# Overview of Electronic Nose and its Application in Waste Water Treatment Process

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Available online 30 December 2024

**ABSTRACT**

This technical paper review aims to let readers have a brief understanding on EN and its application in wastewater treatment. It will be started with the problem background of wastewater treatment. Subsequently, the working principle of EN, material and methods of EN system applied in wastewater treatment.

**Keywords:** Electronic nose, waste water treatment

## 1. Introduction

Electronic nose (abbreviation EN, enose, e-nose) is a technology inspired by the sense of smell which mimics the mammalian olfactory system. It is also known as an odor sensor, aroma sensor, mechanical nose, flavor sensor, multi-sensor array, artificial nose, odor-sensing system, electronic olfactometry. [1]

The very first research on detecting distinctive smell was started by H.Zwaarde maker and F.Hogewind during the 1920s. Until in the early 1980s, only the idea to use a chemical electronic sensor to detect aromas was primarily mentioned in some research papers. Nevertheless, due to the sensor technology limitations, the EN concept cannot be actualized. The term "electronic nose" was then mentioned in the late 1990s which initially means it is a composition of a multisensory array for detecting more than one chemical component. [1]

## 2. Problem background

Wastewater treatment plants (WWTP) are considered as one of the significant nuisance odour sources in urbanized area that can causes people in health problem if prolonged exposure to the odours and it really irritates the surrounding neighborhood. To mitigate odour nuisance, the management strategies that can be taken including monitoring, assessment and controlling the generated substances. Nevertheless, it becomes challenging due to the high variability and complex nature odour emissions together driven by the operational and meteorological condition needed to be characterized and quantified continuously followed by evaluation and remedial actions [2]. Moreover, the smell perception can be a subjective interpretation that varies according to many factors [3]. Hence, it is important to have a suitable measurement instrument to assess odour emissions successfully. Various sensing system have been developed for monitoring air quality at higher temporal resolution.

Chemical oxygen demand (COD), Biochemical oxygen demand (BOD), pH, Oxygen Uptake Rate (OUR), Total Suspended Solids (TSS), Total Organic Carbon (TOC) as well as total total nitrogen or total phosphorus are the typical parameters to determine the quality of wastewater [4]. However, method likes BOD take times to complete experimental procedures and potential inconveniences might cause results obtained inconsistent. Recent ambient odour measurement techniques can be classified into analytical, sensorial, and sensor instrumental. Example of analytical measurements are gas chromatography-mass spectrometry (GC-MS) and colorimetric methods which allow the characterization of odours in terms of chemical composition. Dynamic olfactometry standardized by EN13725:2003 is an example of sensory measurement which provide for using human nose as sensor, defining and measuring the effects of the odours on a panel of qualified examiners. The EN, which falls in sensor-instrumental type technique appears as the most suitable potential sensor-instrumental technique since it allows having a continuous and real time monitoring for odours. Besides, this technique allows defining information about the chemical composition and the smell propriety of the investigated odour. [5]

## 3. Working Principle

The common concept of the biological olfactory system applied on the EN technology is clearly shown in Figure 1. In biological olfactory system, the olfactory nose receptors sense and capture the odor particles in the air. This input signal is then sent to the olfactory bulb to process the odor information. After that, the smell will be characterized and at last olfactory cortex in brain will recognize the smell. In EN system, the electronic sensor array has the function corresponds to the olfactory nose receptors. The captured odour signal is then applied with feature extraction by a preprocessor and after that processed to digitalize them in order to form a dataset [5]. Hence, the sensed signals are appropriately processed, such as amplified, filtered or covered to be easily used in subsequent steps. Data analysis will then go through according to their specific properties in the data gathering stages. After that, the sufficient data acquired from these signals and the obtained data is preprocessed according to the requirements of the employed algorithm [1]. After that, algorithms related pattern recognition and machine learning will be used so that the input signal can be identified and finally classified using the extracted digital signal.

In short, regardless the type of sensor elements of EN systems, the following principal stages are involved in monitoring of multi-component chemical (MCM):

1. Sample preparation that may involve operations of separation and/or concentration of MCM components.
2. Measurement of sensors signal and formation environment specific informative “fingerprint” thereon (“chemical image”).
3. Obtaining of chemical information on MCM by processing the results of measurements and presenting them in terms of calibrated dependencies [6].
4. Hence, most of the EN involves the following functional elements: (i) a sample preparation and injection module that ensures contact between sensors and sample; (ii) a recovery system that is responsible for cleaning of sensor for system to return to the initial state after each measurement; (iii) a data recording unit that records sensors signals and transforms them to a form acceptable for further processing; (iv) a data processing system that executes classification, identification and other operations, depending on the assigned task [6].

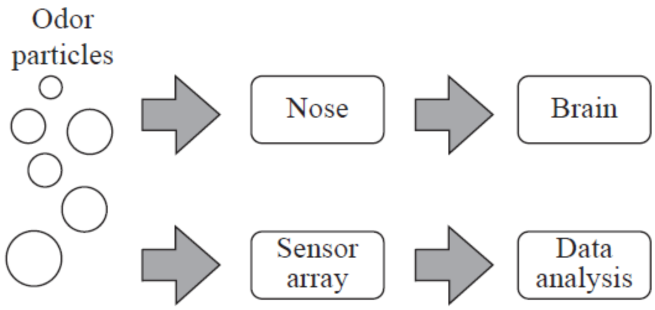


**Figure 1.** Analogy between the biological olfactory system and the electronic-nose technology

## 4. Material and Methods

A common electronic nose system comprised of an array of non-specific gas sensor, a signal collecting unit and a multidimensional pattern recognition software. In the perspective of hardware and software, the hardware part generally is the olfactory receptors while the software part can be thought as the brain which consists a data processing unit which identifies and classifies each individual scent detected using digital signature of the sensed chemicals [1]. Some of the system has an air flow unit which composed of solenoid valves, teflon and silicone tubing; a charcoal filter to obtain the baseline from ambient air; and a vacuum pump. This delivery block allows establishing a four-stage sequence for measurement: baseline (passing reference gas), rise transient (passing odour), steady state (maintaining odour inside the sensor chamber) and recovery transient (passing reference gas again) [3]. An example of simplified schematic representation of the EN system taken from [2] is shown in Figure 2.

Based on [7], for the data collection, voltage divider method was implemented to measure the voltage across each sensor that connected to known-value resistors. Then, the output was sent to multiplexer. By using Ohm’s Law, the resistant of each sensor can be calculated. To receive the sensing data, DAQ card was used to convert data from analog to digital form. The example schematic diagram is shown in Figure 3. By using LabVIEW program, the resistance of each sensor is recorded every second. The measurement time was set for repeating 5 times and every time 2 minutes was given for the reference gas to flow before switching to sample for 3 minutes.

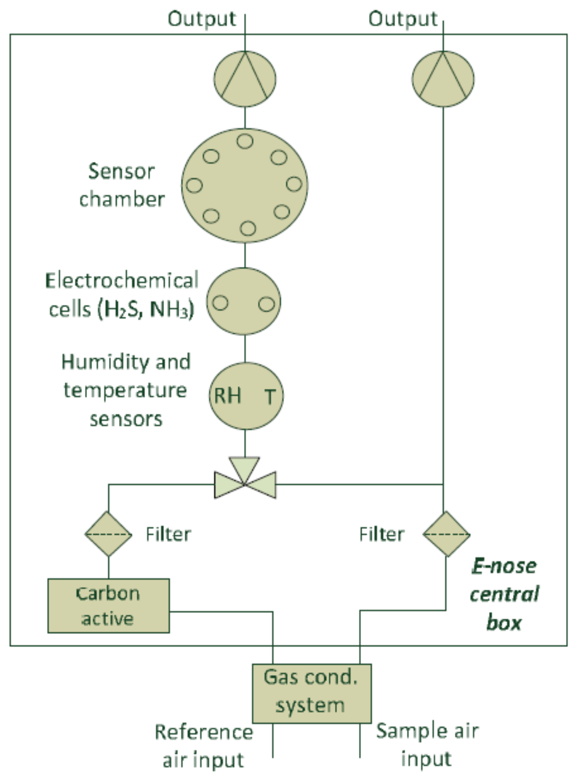


**Figure 2**. Example schematic representation of EN system

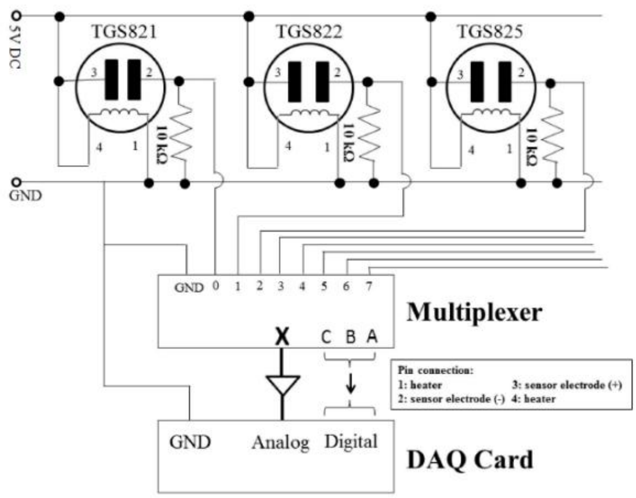


**Figure 3**. Schematic diagram of EN in receiving sensing data

There was another example from [3] where an inbuilt analog to digital converter (ADC) in the Arduino Mega 2560 microcontroller board (ATMEL, U.S.A.) was used to sample the voltage values from the sensors. This board is coupled, through RS232, with a Virtual Instrument (VI) developed in LabVIEW platform. The VI run on the computer to command the acquisition process, stores data from sensors, show graphical information about electrical profiles and manages the air flow unit. For the data pre-processing stage, Matlab (2017a) (MathWorks, U.S.A.) is used to develop a software code.

Common used sensor in EN including metal oxide semiconductor (MOS) resistance sensors, conducting polymers (CP), quartz crystal microbalance (QCM), acoustic wave sensors, electrochemical (EC) gas sensors, catalytic bead (CB) sensors, optical sensors and photoionization detector (PID) sensors [1]. The properties of different sensor type are summarized in Table 1. Based on the review technical papers, for WWTP case, the most common used sensor is the MOS type.

**Table 1.** Sensor types and their properties [1]

| Sensor Type | Detection Range | Usage Area | Advantages | Disadvantages |
|---|---|---|---|---|
| Metal oxide | 5–500 ppm | Food and beverage industry | Suitable to range of gases | High sensitivity and specificity<br>Sulphur poisoning |
| | | Indoor and outdoor monitoring | Operation in high temperature | High power consumption<br>Weak precision |
| Conducting polymer | 0.1–100 ppm | Medical industry | Fast response, small size, easy to use | Humidity sensitive |
| | | Pharmaceutical industry | Sensitive to range of gases<br>Fast response and low cost | Temperature sensitive |
| | | Food and beverage industry | Resistant to sensor poisoning | Limited sensor life |
| | | Environmental monitoring | Use at room temperature | Affected from drift |
| Quartz crystal microbalance | 1.5 Hz/ppm<br>1 ng mass change | Pharmaceutical industry | Good sensitivity | Hard to implement |
| | | Environmental monitoring | Low detection limits | Poor signal-to-noise ratio |
| | | Food industry | Fast response | Humidity sensitive |
| | | Security systems | Small size and low cost | Temperature sensitive |
| Acoustic wave | 100–400 MHz | Environmental monitoring<br>Food and beverage industry | Good sensitivity and response time | Temperature sensitive |
| | | Chemical detection<br>Automotive industry | Response to nearly all gases | Poor signal-to-noise ratio |
| Electrochemical | 0–1000 ppm<br>Adjustable | Security systems | Power efficient and robust | Large size |
| | | Industrial applications | High range operation temperature | Limited sensitivity |
| | | Medical applications | Sensitive to diverse gases | |
| Catalytic bead | Large scale | Environmental monitoring | Fast response | Operate in high temperature |
| | | Chemical monitoring | High specificity for combustible gases | Only for compounds with oxygen |
| Optical | Change with light parameters<br>low ppb | Biomedical applications | Low cost and high weight | Hard to implement |
| | | Environmental monitoring | Immune to electromagnetic interference | Low portability |
| | | | Rapid and very high sensitivity | Affected by light interface |

### 4.1 Metal Oxide Semiconductor (MOS) Resistance Sensors

MOS made up of sensor cap, sensing element, and sensor base as shown in Figure 4. The sensing element constitutes of sensing material and heater to heat up sensing element. Depending on the target gas, the sensing element or the active layer will utilize different materials such as Tin Oxide ($SnO_2$), Tungsten oxide ($WO_3$). The relative abundance of each metal oxide as well as by the addition of other components acting such as gold (Au), silver (Ag), or molybdenum as catalysts can regulate the sensitivity of MOS [8]. Figure 5 indicates that gas concentration level is in part per million orders. The surface chemical reactions between gas molecules and the semiconductor will change the electrical properties of sensing element proportional to gas concentration. The sensing element reveals a significant increase in conductivity in terms of reducing gas atmosphere. [3]

MOS which can operate at high temperature, possess a broad range of electronic, chemical, optical and physical properties that are often stable to vary with the chemical composition of ambient air is suitable for a wide range of gases but high power will be consumed. However, at lower temperature, oxide-surface reactions are too slow. The oxidative chemical reactions are constrained due to the low vapor pressure of water molecules at lower temperatures below 100°c. MOS are divided into two main groups based on their responses to different gases:1) n-type and 2) p-type.

The operating principle of n-type sensors is based on the reactions between the oxygen molecules in the air and the surface of these sensors. As a result of these reactions, free electrons on the surface are trapped resulting in potential barriers between grains which inhibit the carrier mobility that produces large resistance area. The p-type sensors respond to oxidizing gases, remove electrons and produce holes. Their characteristic surface reactivity and oxygen absorption significantly increase the performance of the sensor, while enhancing the recovery speed, boosting the gas selectivity and reducing the humidity dependence of signals.

There are variety types of gases in the air and of course in WWTP. Parameters to be considered to select gas sensors including selectivity, reaction time, sensitivity to a given gas, signal recovery, lifespan, as well as power consumption. Besides, the minimal number of sensors and measurement channels is important for less complexity and system cost. The excessive number of sensors can increase noise level and processing time without useful information [3]. From the review technical papers, the most common selected gas sensors in WWTP are MOS type TGS2611, TGS2602, TGS2610, TGS826 and TGS2600, manufactured by Figaro Inc, Japan. Table 2 shows these common selected gas sensors corresponding sensitivities to the gases. These sensors are relatively small sensors with a power consumption up to 300Mw and require a simple conditioning circuit [4]. Besides, their response capability matched with some major odorants emitted from WWTPs, especially $H_2S$ and $NH_3$. Furthermore, the emission of other odorants can be indirectly measured by chemicals that are by-product of anaerobical activity (such as methane, ethanol and hydrogen). In some system, for example from [4], Dallas DS18B20 and Honeywell HIH-4000 sensors were used to measure gas temperature and relative humidity, respectively. These enable the compensation of temperature and humidity influence on the gas sensor' response. Signals from all these sensors will create an array response.

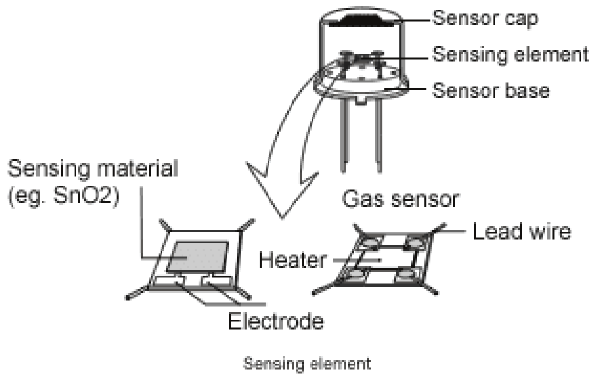


**Figure 4**. The structure of MOS

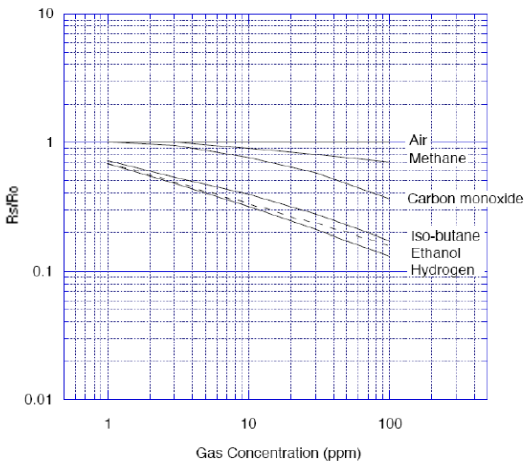


**Figure 5**. Typical response of MOS

**Table 2.** MOS gas sensor sensitivity [3]

| Sensor Name | Sensor Sensitivity |
|---|---|
| TGS2611 (Methane gas) | Methane; Iso-butane; Hydrogen; Ethanol |
| TGS2602 (Air contaminants) | Toluene; Hydrogen sulphide; Ethanol; Ammonia; Hydrogen |
| TGS2610 (LP gas) | Iso-butane/Propane; Methane; Hydrogen; Ethanol |
| TGS826 (Ammonia gas) | Ammonia; Ethanol; Hydrogen; Iso-butane |
| TGS2600 (Air Quality) | Ethanol; Hydrogen; Iso-butane; Carbon monoxide; Methane |

### 4.2 Statistical Analysis

The next step after preprocessing the sensed signal will be analysis step. Statistical techniques including principal component analysis (PCA), cluster analysis (CA), linear discriminant analysis (PLS-DA), generalized linear models with regularized path (GLMNETs), or artificial neural networks (ANNs) can be employed to analyze the obtained complex measurement data. [1] The properties of these algorithm is shown in Table 3. The use of qualitative analysis by odour fingerprints and PCA is seem to be the most frequent among the techniques from the review technique papers. Both are computed to discriminate odours from its sources in the WWTP.

**Table 3.** Properties of data analysis algorithm [1]

| Algorithm | Advantages | Disadvantages |
|---|---|---|
| PCA | Reduce the data dimensionality<br>Provide set of uncorrelated components<br>Measure probability estimations of high-dimensional data | High computational time with large amount of data |
| Discriminant analysis | Easy to use<br>East in classification applications<br>Linear decision boundary | High computational time for training<br>Complex matrix operations<br>Gaussian assumption |
| Regression | Easy to use<br>Usage in several cases<br>Great with small amount of data | Outliers can cause problems<br>Over-fitting occurs |
| ANNs | Can work with incomplete knowledge<br>Fault tolerance is high - Parallel processing<br>Once trained, predictions are fast<br>Effective with the large amount of data<br>For both regression and classification | Hardware dependent computational time<br>Hard to find optimal network structure<br>Over-fitting may occur |
| SVMs | Effective in high-dimensional spaces<br>Relatively memory efficient<br>Fast in both binary and multi-class classification<br>Works great with nonlinear data<br>Effective even in the cases when the number of dimensions is greater than the number of samples | High computational time with large amount of data<br>Noisy data can cause overlapping classes |

#### 4.2.1 Principal Component Analysis (PCA)

PCA is a fast, easy and unsupervised multivariate technique which express the data in term of variance. The main function is to identify data clusters as well as to produce dimensionality by a linear compression of data. The scores produces may be plotted in few dimensions which represent the maximum variance [3]. It also means that the high-dimensional data is represented in a new lower-dimensional subspace which is spanned by the principal components of largest variance in the original variables. These principal components are designated as the eigenvectors of the original variables. The highest eigenvalue in magnitude and its corresponding eigenvector retain the maximum variation, hence the most important contribution among dimensions [1]. Since as few as two or three new PC variables are enough to describe up to 90% of dataset variables, the data can be plotted in two- or three-dimensional graphs. To find homogenous clusters of data based on a distance matrix in multidimensional space, a more specifically method named the k-means method was implemented. Example of 2-D result, 3-D result and result with k-means clustering algorithm of PCA analysis based on the data from Table 4 taken from [9] which was used to explain data dispersion is shown in Figure 6, Figure 7 and Figure 8 respectively.

**Table 4.** Proportion of variance explained by principal component analysis (PCA)

| Statistical Parameters | PC 1 | PC 2 | PC 3 | PC 4 | PC 5 | PC 6 | PC 7 | PC 8 | PC 9 | PC 10 | PC 11 | PC 12 | PC 13 | PC 14 | PC 15 | PC 16 | PC 17 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Standard deviation | 2.19 | 1.73 | 1.37 | 1.22 | 1.07 | 1.00 | 0.96 | 0.91 | 0.85 | 0.76 | 0.54 | 0.46 | 0.32 | 0.17 | 0.14 | 0.08 | 0.03 |
| Cumulative Proportion | 0.28 | 0.46 | 0.57 | 0.66 | 0.72 | 0.78 | 0.84 | 0.89 | 0.93 | 0.96 | 0.98 | 0.99 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |

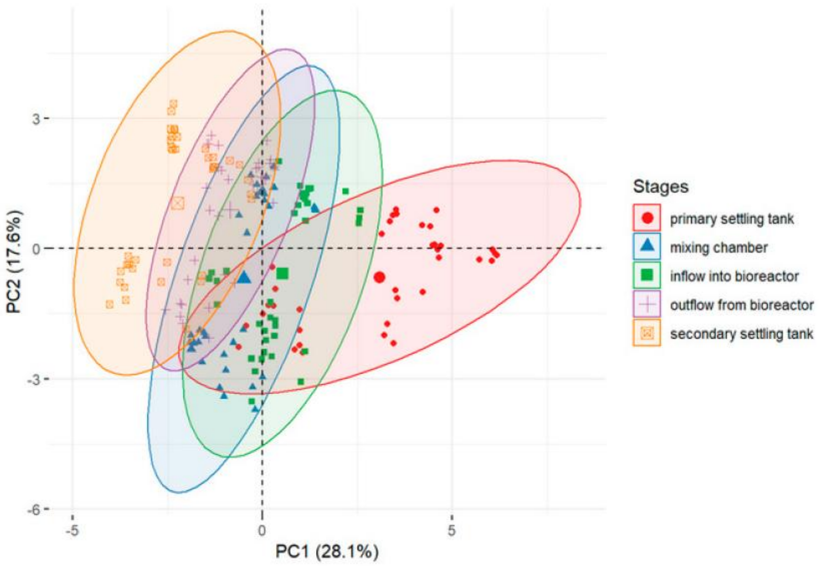


**Figure 6**. Two-dimensional PCA mapping of data. Colors and ellipses correspond to the stage of the wastewater treatment process.

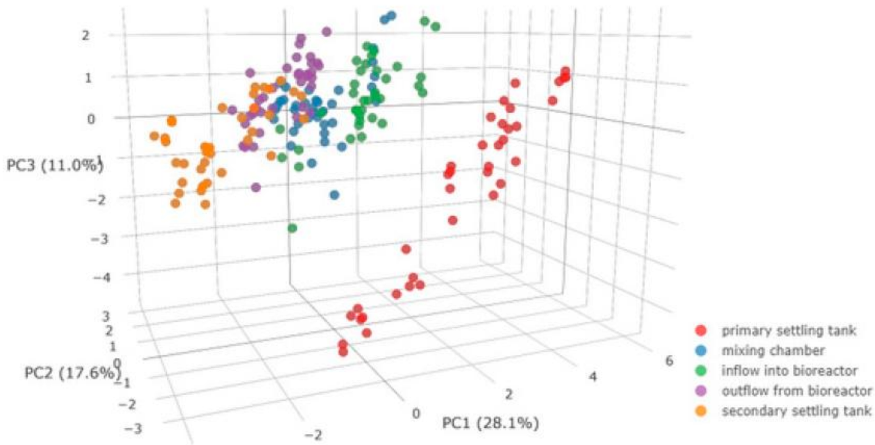


**Figure 7**. Three-dimensional PCA mapping of data. Colors correspond to the wastewater treatment process stages.

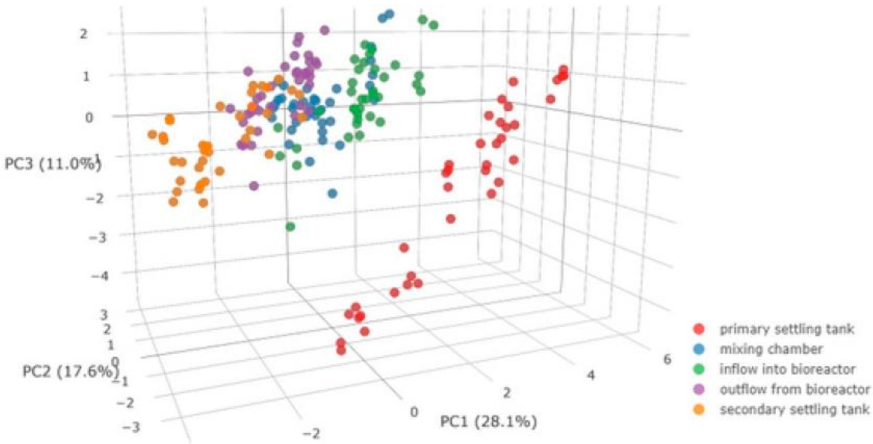


**Figure 8**. Result of the k-means clustering algorithm. Colors denote clusters and shapes correspond to different stages of the wastewater treatment process.

### 4.2.2 Chemical Image (Fingerprint)

Every single sensor forms an array is sensitive to different groups of chemical compounds. When they are exposed to a gas mixture or odour inducing a change in their electric resistance from a reference level, a signal will be provided. Different number of sensors which made up the sensor array will produce a complex, multi-dimensional set of signals. Hence, every gas mixture will create a distinct signal profile, or create the characteristic response or chemical image which also called "fingerprint" [4]. The number of axes of the polar graph or radar plot is depended on the number of sensor involved. For example, taken from [3], in Figure 9, Vmax value was plotted in five axes, one per sensor. The shape obtained are visual qualitative indicators of the samples, which is the fingerprint. In this papers, there are two sample taken from different day, which Campaign 1 is on Monday while Campaign 2 is on Thursday. Campaign 1 is a critical day according to the WWTP operator since population usually have the habit of washing cars and clothes on weekends. The household detergents (sulphonates) influence in the organic Sulphur content of sewage effluents which then causes a lot of foam can be observed during sampling on that day. For Thursday, it is considered as a normal operating day.

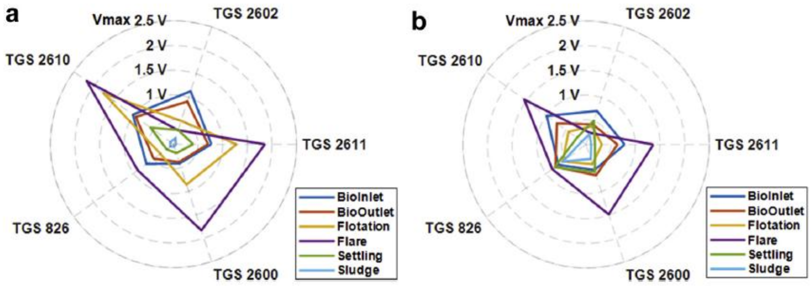


**Figure 9**. Polar graphs of the relative sensors responses computed from samples of a) Campaign 1; b) Campaign 2

## 5. Conclusion

There is continuous improvement of existing methods and development of new methods and systems to develop a sufficient complete, continuous and automatic WWTP monitoring system. Most of it basically face the problem due to the harsh environment and lack of reproducibility and reliability of the available sensors in such condition.

Despite many years of intensive development of EN both in fundamental and applied, most of them focus on the development of physical transducer and sensitive materials for sensors while too little attention is given to the research on the sample handing which include sample preparation, sample introduction and measurement still insufficient. In fact, implementation of EN technology is also limited by current sample handling which is time consuming, expensive and require special personnel. The stage of sample preparation and injection is believed one of the major contributions to measurement errors [6].

## Acknowledgement

The authors would like to acknowledge the CRG Grant from Universiti Teknologi Malaysia (UTM).

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