [16], and the human skin bioimpedance measurements [17].

In this paper, we propose a low-cost, portable, and miniaturized multi-sensing platform for non-invasive impedance measurement of electrochemical sensors. The device, being compact, provides safe and accurate readings, ideal for monitoring bioimpedance nodes. The paper outlines a circuit that runs under a ESP 32-C3 microcontroller, making it suitable for remote monitoring environment air quality or gas detection. Linear discriminant analysis (LDA) and principal component analysis (PCA) based feature reduction algorithms have been used to analyze data obtained from chemical multi-sensor measurements.

II. ELECTROCHEMICAL MULTI-SENSOR SYSTEM DESIGN

A. Impedance analyser chip AD5933

The AD5933 is a highly accurate impedance converter system that uses an I²C bus for communication with a microcontroller. This Integrated Circuit has an internal conversion system and a DDS frequency generator that allows an external complex impedance to be excited with a known frequency. The impedance response is then amplified and sampled by a 12-bit, 1 MSPS ADC. The circuit also includes a 1024 points DFT Processor which performs a Discrete Fourier Transform and provides real and imaginary impedance values at each frequency of the sweep.

The on-board ADC sampling process and the on-board DSP engine perform a discrete Fourier transform (DFT) algorithm. The real (the resistance R) and imaginary (the reactance X) components of the unknown impedance are then stored in two 16-bit registers. The impedance of the device being tested is determined through a calibration process that compares the amplitude with a known resistance (see fig 2). The impedance magnitude and phase are then easily calculated using the following equations:

$$\text{Magnitude} = \sqrt{R^2 + X^2} \quad (1)$$

$$\text{Phase} = \tan^{-1}(X/R) \quad (2)$$

The system requires two external components: the device under test, represented as an impedance \( Z(\omega) = R + jX(\omega) \), and a reference resistor named \( R_{FB} \). This resistor is used as a feedback resistor and its value must be generally known and incorporated into the control code of the AD5933.

The AD5933 requires calibration resistor using a known impedance, achieved by determining the gain factor which represents the system's gain through the calculation of this equation:
Gain Factor = \[ \frac{1}{R_{\text{CAL}}} \frac{1}{\sqrt{R^2 + X^2}} \] \hspace{1cm} (3)

Where \( R_{\text{CAL}} \) is the calibration resistor value while \( R \) is the real component, and \( X \) is the imaginary component of the measured impedance.

**B. Calibration procedure**

There are some limitations, mainly in the calibration process, that must be considered when designing new systems, particularly if precise and repeatable measurements are necessary. In fact, the AD5933 calibration procedure uses a resistor with a similar load to the sample under test. However, if the unknown impedance falls outside the calibration range in a wide frequency range, this may lead to incorrect or noisy data. To overcome this, multiple calibration resistors to cover measurement impedance range or also by reducing the frequency spectrum limits [14]. Additionally, the AD5933 has a fixed user-selectable feedback resistance that limits the lowest measurable impedance in relation to the excitation voltage. These solutions are not suitable in case sensors dynamically changes of nominal resistance scales by orders of magnitude regarding the nature of the volatile environment to be measured, or the pristine conductivity level of the different materials to be used in an array to recognize an environment at a given time.

**C. Proposed platform architecture**

The AD5933 IC is a low-cost solution for impedance measurement, but it also has several limitations that obstruct its suitability for Bioimpedance measurements. Previous research [18] has been developed using an Analog Front End (AFE) to enhance the AD5933’s capability for Bio Impedance measurements.

When calculating gain factor, it is important that the receive stage operates in its linear region. This requires careful selection of the system gain settings (eq. 4). To calibrate the system accurately, the user needs to know the impedance limits. One must then select a resistor with an equal I-V gain setting as the calibration impedance. The gain through the system is defined as:

\[ \text{Gain} = \frac{V_{\text{OUT}} \times R_{\text{FB}}}{Z_{\text{unknown}}} \times \text{PGA Gain} \] \hspace{1cm} (4)

Our calibration method considers the non-idealities of the system and the parasitic contribution of the internal resistance of the analog multiplexers. The solution that we propose consist of using only one calibrating resistor for impedance measurement ranging from 1 k\( \Omega \) to 1 M\( \Omega \) in a frequency space from 10 Hz to 100 kHz. This is done by means of a shift of the calibration resistor out of the unknown’s multiplexed impedances (fig 3).
After calibration, the measurement process is performed, the unknown impedance values are calculated by means of this equation:

\[
Z = \frac{1}{\sqrt{r^2 + x^2 \times \text{Gain Factor}}} \tag{5}
\]

Where \(r\) and \(x\) are, respectively, the real and the imaginary values obtained from the internal register while the measurement process.

III. MEASUREMENTS AND VALIDATION

The AD5933 enables the user to set the peak-to-peak output signal value of 198 mV, 383 mV, 0.76 V, and 1.48 V with different DC offsets and a known frequency, this signal acts as an excitation voltage for external unknown impedances under test. We choose to set the output voltage at the minimum voltage (\(V_{pp} = 198\) mV) proposed by analog device to avoid electrochemically damaging our conducting polymer sensors in moist environments, with frequency sweep around 10 kHz. The clock for the DDS is generated from either an external reference clock which is provided by the user at MCLK or by the internal oscillator. In our case, we use a 16 MHz external clock.
In order to calibrate the system, one must measure the magnitude produced by a two-terminal cell with known resistor values since we are interested in the relative variation of a reactance-less impedance, since no capacitance nor inductance are involved in the sensing transducer model.

Calibration was carried out using a resistor $R_{\text{CAL}}$ and a current-to-voltage resistor $R_{\text{FB}}$. Both of them were set at the same resistance values 20 kΩ.

The receive stage consists of a current-to-voltage amplifier, a programmable gain amplifier (PGA). The PGA allows the user to increase the output of the current-to-voltage amplifier by either a factor of 5 or 1, using the control register (located in the Register Map section at Register Address 0x80). The filtered output is then passed through a 12-bit, 1 MSPS ADC, this stage's schematic is depicted in fig 1. The unknown impedance is connected between the $V_{\text{OUT}}$ and $V_{\text{IN}}$ pins. The current-to-voltage amplifier results in a voltage present at the $V_{\text{IN}}$ pin acting as a virtual ground with a DC value set at $V_{\text{DD}}/2$. The current generated across the unknown impedance flows into the $V_{\text{IN}}$ pin and produces a voltage signal at the output of the current-to-voltage converter. The gain of the current-to-voltage amplifier is established by a feedback resistor $R_1$ that can be selected by the user, between Pin 4 ($R_{\text{FB}}$) and Pin 5 ($V_{\text{IN}}$).

![Fig. 3. Block overview with details of electronic components.](image)

It is crucial for the user to choose a feedback resistor value that, along with the PGA stage's selected gain, keeps the signal within the ADC's linear range. Measurements for feedback resistance: 5 kΩ, 6 kΩ, 8 kΩ, 10 kΩ, 12 kΩ and 15
kΩ and for target impedance ranging from 1 kΩ to 1MΩ were conducted. A proportional increment was observed in the percentage error with the successive increments of the feedback resistor value. The response of the circuit was consistent and showed a maximum error value that does not exceed 10% for R_f = 5 kΩ, indicating linear behaviour of the gain current to voltage amplifier.

To go further in accuracy assessment, our circuit is then tested with different loads from the 1kΩ resistor 1 MΩ. To perform online calibration and update it if needed, we used a 1:16 multiplexer that switches between the known-value calibration resistor to 15 unknown impedances to measure. Results for the measured resistors show the difference between the measured values and the real ones for loads upper than 400 kΩ (fig 5a), which represents an error proportional to the increase in resistance. It is worth highlighting that this study is specifically based on fixed R_FB an R_CAL, while conventionally, calibration requires multiplexing of different R_CAL which is not suited in case of sensor array multiplexing with uncorrelated sensor values that dynamically varies over several order in magnitudes independently. To overcome the accuracy problem, we compensate the deviation to calibration by using a correction equation extracted from the linear fit of the real and measured impedance difference curve to reduce the error below for impedances 400 kΩ (fig 5b). All the obtained measurements were processed several times with a rinsing, falling and random manner. The correction process was applied independently from the measurement process. The implemented linear correction present fitted results for the measured impedances compared to real loads. The system is capable of measuring impedances between 300 kΩ and 1 MΩ at 20 kHz, with impedance error less than 4%. While this accuracy is superior and are appropriate for their intended application in this higher range of resistor, the impedance accuracy below 20 kΩ is much smaller which is unfavorable for lower biological impedance applications.

![Graph](image)

**Fig. 5.** a) Results for the measured resistors compared to with different loads from the 1 kΩ resistor 1 MΩ, for a 20 kHz frequency excitation voltage b) Correction equation extracted from the linear fit of the real and measured impedance difference curve, c) Absolute impedance error at frequencies between 5 kHz and 100 kHz for different known resistor values (1 kΩ, 20 kΩ, 100 kΩ, 1 MΩ) d) Acquisition time response as function as the frequency variation.

The AD5933’s frequency response is limited, causing a variation in the gain factor, and resulting in errors in impedance calculations across a range of frequencies. To reduce these errors, it is better to limit the frequency sweep to a narrow range. We choose to study the response of the system to frequency variation. EIS characteristic for a frequency range from 5 to 100 kHz with 5 kHz step was measured using known resistor values (1 kΩ, 20 kΩ, 100 kΩ, 1 MΩ), (fig 5 c).

By analyzing these results, it can be noticed that for extreme frequency values (very low frequencies and very high ones), large errors in the shape of the measured resistance characteristics occurs, the error can be reduced by adjusting
excitation frequency in the range of [30 kHz – 80 kHz] (Fig 5c). Moreover, given the requirement of conducting real-time measurement, our system must allow fast acquisition time of 15 chemical conductimetric sensors. The theoretical sampling time is the contribution of three characteristic times:

Table 1. List of portable impedance meters based on the AD5933 chip.

<table>
<thead>
<tr>
<th>Ref</th>
<th>Frequency range</th>
<th>Excitation voltage</th>
<th>Maximum error</th>
<th>impedance range</th>
<th>Data communication</th>
<th>size</th>
</tr>
</thead>
<tbody>
<tr>
<td>[14]</td>
<td>10 Hz -100 kHz</td>
<td>200 mV, 400 mV, 1 V, 2 V</td>
<td>1.2%</td>
<td>1 Ω - 25 kΩ</td>
<td>STM32L486 (USB - BT)</td>
<td>75 × 40 mm</td>
</tr>
<tr>
<td>[18]</td>
<td>1 Hz -100 kHz</td>
<td>200 mV, 400 mV, 1 V, 2 V</td>
<td>3.5%</td>
<td>10 Ω - 1 MΩ</td>
<td>USB</td>
<td></td>
</tr>
<tr>
<td>[19]</td>
<td>1 Hz - 100 kHz</td>
<td>20 mV - 200 mV</td>
<td>2%</td>
<td>100 Ω - 10 kΩ</td>
<td>PIC16F877 (USB)</td>
<td>N/A</td>
</tr>
<tr>
<td>[17]</td>
<td>5 Hz - 100 kHz</td>
<td>25 mV, 50 mV, 200 mV, 400 mV, 1 V, 2 V, 3 V</td>
<td>1.6%</td>
<td>178 Ω - 165 kΩ</td>
<td>Arduino (USB - BT)</td>
<td>N/A</td>
</tr>
<tr>
<td>[20]</td>
<td>0.01 Hz - 100 kHz</td>
<td>1 mV - 1 V</td>
<td>6%</td>
<td>10 Ω - 10 GΩ</td>
<td>Zigbee (USB)</td>
<td>65 × 120 mm</td>
</tr>
<tr>
<td>[21]</td>
<td>0.01 Hz - 100 kHz</td>
<td>10 mV - 2 V</td>
<td>3%</td>
<td>N/A</td>
<td>Arduino (USB)</td>
<td>74 × 53 mm</td>
</tr>
<tr>
<td>[12]</td>
<td>1 kHz - 30 kHz</td>
<td>N/A</td>
<td>0.5%</td>
<td>N/A</td>
<td>Raspberry Pi (USB)</td>
<td>N/A</td>
</tr>
<tr>
<td>[24]</td>
<td>0.1 Hz - 100 kHz</td>
<td>N/A</td>
<td>5.6%</td>
<td>100 Ω - 10 MΩ</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>[28]</td>
<td>100 Hz - 200 kHz</td>
<td>N/A</td>
<td>4.5%</td>
<td>10 Ω - 1 kΩ</td>
<td>MSP430F2274 with ZigBee transceiver (RF/ WIFI)</td>
<td>35 × 37 × 8 mm</td>
</tr>
<tr>
<td>Our Platform</td>
<td>1 kHz - 1MHz</td>
<td>200 mV, 400 mV, 1 V, 2 V</td>
<td>4%</td>
<td>10 Ω - 1 MΩ</td>
<td>ESP32-C5 (USB - BT - WIFI)</td>
<td>66 × 35 mm</td>
</tr>
</tbody>
</table>

Fig. 6. a) Results for the measured resistors compared to with different loads from the 1 kΩ resistor 1 MΩ, for a 60 kHz frequency excitation voltage, b) correction equation extracted from a second-order polynomial fitting function of the real and measured impedance difference curve.

$t_{cal}$ which is the time for the AD5933 to calculate the impedance values (generally, it is estimated to be 1 ms for a 16 MHz system clock [11]), the time allowed for serial I’C protocol instruction, such as reading the estimated impedance,
value registers, sending the repeat instruction time, and checking the impedance measurement status. With the Settling Time Cycles $t_{\text{cycles}}$, which is determined by multiplying the total number of settling cycles and the period time of the impedance excitation signal.

In order to reduce the time between each acquisition in compromise with the minimum error, we choose to fix the frequency at 60 kHz and study the accuracy of our platform. We conduct the same study by testing impedance response with various loads ranging from 1 kΩ to 1 MΩ at 60 kHz. The results show a gap between the measured values and real ones for loads above 400 kΩ (as seen in fig 6a), resulting in an error rate exceeding 20% for the highest impedance case. We extract the equation that manages the difference between measured resistances and the target ones, the curve presented in fig 6b shows a curve that follows a second-order polynomial behaviour. To decrease the error observed above 400 kΩ, we implemented a correction equation in the C++ Code.

We might consider applying another correction equation to increase the accuracy response in impedance range below 400 kΩ. The issue is that for low resistances values (typically below 20 kΩ), we have a very small resolution window. Ibba and coworkers propose to incorporate internal calibration resistors using surface-mount technology with a firmware selectable values [14]. This feature provides a significant flexibility to explore different impedance range, allowing the user to opt for either internal or external calibration depending on the desired measurement precision.

The proposed solution is to shift the calibration resistor $R_{\text{CAL}}$ out of the multiplexing toward the analog front-end circuit (fig 3) and replace it by a wire.

By adding a software condition, we can take off this value from the measured resistor value by means of software condition to overcome the accuracy limitation in the 1 kΩ - 400 kΩ load range. Implementing the equivalent circuit model fitting resulted in an error less than 4%, these results were obtained by averaging the ten measurements cycles related to passive loads that cover [1 kΩ - 1 MΩ] range values. Values extracted from fitting resulted in an error less than 4% compared to real value. These results were obtained by averaging the 10 measurements cycles related to passive loads that cover [1 kΩ - 1 MΩ] range values.

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**Fig. 7.** a) 3D view of the printed circuit board of our electrochemical impedance analyser, b) 3D view of our proposed interdigital sensors c) drop-casting process of the sensitive materials: the conducting polymer (electrotransducer), and the doping salt (chemical sensitiser).

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**IV. Chemical Sensing application**

An electronic nose (or e-nose) is an electronic interface that reads out chemically sensitive transducers to recognize environment and on-board multivariate data analysis technique to clusterize information features. Among them, some consist of an array of sensitive gas sensors, usually result in a complex preparation process, high-power consumption, and redundant sensing signals. In contrast, the efficiency of our impedance analyzer system has been evaluated by measuring conductometric sensors matrix fabricated directly on a Printed Circuit Board (PCB). Sensors consist of 15 interdigital electrodes, 1 mm wide and 3 mm long, separated from each other with a 2.3 mm gap. A 3D view of the electrodes is shown in fig 7.

The volatile organic compound (VOC) response analysis was carried out using two approaches: unsupervised and supervised classification. Among these methods: Principal Component Analysis (PCA), an unsupervised technique used for feature extraction and identification and Linear Discriminant Analysis (LDA) a statistical method based on supervised learning technique used for pattern recognition and classification.
A. Clustering Using Principal component analysis (PCA) and Linear Discriminant Analysis (LDA)

PCA is a widely used technique for reducing the complexity of data to be better visualizing. It works by projecting the high-dimensional data matrix to a lower-dimensional space of principal components. The resulting score and loading matrices allows clustering classes without labelling them [22]. The number of dimensions in these matrices is smaller than the original data matrix.

The columns of the score matrix, known as Principal Components (PCs), are orthogonal to each other and organized in such a way most of the data variance is preserved after the information transformation. The scores are then displayed as scatters in two- or three-dimensional plots representing different Principal Components (PC) against each other. The first principal component explains the largest amount of variation in the data, and each subsequent component explains as much of the remaining variation as possible, and objects that were similar in the original space are seen as points that are close to each other in the score plots. The main benefit of this approach is the transformation of multidimensional data into easily understandable two- or three-dimensional graphs, while retaining most of the data variance.

Linear Discriminant Analysis (LDA) is a supervised technique that uses labels and features in the dataset to reduce the dimensionality [23]. The features that contribute the most variance among the species (in our case vapor saturation of different solutions), are selected through LDA which accomplishes this by maximizing the variance between species and minimizing the variance within species, resulting in improved separability in the dataset. Unlike PCA, which looks for directions with the greatest variation in the dataset and ranks components based on the variation they explain, LDA focuses on ranking features based on the variation they explain among species. Most of feature reduction algorithms are used to reduce the size of data by keeping enough information that ensure discrimination between the classes. These algorithms are executed based on post process approach. In our case, we developed all these algorithms with Python code to fulfill real-time requirements in the future.

B. Classification Results

The electrical performance of eight triflate salts commercially available (Gd(OTf)$_3$, La(OTf)$_3$, Nd(OTf)$_3$, Dy(OTf)$_3$, Ce(OTf)$_3$, Ho(OTf)$_3$, Eu(OTf)$_3$) were tested by drop casting them on poly(3-hexylthiophene) (or P3HT). The experiment mains to mimic olfactory system that identify odor patterns by chemisorbing elementary components of a volatome on different cells that gathers different complexes which differently with their environment on a chemospicific manner [26]. Simultaneous multidimensional data processing was performed to recognize a variety of vapor saturation solutions. Fig. 8 a shows the experiment protocol including sensors, system for acquisition, preprocessing, and feature extraction. Data processing such as-noise filtering, normalization and post-classification of the collected data were performed using Python code based on Scikit-learn, an open-source library for machine learning [24] [25]. Five solutions including acetone, alcohol, whisky, vodka, and beer were selected for this experiment. Selected solutions were determined in order to have target molecules with different chemical compositions to study the response of our E-nose system. In our case, all six sensor responses from the array were the correlated attributes which had been transformed into a set of uncorrelated principal components. We exposed our E-nose to each vapor saturation for 90 seconds with a purge time of about 30 seconds in air, the transient changes in resistances of the triflated polythiophene coatings towards vapor saturation were recorded.
Fig. 8. a) The Setup of electronic-nose base AD5933 impedance analyser b) response over time of sensor number 2 for different exposed solutions (Acetone, Butanol, Whisky, Vodka, Beer), c) Zoom of the sensor 2 impedance response.

We should mention that the peak resistance values of the graph represent the response of sensors to pure air and the minimum values of the graphs are the respective response of sensors to each gas (fig.8 b and c). Then, the six responses from sensor matrix were used as input parameters in PCA analysis.

Fig. 9. Explained variance ratio plot showing that 90% of variance is included into the first three principal components.

By examining the six-loading data of the principal components, one can determine which combination of sensors in the array is most effective for distinguishing the target gases. Fig10 a and b show the responses and the correlation of each sensor within the array toward all the target gases. Each response value plotted is the average response of two consecutive resistance values. The heat map clearly shows that all the individuals triflated polythiophene coatings exhibited high sensitivity and dynamics to butanol and acetone vapor saturation. In contrast, the relative variation is smaller in the case of beer, Whisky and Vodka which can be attributed to the fact that these solutions are less volatiles than organic solvents (as the beverages mainly contains water), which clearly affect the relative variation of resistance values of each sensor. It was found from previous research that the charge transfer modulation within the semiconductor is not only related to gas nature, but also involves the participation of the dopant in the polymer [26]. Specifically, changes in the resistance of the polymer due to gas exposure have been attributed to a decrease of the charge carrier’s
concentration, which is correlates with the ability for a molecular gas to transfer electrons with an electrophilic Lewis acid dopant [26][27].

Using a sensor array instead of a single sensor, the collective effect of several triflated polythiophene coatings on a same tool can be effectively exploited to extract multiselectivity from a single AFE. This is because each gas produces a distinct pattern imprint on the sensing array, which can be further analyzed with multivariate data analysis techniques and machine learning algorithms. Using these analytical tools, it becomes possible to accurately detect and identify specific gases with greater precision.

The component loadings in a principal component analysis (PCA) represent the correlation coefficients between the sensors in the array and the principal components, as demonstrated in the data. New datasets are created as linear

![Graph](image1.png)

**Fig. 10.** A) Statistics of sensor impedance responses toward vapour exposures b) Correlation heatmaps showing the connection coefficients between gas and the relative variation of each sensor impedance c) 2D LDA plot showing the discrimination of different vapor saturation based on normalized from different sensors datas. D) 3D LDA representation e) 2D PCA plot showing the clustering of different vapor saturation based on normalized datas acquired from different sensors f) 3D PCA representation.

Combinations of the original ones and they are highly correlated with each other. The features extracted from the training data using PCA were then being applied to the test dataset for gas identification. Responses from the array
were resolved by smaller number of principal components that consider most of the variance in the observed attributes. The first three principal components (PC1 – PC2 – PC3) capture the maximum of the variance from the original data set. Fig. 9 shows explained PCA ratio plot where the relative contribution of the principal components PC1, PC2 an PC3 reflect 60%, 20% and 10%, respectively, resulting in 90% of the total variance. The rest of the principal components captured variance that do not affect the results. We should note that although six sensors we are able to support data separation. The largest sensors array we have, and the richest response pattern with the most robust classification model to accommodate large calibration variations.

Standardizing features is a crucial pre-processing step, it refers to the process of scaling the input data, so that they have zero mean and unit as standard deviation. This is typically done before performing PCA to ensure that the results are not biased by differences in the scale of the input. In fact, if the input data have very different scales, variables with the largest scales will dominate the analysis, regardless of their contributions as the principal component loadings.

The 2D and 3D PCA plots shown in fig.10 e and f are based on normalized data. It appears obvious from these plots that the data of each solution are widely separated from each other, which is an accurate result for classification. We can also observe a drift in the PCA projection, measures of the acquisition test tend to drift toward a direction that is perfectly visible on the first two principal components. This can be explained by the fact that sensor’s response exhibits small and unpredictable temporal fluctuations when exposed to the same analytes in identical conditions. Sensor aging is a common cause of this issue, it can also be influenced by other factors such as environmental conditions, hromos-mechanical degradation, and exposure to humidity. Nevertheless, this feature can be overcome by combining multiple measurements taken over a certain period of time, instead of relying on a single measurement series for training.

Generally, LDA classification algorithm is considered to be a better choice for classification tasks compared to PCA, since it takes into account the class labels and is designed to optimize the separation between classes [28]. Fig 10 c and d show the result of the 2D and 3D discrimination of the different studied solutions. For the calculation, all extracted features have been normalized. Discrimination of the five-vapor saturation independent of their nature is easily possible, we can see through the first two discriminant functions mainly separate butanol from the other gases, which can be explained by the fact that sensors have the highest sensitivity towards this solution. We can also see that in the case of ethanol-based beverages, the clustering groups are located in the same region as these solutions are water-rich. Additionally, the same LDA plot also allows direct correlation between groups nature of the ethanol concentration in these solutions.

V. Conclusion

In this paper, we focused on the development of a miniaturized, connected, and portable impedance analyzer. The AD5933-based system operates efficiently in [35 kHz – 80 kHz] frequency range with high accuracy impedance measurement (error less than 4% for [1 kΩ - 1 MΩ] impedance range) using only one calibration resistance. To go further in sensor application, we demonstrate a proof-of-concept for a low-cost, and portable e-nose. Our platform has been tested and optimized to be used for multi-selective chemical organic sensor nodes. The electrical performance of eight triflate salts combined with organic semiconductor poly(3-hexylthiophene) were used as active layers. Sensor’s impedances were used as input data of two classifications algorithms (PCA and LDA). The goal of this research is to analyze the appropriate feature reduction approach between LDA and PCA, which can be used for software implementation for real time applications. The obtained results reveal that the data of each target gas are widely separated from each other, with a better classification provided by fewer components LDA than PCA classification.

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REFERENCES


**L. ROUTIER** (M'25) is born in Boulogne-sur-Mer, Pas-de-Calais, France, in 1998. He received the B.S and the M.S. degrees in engineering from ICAM school engineering, Lille 59800, France. Currently, he is a second year Ph.D. student in electronics from Université de Lille, Lille. From 2020 to 2021, he was in an engineering internship in intech Medical, Rang-du-Flier, France. His research interests include the development of electronic platforms for environment monitoring including the development of electrochemical sensors.

**A. WESTRELIN** (M'24) recently graduated from the ICAM engineering school in Lille. He holds an engineering degree specializing in the fields of transport, logistics, and energy. During his studies in 2022, Alexandre actively participated in a research memoir focused on applied material science. His research involved the design and development of an integrated platform for the characterization of SAWs (Surface Acoustic Wave) sensors. This project showcased his expertise and interest in cutting-edge technologies. Currently, Alexandre is employed at “MC2 Technologies,” a prominent company based in Villeneuve d’Ascq. The company specializes in the development of advanced RF microwave-based protection systems. Within MC2 Technologies,
Alexandre serves as an automation engineer, responsible for system installation and testing. His role involves ensuring the smooth integration and functionality of the company’s cutting-edge systems.

**Anthyme CERVEAUX**, born in Armentières, he worked on a research master thesis with Dr HAFSI. The aim of the dissertation was to characterize the analysis of SAW sensor data, in order to achieve gas discrimination by point clustering, obtained after a principal component analysis (PCA). He made an industrial thesis at Safran involved leading a team to reduce drift on a production line, using lean tools (DMAIC, PDCA, GANTT, etceterra). After 3 years of constant development as an apprentice method engineer for the aeronautics industry, he is now heading for the USA, to research, purchase and install a new production site for item, a German company.

**Thomas HORLACH** is born in Lille, France in 2001. He received his General Engineering degree in 2023 from ICAM school of engineering. He made two internships in Renault between 2018 and 2019, where he worked on the assembly production line. He did in 2023 a master’s thesis within the Electrical Department of ICAM under the supervision of Dr. Bilel Hafsi. His research focused on the non-supervised clustering of atmospheric gases in real time using different Machine Learning algorithms such as Principal Component Analysis, Kernel Principal Component Analysis and Independent Component Analysis.

**Gaël LOUIS**, currently he is an engineering student at ICAM school engineering in Lille, he is doing his Master thesis on a work-study program with the Atlantic Group company in Billy-Berclau since 2020. During this work-study program, he works on optimizing the maintenance department in technical interventions and shutdowns. He worked on conducting sensors based organic materials and developed python algorithm to ensure gas discrimination by point clustering, obtained after a principal component analysis (PCA) and Linear discriminant analysis (LDA).

**Pierre FOULON**, He received the B.S and the M.S. degrees in engineering from ICAM school engineering, Lille 59800, France. Recently He won the First award in the ecological transition trophies competition organized by VEOLIA in Paris. His work was focused on the development of an android application to control the electronic nose presented in this paper. Currently, he works as engineer in SCNF company in Lille.

**Pr. Kamal Lmimouni** received the Degree in electronics, the Ph.D. degree, and the Research Direction Diploma from the University of Lille, Lille, France, in 1997 and 2006, respectively. He was appointed as an Assistant Professor with the University of Lille in 2001, where he focused on charge transport in organic materials and design of new organic field-effect transistor structures including memory devices. He is a currently a Full Professor at the University of Lille.

**Dr. Ing. Sébastien Pecqueur** received his MSc. double major in chemical engineering and inorganic chemistry at the National Graduate School of Physical Chemistry in Bordeaux/France (ENSCPB) & the University of Bordeaux/France in 2010, and his Ph.D. (Dr.-Ing.) in material sciences at the Friedrich Alexander Erlangen-Nuremberg University/Germany in 2014. He is currently CNRS tenured researcher at the Institute for Electronics, Microelectronics and Nanotechnologies (IEMN) based in Villeneuve-d’Ascq/France. His main research interests focus on organic electronic materials & devices, and particularly their potential for future-emerging sensing technologies exploiting in materio information classification with organic electronic materials.

**Dr. Bilel HAFSI.** (M’36) received the master’s degree in materials, nanostructures, devices et microelectronics systems from Monastir University, Tunisia, in 2012 and the PhD. degree in micro et nanoelectronics, acoustic and telecommunications from Lile University, France, in 2016. From 2016 to 2018, he was a Teacher and Research Assistant with the central Lille institute. His research interest includes the development of Devices based organic materials, and fabrication of micro- or nanostructured surfaces. To expand these concepts, he focused on developing new kind of memory devices based on double floating gate made of gold nanoparticles and reduced graphene oxide. His main interest was to boost the memory performance (endurance, memory window and retention time). From 2018 to 2019 he has experienced the Job of a Dream consultant in private company "Techshop Les Ateliers Leroy Merlin" where he supervised many projects in the field of IOT’s, Robotics ... . Currently, he works as associate professor in the electrical department in ICAM school of engineering, Lille 59800, France. Dr. Bilel HAFSI was a recipient of the International research Young Scientist Award in 2018 from the doctoral college in the north of France.