Indonesian Journal of Electrical Engineering and Computer Science
Vol. 30, No. 1, April 2023, pp. 70~80
ISSN: 2502-4752, DOI: 10.11591/ijeecs.v30.i1.pp70-80

Detection of harmful gases present in the environment

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Article Info

Article history:

Received Oct 31, 2022
Revised Nov 13, 2022
Accepted Nov 23, 2022

Keywords:

Discrimination
E-nose device
Multi sensor array
Odor concentration
Partial least square

ABSTRACT

The electronic nose (e-nose) is demonstrated in this research for detecting and identifying several forms of hazardous gases. We describe an e-noses for detecting several gases, including butane, acetone, methane, and ethanol. For dimensionality reduction in 3D representation, data processing approaches are based on the partial least square (PLS) method. The suggested system can be utilised for sensor optimization since different sensors with varied operating temperatures can be tested in many devices to find the best array for a specific detection or application. The results reveal that, depending on the sensor array characteristics, varying success rates in classification can be attained when discriminating contaminants. The preceding criteria lead to a new search for a portable, dependable, low-cost, and most efficient gas sensor. The major purpose of this study is to create a gas sensor array that can detect and monitor toxic and poisonous gases in the environment, as well as warn against dangerous organic compounds. Our goal is to create a sensor system that can distinguish the most significant decontamination gases while also being highly responsive, precise, low-effort, and low-power demanding.

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1. INTRODUCTION

There are numerous uses for detecting volatile organic compounds (VOCs) in solid waste. VOCs are a group of highly hazardous pollutants that are often present in the environment and may constitute a serious health risk to humans [1]. Human breathing, on the other side, contains VOCs which can be utilised to diagnose a variety of ailments. The presence of a particular quantity of acetone, for example, is considered to be a sign of diabetes [2]. The same principle can be applied to abnormal ethanol concentrations [3]. Metal oxide semiconductor (MOS) sensors are useful because of their quick reaction time and low cost. When dealing with a single sensing element in the presence of many gases that elicit sensitivity, this lack of selectivity can be seen as a disadvantage. Highly selective gas detecting systems can be produced employing arrays of multiple sensors, each with a distinct reaction to the gases of interest, and are usually referred to as nanosensors [4].

The propelled nose is a gadget that detects smells more accurately than the human sense of smell. A component for substance declaration is consolidated by an electronic nose. The automated nostrils are a perceptive differentiating device that makes use of a variety of gasoline sensors that can cover specifically near a previous revision section. By and by, pushed noses have offered outside focal points to a variety of corporate ventures, agriculture, biomedical, someone very, environmental, food, water, and various helpful research disciplines. Electronic nostrils have been employed in a variety of corporate green-related initiatives, including agronomy, biochemical handling, plant science, cell customisation, and plant cultivar selection [5]. Pollution can take the form of a mixture of chemicals, such as solid particles, liquid dots, or gasoline [6], as well as a characteristic that combines commotion, warmth, and light. Both natural and man-made assets contribute to

air pollution. As a result of the rise in polluted gases, there is a growing demand for more space and monitoring of ozone-depleting compounds [7]. However, in this paper, we will likely deal with the hallmark gases that are transported by ways for solid waste, and we can respect Air quality poisons due to the fact that it is the most significant natural threat to prosperity [8]. As a result, the proposed structure satisfies the majority of the requirements for defilement. It collects data and measures various sullied gases such as CO, CO_2, and LPG. The most problematic issues were related to zone programmes, as the most often utilised sensors are sensitive to barometrical circumstances [9], [10]. After the surface overflow and endorsement of the association between propelled nasal reactions and notice power, the electronic septum cause is too dependable. Because consistency is essential for maintaining customer seal image and pleasure, quality controls of the fragrance features of produced stock are of critical importance.

The authors describe how the main goal of this research is to identify butane, acetone, propane, ethane, liquefied petroleum gas (LPG), as well as other producer gas in hazardous waste as well as perform quality checks. Our goal is to create a sensor cluster framework that can detect the most severe contaminated gases while also being very rapid, low-effort, and low-power consuming. We used three sensors in place of six and calculated the results as fluctuation, scoring plot, as well as stack plot. For gas recognition, we use parallel factor analysis (PARAFAC) and compare it to the key element research principal component analysis (PCA). Three sensors were confiscated in place of six sensors, and the results were presented as variance, scoring plot, as well as loading plot. Our goal is to create a sensor exhibit framework that can distinguish the most extreme contaminated gases while also being extremely responsive, precise, and low power consuming. For the finding of gases, we use the (PARAFAC) and compare it to the (PCA) [11].

This paper offers a feature selection technique based on k-means clustering to address the shortcomings of traditional feature selection techniques like principal component analysis which take a long time to convert all of the input data. Depending on the importance value of a particular coordinate in a cluster, this suggested technique determines which features to keep. When comparing k-means clustering to PCA as a feature selection strategy, it is clear that the suggested technique outperforms PCA, particularly in terms of computing time. As a result, k-means clustering is found to be more effective than PCA in reducing data dimensionality while maintaining the efficiency of the k-nearest neighbors (KNN) model for high frequency information [12].

In 2016, a four-sensor display with neural networks was developed to detect formaldehyde in three potentially interfering (VOCs), such as $(CH_3)_2CO$, ethanol, or toluene. The sensor display included four MOS gas sensors: two were commercial SnO_2 sensors, and the other two were made in a research lab. The PCA helps ensure the accuracy of the ELM by pre-preparing sensor data, whilst the SVM method achieves the highest precision. With reduced preparation time and more precision, the ELM methodology offers a superior way for creating the sensor clusters and distinguishing specific gas types [13].

The accuracy of half and half air ID and focus recognition is low in 2018, as a standard machine sensory framework file. CO and CH_4 are used as exploratory framework testing to approve the suggested strategy. According to the trial results, the proposed technique has a precision of 98.33%, which is 5.83 percent and 14.16 percent greater than head part examination (PCA) and autonomous segment inquiry, respectively. CO and CH_4 fixation finding normal relative blunders are reduced to 5.58 percent and 5.38 percent, respectively, using the half breed gas concentrate recognition approach [14].

In 2020, a statistical tool based on partial least squares regression (PLSR) able to retrieve single-component Concentrations in a multiple-gas mixture are characterized by spectrally overlapping absorption features. Absorption spectra of mixtures of $CO{-}N_2O$ and mixtures of $C_2H_2{-}CH_4{-}N_2O$, both diluted in N_2, were detected in the mid-IR range by exploiting quartz-enhanced photoacoustic spectroscopy (QEPAS) and using two quantum cascade lasers as light sources. The concentration range explored in the analysis varies from a few parts-per-million (ppm) to thousands of ppm. PLSR predicted gas concentrations with a calibration error up to 5 times better, even with absorption features with spectral overlap greater than 97% [15].

With the advancement of internet of things (IoT) technology, the application of gas sensors in smart homes, wearable devices, and bright flexible terminals has increased dramatically in 2019. The gas sensor exhibits cross affectability and limited selectivity in such complicated detecting settings. As a result, bright gas detecting solutions have been introduced to address these challenges by combining sensor clusters, signal processing, and artificial intelligence technologies with traditional gas detecting improvements. This report examines the overall structure of smart gas detection innovation, focusing on three main issues: gas sensor clusters built of diverse materials, signal processing for float pay and highlights extraction, and air design recognition, which includes PLS, ANN, and other approaches [16].

2. METHOD

In this paper, the partial least square model is used in the MATLAB computing environment to find the results. The whole process of model is shown in Figure 1, where the data set is collected and then this sigher dimention data is converted to lower dimention data using partial least square method after that the accurate principal component is detected using cluster alalysis and the detected data results. All the necessary steps are shown below.

2.1. Data analysis

In order to give, the improved yield created by electronic nasal sensors must be dissected and understood. Graphical examination, multimodal information inquiry [17], and network inquiry are the three main types of economically available approaches. The most practical condition of an estimates refund is a graphical analysis useful for surveying tests or comparing odours recognising evidence components of online agents to those of saw assets in references libraries [18]. The multidimensional facts examination generates a rigid set of processes for the examination of educated or unskilled information. Untrained frames are employed, and a little knowledge base of realised precedents is never built ahead of time. Kinds of pears turned into made in a study that utilised this automatic method, and the dazzling was chosen based on their amassing dates [19]. They got struck impacts by combining backslide counts with electronic nose guarantees [20]. Hikmah *et al*. also mentioned the z-nose in a study that determines the type of food [21].

Figure 1. Whole process of detection for the proposed e-nose system

To achieve an inspection state mode, the value1 was closed and the sensor obstruction was provided 60 seconds. On the LCD, the order impact of the sensor's distinctive esteem was seen. The sensor cluster tank was disconnected from the organic food test breaker, as well as the valve 1 was unlocked to allow natural air to flow in, while the valve 2 being opened to allow the fragrances to escape. For 2 seconds, natural air was aired out of the chamber.

While no respected model is available, the PLS is a most outrageously supporting model. The neural system is a common recognised and widely used decision assessment way in quantifiable programming programme groups for modernly open propelled nostril. Strategies for putting a case of natural products within the breakers fixed with a spread were used to cope with the odours. The sensor charge is displayed on the LCD when the structure is in teaching mode. When the gadget is in seeing mode, the LCD displays the most recent result of the target natural item. The gas is delivered to the sensor group via valve 1, which is currently closed. To coordinate the gases out of the sensing display, the suction syphon is turned on for 20 seconds.

2.2. Classification of sensors

Here we are defining all sensor set those are used in research work, there resistance, voltage, and detection material. Here Table 1 shows the types of sensors. First column includes different sensors, second includes the detection material, third concludes voltage and resistance of sensors and fourth includes power (mw) for sensors.

Table 1. Types of sensors

Sensor	Detection material	Voltage/R_B	Power (mW)
TGS 2602	Ethanol, Ammonia, Hydrogen, Toluene	5 V DC,59 Ω	15
MICS 5135	CO, HC, ethanol, and VOC.	3.2 V, 97 Ω	102
TGS 2620	Methane, Ethanol, Iso-butane, CO, Hydrogen	5 V DC/AC, 83 Ω	15
TGS 2600	Methane, Ethanol, Iso-butane, CO, Hydrogen	5 V DC, 83 Ω	15
TGS 2611	Methane, Ethanol, Iso-butane, Hydrogen	5 V DC, 59 Ω	15
MICS 5521	CO, hydrocarbons (HC), and VOC	5 V DC, 74 Ω	76
TGS 822	Ethanol, Methane, CO	5 V DC/AC, 38 Ω	660
TGS 825	H2S, CO	5 V DC/AC, 38 Ω	660
TGS 880	Ethanol, hydrogen	5 V DC, 30 Ω	15
TGS 810	Methane, LPG	3 V DC/AC, 32 Ω	525

In this section, we looked at the features of various gas sensors, such as temperature, turnaround time, and energy consumption, based on materials used throughout the sensors as well as the technologies used to classify distinct gas sensor technology. We gave all of the above qualities in a tabular format in this study, which gives us a clear picture of sensing technology. In Table 2, first column contain material which is used for different gas sensor, 2nd columm is given for concentration range for gas sensor, 3rd taken response time, 4th given the temperature for different gas sensor as well as 5th includes remark of gas sensors.

Table 2. Based on the materials used in the design of different gas sensors

Material	Concentration range	Response time temperature (℃)		Remark
SnO_2/Pt, Au/Pt	1000-8000 ppm H_2	2-6 Sec	200	Nano-structure doped SnO_2
SnO_2/ZnO, WO_3	12.5-100 ppm, chloroform, benzene	10 min	200	Response time is 50 sec at temperature 400 ℃
In_2O_3, Pt, Pd		5 min	300	
SnO_2/Pt, WO_3 /Au, ZnO	Up to 2000 ppm CH_4	7 min	300	Sputtering authentication
SnO_2, SnO_2/Pt, Nb_2O_5	100-10000 ppm CO, NH_3	20 min	450	20 sec response time for Nb_2O_5
SnO_2, SnO_2, Al_2O_3	10-20000 PPM CH_4	2–250 sec	350	Sputtering deposition
SnO_2, SnO_2/Pt, Pd	750 ppm C_2H_5OH, 1% CH_4, 1% CO_2	2-18 min	400	Sputtering deposition, doped Pt sensor fastest.
SnO_2	1-4000 ppm CO	<2 min	450	
	5-100 ppm NO	5 min	300	
SnO_2/Pt, SnO_2/Cr,	50–200 ppm CO	3-5 min	250	Sputtering authentication
	0.5–2 ppm NO_2	5-10 min		

2.3. Odor classification

Two modernised noses with MOS detectors were used in the experiment, and they were transferred to six distinct spots in the following plan of action at regular intervals. To imagine the bundling of the estimates, the sensor reaction encounters had already been destroy at about PLS [22]. By that time, the use of an ANN to anticipate aroma care had been investigated, as well as approaches for isolating testing between high, medium, and low thinking degrees. The device was designed to predict smell obsessions that surfaced to be clear with people present at various testing facilities, and the results are promising. Sensor-mix estimations that are agreeably modified by methods for coordinating preparing are required for achieving extreme field modification frameworks with built-in poisons full standards using sensor-mix evaluations [23], [24].

2.4. Proposed methodology of partial least square

The properties of PLS regression can be analyzed from a sketch of the original algorithm. The first step is to create two matrices: E = X and F = Y. These matrices are then column centered and normalized (i.e., transformed into Z scores). The sum of squares of these matrices is denoted SSX and SSY. Before starting the iteration process, the vector u is initialized with random values. (In what follows the symbol/means "to normalize the result of the operation").

Step 1. $w \propto E^T u$ (estimate X weights).

Step 2. $\mathbf{t} \propto \mathbf{Ew}$ (estimate **X** factor scores).

Step 3. $\mathbf{c} \propto \mathbf{F}^T\mathbf{t}$ (estimate **Y** weights).

Step 4. $\mathbf{u} = \mathbf{Fc}$ (estimate **Y** scores).

If **t** has not converged, then go to Step 1, if **t** has converged, then compute the value of b which is used to predict **Y** from **t** as $b = \mathbf{t}^T\mathbf{u}$, and compute the factor loadings for **X** as $\mathbf{p} = \mathbf{E}^T\mathbf{t}$. Now subtract (i.e., partial out) the effect of **t** from both **E** and **F** as follows $\mathbf{E} = \mathbf{E}\ \mathbf{tp}^T$ and $\mathbf{F} = \mathbf{F}\ b\mathbf{tc}^T$. The vectors **t**, **u**, **w**, **c**, and **p** are then stored in the corresponding matrices, and the scalar b is stored as a diagonal element of **B**. The sum of squares of **X** (respectively **Y**) explained by the latent vector is computed as $\mathbf{p}^T\mathbf{p}$ (respectively b^2), and the proportion of variance explained is obtained by dividing the explained sum of squares by the corresponding total sum of squares (i.e., SS_X and SS_Y) [25].

3. RESULTS AND DISCUSSION

The e-nose utilised in this test is made up of four distinct MOS gas sensors, the readings of which are recorded to create an aroma unique finger impression of the fragrance. Figaro TGS-822, TGS-880, TGS-825, and TGS-810 are the sensors in question. We will draw a graph for gas $(CH_3)_2CO$ and ethanol using these detectors. This is the smelling procedure of e-nose data that has been taken from the University of Malaga, 'odor classification data-set for mobile robotics': controlled gas pulses. (0-20) sec: for the first 20 seconds, the scent holder was kept closed and isolated from the e-nose desire tube, allowing estimation of the patterns level (sensor reaction without the target gas) for each sensor. (20-30) sec: after that time, the jar was reopened and left unsupervised for another 10 seconds, allowing the gas scattering rate to be adjusted (30-90) sec: at second

30, the e-nose was located closer to the jug, around 10 cm away from the jug's "mouth," allowing the e-nose to sniff the gas and record its results for 60 seconds. (90-X) sec: the e-nose urge was finally eliminated, and the jug was closed to avoid debasing the testing chamber. Because MOS sensors have a long recovery time, the e-nose was permitted to recoup its usual dimension for roughly 10 minutes before starting another run.

Loading plot shows the sensors performance classification. Score plot used to show the sample clustering. Variance plot shows the variance of cluster from one parameter to other. Scattering of cluster is measured in terms of variance. Less the variance better the detection of gases. A=acetone; B=butane; M=methane; E=ethanol. Here, Figure 2 and Figure 3 considers the raw data, and pre-processed data for different sensors, respectively.

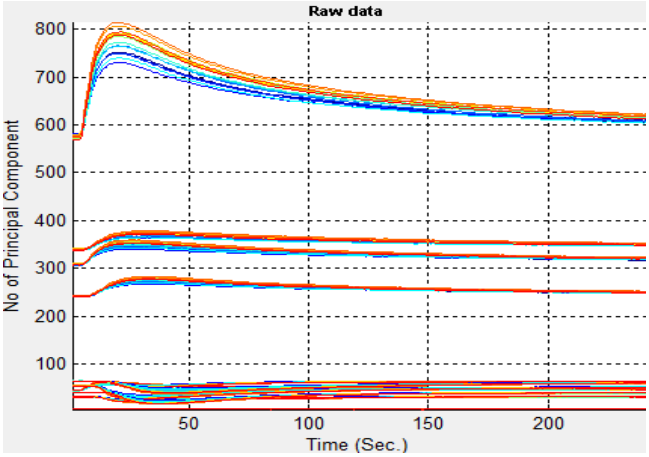


Figure 2. Raw data for different sensors (data has been taken from University of Malaga [26])

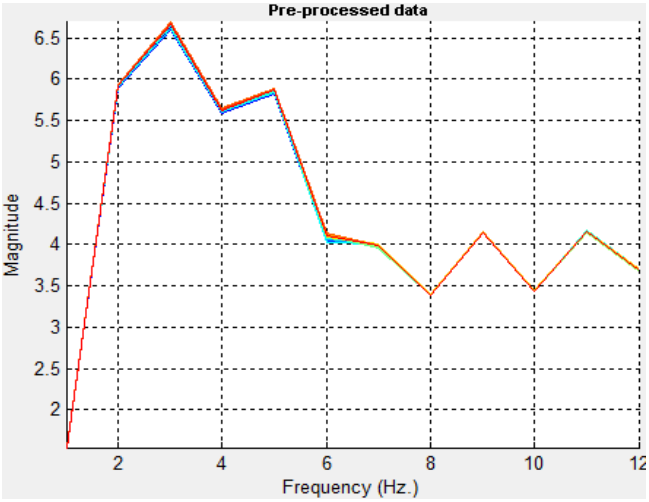
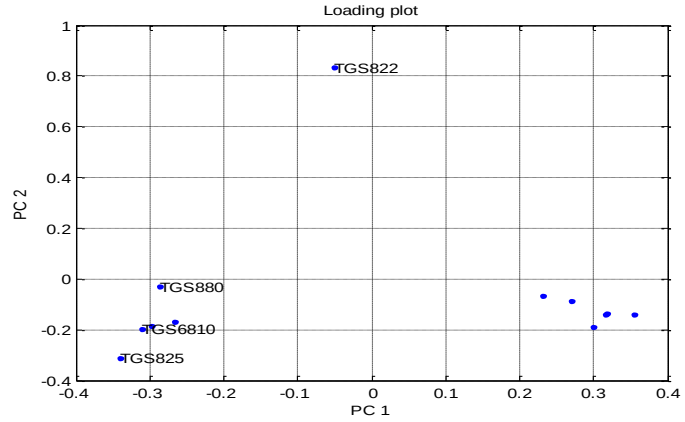
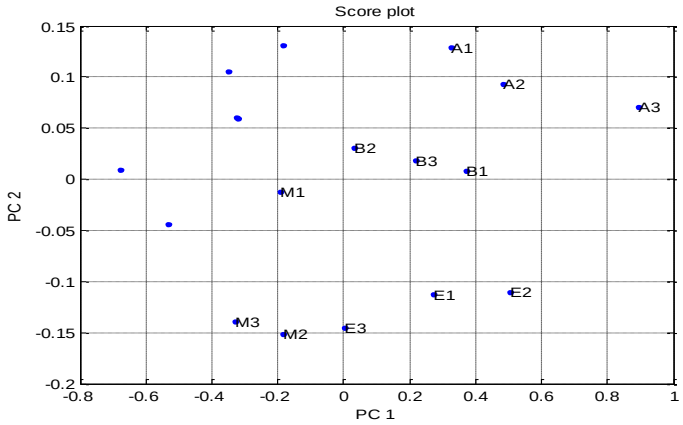


Figure 3. Pre-processed data (data has been taken from University of Malaga [26])

Figure 4 contains loading, score and explained variance plots. In which Figure 4(a) concludes loading plot that define discrimination of gases. For acetone and butane, it discriminates in best way and for ethanol and methane it discriminates poor. In Figure 4(b) score plot is using that define discrimination of gases. For acetone and butane, it discriminates in best way and for ethanol and methane it discriminates poor. Figure 4(c) is explained variance plot. In these two plots of principle components (PC) are shown. In which for variance the values of principle components are at X=1, Y=21 and at X=2, Y=45.3 that is good. For cross validation value of principle components are at X= 1, Y=11.2 and at X=2, Y=30.5. So cross validation value for variance along the principle components is very good.



(a)



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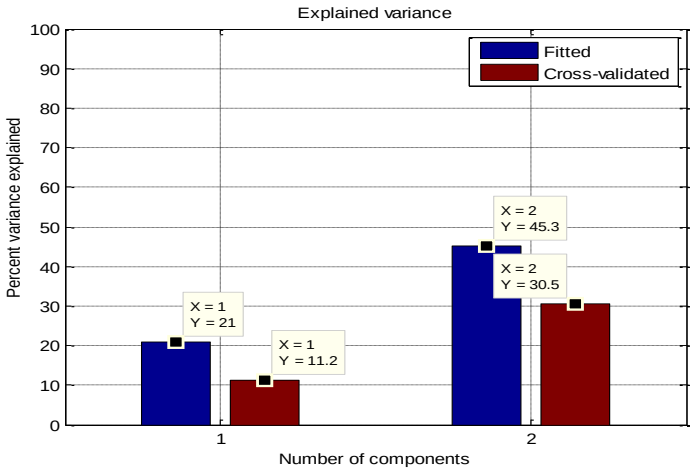
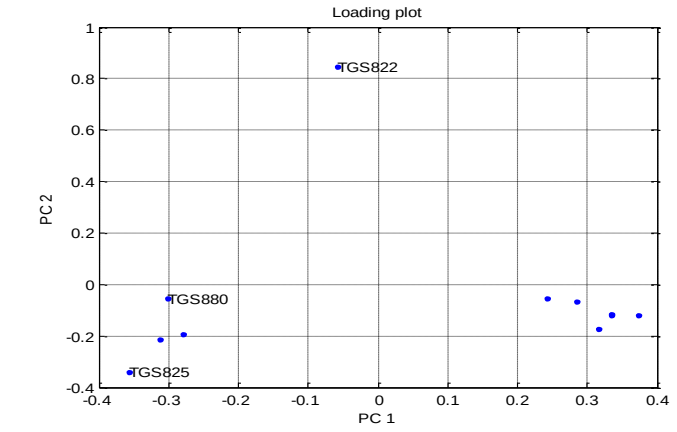


(c)

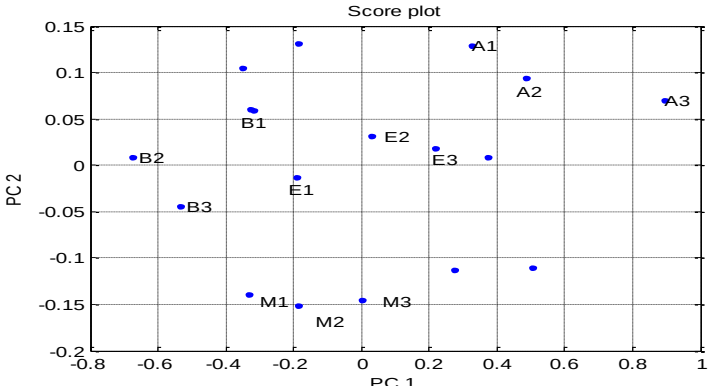
Figure 4. The loading, score and explained plot, (a) loading plot for four sensors (TGS822, TGS880, TGS810, TGS825), (b) score plot for four gases (acetone, butane, methane and ethanol), and (c) explained variance plot for TGS822, TGS880, TGS810, TGS825 sensors

Figure 5 contains loading, score and explained variance plots. In which Figure 5(a) shows the loading plot that defines sensor classification of gases. The TGS822 and TGS825 define in a best way of gases and Figure 5(b) shows the score plot that defines discrimination of gases. For acetone and methane it discriminates in best way and it also discriminates butane and ethanol. Figure 5(c) is explained variance plot. In these two plots of principle components (PC) are shown. In which for variance the values of principle components are at

X=1, Y=21.2 and at X=2, Y=45 that is good. For cross validation value of principle components are at X= 1, Y=11.4 and at X=2, Y=30.2. So cross validation value for variance along the principle components is very good.



(a)



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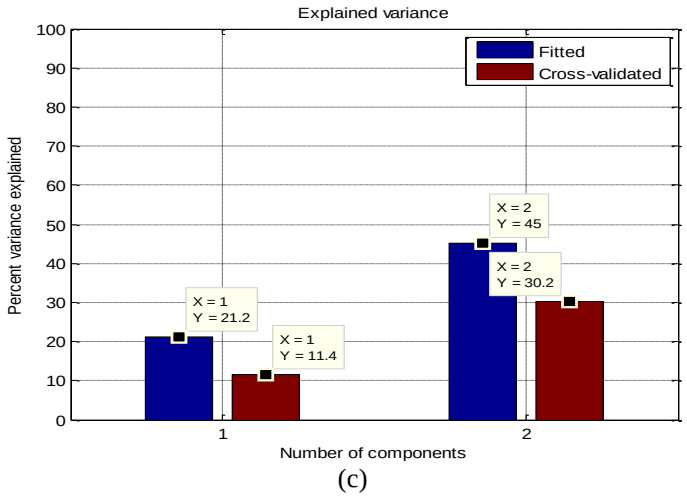
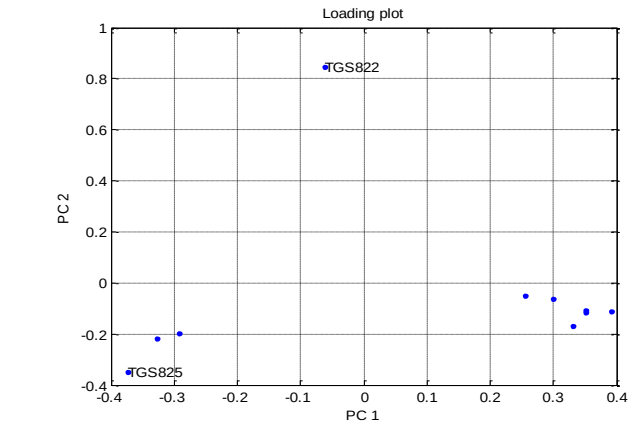


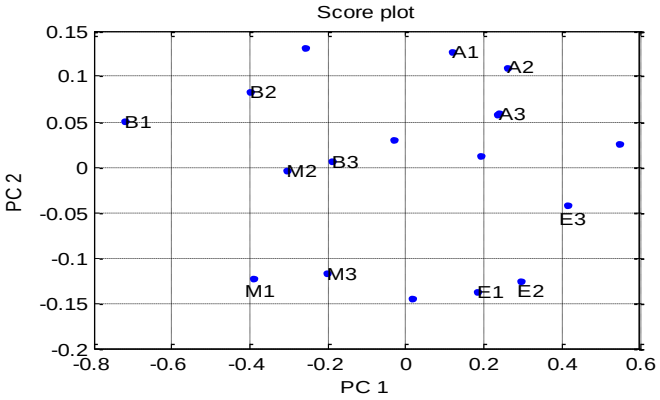
(c)

Figure 5. Shows loading, score as well as explained plot, (a) loading plot for three sensors (TGS822, TGS880 and TGS825), (b) Score plot for four gases (acetone, butane, methane and ethanol), and (c) explained variance plot for TGS822, TGS880 and TGS825 sensors

Figure 6 shows the loading, score as well as explained variance plots. In which Figure 6(a) shows the loading plot that defines sensor classification of gases. The TGS822 and TGS810 define in a best way of gases. Figure 6(b) gives the score plot that defines the discrimination of gases. For acetone and ethanol it discriminates in best way and for butane and methane it discriminates poor. Figure 6(c) is explained variance plot. In this two plots of principle components (PC) are shown. In which for variance the values of principle components are at X=1, Y=21.3 and at X=2, Y=45.1 that is good. For cross validation value of principle components are at X= 1, Y=11.5 and at X=2, Y=30.3. So cross validation value for variance along the principle components is very good.



(a)



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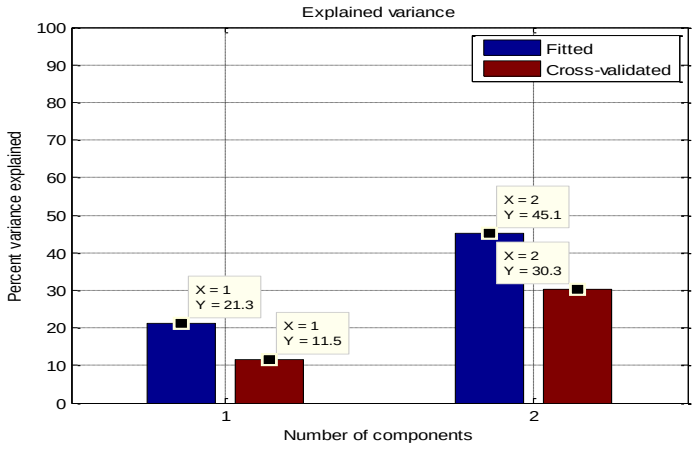
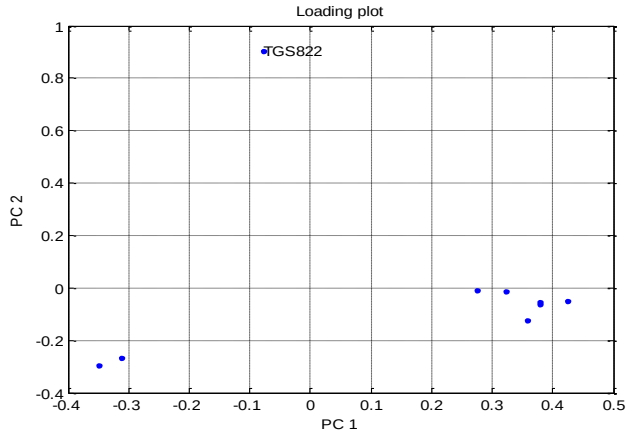


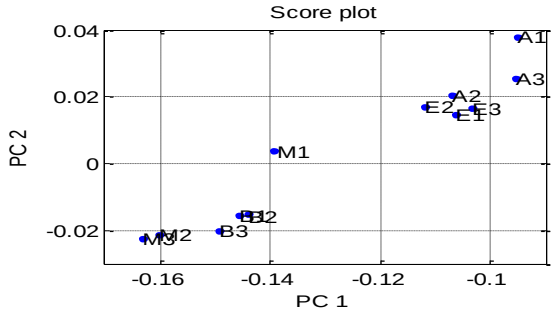
(c)

Figure 6. The loading, score and explained plot, (a) loading plot for two sensors (TGS822 and TGS825), (b) score plot for four gases (acetone, butane, methane and ethanol), and (c) explained variance plot for TGS822 and TGS825 sensors

Figure 7 includes loading, score as well as explained variance plots. In which Figure 7(a) shows the loading plot that defines sensor classification of gases. The TGS822 define in a best way of gases. Figure 7(b) concludes the score plot, define discrimination of gases. No one gas can be discriminated with single sensor. All gases are overlapping to each other. Figure 7(c) is explained variance plot. In this two plots of principle components (PC) are shown. In which for variance the values of principle components are at X=1, Y=21.6 and at X=2, Y=43.1 that is good. For cross validation value of principle components are at X= 1, Y=11.7 and at X=2, Y=28.2. So cross validation value for variance along the principle components is very good. In given below the Table 3 for explained variance plot conclude different sensor set in sensor set column, variance plot and variance plot with cross validation is showing for different sensor with different values.



(a)



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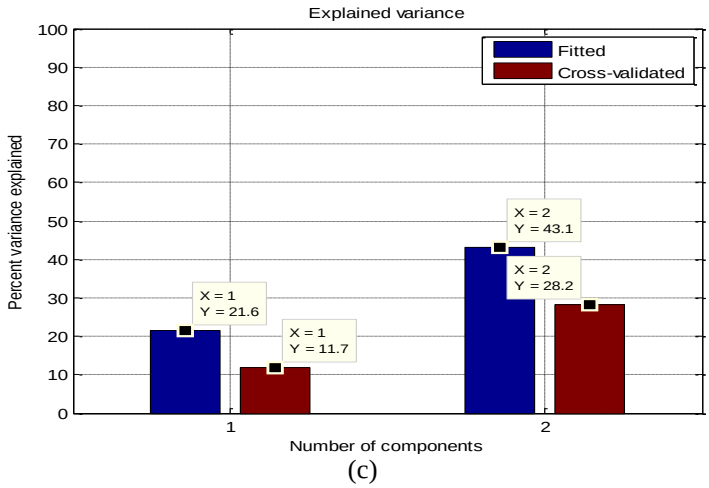

(c)

Figure 7. The loading, score and explained plot, (a) loading plot for one sensor (TGS822), (b) score plot for four gases (acetone, butane, methane and ethanol), and (c) explained variance plot for TGS822 sensor

Table 3. For explained variance plot

Sr. No	Senor set	Variance plot		Variance plot with cross validation	
1	TGS822, 880, 825, 810	X=1, Y=21	X=2, Y=45.3	X=1, Y=11.2	X=2, Y=30.5
2	TGS822, 880, 825	X=1, Y=21.2	X=2, Y=45	X=1, Y=11.4	X=2, Y=30.2
3	TGS822,825	X=1, Y=21.3	X=2, Y=45.1	X=1, Y=11.5	X=2, Y=30.3
4	TGS822	X=1, Y=21.6	X=2, Y=43.1	X=1, Y=11.7	X=2, Y=28.2

4. CONCLUSION

Because of the properties of volatile organic molecules, the e-nose could be used to detect other potentially dangerous gases. As a result, an electronic nose is a trustworthy tool for detecting dangerous gases. A comparative comparison of several pattern recognition approaches is required for the accuracy, sensitivity, and selectivity of an e-nose. On a broader scale, an array of similar sensors can be utilised to build an e-nose, and several approaches for analysing a mixture of volatile organic molecules can be used. When it comes to sensors, a few studies have looked into the issue of consistency in response to temperature and dampness variations, as well as sensor response coasting after a period of time, despite what might be expected. These issues necessitate refined and complex innovation with the specific goal of delivering definite and strong results. In any case, there are a few mechanically available absolutely basic gadgets that are nonexclusively referred to as "electronic noses," which can be used to differentiate gas discharges or survey solitary gas obsessions. It is critical to emphasise that such simple instruments are unsuitable for natural checking purposes. We've now completed all of the data connected to sensors as well as the charts that are relevant to the task. The partial least squares method was used to arrive at the results. Section 12 demonstrates the square technique. The output of the explained variance plot is based on the score plot plus loading plot. According to explained vaiance plot which is showing in result section, the values of variance plot for three sensors is best means the variance values are less along the principal components X=1, Y=21.2 and X=2, Y=45. Same as for these sensor sets cross validation values are X=1, Y=11.4 and X=2, Y=30.2. So, the detection of gases, for three sensors is very good. For three sensors, score plot that all the four gases can be discriminates in a very good way, which validates the results in the form of variance plot and score plot compared to all other plots. So, it concludes that less the variance better the detection of gases.

ACKNOWLEDGEMENT

We would like to thanks Integral University, Lucknow that has provide me the MCN number IU/R&D/2021-MCN0001311 for research work.

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