



Design and Implementation of a Multi-Sensor Hazard Detection System Using Predictive Analysis

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Abstract: Electrical substations face critical risks such as fire, seismic activity, and unauthorized access that threaten safety and reliability. Conventional single-sensor detection systems often generate false alarms and fail to provide dependable protection. This study presents a cost-effective multi-sensor hazard detection system that integrates an MQ2 smoke detector, infrared motion sensor, and vibration sensor with a microcontroller. The system interprets signals, compares them against defined thresholds, and activates alarms through light emitting diodes (LEDs), a buzzer, and liquid crystal display (LCD) display when hazards are detected. Experimental tests under simulated fire, motion, and vibration scenarios showed that the smoke sensor achieved the highest reliability at a threshold of 300 PPM, while the infrared sensor was prone to occasional false alarms and the vibration sensor effectively detected shocks. By combining sensors, overall reliability improved compared to single-sensor systems. The proposed design demonstrates the potential for affordable hazard detection in substations and industrial plants. Future extensions could integrate IoT connectivity, lightweight machine learning, and digital twin technologies for predictive monitoring and remote management.

Index Terms – Hazard detection, Predictive analysis, Internet of Things (IoT), Multi-sensor system, Smart grid monitoring

I. INTRODUCTION

Automation and intelligent monitoring play a critical role in industrial safety and infrastructure resilience. Globally, workplace accidents exceed 2.3 million annually [1], with developing regions such as sub-Saharan Africa experiencing higher risks due to limited adoption of advanced systems [2]. Traditional smoke, infrared, and vibration detectors are widely available but single-sensor systems often produce false alarms [3]. Recent advances in internet of things (IoT) and artificial intelligence (AI) provide opportunities for multi-sensor systems that improve accuracy through sensor fusion and predictive analysis [4]-[5]. This study develops a low-cost hazard detection system combining smoke, infrared, and vibration sensors with a microcontroller to reduce false alarms and improve detection reliability. The system targets substations and industrial plants but is adaptable to broader applications such as predictive maintenance, safety monitoring and smart grids.

Modern hazard detection research emphasizes AI integration, sensor fusion, and digital twins. However, AI-enabled systems [6]-[7] achieve high accuracy but face cost and infrastructure challenges in developing countries. [8] Demonstrated approximately 99% fire detection accuracy with sensor fusion and lightweight convolutional neural networks (CNNs), while [9] reported approximate 92% accuracy using smoke, flame, and temperature sensors. Sensor fusion consistently outperforms single-sensor setups in [9] study. Comprehensive reviews [10]-[12] summarize deep-learning pipelines, datasets, and strategies for false-alarm reduction in fire detection, indicating a clear research trajectory for substation safety. [13] developed a fire and gas detection system with short message service (SMS) alert and sprinkler activation; however, their design suffered from circuit complexity, reliance on a single sensor, and lack of predictive intelligence, limiting scalability. Similarly, [14] implemented an infrared (IR)-based motion detection system effective for intrusion alarms, but the design fixed to a single position, vulnerable to false triggers, and unsuitable for multi-hazard detection. These limitations highlight the need for multi-sensor, predictive systems such as the one proposed in this study.

The MQ2 sensor remains common for gas detection due to its broad sensitivity (to Liquefied Petroleum Gas (LPG), CH₄, CO, and H₂) and widely used sensor in IoT-enabled prototypes [15]. Calibration via R_s/R₀ curves [16] ensures reproducibility. According to [17]-[18], Standards such as IEC TR 61850-7-6 (2024) and NFPA 72 (2025) provide guidelines for substation safety. Digital twin approaches [19]-[20] highlight future opportunities for predictive management. This paper contributes a cost-effective prototype that validates the benefits of multi-sensor fusion, with potential extensions to IoT and AI applications.

II. SYSTEM ARCHITECTURE & EXPERIMENTAL SET UP

The system integrates an MQ2 smoke detector, infrared sensor, and 801S vibration sensor with a microcontroller (AT89C51/Arduino Uno). Sensor outputs are compared against defined thresholds. When hazards are detected, alarms are

triggered through LEDs, a buzzer, and an LCD display as illustrated in figure 1. A flowchart showing the sequence of the design process shown in figure 2.

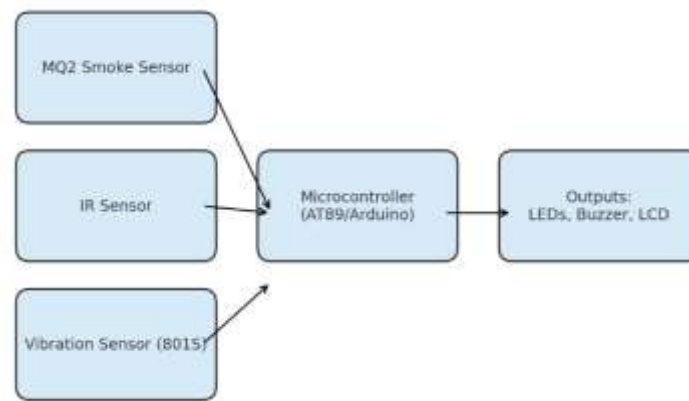


Figure 1. System architecture of the multi-sensor hazard detection system.

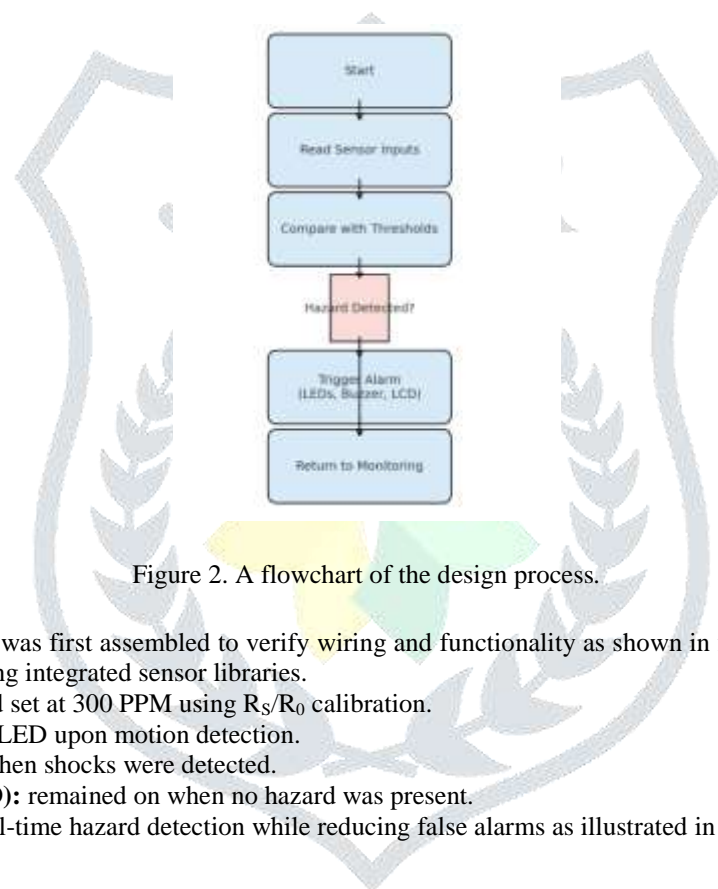


Figure 2. A flowchart of the design process.

A breadboard prototype was first assembled to verify wiring and functionality as shown in figure 2. Embedded C code was uploaded via Arduino IDE using integrated sensor libraries.

MQ2 smoke sensor: threshold set at 300 PPM using R_S/R_0 calibration.

IR sensor: triggered a yellow LED upon motion detection.

Vibration sensor: activated when shocks were detected.

System indicator (green LED): remained on when no hazard was present.

This configuration allowed real-time hazard detection while reducing false alarms as illustrated in figure 3 and 4 respectively.

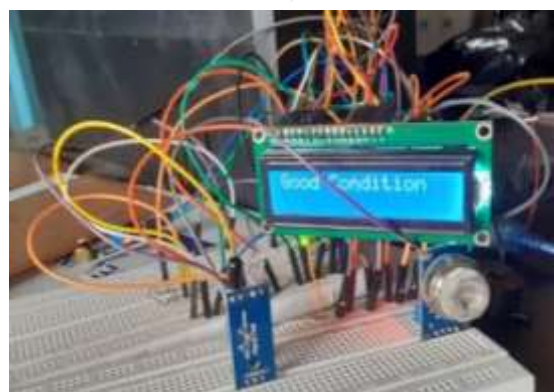


Figure 3: Connection when no hazard detected

Predictive Extension: Although current testing was threshold-based, collected readings (PPM, vibration spikes, IR activity) can serve as features for lightweight ML models (e.g., logistic regression, random forest, CNN). Future extensions could include TinyML deployment on ESP32 boards, GSM/LoRaWAN connectivity [21]-[22], and IEC 61850 mapping for smart substations.

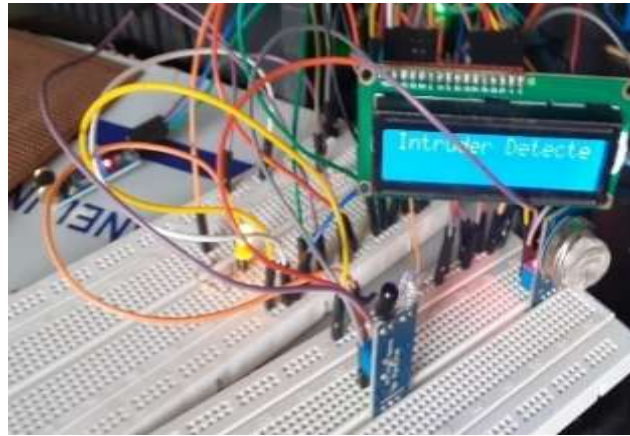


Figure 4: Connection when an intruder detected

III. RESULTS AND DISCUSSION

Sensor Performance: The system demonstrated stable operation across all tests as illustrated in the Table 1-3.

Smoke (MQ2): Most reliable; consistently activated at >300 PPM as indicated in Table 1.

Infrared (IR): Detected motion but generated false alarms under fluctuating temperatures. The results of infrared sensor tabulated in Table 2.

Vibration (801S): Effectively sensed shocks; suitable for seismic or fault monitoring. The results of 801S vibration sensor shown in Table 3.

Table 1 Results of MQ2 Smoke Sensor (Threshold = 300 PPM)

Trial	Smoke Present	Measured PPM	Digital Output	Alarm (LED/Buzzer)	LCD Display
1-3	No	258-262	LOW	OFF	Good condition
4-5	Yes	486-495	HIGH	ON	Smoke Level ALERT
6-9	Yes	312-458	HIGH	ON	Smoke Level ALERT
10	No	294	LOW	OFF	Good condition

Table 2 Results of Infrared Sensor

Trial	Motion Detected	Sensor Output	Alarm (LED/Buzzer)	LCD Display
1-2	No	LOW	OFF	Good condition
3-4	Yes	HIGH	ON	Intruder detected
5-7	No	LOW	OFF	Good condition
8-9	Yes	HIGH	ON	Intruder detected

Table 3 Results of 801S Vibration Sensor

Trial	Vibration Detected	Sensor Output	Alarm (LED/Buzzer)	LCD Display
1-2	No	LOW	OFF	Good condition
3-4	Yes	HIGH	ON	Vibration detected
5-7	No	LOW	OFF	Good condition
8-9	Yes	HIGH	ON	Vibration detected
10	No	LOW	OFF	Good condition

Multi-sensor integration improved accuracy compared to single-sensor approaches. Smoke detection had the lowest false alarm rate, while IR required better calibration. The smoke sensor achieved the highest detection reliability with accurate detection at threshold 300 PPM, followed by the vibration sensor (detected shocks effectively but required calibration for sensitivity) and IR sensor successfully detected movement but produced more false alarms. Table 1-3 summarize sensor performance, while figure 5 compares response accuracy. As indicated in the figure 6 (compare smoke (MQ2), IR, and vibration sensors), detection accuracy (%) on the y-axis while sensor type on the x-axis. The visualization confirms smoke sensor was the most reliable.

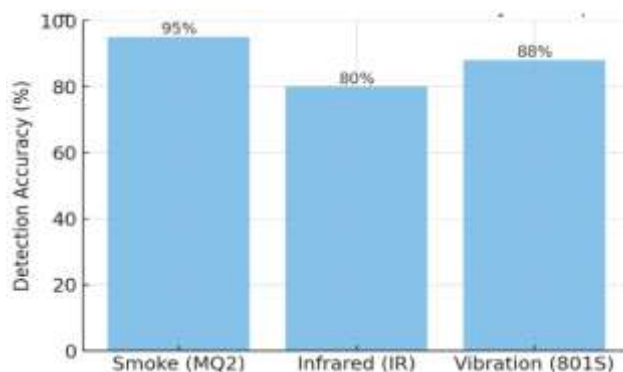


Figure 5 Sensor Detection Accuracy Comparison

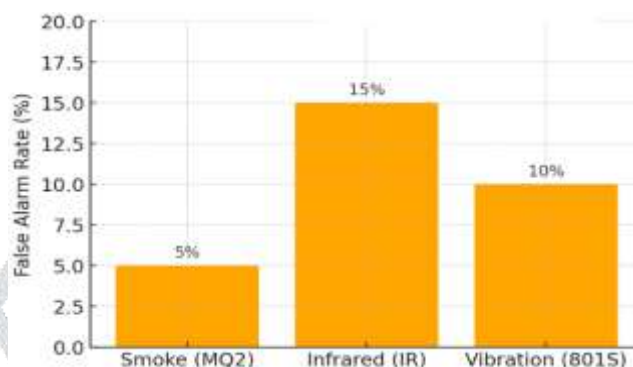


Figure 6 False Alarm Rate by Sensor Type

The Smoke Sensor PPM vs Response as shown in line graph figure 7 indicate the plot measured PPM on x-axis vs sensor output (ON/OFF) or response intensity on y-axis. Result shows how the system responds around the 300 PPM threshold.

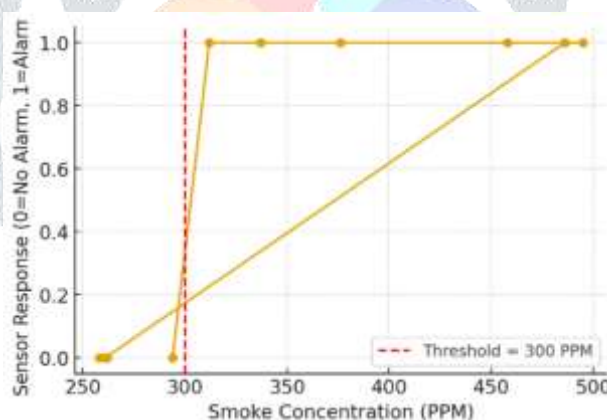


Figure 7 Smoke Sensor Response at Different PPM Levels (threshold = 300 PPM)

The results demonstrate that multi-sensor integration reduces false alarms and enhances reliability. Compared with single-sensor studies [13]-[14], the proposed system offers improved performance and lower cost. Modern works (Deng et al., 2023; Zhou et al., 2024; Singh & Zhang, 2025) suggest AI/IoT extensions would further enhance predictive accuracy, aligning with our future research direction. However, limitations include sensor calibration, potential false alarms, and lack of wireless communication, which restrict scalability for large substations. Results confirm sensor fusion enhances reliability for industrial applications.

IV. CONCLUSION

This study designed and tested a multi-sensor hazard detection system for substations. By integrating smoke, infrared, and vibration sensors, the prototype achieved improved accuracy and reduced false alarms compared to single-sensor setups. The system provides an affordable solution for industrial safety, particularly in resource-constrained environments. Limitations include calibration challenges, occasional false IR alarms, and the absence of wireless communication. Future work will explore IoT dashboards, embedded machine learning, and digital twin integration to strengthen predictive monitoring and scalability.

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