ECOSPHERE MONITOR

Joshua Muthenya Wambua.

Reg no: EG209/109705/22

Department of Electrical Engineering, SEA, Meru University of science and technology

Supervisor: Eng. Job Kerosi

Date of Submission: September 16, 2025

Table of contents

Abstract

Air quality degradation and hazardous gas emissions represent critical challenges to public health, safety, and environmental sustainability. Urbanization and industrialization have intensified the release of pollutants such as carbon monoxide, methane, nitrogen oxides, and particulate matter (PM2.5 and PM10), while domestic environments remain vulnerable to liquefied petroleum gas (LPG) leaks and other combustible gases. These pollutants are linked to respiratory illnesses, cardiovascular diseases, climate change, and fire outbreaks. However, existing monitoring approaches are often centralized, costly, and inaccessible to individuals for real-time decision-making. This project proposes *EcoSphere Monitor*, an IoT-based air quality monitoring system designed to provide real-time data acquisition, cloud-based storage, and predictive analytics. The system integrates low-cost MQ gas sensors, particulate matter sensors, and environmental sensors with an ESP32 microcontroller for data collection. Data are transmitted to Firebase for secure storage, visualization, and alert dissemination through a web application. Furthermore, predictive models are employed to forecast pollution levels, detect anomalies, and assess potential fire hazards. The proposed system contributes to environmental health research by offering a scalable and affordable solution for continuous monitoring, early warning, and risk mitigation in urban, domestic, agricultural, and healthcare settings.

Introduction

Air quality degradation has become a global concern, with urbanization, industrial activities, and transportation being major contributors. Pollutants such as particulate matter (PM2.5 and PM10), carbon monoxide, nitrogen oxides, and volatile organic compounds not only impair air quality but also pose serious health risks. According to the World Health Organization (WHO), exposure to poor air quality contributes to millions of premature deaths annually. Moreover, gas leaks in domestic environments—especially LPG and methane—create hazards of poisoning and explosions. While large-scale monitoring stations exist, these solutions are often centralized, expensive, and inaccessible to individuals or households.

The need for affordable, real-time, and predictive monitoring systems is therefore critical. *EcoSphere Monitor* addresses this gap by combining IoT technology, cloud computing, and machine learning to provide localized and actionable insights into air quality.

Problem statement

Air quality in urban areas is steadily deteriorating due to industrial emissions, vehicular exhaust, and dust pollution. These pollutants pose serious health risks, contributing to respiratory illnesses, allergies, and reduced overall quality of life. In addition, leakages of gases such as LPG, methane, and propane create significant safety hazards, leading to risks of fire, explosions, and poisoning. Currently, most air quality monitoring solutions are centralized, large-scale, and inaccessible to individuals. They do not provide real-time, localized, and affordable monitoring that households and small businesses need for timely action. This gap leaves individuals vulnerable to invisible threats in their immediate environment.

Objectives

1. To monitor air pollutants such as particulate matter and harmful gases in real time.
2. To measure environmental parameters like temperature and humidity.
3. To provide instant alerts when air quality exceeds safe thresholds.
4. To enable remote monitoring through a web application.
5. To raise awareness on health and safety by making air quality data easily accessible.
6. To design a scalable system adaptable for homes, industries, and cities

Literature Review

Air quality monitoring has been the subject of extensive research due to the growing health and environmental risks associated with urban pollution. Traditional air quality monitoring networks rely on fixed, government-operated stations that provide accurate but highly localized measurements. For example, the London Air Quality Network operates several fixed monitoring sites to collect data on particulate matter and gaseous pollutants [1]. While effective for citywide management, such systems are costly to install and maintain, making them inaccessible to individual households.

Recent years have seen the rise of **low-cost sensor-based approaches** that leverage the Internet of Things (IoT). Clarity Movement deployed low-cost sensors across more than 85 countries, including London and Bogota, demonstrating the scalability of distributed sensing networks [2]. Similarly, in Nairobi, a 50-sensor citywide monitoring project was launched in 2024 under the Breathe Cities initiative to provide near real-time pollutant data [3]. While these efforts improve spatial coverage, they remain centralized and do not address household-level monitoring needs.

Several studies have validated the performance of MQ-series gas sensors and particulate sensors in low-cost monitoring systems. The MQ-135 sensor, for example, has been evaluated for detecting CO_2, NH_3, and volatile organic compounds in urban environments [4]. Likewise, PM2.5 and PM10 sensors have been widely studied for their correlation with respiratory illnesses, particularly in dense urban centers [5]. However, sensor drift and calibration challenges remain critical issues that require preprocessing and data correction techniques.

In Kenya, localized studies have applied low-cost particulate sensors in high-risk areas. For instance, in Kisumu and Dandora, academic studies demonstrated the feasibility of using affordable PM sensors to map pollution hotspots [6]. The Kenya Meteorological Department, in collaboration with SEI Africa, has also installed pollutant monitoring systems for climate and health research [7]. These studies provide important regional insights but are often limited in scope to research projects rather than household adoption.

Beyond sensing, **machine learning (ML) techniques** are increasingly being used for air quality forecasting and anomaly detection. Regression-based models, Support Vector Machines (SVM), and Random Forests have been applied for short-term pollution prediction with promising results [8]. More advanced methods such as Long Short-Term Memory (LSTM) networks have demonstrated effectiveness in time-series forecasting of air pollutants [9]. Anomaly detection techniques, including Isolation Forests, have been successfully applied to identify hazardous gas leaks and unusual pollution patterns [10]. These predictive capabilities transform monitoring systems from reactive tools into proactive solutions.

Overall, the literature indicates a clear shift from centralized monitoring to distributed, IoT-enabled, and ML-powered systems. However, gaps remain in affordability, accessibility, and integration of predictive analytics for individual households. The proposed **EcoSphere Monitor** addresses these limitations by combining low-cost MQ-series and PM sensors with cloud-based data storage, a web application for visualization, and machine learning models for forecasting and anomaly detection. This integration positions EcoSphere as a scalable, practical, and impactful solution for both households and communities.

Methodology

The proposed system will be developed in four phases:

1. ## Sensor Integration:

   MQ-series gas sensors (MQ-2, MQ-7, MQ-9, MQ-135), PM2.5/PM10 sensors, and environmental sensors (temperature, humidity) will be used for data collection.

2. ## Edge Processing:

ESP32 microcontrollers will interface with sensors, preprocess signals, and transmit data wirelessly.

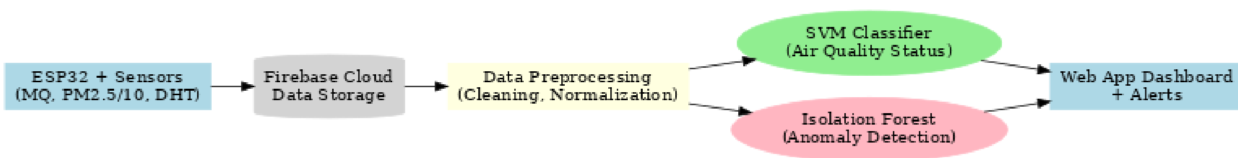
3. ### Cloud Storage and Access:

Firebase will serve as the cloud backend for real-time storage, data retrieval, and user notifications.

4. ### Web Application and Alerts:

A responsive web application will be developed to visualize air quality indices and provide alerts. Predictive models will be implemented to forecast pollution levels and detect anomalies.

Data Analysis Methods



1. ### Data Preprocessing:

Cleaning, normalization, and calibration of sensor data.

2. ### Exploratory Data Analysis (EDA):

Visualization of temporal and spatial pollution patterns.

3. ### Predictive Modeling:

Regression models (e.g., Linear Regression, Random Forest, LSTM) will be applied for forecasting pollution levels.

4. ### Classification and Anomaly Detection:

Models such as Support Vector Machines (SVM) or Isolation Forests will detect hazardous levels and abnormal patterns.

5. ### Evaluation Metrics:

RMSE, MAE, accuracy, and confusion matrices will be used to assess model performance.

Expected Results & Discussion

The system is expected to:

1. Provide real-time and localized monitoring of air pollutants and hazardous gases.
2. Accurately detect pollution spikes and gas leaks, triggering timely alerts.
3. Forecast short-term air quality trends using predictive models.
4. Enable households, agricultural users, and healthcare facilities to make informed decisions.
5. Demonstrate the feasibility of deploying affordable and scalable IoT-based monitoring systems in urban and domestic environments.

Project Timeline

Phase	Task	Duration (weeks)
1	Research & Planning	**Weeks 1–2**
2	Hardware Setup	**Weeks 3–5**
3	Cloud Integration	**Week 6**
4	Web App Development	**Weeks 7–8**
5	Data Collection	**Weeks 9–10**
6	ML Modeling	**Weeks 11–12**
7	Testing & Final Report	**Weeks 13–14**

Project budget

Serial No.	COMPONENT	UNIT COST	QUANTITY	TOTAL COST
1	ESP 32	2000	2	4000
2	Nova pm sensor	3000	1	3000
3	MQ series sensors	700	7	4900
4	lEDs	10	10	100
5	dht11 sensor	700	1	700
6	jumbers	500	1	500
7	solder wick	400	1	400
8	strip board	200	2	400
9	bread board	200	1	200
10	enclosure(package)	600	2	1200
11	buzzer	150	2	300
			total	**KES 15,700.00**

Conclusion

EcoSphere Monitor represents a low-cost, scalable, and practical solution to the challenges of air quality monitoring and hazard prevention. By integrating IoT sensors, cloud computing, and predictive modeling, the system bridges the gap between centralized monitoring systems and individual accessibility. The project not only contributes to academic research in environmental monitoring but also holds practical value in improving public health, enhancing environmental awareness, and preventing gas-related disasters.

References

[1] F. J. Kelly and K. Julia, "London air quality: a real world experiment in progress," *Biomarkers,* vol. 14, no. sup1, pp. 5-11, 2009.

[2] K. Okorn and L. T. Iraci , "An overview of outdoor low-cost gas-phase air quality sensor deployments: current efforts, trends, and limitations," *Atmospheric Measurement Techniques,* vol. 17, no. 21, pp. 6425-6457, 2024.

[3] Nairobi county govenment; environmenta compliance institute;, "NAIROBI CITY AIR QUALITY ACTION. "STOCK-TAKE REPORT," Breathe cities, Nairobi, 2025.

[4] S. U. Rani, S. Rajarajeswari, . J. Jaimon and R. Ravichandran , "Real-time air quality monitoring system using MQ-135 and thingsboard," *Journal of critical reviews,* vol. 7, no. 18, pp. 4107-4115, 2020.

[5] L. H. Tecer, O. Alagha , F. Karaca, G. Tuncel and N. Eldes, "Particulate matter (PM2. 5, PM10-2.5, and PM10) and children's hospital admissions for asthma and respiratory diseases: A bidirectional case-crossover study," *Journal of Toxicology and Environmental Health, Part A,* vol. 71, no. 8, pp. 512-520, 2008.

[6] S. Tékouaboua , J. SC, R. Azmia, E. Diopa, H. Toulnic and N. A. de Padoue , "Towards air quality particulate-matter monitoring using low-cost sensor data and visual exploration techniques: case study of Kisumu, Kenya," Procedia Computer Science, Kisumu, 2022.

[7] C. Muhoza, "Planning a new urban research programme for SEI Africa.," Kenya meteorology department, nairobi, 2015.

[8] M. Méndez , M. Merayo and M. Núñez, "Machine learning algorithms to forecast air quality: a survey," *Artificial Intelligence Review,* vol. 56, no. 9, pp. 10031-10066, 2023.

[9] F. Hamami and I. Dahlan , " Univariate time series data forecasting of air pollution using LSTM neural network," in *International conference on advancement in data science, E-learning and information systems (ICADEIS). IEEE*, 2020.

[10] M. Tabassum, S. Mahmood, A. Bukhari, B. Alshemaimri, A. Daud and F. Khalique, "Anomaly-based threat detection in smart health using machine learning," *BMC Medical Informatics and Decision Making,* vol. 24, no. 1, p. 347, 2024.