Optimizing a Sensor to Detect Ammonium Nitrate Based IEDs in Vehicles Using Artificial Neural Networks

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Abstract:
Ammonium nitrate based explosives are a choice weapon for many terrorist groups due to its ease in manufacturing and high velocity of detonation (VOD). These explosives deflagrates in the field to release ammonia gas in traces of about 5-25 PPM. We present the optimization of MQ137 metal oxide semiconductor electrochemical sensor to improve its selectivity and sensitivity for the detection of ammonia gas in low PPM ranges as a sign of these explosives in vehicles. ARDUINO was used to extract features of ammonia gas with MQ137 sensor for optimization with artificial neural networks in MATLAB. The multi-layer artificial neural network with a hidden layer for recognizing the sensitivity characteristics of ammonia with MQ137 has an accuracy of 100% with test performance.

Keywords: IED Detection, MQ137 Sensor, Neural Networks, Ammonia Gas, Optimization, ANFO.

I. INTRODUCTION
In Africa and Nigeria, particularly the northern Nigeria where the activities of Boko Haram insurgents are prevalent, the use of ammonium nitrate based improvised explosive devices is common. This is due to the availability of the chemical compounds and the ease at which they are manufactured. These explosives were initially used for rock blasting and mining activities [1]. They are made locally from chemical compounds and fertilizers which are easily gotten due to the prevalence of farming in northern Nigeria, the resulting mixture gives Ammonium nitrate fuel oil (ANFO) explosive when dry [2]. This is the major aim of using a sensor to detect the properties of ANFO since the sensor is readily available, affordable and offers a viable alternative in overcoming current challenges in the field. MQ137 sensors have tin oxide as their sensing compound and when heated, its free electrons increase thereby decreasing its resistance. In the presence of fresh air (oxygen), these free electrons are absorbed by oxygen molecules which are oxidizing agents to increase its resistance and thus no conduction. When in the presence of a reducing gas (e.g, CO₂, NH₃, etc), the oxygen molecule on the surface of the tin oxide sensor gets desorbed by the reducing gasses thus decreasing the resistance of the sensor.

MQ137 sensors have a problem of selectivity, in that they react with similar reducing gasses thus increasing the rate of false alarm [3] [4] [5] [6]. Many applications of tin oxide sensors for detection of ammonia or other gasses have used several MQ137 sensors, like Silva et al developed a tin oxide sensor to detect ammonium nitrate based IEDs as a first step in detecting these explosives (ANFO) and proposed the use of an additional sensor which would detect diesel, to confirm the presence of these explosives [2]. This was because of the selectivity problem of these sensors. Dogs have also been used to detect these explosives over time but this remains an expensive option, training and feeding these dogs is capital intensive. With all being said we optimize MQ137 sensors to detect ANFO explosives in vehicles, less than 25PPM range which is below the olfactory threshold [2].

II. EXTRACTED FEATURES
MQ137 sensors are produced by different manufacturers and thus slightly differ in their sensitivity characteristics as a result of differences in doping the semiconductor and different testing conditions. Typical sensitivity characteristics of the sensor from two manufacturers are compared below.

Figure 1. Comparing Characteristics of MQ137 sensor with Ammonia from Zhengzhou WINSEN and HANWEII electronics companies respectively [6] [7]
From the datasheets above, the x-axis is concentration in PPM against sensitivity constant on the Y-axis. The sensitivities of MQ137 showed gradual reduction as the concentration of ammonia increased, this decreasing values of sensitivity is different for every reducing gas. This is directly proportional to their relative densities in air and ammonia is light and diffuses faster which makes the tin oxide sensing element more sensitive to it than other reducing gases. For our application range of 5-25PPM concentration, sensitivity range of the sensor is unique to only ammonia gas and thus we extract both features (concentration in PPM and Sensitivity constant) for the optimization of the sensor. ARDUINO will be used to extract these features from an MQ137 sensor manufactured by ZHENGZHOU WINSEN electronics company LTD [6] [8] [9]. Neural networks will be trained to recognize this pattern, just as humans are able to recognize numerous patterns, like recognizing a face in the dark because they have seen it before, differentiating between different colours etc [8] [9] [10].

III. MATERIALS AND METHODS

The materials used were acquired and setup to extract features of ammonia gas with MQ137 sensor for optimization using pattern recognition in neural networks.

A) Feature Extraction Prototype Setup

The materials used are:

i. ARDUINO Microcontroller with ARDUINO 1.8.5 Integrated Development Environment (IDE)

ii. MQ137 sensor module from ZHENGZHOU WINSEN Electronics Company.

iii. Jumper wires, breadboard, buzzer, display and a 47K ohms resistor to maximize the sensitivity of the sensor in order to detect ammonia at lower PPM range.

![Figure 2. Prototype setup](image)

B) The Feature Extraction Process: Using the simple circuit of the gas sensor module and the datasheet, formulas for Sensitivity and concentration in PPM were derived. These formulas were used to write program codes in the ARDUINO IDE for calibrating the response of the sensor module after the sensor was preheated for 12hours.

![Figure 3. Sensor Module Circuit Diagram](image)

We apply ohms law to get the formula for finding RS:

$$ RS = \frac{V C}{(R S + R L)} $$

Where: $V = $ voltage; $I = $current; $R = $resistance

Therefore making current the subject of formula,

$$ I = \frac{V C}{(R S + R L)} $$

Also from fig 3 , we can say that,

$$ V R L = I \times R L $$

Substituting I from equation (2) into (3),

$$ V R L = \frac{V C}{(R S + R L)} + R L $$

Solving for RS we get

$$ RS = \frac{V C R L}{V R L} - R L $$

Where;

$V C = $ sensor input voltage (5V)

$R L = $load resistance (47K ohms)

$V R L = $voltage drop across the load resistance

This will give us the values of the sensor resistance at various concentrations of the gas.:

From the datasheet; $R S / R O = 1$ for fresh air

$R O = $ sensor resistance in fresh air

Concentration in PPM was calculated as

$$ \log(x) = \frac{[\log(y) - b]}{m} $$

Where;

$b = $Y-intercept value

$m = $slope;

$x = $the x value

$y = $the y value

these values and formulas were programmed into the arduino microcontroller using a digital computer after preheating for over 12 hours and exposing it to ammonia gas gotten from the heated mixture of calcium and mmonium hydroxide. The ARDUINO codes for extracting these features are open source an can be gotten at Jaycon systems [8].

C) Artificial Neural Network Optimization

150 data samples of the extracted features were collected for sensitivity and concentration each and 50 samples of noise (values from other gasses, and over concentration of ammonia beyond 25 ppm) were added making 200 data samples which was used as input to the neural network. The targets were correctly designated And ten neurons were used for the simulation. The training algorithm used was Scaled Conjugate Gradient.
IV. RESULTS

a) The samples extracted from the arduino serial printer showing the detected ppm values RS/RO values are shown below with their respective codes. It should be noted that these values were gotten after the sensor has been pre heated for over 12 hours.

b) The results from the neural network optimization are presented as follows:

The performance plot shows a good convergence and the test and validation characteristics were showing almost similar patterns. The receiver operating characteristics curve shows the true positive versus the false positive as the threshold is varied. In the upper left corner of the receiver operating characteristics, the sensitivity and selectivity were both 100% for this problem and it shows that the system performs very well.
Figure 7. Training Confusion Matrix

From the diagonal matrix, 100% of the cases (all 200 samples) were correctly classified and no cases were misclassified.

V. CONCLUSION

The simulation training was done several times in order to get best performance results. From the analysis gotten so far, the neural network performed well enough in classifying the recognized patterns with 100% accuracy for the required detection range of five to twenty five parts per million, this was due to having only two features which is good as more features will require expensive means to extract and may over complicate the system. The reducing gas that can interfere with detection in vehicles mostly is carbon monoxide since it is given off by vehicle exhaust pipes and it will likely be in large concentrations, this will be seen as noise by the neural network. With neurons trained to classify these patterns and discriminate between ammonia and other reducing gasses seeing them as noise, our detection system has been greatly optimized. Its implementation can come in handy as a microcontroller programmed to operate like the neural network with value ranges suitable for only ammonia gas. More sample data can be generated to observe the networks performance.

VI. REFERENCES

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