Gas Concentration Analysis of Resistive Gas Sensor Array

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***Abstract*—The concept of Mobile Electronic Nose (MoLen) is very promising for Sensing as a Service (S^2aaS) applications. In Internet of Things (IoT) era, MoLen can be implemented in many real-world applications such as food quality assessment, medical applications, gas leakage detection, home or automotive safety system, environment monitoring, etc. The most important component of MoLen is gas sensor array used to detect and to collect the odor data. In this study, the resistive gas sensor is used to detect various gasses associated with beef spoilage. Metal-Oxide Semiconductor (MOS) gas sensor is one example of resistive gas sensor which is utilized to arrange MoLen gas sensor array. This work has following contributions to assist researchers and practitioners for MoLen applications. First, the mathematical model is proposed to analyze various gas concentrations based on low-cost MOS gas sensor. Second, we demonstrate gas sensor response and MoLen capability to detect various gasses associated with beef spoilage based on proposed model. The experimental result shows that the MoLen and the proposed model are feasible to be implemented for real-world applications.**

***Keywords*—Mobile electronic nose; Gas sensor response; Beef quality detection; Mathematical model for gas analysis**

I. Introduction

In the recent years, gas monitoring and analysis are an essential part in many areas. For example in product quality monitoring, the gas analysis is important to determine the product quality. Carbon dioxide (CO_2) is the main indicator of microbial growth in food quality monitoring [1][2]. In the source of protein meal (e.g. meat, fish, etc), hydrogen sulfide (H_2S) [3] and ammonia (NH_3) [4] are also considered as biomarkers. Moreover, gas detection and monitoring are also important for home and industry safety system. For instance, carbon monoxide (CO) is deadly for a human. It was reported that more than 400 cases of death caused by carbon monoxide poisoning in US every year [5]. Carbon monoxide is very dangerous for human because odorless, colorless, and tasteless so it is also called *"the silent killer"*. World Health Organization (WHO) also estimates that about 7 million people in around the world die caused by air pollution. In addition, it was also reported that more than 500 cases of LPG gas leak accident in Jordan in 2007 and increasing every year [6]. Actually, gas analysis can be accurately performed using mass spectrometry and gas chromatography but it has some disadvantages such as high-cost, needing special skills, and unsuitable for online or real-time systems. An alternative way to do gas and chemical analysis is to utilize gas sensor. A resistive gas sensor such as Metal-Oxide Semiconductor (MOS) gas sensor can be considered as a low-cost solution. Although MOS gas sensor is less accurate than mass spectrometry or gas chromatography, it has promising advantages that should be considered to perform gas monitoring and analysis. MOS gas sensor is low-cost, easy to use, and has a wide range of gasses target. It should become considerations for massive-used of gas monitoring and analysis.

In chemical analysis, gas sensor array refers to a set of gas sensors with different selectivity used to collect chemical information from the particular object. It is utilized independently and simultaneously to convert chemical information associated with multi-component gas mixtures to measurable signals in a sample chamber. A tested sample and a gas sensor array must be in the same location (sample chamber). It guarantees each of individual sensor has the same environment for gas mixture analysis. The multivariate response is generated by gas sensor array in accordance with the selectivity and sensitivity of each gas sensor [7]. For instance, it is used to detect tea aroma [8][9], wound infection monitoring [10], beef quality classification [11], etc. Integrating MOS gas sensor with wireless sensor network (WSN) technology will present MOS Sensor Network (MOS-SN) for a wide area of gas monitoring and analysis. It can be considered to develop Sensing as a Service (S^2aaS) for many real-world applications [12]. This paper proposes a mathematical model to estimate gas concentration using MOS gas sensors. Moreover, it also demonstrates the feasibility of MoLen technology to detect and collect odor data in accordance with beef spoilage detection.

The remainder of this paper is organized as follows: Section II describes materials and methods that be used in the experiment. Section III explains result and discussion including a comparison of various mathematical model, proposed mathematical model for gas analysis, and relationship between the bacterial growth and the estimation of gas concentration. Finally, section IV is the conclusion of this work.

II. Materials and Methods

In this study, we used six MOS gas sensors from Hanwei electronics which have been optimized [11]. MOS gas sensor

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used in this work is resistive sensor type with Tin Dioxide (SnO_2) as sensing material. Resistive sensor means a sensor resistant value will change according to the changes of particular gas concentration. The resistant value will decrease if the sensor detects the gas in a particular concentration. These sensors are deployed in Arduino microcontroller platform with additional wifi-shield for wireless communication. The scheme can be described in the Fig. 1.

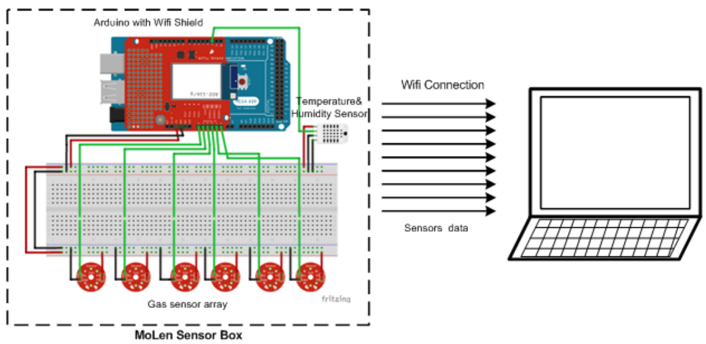


Fig. 1: Schematic diagram of MoLen based on metal-oxide semiconductor gas sensor

Various gasses produced by beef spoilage are analyzed by six MOS gas sensors with different selectivity. The selectivity of each gas sensor can be seen in Table I. The selectivity of gas sensors are obtained from the gas sensor datasheets. All of the gas sensors have a potentiometer for sensitivity adjustment. In this experiment, we set all of them for maximum sensitivity for the best result of analysis. The gas sensor box used in this experiment can be seen in Fig. 2.

TABLE I: Six Gas Sensors with Different Selectivity

Sensor	Selectivity
MQ135	NH_3,NO_x,alcohol,benzene,smoke,CO_2
MQ136	Hydrogen Sulfide (H_2S)
MQ2	LPG,i-butane,propane,methane,alcohol,H_2,smoke
MQ4	Methane (CH_4)Natural gas
MQ6	LPG,iso-butane,propane
MQ9	Methane,Propane and CO

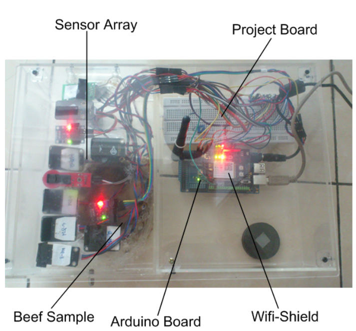


Fig. 2: Experimental environment using MoLen sensor box

This experiment observes 500g of lean meat during 3 days at ±38°C of temperature and 75% of average humidity to investigate the gasses produced by mesophilic bacteria. Mesophilic bacteria grow optimally at room temperature. According to Fig 2, additional wifi-shield is needed as communication module which transfers data from gas sensors to the computer every minute. The packet data sent to the computer is encoded in accordance with the Fig. 3.

Packet start	Sensor ID-1	Sensor Value	......	Sensor ID-n	Sensor Value	Packet end

Fig. 3: Packet data transferred from gas sensor array to computer

III. Result and Discussion

In another study, the authors propose the linear signal model of MOS gas sensor. This model is based on the amount of odorant absorbed into sensors but unfortunately, it does not provide validation of proposed model [13]. Actually, Tin Dioxide MOS gas sensor has high sensitivity [14][15]. However, we disagree that the signal of MOS gas sensor has a linear relationship with gas concentration because we have different result compared with other works. In the previous works, several studies propose a mathematical model for gas concentration prediction using MOS gas sensor. Logarithmic linear model is proposed to detect single and mixture gas, the authors claim the error of model is lower than 4% though they only use two gas sensors in the experiment [14]. Another work attempts to use Backpropagation Feedforward Neural Network to estimate the concentration of three different gasses. This work claims that proposed approach can recognize 100% qualitative recognition and lower error of quantitative recognition [16]. However, this proposed method is too complex because this problem should be solved by deterministic or mathematics approach rather than employs machine learning.

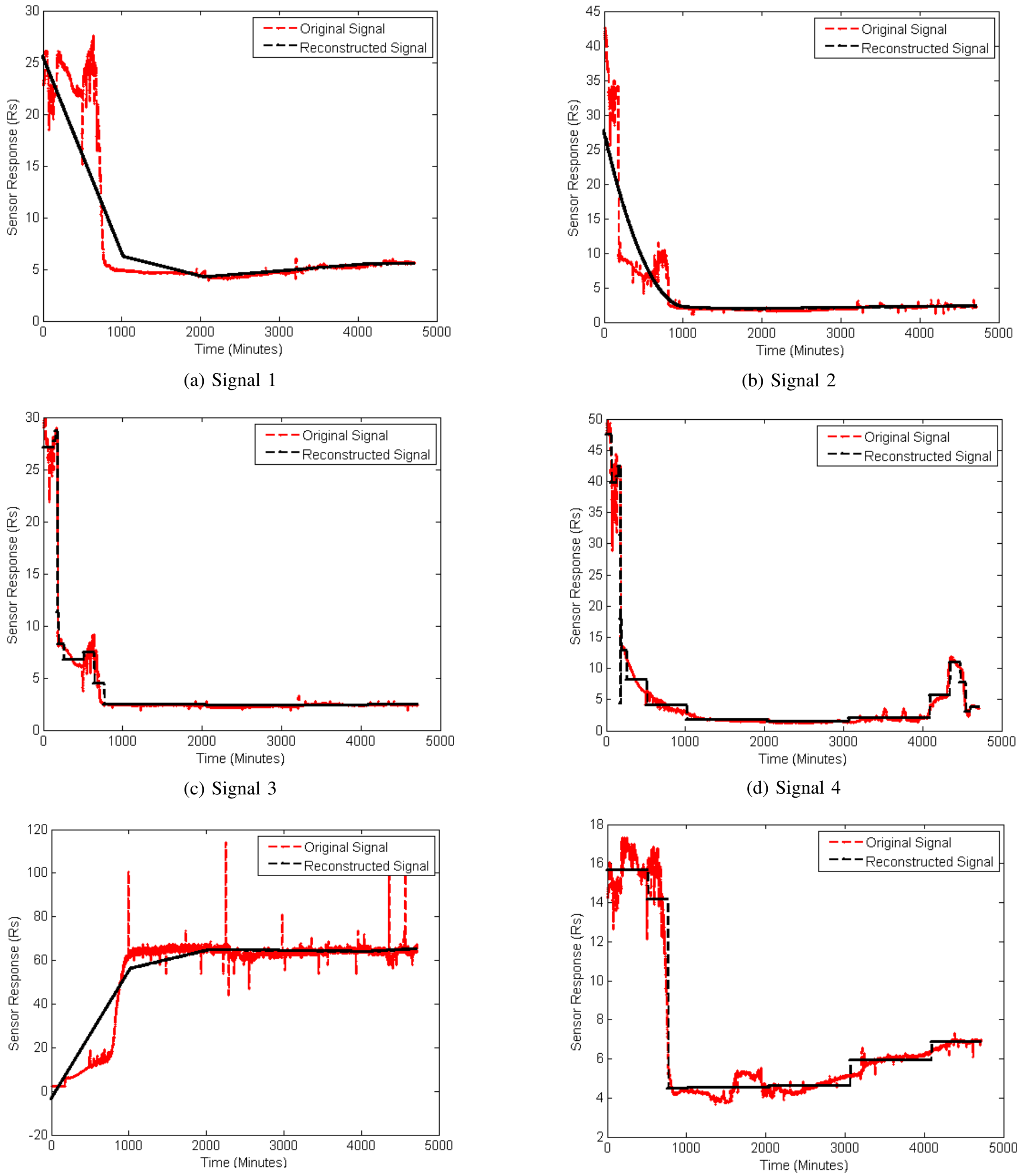
A. *Signal Denoising*

Actually, the resistive sensor has several types of noises such: thermo-noise, Schottky noise, flicker noise. In severe cases, the signal can contain up to 20% of noise power [17]. In this study, the signal contains maximum 14.41% of noise power [11]. So, if it is not handled properly then it will lead to misleading results for further analysis. Wavelet transform is common technique for signal denoising. It provides both time and frequency resolution for non-stationary signals analysis [18]. Previous work reported that wavelet transform successfully performs signal denoising in electronic nose application [19]. In this work, wavelet transform is employed for signal denoising according to the parameters in Table II.

TABLE II: The parameters of wavelet transform [11]

Signal	Max Frequency	Dec Level	Base Wavelet	% of reduced noise
1	0.43	11	bior2.4	2.65
2	0.43	11	bior3.3	14.41
3	0.43	11	db1	1.04
4	0.65	10	db1	1.25
5	0.43	11	bior2.2	1.26
6	0.65	10	db1	1.02

The results of wavelet denoising can be seen in Fig 4. Red and black line show original and reconstructed (denoised) signals, respectively.



(a) Signal 1 (b) Signal 2

(c) Signal 3 (d) Signal 4

(e) Signal 5 (f) Signal 6

Fig. 4: Gas sensor array signal denoising using discrete wavelet transform [11]

B. MOS Gas Sensor Response

MOS gas sensor is an analog sensor, so the response values are the result of analog to digital conversion (ADC). The resistance of sensor (R_S) must be quantified from ADC values showed in (1) and (2).

$$R_S = \frac{V_c - V_{RL}}{V_{RL}} * R_L \tag{1}$$

Where,

$$V_{RL} = \frac{ADC * V_C}{1023} \tag{2}$$

Where V_C is a voltage of the microcontroller board. V_{RL} is a voltage of sensor in the sample space. R_L is sensor load resistance (measurement using Ω meter). ADC is analog to digital value conversion. In this work, we observe the response of the sensor in accordance with beef spoilage. Fig. 5 shows the typical response of sensor for beef spoilage detection obtained from the sensor which has the highest correlation with beef spoilage. Basically, the response is divided into two phase (fresh and spoiled). In the first 1201 minutes, beef still in a fresh state. The resistance value of sensor decreases exponentially. Later, it enters the stagnant phase that indicates the meat has begun to rot. Mathematically, it can be expressed by the following function:

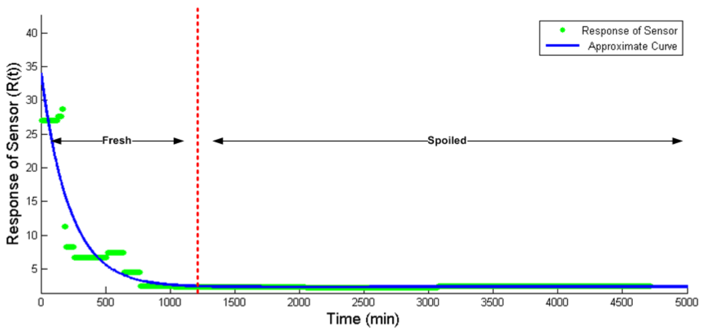


Fig. 5: Typical Response of Sensor for Beef Quality Detection

$$R(t) = \begin{cases} 30.97e^{-0.004745t} + 3.252e^{-0.0002803t} & \text{, if} \quad t \leq 1201 \\ -3.307 * 10^{-18}t + 2.389 & \text{, if} \quad t > 1201 \end{cases}$$

C. Mathematical Models Comparison

According to the datasheet of sensors, the ratio between R_S and sensor resistance in the clean air (R_O) is used to determine the particular gas concentration. The datasheets only provide a sample chart with a R_S/R_O as y-axis and a gas concentration (ppm) as x-axis. So, the sample of data in the chart should be mathematically modeled to estimate the concentration of gas in particular Rs/Ro value. In this study, we investigate the best-suited mathematics function using MATLAB with 95% confidence level for each gas concentration based on the adjusted coefficient of determination ($\bar{R}^2$) expressed in (3) as follows:

$$\bar{R}^2 = R^2 - \frac{(1 - R^2)t}{s - t - 1} \tag{3}$$

where R^2, t, and s are total coefficient determination, the number of explanatory variables, and sample size, respectively. R^2 is expressed by (4) as follows:

$$R^2 = 1 - \frac{\sum\limits_{i=1} (y_i - f_i)^2}{\sum\limits_{i=1} (y_i - \bar{y})^2} \tag{4}$$

Where $y_i, f_i, \bar{y}$ are observed data, predicted value, and mean of observed data, respectively. Moreover, Root Mean Square Error (RMSE) is also used to measure the differences between actual and predicted values. RMSE can be expressed in (5) as follows:

$$RMSE = \sqrt{\frac{\sum\limits_{i=1} (y_i - f_i)^2}{n}} \tag{5}$$

Where y_i, f_i, n are actual value, predicted value, and the number of data, respectively. Further, we also observe the trend of the curve for backward and forward forecasting for consideration.

Table III and IV demonstrate the comparison of several mathematical functions (e.g. linear, exponential, logarithmic, and power) to estimate the gas concentration.

TABLE III: $\bar{R}^2$ Values Comparison of Mathematical Functions Associate With Gas Concentration (*bold red font means the highest $\bar{R}^2$ value)

Sensor	Gas	Linear	Exponential	Logarithmic	Power
MQ2	H_2	0.4997	**0.993**	0.8445	0.9675
	LPG	0.4255	0.9803	0.7156	**0.9997**
	C_3H_8	0.4736	**0.9941**	0.8461	0.9597
	CH_4	0.5743	0.977	0.7937	**0.9945**
	Alcohol	0.5876	0.9753	0.8069	**0.9907**
MQ4	CH_4	0.5178	0.9949	0.7382	**0.9997**
MQ135	CO_2	0.7294	**0.9974**	0.8593	0.9946
	NH_3	0.623	0.99	0.7468	**0.9986**
MQ136	H_2S	0.7467	**0.9986**	0.8554	0.9952
MQ6	LPG	0.439	0.9721	0.686	**0.9942**
MQ9	CH_4	0.7244	0.9897	0.8774	**0.9948**

TABLE IV: Root Mean Squared Error (RMSE) values Comparison of Mathematical Functions Associate With Gas Concentration (*bold red font means the lowest RMSE value)

Sensor	Gas	Linear	Exponential	Logaritmic	Power
MQ2	H_2	2208	**260.9**	1231	562.7
	LPG	2366	438.3	1665	**50.63**
	C_3H_8	2265	**240.7**	1225	626.4
	CH_4	2037	473.8	1418	**231.5**
	Alcohol	2005	490.6	1372	**300.4**
MQ4	CH_4	3117	322.1	2296	**73.92**
MQ135	CO_2	49.44	**4.833**	35.65	7.007
	NH_3	58.36	9.518	47.82	**3.534**
MQ136	H_2S	47.83	**3.544**	36.15	6.583
MQ6	LPG	2341	521.9	1752	**238.9**
MQ9	CH_4	1639	317.2	1093	**225.2**

According to Table III, power function has the highest $\bar{R}^2$ value than others except MQ2 for H_2 and C_3H_8, MQ135 for CO_2, and MQ136 for H_2S are compatible with exponential function but with a small difference of $\bar{R}^2$ values than a power function. Furthermore, Table IV also shows that the power function has the lowest RMSE than others with the average RMSE is 211,52. So, based on the investigation, the gas concentration can be estimated by the response of sensor as an explanatory variable using the power function with only 1% of the average inherent variability. In addition, this investigation does not include polynomial function because it has an inconsistent and unsatisfied result for backward and forward forecasting.

D. Proposed Mathematical Model for Gas Concentration Estimation

Based on the prior explanation, power function has a very convincing performance with the smallest error. Hence, our proposed model can be mathematically expressed in (6) as follows:

$$C = \gamma \left[\frac{R_O}{R_S} \right]^{\tau}, \qquad \gamma, \tau \epsilon R^{+} \tag{6}$$

Where C, R_S, R_O are gas concentration, actual sensor resistance, and initial sensor resistance, respectively. While γ and τ are constant values that can be determined using MATLAB data fitting toolbox. Moreover, R_O is determined when performing sensor calibration in the fresh air. Table V shows constant and R_O values of each sensor.

TABLE V: The Parameters of Mathematical Model for Gas Analysis

Sensor	Gas	γ	τ	R_O
MQ2	H_2	1416	1.346	9.8
	LPG	601.9	2.144	
	C_3H_8	1137	1.282	
	CH_4	4207	2.394	
	Alcohol	4203	2.399	
MQ4	CH_4	1083	2.786	4.4
MQ135	CO_2	120.3	2.304	3.75
	NH_3	101.1	2.737	
MQ136	H_2S	48.44	2.786	3.75
MQ6	LPG	925.2	2.577	10
MQ9	CH_4	4395	2.32	9.8

Based on Table V, an approximation of gas concentration associated with beef spoilage can be quantified. Fig. 6 demonstrates three main biomarkers of beef spoilage during more than 4000 minutes observation.

It shows that beef still in fresh condition and bacteria in lag phase at first 700 minutes. The gas concentration rises significantly by minute 1000. Then, it decreased progressively indicating the bacterial growth enter the stationary phase. In addition, we also compare the trends bacterial growth and the changes of gas concentration. It can be seen in Fig. 7. In this experiment, spectrophotometer (Genesys 20) is used to measure optical density and haemocytometer is utilized to calculate the number of bacteria cells.

The correlation coefficient is calculated to quantify the relationship between bacterial growth and gas concentrations. A correlation coefficient can be calculated using (7) as follows:

$$Coef(A,B) = \frac{\sum\limits_{i=1} (a_i - \bar{a_i})(b_i - \bar{b_i})}{\sqrt{\sum\limits_{i=1} (a_i - \bar{a_i})^2} \sqrt{\sum\limits_{i=1} (b_i - \bar{b_i})^2}} \tag{7}$$

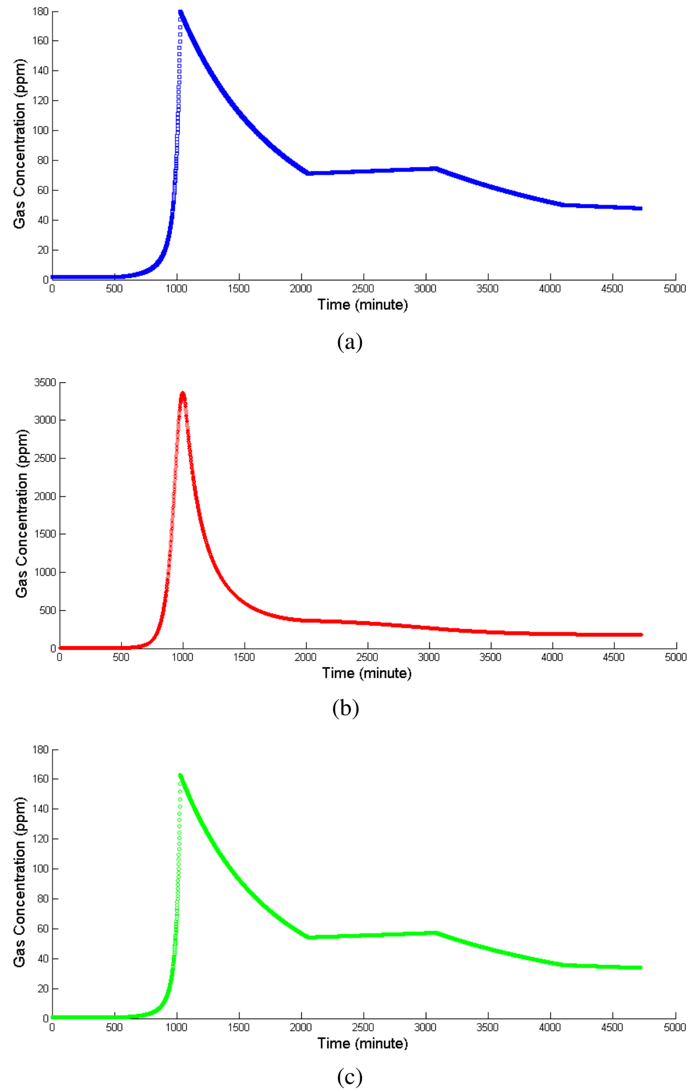


Fig. 6: Approximate concentration of the main biomarkers in beef spoilage: (a) CO_2 (b) H_2S (c) NH_3

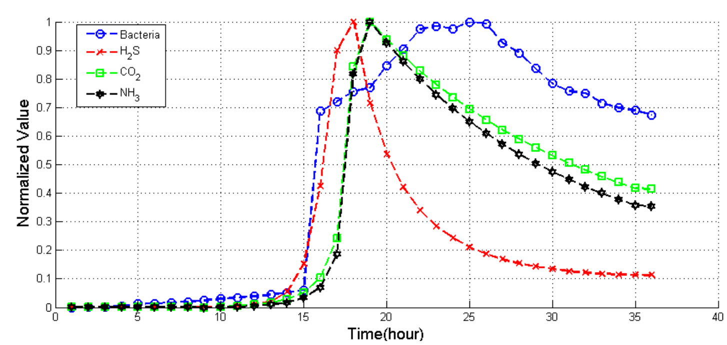


Fig. 7: Comparison between bacterial growth and main biomarkers

Where $\bar{a_i}$ is mean of vector A and $\bar{b_i}$ is mean of vector B. The range of coefficient is between 0 and 1. The correlation between bacterial growth and concentration of H_2S, CO_2, and NH_3 are 0.56, 0.91, and 0.88, respectively. It shows that the analysis get a satisfactory result because the gas estimation based on MOS gas sensors has a high correlation with bacterial growth.

IV. Conclusion

According to the experimental results, we successfully perform analysis of various gas concentrations using MoLen in beef spoilage. A proposed mathematical model has the convincing performance to estimate the concentration of particular gas based on a signals from MOS gas sensor. It only has 1% of the average inherent variability which means this model can predict 99% of response variable based on the explanatory variables. Moreover, the correlation coefficient shows that the estimation of gas concentration has a significant correlation with bacterial growth (> 0.5). It shows that this model is proper to be used in the real-world applications. Finally, this study shows the feasibility of electronic nose implementation in Sensing as a Service (S^2aaS) environment. For future work, we will develop multiclass classification technique for beef quality classification.

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