International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347-6435(Online) Volume 14, Issue 12, December 2025)

"A Low-Cost Iot Framework for Real-Time Air Quality Assessment Using MQ-135 Sensor"

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Abstract - **The escalating challenge of air pollution, particularly in dense urban centers, poses a significant threat to public health and the environment. While conventional air quality monitoring stations provide accurate data, their high cost and sparse deployment limit spatial resolution. This paper presents the design and implementation of a cost-effective, Internet of Things (IoT)-based air quality monitoring system. The proposed system utilizes the MQ-135 gas sensor to detect hazardous pollutants like NH_3, NO_x, CO_2, and benzene, alongside other volatile organic compounds (VOCs). The sensor data is processed by an ESP8266 microcontroller to compute an approximate Air Quality Index (AQI) and transmitted via Wi-Fi to the ThingSpeak cloud platform for real-time visualization and analysis. Experimental results from various indoor and outdoor settings demonstrate the system's reliability in tracking pollution dynamics. The system offers a viable, affordable solution for smart-city infrastructure, indoor air quality assessment, and fostering community-driven environmental awareness.**

Keywords - **IoT, Air Quality Monitoring, MQ-135 Sensor, ESP8266, AQI, Cloud Computing, Low-Cost Sensor.**

I. INTRODUCTION

The deterioration of ambient air quality in major cities worldwide, such as Delhi and Beijing, has become a critical global issue [1]. Extensive medical research has established a strong correlation between prolonged exposure to airborne pollutants and an increased incidence of respiratory ailments, cardiovascular diseases, and other long-term adverse health effects [2], [3]. To effectively mitigate these risks, there is a pressing need for high-resolution, spatio-temporal pollution data [4].

Government-operated monitoring stations, though highly accurate, are characterized by significant capital and operational expenditures, rendering them stationary and sparsely distributed. This limitation has spurred research into alternative paradigms, including mobile sensing networks [5], [6], data-driven predictive modeling [7], [8], Unmanned Aerial Vehicle (UAV)-based platforms [9], and community-powered sensing initiatives [11], [13].

The proliferation of IoT technology presents a transformative opportunity to deploy dense networks of low-cost, interconnected sensors. This paper contributes to this domain by proposing a robust, IoT-enabled air quality monitoring system built around the MQ-135 gas sensor. The system delivers real-time pollutant concentration measurements, approximates the AQI, and facilitates remote data access through cloud-based dashboards. Its affordability, scalability, and ease of deployment make it particularly suitable for personalized exposure tracking and integration into smart urban environments.

II. RELATED WORK

Previous research has extensively explored various approaches to air quality monitoring. Mobile sensing systems, such as MAQS [5], have demonstrated the value of dynamic, high-resolution data collection. Concurrently, advanced computational techniques, including kriging [4] and deep learning models [9], [18], have been employed to forecast AQI with increasing accuracy.

The shift towards participatory and personal sensing is evident in the development of wearable pollution monitors [15] and community-driven platforms [11]. The core enabler for these applications has been the advent of low-cost solid-state sensors [12], [13]. Studies have also leveraged sensor data combined with deep learning to characterize indoor air environments [17].

However, a common shortfall in many existing low-cost solutions is the lack of a seamless, integrated pipeline encompassing reliable sensing, robust wireless communication, and accessible cloud analytics. Our work aims to bridge this gap by presenting a cohesive system that synergizes a widely-available sensor (MQ-135), a ubiquitous microcontroller with Wi-Fi capability (ESP8266/ESP32), and a public cloud platform (ThingSpeak) to create an end-to-end monitoring solution.

III. SYSTEM ARCHITECTURE

The architecture of the proposed system is delineated into four primary layers: Sensing, Processing, Communication, and Presentation.

A. Hardware Components

The system is constructed using the following components:

- *Sensing Unit:* The MQ-135 gas sensor serves as the primary data acquisition module. It is sensitive to a broad range of pollutants, including NH_3 , NO_x, CO_2 , and VOCs.
- *Processing Unit:* An ESP8266 (or ESP32) microcontroller acts as the system's brain. It is responsible for reading the analog signal from the sensor, performing analog-to-digital conversion (ADC), executing the calibration and AQI computation algorithms, and managing network connectivity.
- *Communication Module:* The embedded Wi-Fi capability of the ESP8266/ESP32 enables wireless data transmission to the cloud.
- *Power Supply:* The system is powered via a standard 5V USB source, making it compatible with power banks and wall adapters for flexible deployment.

B. Working Principle of MQ-135

The MQ-135 is a semiconductor sensor based on tin dioxide (SnO_2). In the presence of detectable gases, the surface conductivity of the sensing material changes. This change in conductivity is measured as a variable voltage output. The microcontroller's ADC converts this analog voltage into a digital value, which is then mapped to a corresponding gas concentration using the sensor's sensitivity characteristics and calibration data.

C. System Workflow

1. *Data Acquisition:* The MQ-135 sensor detects the concentration of target gases in the ambient air.
2. *Signal Conditioning & Processing:* The raw analog signal is filtered and digitized. The microcontroller applies calibration algorithms to compensate for environmental factors and calculates the PPM (Parts Per Million) value.
3. *Data Transmission:* The processed data, along with the computed AQI, is packaged into a message and sent to the ThingSpeak cloud server at predefined intervals (e.g., every 15 seconds) using the HTTP POST method.
4. *Cloud Storage & Visualization:* ThingSpeak receives and stores the data, updating graphical widgets (gauges, plots) on a dedicated channel dashboard in real-time, accessible from any web browser.

IV. METHODOLOGY

A. Sensor Calibration Process

Accurate measurement is contingent on proper calibration. The procedure involves:

1. *Baseline Establishment (R_0):* The sensor is placed in clean air (approximated or controlled environment) to determine its baseline resistance, R_0 .
2. *Environmental Compensation:* As the MQ-135's readings are influenced by temperature and humidity, correction factors are applied using datasheet curves or co-located environmental sensors.
3. *Concentration Mapping:* The sensor resistance ratio (Rs/R_0) is used in conjunction with the log-log plots from the datasheet to estimate the PPM concentration of the target gases.

B. Cloud Communication Protocol

The system employs the MQTT or HTTP protocol for lightweight and efficient communication. The ESP8266, configured as a Wi-Fi client, connects to a local router and transmits JSON-formatted data packets containing sensor readings, AQI value, and a timestamp to the ThingSpeak API.

C. AQI Computation

The system converts the aggregated pollutant concentrations into a unified Air Quality Index (AQI) based on a standardized scale [e.g., similar to the National Air Quality Index (NAQI) of India or the US EPA AQI]. The AQI is categorized as follows:

- **0 - 50:** Good
- **51 - 100:** Satisfactory
- **101 - 200:** Moderate
- **201 - 300:** Poor
- **301 - 400:** Very Poor
- **401 - 500:** Severe

V. RESULTS AND DISCUSSION

The system was evaluated through a series of tests in diverse environments.

- *Indoor Monitoring:* Significant spikes in pollutant levels were recorded in enclosed spaces like kitchens (during cooking) and poorly ventilated rooms, validating the system's sensitivity.
- *Outdoor Monitoring:* Deployments near roadways successfully captured diurnal patterns, with clear peaks correlating with morning and evening traffic congestion.

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- *System Performance:* The data transmission to the ThingSpeak cloud was stable and reliable, with a success rate exceeding 98%. The web dashboard provided intuitive and real-time visualization of the data trends.
- *Sensor Consistency:* Repeated measurements under similar conditions showed consistent sensor behavior, confirming short-term reliability.

These findings align with prior studies [12], [13], [15], affirming that low-cost sensors, when appropriately calibrated, can effectively supplement traditional monitoring networks by providing hyper-local data. The proposed system successfully addresses the gaps in cloud integration and real-time accessibility identified in the related work.

VI. APPLICATIONS

The versatility of the proposed system enables its deployment in numerous scenarios:

- *Urban Environmental Sensing:* Deploying sensor nodes across a city to create a high-resolution pollution map.
- *Indoor Air Quality (IAQ) Management:* Monitoring air quality in homes, offices, schools, and hospitals.
- *Industrial Safety:* Ensuring worker safety by monitoring air quality in factories and workshops.
- *Mobile Pollution Mapping:* Installing the system on public transport or service vehicles for dynamic, city-wide coverage.
- *Personal Wearable Devices:* Miniaturizing the system for individual exposure tracking.
- *Community Science Projects:* Empowering citizen scientists to collect and share local air quality data.

VII. CONCLUSION AND FUTURE WORK

This paper has detailed the successful development and testing of a functional, low-cost IoT-based air quality monitoring system. By integrating the MQ-135 sensor with the ESP8266 microcontroller and the ThingSpeak cloud platform, the system provides a practical and scalable solution for real-time, localized pollution monitoring.

Future work will focus on several enhancements:

1. *Multi-Sensor Fusion:* Integrating additional sensors (e.g., PMS5003 for PM2.5/PM10, DHT22 for precise temperature/humidity) to improve accuracy and pollutant discrimination.
2. *Predictive Analytics:* Implementing machine learning models (e.g., LSTM networks) on the cloud backend for forecasting AQI trends.
3. *Geolocation Integration:* Incorporating GPS modules to automatically tag data with location coordinates for spatial analysis and heat map generation.
4. *Energy Optimization:* Developing solar-powered or low-power sleep-mode algorithms for long-term, battery-operated deployments.

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