Design and Development of an Embedded Fire Detection System using Neural Networks

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***Abstract*— The failure to respond to a fire alarm is a prominent threat to the safety of human and property in the fire area and the nearby area. One of the reasons for the lack of response to a fire alarm is the tendency to ignore most alarms due to the repeated false alarms. This study proposes an intelligent fire detection system based on the detection of smoke density, temperature, and carbon monoxide in the environment where the fire happens. The optical smoke detector represents the main device to detect fire by activating the other sensors to analyze data from the environment. The fire detection algorithm of this system is based on an ANN (artificial neural network). The emergency case is controlled by the ATMEGA16 microcontroller and confirmed by alarm, which subsequently sends SMS with Specify fire location via Global System for Mobile Communications (GSM). This proposed system proves, through its hardware and software design, a remarkable improvement of system performances in terms of the low cost of the design by dividing the structure into two units; fire detection unit and setup unit, in terms of low power consumption by controlling the working time of each element, and other features such as the calibration, where it allows the system to adapt in their environment. This system detects fire after analyzing chemical and physical features during a period of fewer than 30 seconds to trigger the alarm, including preheat time of the gas sensor. The results show that the proposed system can distinguish between fire and no fire situation, where some situations can be considered as a false alarm when using the smoke alarm, whereas the results of our system were similar to the expected states; therefore, false alarm will be reduced or eliminated.**

***Index Terms*— Artificial Neural Network; Embedded System; Fire Detector; Sensors.**

I. INTRODUCTION

Fires may lead to many deaths and injuries as well as massive financial loss, despite the widespread use of fire detectors in both residential and industrial environments. In 2015, the World Fire Statistics Center (FSC) that gathers data from fires worldwide) for the International Association of Fire and Rescue Services (CTIF) reported to an estimated 3,503,425 fires, from 31 countries and 35 cities in the World. These fires caused 18,454 civilian deaths and 44,973 civilian injuries as well as significant material damage [1]. For example, in 2016, the US experienced a loss valued at $14.3 billion due to fire. Similarly in the same year, Algerian Civil Defense responded to an estimated 60,989 fires that result in 2,154 injuries and 60 persons deaths [2].

Fires are characterized by several phenomena whose associated physical or chemical manifestations can be measured and used to trigger an alarm. All of these phenomena are used in fire detection systems, where many different sensing technologies are employed in commercial fire detection products; however, no single technique can satisfy all uses. The characteristics of fires, the variables measured, and the main sensing techniques employed are shown in Table 1 [3].

Table 1
Fire-related Phenomena and Commonly Used Sensing Techniques

Characteristic	Measured Variables	Sensing Techniques
Smoke	Particulates	Optical, ionization, visual surveillance, etc.
Flames	Light	Photodetectors, visual surveillance
Heat	Temperature or rate of temperature rise	Point and linear temperature sensors, thermal imaging
Combustion Products	Gases	Carbon monoxide sensors

Optical smoke detectors are the most widely used means of detecting fires. It is the basis of many alarms and detection systems. Although this kind of smoke detector has a high false alarm rate., it is considered as the best compared to other commercial smoke detectors, such as ionization smoke detectors. Studies have proven that homes with ionization alarms had more than 8 times the rate of false alarms as those with photoelectric alarms [4]. In 2018, the International Association of Fire & Rescue Services reported that the fire departments from 25 countries responded to almost 3.3 million false alarms, which are almost 150 percent of the total number of reported fires, and four times the number of structure fires [5]. There are several reasons for false alarms, most of them are due to nuisance aerosols, like steam and dust. These reported fires have the same properties as the smoke of fire, such as the particle size distribution [6].

The core of any combustion process is a global exothermic reaction that results in the release of heat as well as gas and solid products. Whether smouldering or flaming will be the dominant mod, it is dictated by which chemical species are oxidized. If the oxidation takes place in the solid phase, smouldering is dominant; if the oxidation takes place in the gas phase, then flaming dominates [7].

The gas emissions from smouldering fires differ significantly to those from flaming fires. First, the emissions rate per unit area is much lower, although the chemistry is different. Smouldering is characteristically an incomplete combustion, releasing species and quantities that substantially depart from each other in stoichiometries and complete combustion. For example, the CO/CO2 ratio, which can be thought of as an index of the incompleteness of combustion is ~0.4 in smouldering, but ~0.1 in flaming combustion [8].

A study [9] that investigated the use of different gas sensors on a fire dataset of the National Institute of Standards and Technology (NIST) discovered the best sensor combinations that distinguish fire from nuisance sources. The author concluded that rising the rate of CO concentration can appropriately indicate non-flaming fires (smouldering fire).

There are different gas sensor technologies that can be used in such devices [10]. Metal-Oxide Semiconductor (MOX) gas sensors are cheap, small in size and lightweight, which is beneficial for their use in pervasive mobile sensing systems for environmental monitoring [11][12]. Their biggest downsides are problems related to drift, especially their significant energy consumption.

The main objective of this project is to design a fire detection system to reduce false alarm rate by integrating two sensors with the main optic smoke detector for analysis of carbon monoxide, temperature, and smoke density from the environment. The fire detection equation of this system is depended on Neural network algorithm that processes the input data from these sensors for low power consumption during the operation mode of the optic smoke detector. The electronic design method allowed the system to be low cost, by dividing the into two parts: the setup unit, and the detection unit, in which one setup unit can work with detection units. Figure 1 illustrates how the project works.

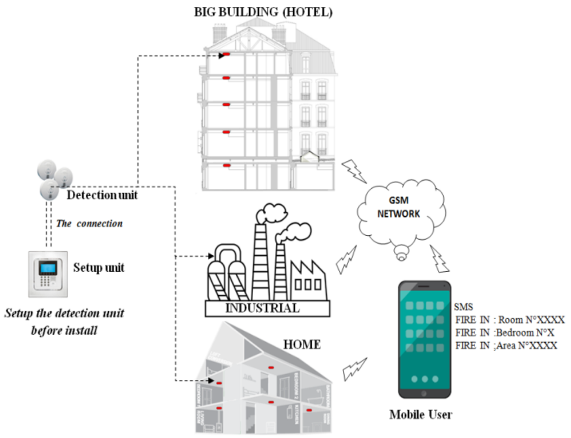


Figure 1: Fire detection system work

II. EXPERIMENTAL METHODS

As shown in Figure 2, the main components of the fire detector is divided into two units: detection unit and setup unit. The detection unit consists of a processing unit, Gas sensor MQ2, temperature sensor LM35, optical smoke detector, Alarm, Power supply, and GSM Global System for Mobile Communications, whereas the setup unit consists of keypad, Liquid Crystal Display (LCD) and transceiver module RS232. The detailed electronic circuit of the system: (a) Electronic circuit of Setup Unit, (b) Electronic circuit of Detection Unit are shown in Figure 3.

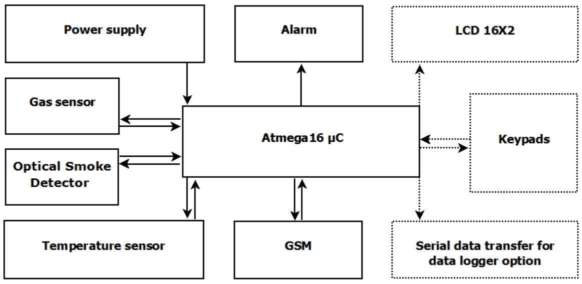
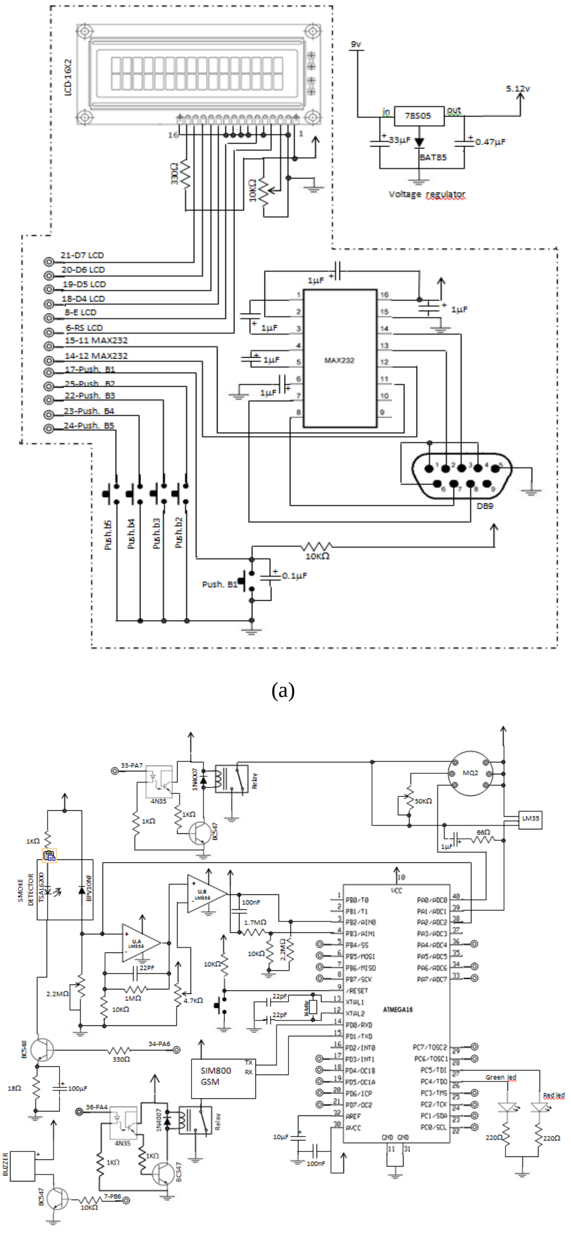


Figure 2: Functional block systems



(a)

(b)

Figure 3: The electronic circuit of the realized system where (a) electronic circuit of setup unit, and (b) electronic circuit of detection unit

The hardware and software of the embedded system design are described as follows.

A. Hardware Design

The circuit design of the system is divided into two sections: a setup unit and a detection unit.

1) Setup Unit

The setup unit is the mobile part in the system. To set up the fire detectors prior the installation, the unit is connected to the detection unit. The realized setup unit is shown in Figure 4. This unit circuit of the system contains the following parts:

a) LCD Display

To setup the fire detector before installing, it is essential to display data and information from the microcontroller. In this case, a 2x16 line display will be used by choosing 4 bits mode, and 6 pins (input/output) [13].

Figure 4: The setup unit of the realized system (mobile part)

b) Push Buttons

Push buttons are used to set several options, such as setting the number of area location where the detection section will install, enter the phone number of the emergency addressee, calibrate the detector, and display all data and information saved in the EEPROM memory of the microcontroller. It also allows to convert the system as a data logger after connecting with PC.

Each push button has a specific function, where the PUSH.B1 is pressed to start the setup of the detection unit after connecting both units together, detection unit and setup unit. Meanwhile, the PUSH.B2 is used to move between LCDs, where the first LCD functions to display the area number in the first row and phone number in the second row. The second LCD functions to display the calibration option in the first row and display option of all saved data in the EEPROM memory of the microcontroller in the second row. The third LCD is used to display the data logger option. This push button is used to move the cursor from right to left in each row of the first LCD and is used to choose the system as fire detector in the third LCD.

The PUSH.B3 is used to move the cursor from left to right in each row of the first LCD and select option in the second and third LCDs. The PUSH.B4 is used to move the cursor from the second row to the first row and increment numbers and letters. The PUSH.B5 is used to move the cursor from the first row to the second row and decrement numbers and letters. The Reset button is used to restart the system setups.

c) Serial Communication

We used RS232 to easily create a data link between our MCU based projects and the standard PC [14].

2) Detection Unit

The detection unit is the part that will be installed in the detection area. The prototype of realized detection unit is shown in Figure 5. It contains the following components:

a) The Microcontroller

The MCU is an Atmega16 chosen for the future development part of the system It has 16KB of programmable flash memory, 1KB SRAM, 512 Bytes EEPROM [15].

b) The Power Supply

We used a classic regulator circuit; a 78L05 with an increasing stable voltage from 5V to 5.12V through the addition of a Schottky diode BAT85 in the bias circuit of this regulator [16], to obtain a sensitivity of exactly 5mV from the 10-bit resolution of the internal ADC of the atmega16 microcontroller.

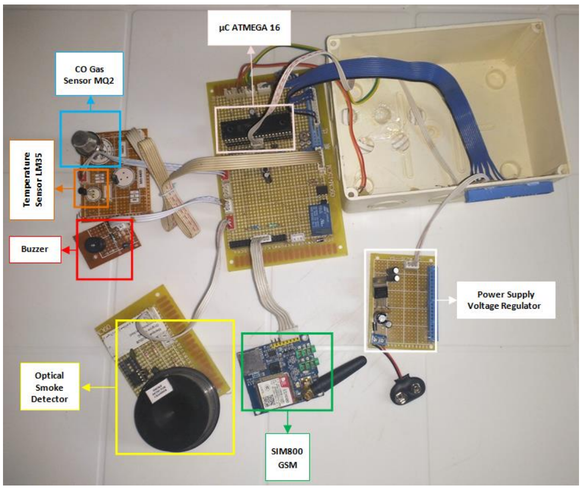


Figure 5: The prototype of realized detection unit

c) Optical Smoke Detector

This detector represents the main device in the system. It has two functions: detecting the presence of smoke and determining smoke density. Operating on the light scattering principle, it detects smoke through optoelectronic techniques. It uses a beam of light emitted by an infrared light-emitting diode (LED), where the light emission time during operation mode is 100 ms with 40 s as sleep mode (stop light emitted). The light emitted is driven in a labyrinthine dark chamber, and this black material absorbs the light to prevent the receiver to detect the passage of light. In this chamber, the scattering signals for the measurement of volume concentration are [140°–950 nm] [17]. Figure 6 shows the smoke detector chamber geometry. When smoke particles enter the light path, a light strikes the particles and is reflected onto the photosensitive device, where the output signal from the second comparator of lm358 will activate the internal comparator of atmega16 and activate sensors to start analysis and get data. The smoke density in this system is determined by the relation between photosensitive device outputs voltage and reflected light intensity, where the intensity of reflected light is increased by increasing smoke density inside the smoke detector chamber. In this case, the smoke density inside the smoke chamber and the reading photosensitive device outputs voltage is positively correlated, and the percentage of smoke density is given by smoke density (%) = (photodiode outputs voltage/VCC)*100.

The VCC is the power supply voltage, where the photosensitive device outputs voltage variate from 0V to VCC.

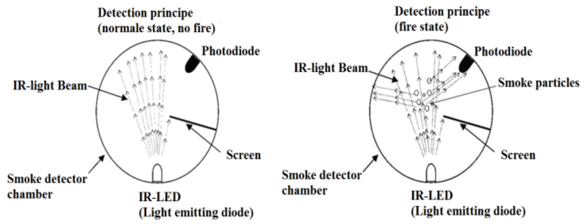


Figure 6: Smoke detector chamber geometry

d) Gas Sensor MQ-2

It is a suitable device for detecting carbon monoxide gas concentration from fire gas emission [18]. This device consists of an analog output sensor connected to ADC pins of the microcontroller (ADC 0). The internal Resistance value of MQ-2 varies according to the type of gas detected and its concentration. To increase the circuit efficiency of gas analyses, we connect the same analog output to the ground via a potentiometer (adjustable resistor) as a load resistor.

e) GSM Module

In the present work, a SIM800 GSM kit has been used [19]. This module is used to send SMS using AT commands with low power consumption, where it is controlled by the main microcontroller.

f) Temperature Sensor

Air temperature measurements are made using an LM35 analog temperature sensor (National Semiconductor, Santa Clara, CA), which is calibrated in °C and is linear in +10 mV/°C scale factor [20]. We powered the system by 5.12V for the imperatives of the 10-bit internal ADC of the atmega16. With a 10-bit resolution, there are 1,024 steps of measurements, and by setting a voltage of 5.12 V, we then obtain a sensitivity of 5 mV. This sensitivity is sufficient to get high accuracy measurement from this sensor (0.5°C). The analog output of this sensor connected to ADC pins of microcontroller (ADC 1) and to ground via resistor and capacitor in series as RC low pass filter to stabilize the output signal.

B. Software Design

The firmware level of this system is controlled by a code implemented in embedded C, with a specific protocol stack for GSM communications and built by the compiler [21]. After compiling the code, we implemented it to the 8-bit Atmega16 microcontroller. The development of the algorithm for this system is designed to ensure the functionality of both units together during the setup and detection operation. The development algorithm presented in the flowchart is as illustrated in Figure 7. This algorithm will ensure the implementation of process fire detection, reducing the false alarm rates and the power consumption by controlling the necessary time of each task to ensure low response time.

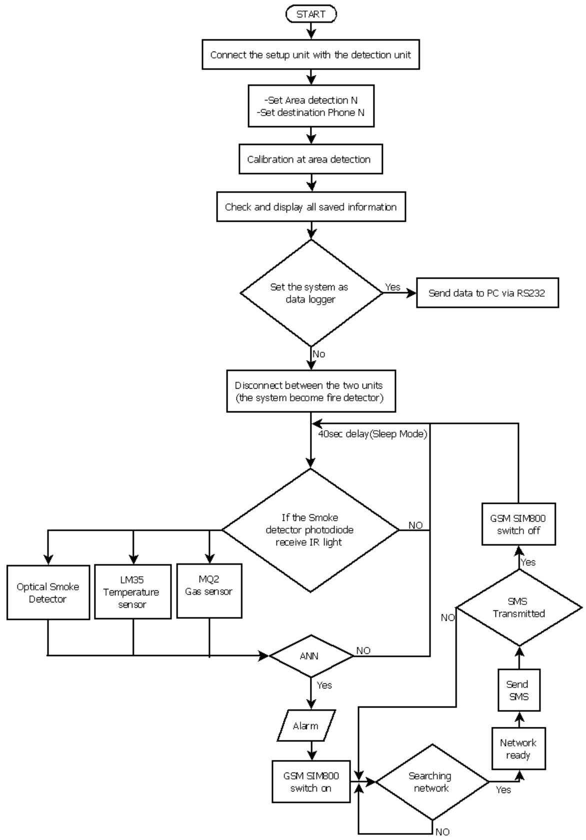


Figure 7: The flowchart of the setup and detection process

C. ANN Algorithm

The classification in artificial neural networks represents the most active research and application. This kind of neural network was trained by the back-propagation algorithm BP [22]. Learning algorithm of this artificial neural network (BPNN) is based on the deepest-descent technique. If provided with an appropriate number of hidden units, they will also be able to minimize the error of nonlinear functions of high complexity [23].

The backpropagation neural network (BPNN) of this system has one input layer with three features as inputs from the real-time sensing values of each sensor (Smoke density, CO concentration, and temperature). When the fire happened, one hidden layer with four neurons and one output layer with one neuron is used to determine whether or not the situation is on fire. Figure 8 shows the architecture of the BP neural network used in this system. The number of hidden neurons is determined by increasing the number of neurons from 3 to 8, inwhich the best result is with 4 neurons. The 3D scatter plot between on fire and not on fire is stated from several tests and scenarios. Figure 9 shows the training case for a nonlinear classifier.

The logarithmic sigmoid transfer function and the tanh function were used as activation functions in hidden layer and output layer respectively. All layers are connected by randomly initialized weights that will be updated based on error back-propagation algorithm [24].

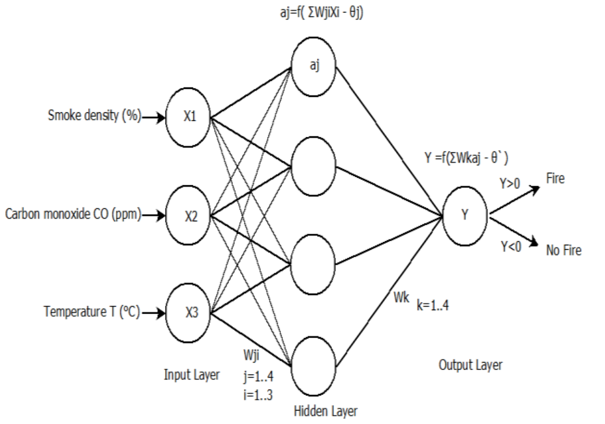


Figure 8: The structure of artificial neural networks that designed for fire detection

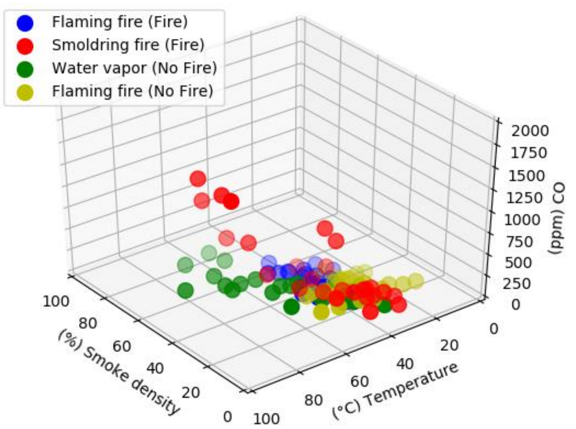


Figure 9: 3D scatter plot that shows four scenarios between fire state and no fire state

D. Learning Algorithm and Implementation

The BPNN was trained by 300 samples, which 70 percent of the samples are used for training, 20 percent for testing, and 10 percent for validation. The sample data for training in the Artificial neural networks of this system was collected from different types of fire, fire state in smouldering and flaming fire, and other scenarios as water vapour and dust. Figure 10 shows the comparison of the CO concentration, temperature, and smoke density between these scenarios.

We observed that carbon monoxide concentration in smouldering fire was higher than the flaming fire scenario, whereas we observed the absence of carbon monoxide in dust and water vapour scenarios.

The comparison of temperature between the scenarios, we observed that the temperature in flaming fire was higher than the temperature in water vapour scenarios and the smouldering fire. Further, the temperature in the three scenarios was not constant as it increases with time, whereas the temperature in dust scenario stayed steadily.

The comparison of smoke density between scenarios showed that the smoke density was high in the three scenarios, smouldering fire, water vapour and dust scenario. For this reason, the last two scenarios increase the false alarms problem, while the smoke density was low in the flaming fire.

The math equation of this Artificial neural networks represents the fire detection equation, after implementing the neural network in Embedded System for the detection equation. The detection equation is:

$$Y = f(x') \tag{1}$$

where: Y = Final result of the neural network output layer depends to the f(x')

$$f(x') = \frac{2}{1 + e^{-2x'}} \tag{2}$$

$$x' = \sum w_k\, a_j - \theta^{`} \tag{3}$$

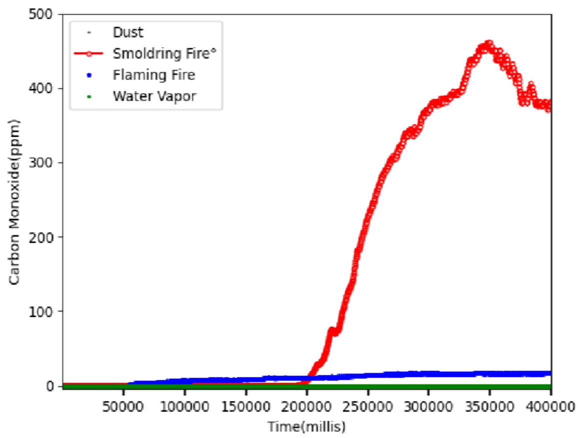
$$a_j = f(x_j) \tag{4}$$

where: f(x') = Hyperbolic tangent activation function
a_j = Output of the hidden layer node
W_k = Weight
θ` = Node's threshold
f(x) = sigmoid activation function

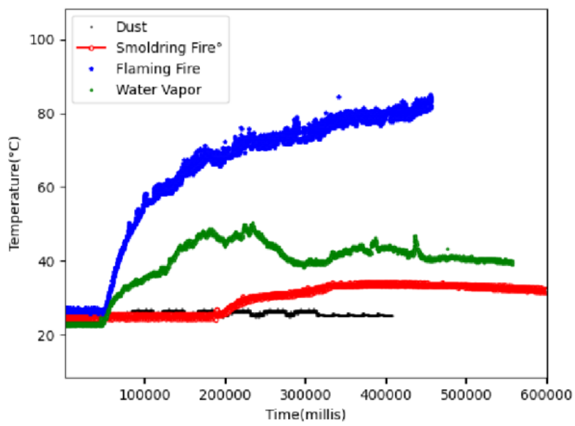
$$f(x_j) = \frac{1}{1 + e^{-x_j}} \tag{5}$$

$$x_j = \sum w_{ji}\, X_i - \theta_j \tag{6}$$

where: W_{ij} = Weight
θ_j = Node's threshold
X_i = Data of input layer, represents the physical and chemical values analysis, such as smoke density, CO concentration and the temperature



(a)



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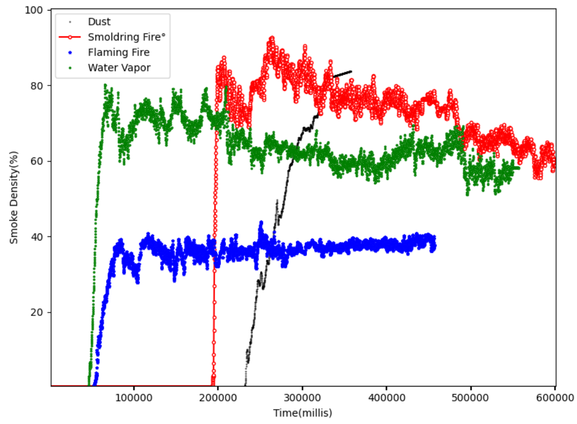

(c)

Figure 10: Comparison of fire detection parameters between different scenarios for (a) carbon monoxide, b) temperature, and (c) smoke density

III. Results and Discussion

In this section, we conducted experiments from different perspectives to improve and confirm the reliability of the system.

A. Calibration

It is important to set up the calibration of a fire detector before installing the fire alarm in order to adjust the zero and the sensitivity of gas sensor MQ2. The calibration should be done in the ambient air of the area, in which the detector should be installed to establish the zero point reading.

When this system starts calibrating, it will determine the value of internal resistance R0, by determining the RS air, air sensing resistance value during calibration time, where Rs_air =average sensing voltage during calibration time * load resistance RL. After getting Rs_air value, we found R0 According to MQ2 datasheet table, where Rs_air/R0 = constant value.

The internal resistance value will be used to get the concentration value of carbon monoxide, where the value of this resistor depends on the quality of ambient air, and the load resistance.

The value of the internal resistor is saved in the EEPROM memory of the ATMEGA 16 microcontroller for use in the equation to determine carbon monoxide concentration. From different areas and at 22kΩ load resistor, the results of internal resistance values of ambient air are shown in Table 2.

Table 2
Variation of Internal Resistor Value of the Gas Sensor MQ2 With the Area Ambient Air Quality

Area	Internal Resistor (kΩ)
Kitchen	7.90
Bedroom	6.23
Parking	6.45
Office	6.03

B. Response Time

Response time is the time-lagged between the input and the output signal, which depends upon the used of detection process steps. In our system, it is the time between detection of the presence of the smoke and the fire alarm launching.

In our system, the MQ2 gas sensor represents the main component responsible for the response time. We define the response time as the necessary time to get the CO gas concentration (in ppm). This time is divided into two parts: the necessary time to stabilize the gas sensor MQ2 (preheat time), and the uncontrollable part-time, which is suitable for the physical and chemical characteristic of the sensor. The second part is the time to get the analog signal from the sensor. It is controlled by programming the microcontroller to get measurements from the sensor in each 100 ms in 10 second duration time to determine the average value. To determine the necessary preheat time for stabilization of the gas sensor, we connected the output of the sensor to a data logger at different load resistors and after every 24 hours of sleep mode (gas sensor not powered), the results are shown in Figure 11. We observe that the necessary duration time to preheat the gas sensor for stabilization is 20 seconds in 10kΩ and from 20 to 35 s in 30KΩ and 50KΩ.

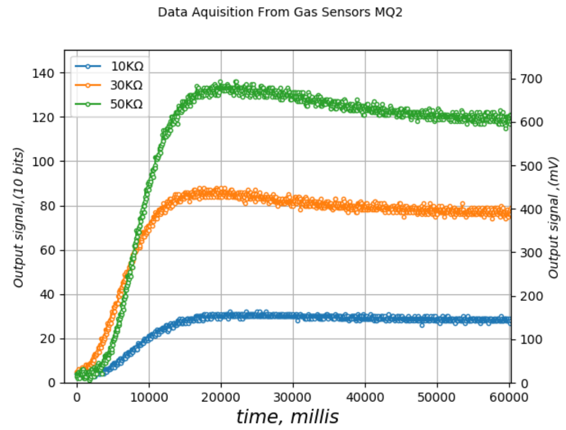

Figure 11: Preheat time of gas sensor MQ2 in ambient air with different values of the load resistor

C. Simulation Model

We used samples from data acquired from different situations to train our model network. Some of these samples are listed in Table 3. After training in MATLAB, the network training results, Figure 12 shows that the error is less than the preset error after 25 epochs, and has fast convergence with a short training time. The neural network weights represent the relationship between the multiple information rules and the input signals. The weights and thresholds values of our model was used as constants in the main fire detection equation.

Table 3
BP Network Training Samples

Sample N°	Input Samples			Expected State
	S (%)	CO (ppm)	T (°C)	
1	44	18	56	Fire
2	80	300	38	Fire
3	58	0	28	No Fire
4	60	135	42	Fire
5	38	10	44	Fire
6	70	0	55	No Fire

After ported the fire detection equation to the embedded platform, we tested with the PC based ANN, where they were both subjected to the same sets input. The output results of both networks were matched in all test cases, where we observed that some situations have very high smoke density. For example, sample 1 from Table 4 summarizes the result of this test. We consider as a false alarm when using the smoke alarm, whereas the results of our system were similar to the expected states, where it is considered no fire. Therefore, by employing the proposed technique, false alarm will be reduced or eliminated.

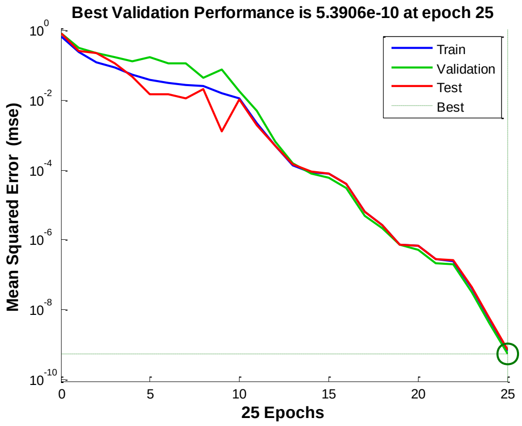

Figure 12: The evolution of training error curve of BPNN performance with epoch

Table 4
System Performance by Comparison of Simulation Results With Expected Values In Different Situations

Sample N°	Input Samples S	CO	T	ANN Output	Expected State	Alarm	SMS
1	90	0	34	-1.0000	No Fire	No	No
2	70	100	42	0.4478	Fire	Yes	Yes
3	10	2	24	-1.0000	No Fire	No	No
4	40	4	36	-0.9999	No Fire	No	No
5	60	120	30	0.9984	Fire	Yes	Yes
6	20	70	59	0.5344	Fire	Yes	Yes

IV. Conclusion

This paper describes several features in our fire detection system can be summarized below.

Low-cost design by dividing the system into two units, setup unit, and detection unit, where one setup unit can control the detection units.

This system can be used as a data logger to save and monitor data. The setup steps in this system represent a positive advantage to edit several options as identifying the area and phone number, calibration to adapt to with air environment.

Uploading the neural network model to a limited memory space of a low-cost microcontroller that can be used in the real-life situation as a low-cost price fire detector device, this system will become a safer and more credible device of fire protection by reducing or eliminating the false alarm rates and missing detection rates, with response time less than 30 seconds to trigger the alarm.

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