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IOT-BASED OUTDOOR AIR QUALITY MONITORING IN CAMPUS ENVIRONMENTS: AN APPLICATION-ORIENTED STUDY USING LOW-COST SENSORS

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ABSTRACT: Outdoor air quality has a significant impact on the health and comfort of academic environments, particularly on university campuses where students and faculty spend considerable time. The conditions in the indoor lecture building are greatly influenced by outdoor air quality. Putting environmental air quality in terms of health will help show the risk from pollution. This study introduces a simple and affordable solar-powered IoT air quality monitoring system, which was carefully designed, tested in the lab, and then deployed for a certain period on a university rooftop. The system consisted of an ESP32 microcontroller installed with sensors for temperature, humidity, CO_2, CO, NO_2, and $PM_{2.5}$. A 20-WP solar panel, along with a rechargeable battery, ensures it runs independently. Sensor characterization was performed using manufacturer datasheets, using regression models and reference data to improve accuracy. Environmental measurements were recorded every 7 minutes, which generates 6,000 data in average during the study period every month. Real-time data transmission to Google Sheets enabled continuous monitoring, revealing hourly pollutant fluctuations linked to campus activity patterns. Analysing data reported in real time, the air quality parameters detected hourly variations in concentrations and the impact of human activity on air quality by analysing real-time reported data. The results showed that CO was rated between 260 and 290 ppm, CO_2 shot up past 1500 ppm during busy hours, NO_2 spikes reached over 60 ppm in a few cases, and $PM_{2.5}$ reaching up to 20 µg/m³. These findings show how pollution levels fluctuate with campus activity, underscoring the need for continuous air quality monitoring. In addition, the results confirm that the proposed system successfully demonstrated continuous environmental monitoring under field conditions.

Keywords: Air quality, Buildings, Environment, Measurement, Sensor

1. INTRODUCTION

Air quality significantly impacts our health and the environment [1], [2], [3]. Lately, pollution has become a worldwide concern, fueled by quick industrial growth, increased transportation, and changes in land use. In Indonesia, this is exacerbated by such disasters as forest and land fires that happen almost every year, particularly in South Sumatra. These fires significantly increase the levels of tiny harmful particles and toxic gases, which can threaten public health and the environment [4], [5], [6]. Outdoor air quality directly influences indoor environments through natural infiltration, making localized monitoring critical for protecting academic populations, as faculty, students, and staff are exposed to outdoor air both in outdoor settings, possibly having significant consequences for exposure, and through natural ventilation of buildings [2], [7]. Pollutants from vehicles, construction, and haze events may pool in semi-open areas and affect breathing, concentration, and comfort [8], [9]. However, there remains limited access to continuous, real-time outdoor air quality monitoring near academic buildings, especially in developing regions where high-cost monitoring tools are less accessible in developing regions where access to high-cost monitoring infrastructure is restricted [10], [11].

The selection of temperature, humidity, CO, CO_2, NO_2, and $PM_{2.5}$ in this study is based on their important connection to health and their proven ability to indicate specific sources of emissions in the area. Temperature and humidity influence how gases spread in the atmosphere and can cause sensor response drift. CO and NO_2 are useful as tracers to indicate incomplete combustion and vehicle emissions. CO_2 is a good indicator of human presence and how well ventilation is working, while $PM_{2.5}$ represents tiny particles that can reach deep into the lungs, potentially causing oxidative stress and health issues. Despite their importance, few low-cost IoT deployments in academic settings are explicitly.

Recent advances in inexpensive sensors and IoT technologies continue to open up new opportunities for environmental monitoring at scale [12], [13], [14]. So, if it is compared with conventional air quality monitoring stations, which are typically expensive and limited in spatial coverage, low-cost sensor systems provide a more flexible and scalable solution for real-time environmental monitoring. All this at a fraction cost of traditional high precision instruments[15], [16]. In addition, many existing implementations still face challenges related to system integration, long-term power supply, and accessible data management platforms.

Although interest in low-cost environmental monitoring systems is growing, there are still several research gaps that remain. First, integration with existing systems and reliability of data remain relatively limited in campus-scale monitoring applications. Second, the air quality data in academic microenvironments are still scarce, particularly in developing regions where environmental monitoring infrastructure is limited. Therefore, building cost-efficient, open-source monitoring platforms is the key to environmental assessment in higher education institutions. Third, most studies investigated indoor air quality in educational buildings. In reality, outdoor air quality also makes a significant contribution to determining indoor air quality [10], [17], [18] because the ambient pollutants can easily infiltrate buildings through ventilation systems, open windows, and natural air exchange processes.

For addressing these gaps, this study reports the design, characterization, and deployment of an affordable IoT-based multisensor air quality monitoring system installed on a lecture building at Universitas Sriwijaya. The system will continuously monitor temperature, relative humidity, CO, CO_2, NO_2, and $PM_{2.5}$ levels. It was designed to provide information on how pollutants fluctuate over time due to campus activities and nearby emission sources. In addition, a solar-powered energy system using a 20-WP solar panel and rechargeable battery is implemented to enable autonomous operation without reliance on grid electricity. Also, the system incorporates a cloud-based data logging platform interface using Google Spreadsheet to allow real-time monitoring, visualization, and long-term environmental data storage.

The structure of this paper is as follows. The study area and research methodology, including the design of the IoT-based monitoring system and sensor characterization procedures are elaborated in Section ‘‘Material and Methods”. Section ‘‘Results and Discussion” details the implementation of the multisensor monitoring platform and the data acquisition interface. This section discusses measurement results and the observed air quality dynamics around the campus environment. “Section Conclusions” summarizes the main findings and outlines future research directions for improving distributed air quality monitoring systems.

2. RESEARCH SIGNIFICANCE

This study presents a low-cost, solar-powered IoT air quality monitoring system tailored for outdoor academic settings. The novelty of this work lies in the integration of multiple low-cost gas and meteorological measurements within a single autonomous IoT-based platform powered by a solar energy system. The system offers real-time environmental data logging and visualization through the cloud using Google Spreadsheet, ensuring accessible and continuous air quality updates. Additionally, the proposed system brings real-time cloud monitoring with continuous operation. It allows to collect high-frequency environmental data in real conditions. The study also discusses insights through operational performance and environmental observations from deployment on a university campus. This highlights the practical potential of affordable environmental monitoring solutions, especially in tropical regions.

3. MATERIALS AND METHODS

3.1 Study site description

Monitoring of the site was carried out on the rooftop of the lecture building in Sriwijaya University, as shown in Fig. 1. Thus, the selected site represents a semi-open campus model of mixed programmatic use, encompassing academic structures, car parks, and a surrounding green enclave. While placing equipment on rooftops helps minimize some ground turbulence, it is good to keep in mind that these measurements mainly show the overall campus air quality, rather than very specific details like what pedestrians experience or indoor air exchange.

Fig.1 Location of the monitoring station on the rooftop of a lecture building to provide representative measurements of ambient environmental conditions.

The area is surrounded by thick vegetation on several sides, with open spaces between buildings that can affect how pollutants spread and how air circulates, including outdoor-to-indoor and indoor-to-outdoor exchanges. The monitoring station was positioned at the rooftop height in order to avoid several kinds of obstacles present on ground level, which would alter ambient air conditions.

The movement of vehicles and people around the lecture buildings significantly affects the air quality, particularly during busy campus times. Motorcycles, cars, service vehicles, and the many pedestrians all contribute to higher emissions of CO, CO_2, NO_2, and tiny $PM_{2.5}$ particles, which can affect the local air quality environment. These characteristics make the site suitable for evaluating short-term fluctuations in pollutant concentrations in a semi-urban academic setting. The environmental configuration of the campus, including vegetation buffers and building geometry, also provides an opportunity to examine the interaction between emission sources and atmospheric dispersion [13].

3.2 Design an instrumentation system

This paper presented an IoT-based air quality system based on the ESP32 microcontroller. It integrates multiple sensors to determine environmental parameters like temperature, humidity, and important atmospheric gases, such as CO_2, CO, NO_2, and particulate matter ($PM_{2.5}$). Using this system design, the ESP32 can easily connect to multiple gas and particulate sensors for real-time monitoring of environmental factors.

Temperature and humidity were measured with a DHT22 digital sensor. Since it provides reliable signals and steady performance, it is a great choice for monitoring environmental conditions. To detect carbon dioxide, we used an MG-811 electrochemical gas sensor module. The sensor is appreciated for its sensitivity to common changes in ambient CO_2 levels. While for monitoring carbon monoxide, we chose a GM-702B semiconductor gas sensor, and for nitrogen dioxide, a GM-102B sensor module was employed. The fine particulate matter ($PM_{2.5}$) was measured with the GP2Y1014AU optical dust sensor, which uses infrared light scattering to estimate particle concentrations effectively. These sensors were chosen by considering low-cost sensor characteristics, such as small size and weight, relatively low power requirements, short response time, and real-time network adaptability [20], [21], [22].

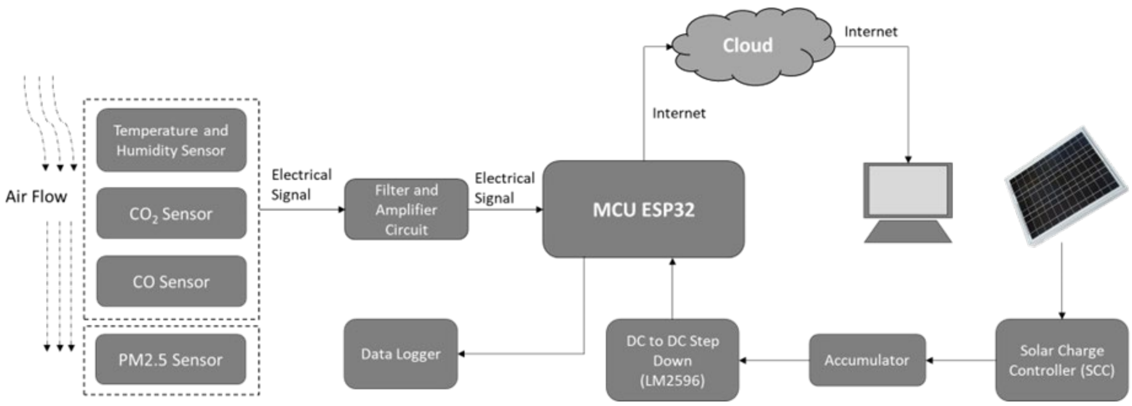

Fig.2 Block diagram of the instrumentation system and measurement. It integrates multiple environmental sensors to enable continuous monitoring of air-quality data in real time.

According to Fig. 2, processing and communication were performed by the ESP32 microcontroller. Sensors connected through several analog and digital inputs worked hand in hand to collect wide environmental data for a full view of the environment. ESP32 ADCs integrate the conversion of analog signals from the gas sensor to digital ones. These signals were finalized and translated into concentration units with equations to ensure their accuracy. Digital sensors, such as DHT22, use digital protocols for data transmission. It offers fast and accurate communication.

Collecting data every 7 minutes allowed for continuous updates on the subject's condition during the monitoring period. The data was then formatted into string packets, sent by the ESP32 Wi-Fi connected to the cloud server for easy remote access and analysis. The data was stored in a Google Sheets database, which supported real-time visualization and remote access.

To ensure our outdoor system runs smoothly and helps us become more energy-independent, the system is powered by an off-grid solar panel system. It is set up, comprising a 20-WP monocrystalline photovoltaic panel, a 12V 70 Ah sealed lead-acid (SLA) battery, and a PWM charge controller. This includes a small but efficient 20-WP photovoltaic (PV) solar panel combined with a rechargeable accumulator to store energy. Throughout the day, the solar panel effectively collects sunlight and converts it into electrical power. This power is managed by a solar charge controller (SCC) to ensure the battery remains healthy and is not overcharged. The energy stored in the battery then provides steady DC power [23]. However, before it is used to power the ESP32, internet modem, and sensor modules, the accumulator voltage must be step-down-converted to 3.3 V. The purpose is to adjust the working voltage of the circuit in the system.

On average, the power consumption was around 3.2 W when actively sensing and transmitting data, which results in a daily energy use of about 38 Wh with a 7-minute sampling interval. This amount is comfortably below the standard tropical isolation level of about 4.5 kWh/m²/day. The PV panel generates roughly 90 Wh each day, supplying an energy of 52 Wh after consumption. The sturdy 70 Ah battery (with a theoretical capacity of 840 Wh and a safe discharge depth of 50%) can power the system for approximately 10.5 hours without any solar input, and during the monitoring period, the system stayed operational over 98% of the time. Thus, this off-grid setup improves system sustainability, allows flexible outdoor deployment without needing grid access, and helps reduce long-term operational costs.

The system workflow consists of four main stages: sensing environmental signals, converting analog data to digital, characterizing, wirelessly transmitting data, and storing and visualizing data in the cloud. This enables us to be modular in our design, enabling flexibility and the potential for future upgrades with additional environmental sensors or a switch in communication method. Thus, the platform represents a scalable and cost-effective solution for the monitoring of outdoor air quality, particularly in semi-urban academic environments [19].

3.3 Design of experiment

This experiment aimed to assess variations in outdoor air quality around a lecture hall. The key parameters measured included $PM_{2.5}$, NO2, CO2, CO, relative humidity, and air temperature. These particular pollutants and climate indicators were chosen because they directly affect comfort and health, especially for the campus academic community [13]. It was installed right above the lecture room but well exposed and placed, so as to be low enough to avoid all coverings from nearby buildings and vegetation before monitoring started. It collected the data from the morning to the evening. It combined the supplied data from the morning and the evening. Morning and afternoon were especially significant because these are peak times when most students are engaged in their activities, so the data likely represent what they normally experience during school hours and after-school periods. Over the course of several days, sampling is repeated, aiming at reducing weather-related errors and understanding air quality for more than just the activity in the lecture hall. It was examined for exposure risks and to assess whether the campus environment is conducive to healthy learning.

The air quality monitoring system was set up on the rooftop of the lecture building. It began operating on 8 October 2025 and is still running as part of an ongoing environmental monitoring program. Measurements were taken every 7 minutes, so it should generate about 6,377 observations for each parameter monitored, in theory. Although data outside this specific period wasn't included in our current analysis, it's still available and can be used for future, longer-term research.

3.4 Sensor Characterization and Verification

Prior to field deployment, sensor outputs are converted into physical units using transfer functions and calibration curves provided by the manufacturers in their datasheets. The algorithms used for the MG-811, GM-702B, GM-102B, and GP2Y1014AU sensors followed methods detailed in previous research [21], [24] and manufacturer instructions. The details of the specifications of the system are summarized in Table 1.

Because the objective was to evaluate the performance of a low-cost IoT monitoring system in actual field conditions, we used regression-based techniques to improve measurement accuracy and reduce any systematic errors.

In addition, a verification procedure was implemented by comparing the resulting measurements with expected environmental ranges and publicly available meteorological observations and data from the Indonesian Agency for Meteorology, Climatology, and Geophysics (BMKG). This verification was designed to assess the plausibility and consistency of the sensor outputs under real environmental conditions, rather than to establish precise measurement accuracy.

In an experimental indoor setup, we used a commercial device as the standard to calibrate our DHT22 sensor [25]. Once it was confirmed that no errors were arising from the sensor and that it was working as required, we could finally start monitoring.

In the case of the MG-811 sensor, the characterization is based on a log model extracted from the Nernst equation in electrochemistry [21]. Sensor output voltage as a function of CO_2 concentration behaves according to a semi-logarithmic Nernst-type response. The equation can be written as Eq. (1), which uses regression methods.

$$CO_2\ (ppb) = 10^{\frac{V-V400}{m}} \tag{1}$$

where V is the measured sensor output voltage (volt), V_{400} is the sensor output voltage in air, and m is the slope parameter through regression analysis on a logarithmic scale. This approach compensates for the MG-811 sensor's nonlinear sensitivity and improves quantitative estimation. When the sensor is exposed to a gas atmosphere, its conductivity changes in proportion to the gas concentration detected in the air. The greater the gas concentration, the higher the conductivity becomes. Afterward, if the sensor's response shows consistent and reliable data, it can then be used for monitoring.

The calibration model for the MG-811 sensor is based on the response characteristics detailed in the manufacturer's datasheet and previous research using the Nernst-type logarithmic relationship between sensor voltage and CO_2 levels. This model is reliable within the range specified by the manufacturer. It performs optimally when temperature and humidity remain stable, and the sensor has fully stabilized after warm-up.

In line with MG-811, the GM-702B sensor also needs around 3 minutes of preheating from the time it is powered on before it can start normal testing after the module fully stabilizes. Then, by giving a load resistor (RL) and a gas resistance (Rs), it is possible to run gas characterization. The process needs to take several parameters into account. It is because RL = 10 kΩ, and *Ro* is the sensor resistance at which the CO concentration in clean air [26]. Therefore, the algorithm we used to get the ppm value of CO in the air followed Eq. (2).

$$\boldsymbol{CO = 10\, x\, V \times (0.389)} \tag{2}$$

Table 1. Sensors Specification of the IoT-Based Air Quality Monitoring System

Sensor	Parameter	Detection Range	Limits of Detection	Cross-Sensitivty	Response time	Expected drift/Lifetime
DHT22	Temp & RH	-40–80°C / 0–100%	0.1°C/0.1%	None	2 s	±0.5°C, ±2% RH / 5 yrs
MG-811	CO_2	300–10,000 ppm	350 ppm	High temp/RH	60 s	±15% / 2 yrs
GM-702B	CO	10–1000 ppm	5 ppm	VOCs, H_2	30 s	±20% / 1–2 yrs
GM-102B	NO_2	10–1000 ppm	5 ppm	O_3, humidity	30 s	±25% / 1–2 yrs
GP2Y1014AU	PM2.5	0–500 µg/m³	5 µg/m³	High RH, non-spherical particles	1 s	±30% / 2 yrs

where V denotes the sensor output voltage. Although simplified for embedded implementation, this equation was validated against datasheet characteristic curves to ensure reasonable approximation within the ambient concentration range.

The CO estimation equation was developed based on the sensitivity curves from the manufacturer's datasheet. It relates the sensor resistance ratio (Rs/Ro) to the gas concentration using a simple regression model that is easy to implement on embedded microcontrollers. Thus, this model is accurate only within the concentration range shown in the characterization curves. It also assumes the sensor's aging remains stable and that the sensor is properly preheated before taking measurements.

For particulate matter measurement, the GP2Y1014AU, an optical sensor, operates based on infrared light scattering principles. This sensor works by emitting light from an infrared LED into the detection chamber [27]. A phototransistor then receives the light reflected by the dust particles. The relationship between the output voltage and particle concentration is linear and can be expressed by Eq. (3).

$$\mathrm{PM}_{2.5} = \alpha \cdot (V_{out} - V_{oc}) \tag{3}$$

where V_{oc} is the offset voltage when there is no dust (no-dust voltage), and α is the sensitivity coefficient, which indicates the change in voltage with increasing particle concentration, in units of μg/m³ per volt. The sensor characterization process is carried out by determining the V_{oc} and α values through a series of measurements under air conditions with known particle concentrations. The measurement data is then analyzed using linear regression to determine the slope (α) and offset (V_{oc}) values that best match the sensor's characteristics [24].

3.5 Interface and Data Visualization

To facilitate real-time monitoring and remote access more conveniently, we set up a cloud-based interface using Google Spreadsheet as the main platform for storing and visualizing data. We selected Google Spreadsheet due to its straightforward and lightweight design. It allows for fast response, updates, and easy API integration. Additionally, it integrates smoothly with embedded IoT systems without a dedicated server, so it is a practical and efficient infrastructure solution.

The sensor data collected by the ESP32 microcontroller was organized into data packets. These packets contained information such as timestamp, temperature, relative humidity, CO_2, CO, NO_2, and $PM_{2.5}$ levels. For proper operation, the packets were sent through the internet using HTTP requests to a Google Apps Script, which served as a bridge between the ESP32 and the spreadsheet database. Once received, the data were automatically added to designated columns in the spreadsheet, and then continuous time-series data collection was conducted. Additionally, real-time visualization was achieved through line charts and scatter plots to show the temporal changes of each environmental parameter. The dashboard, as shown in Fig. 3, offers graphical displays of pollutant level trends with dynamic charts directly connected to the processed data dataset.

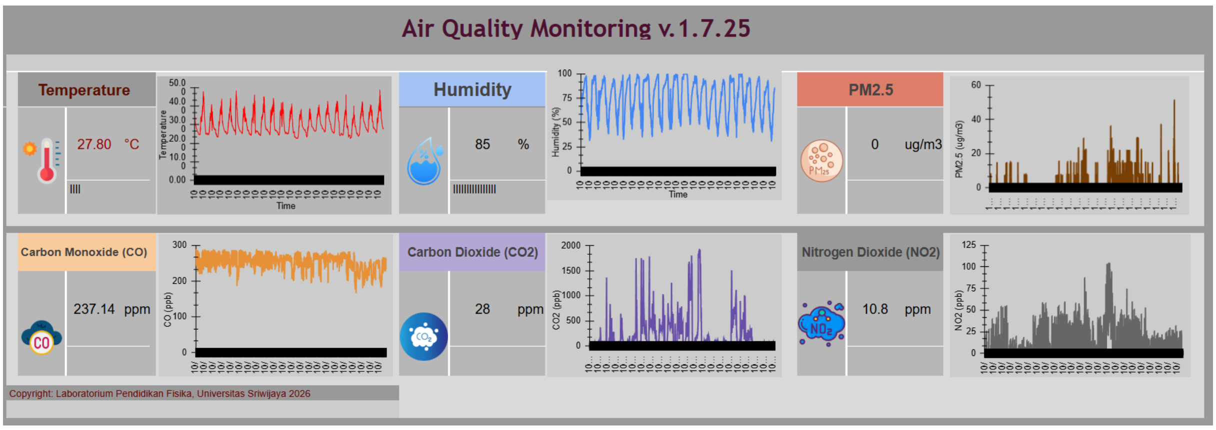

Fig. 3 Dashboard and interface of an IoT-based air quality monitoring system

4. RESULTS AND DISCUSSION

4.1 System Operational Performance

Air quality monitoring in outdoor lecture building areas was successfully done. The observation started from 8 October 2025, and the operational performance of the IoT-based air quality monitoring system was assessed through continuous outdoor deployment on the campus environment. The monitoring station was deployed on 8 October 2025. and has remained operational continuously. Although the monitoring program is ongoing, the present study focuses on data collected during October 2025 in order to provide a consistent observation period for analysis and interpretation. The average dataset successfully recorded for every month is about 6,000 observations, so only representative time windows are shown graphically to make it easier to understand the overall trends over time.

According to Table 2, the IoT-based instrument project could send the data to the web in real-time. Sending data to the web based on the Internet of Things (IoT) enables devices to connect and communicate with each other over the internet. It can be seen that the data completeness could achieve 91.36%. To do this, the sensors were connected to an ESP32 microcontroller, which processed the data and prepared it for transmission by converting it to a string.

Table 2. Summary of the observation and data availability for October 2025

No	Items	Value
1	Monitoring deployment	October 2025 – Present
2	Analysis period	1–31 October 2025
3	Sampling interval	7 min
4	Expected observations	6,377
5	Valid observations	5826
6	Data completeness	91.36%
7	Operation battery voltage	11.5 – 13.7 V
8	Solar charging period	4.2 – 4.8 h/day

Furthermore, by ensuring that the device is connected to the internet, the ESP32 microcontroller can send sensor data to the Google Spreadsheet, as shown in Figure 4. Data transmission stability was negotiated with the help of an integrated Wi-Fi module installed in the ESP32 microcontroller that formatted sensor outputs as structured data strings before HTTP-based upload. The communication protocol allowed the field unit and cloud database to sync extremely close to real-time. Even though it continues to function, any data loss events occurred in the primary observation window. It suggests that the firmware is working stably and network connectivity is reliable.

Time	Temp (C)	Relative Humidity (%)	CO (ppb)	CO2 (ppb)	NO2 (ppb)	PM2.5 (µg/cm3)
10/10/2025-09:42:22	32.10	67.3	278.74	2	0	0
10/10/2025-09:47:21	34.00	63.5	279.4	3	0	0
10/10/2025-09:52:22	34.70	59.7	245.21	2	54.31	0
10/10/2025-09:57:22	36.30	56.9	277.98	0	0	0
10/10/2025-10:02:23	36.00	57.2	257.47	3	1.54	0
10/10/2025-10:07:24	35.60	57.8	276.27	0	0	0
10/10/2025-10:12:23	35.10	57.9	267.15	3	0	0
10/10/2025-10:17:23	36.10	58.1	275.04	0	0	0
10/10/2025-10:22:24	34.50	61.1	279.31	3	0	0
10/10/2025-10:27:25	34.70	61	258.99	5	4.32	14.49
10/10/2025-10:32:26	33.40	62.7	261.36	3	0	0
10/10/2025-10:37:27	32.80	65.7	282.35	13	0	7.24
10/10/2025-10:42:28	33.60	64	265.73	0	0	7.24
10/10/2025-10:47:29	32.60	65	270.76	9	0	7.24
10/10/2025-10:52:30	32.80	66.2	271.71	16	0	0
10/10/2025-10:57:31	33.10	63.9	269.53	31	0	0
10/10/2025-11:02:30	32.10	67.6	276.84	34	0	0
10/10/2025-11:07:31	33.30	65	238.95	3	8.33	7.24
10/10/2025-11:12:33	34.30	61.6	280.07	9	0	0

Fig. 4 The captured air quality monitoring data was recorded in a Google Spreadsheet

Meanwhile, during the daytime, a 20-WP solar panel was used to recharge a battery system with a charging period of 4.2 – 4.8 h/day. It kept the power on 24 hours a day. In the process, the stored energy kept voltage levels stable at 3.3 V, which is stepped down from the operation battery voltage of 11.5 – 13.7 V. This enables sensor functionality and wireless data communication. This standalone power system eliminated reliance on grid electricity and enhanced flexibility for outdoor deployments.

4.2 Descriptive Statistics of Environmental Parameters

Table 3 presents the descriptive statistics of the dataset. These values offer a quantitative foundation for understanding the temporal patterns in the measurements and help compare different environmental parameters. Overall, the results demonstrate temporal variability in both meteorological parameters and pollutant concentrations. It highlighted the monitoring system's capability to capture dynamic environmental conditions on campus.

Table 3. Descriptive statistical analysis for each parameter

Parameter	Minimum	Maximum	Mean	Standard Deviation
Temp (°C)	22.60	48.70	30.41	5.23
RH (%)	31.10	100.00	75.09	18.61
CO (ppm)	168.67	286.72	254.56	21.21
CO_2 (ppm)	0.00	1937.00	199.80	330.29
NO_2 (ppm)	0.00	104.30	5.40	13.59
$PM_{2.5}$ (μg/cm³)	0.00	50.72	1.46	4.31

4.3 Temperature and Relative Humidity

The graph in Fig. 5 shows the results of monitoring temperature (blue line) and relative humidity (red line) change over time at a monitoring site, using sensors from an IoT-based environmental quality project. Generally, relative humidity (RH) tends to fluctuate quite a bit, sometimes reaching up to 100%, especially during the transition from nighttime to morning. It occurred when it was cooler outside. As daytime temperatures increase, relative humidity often decreases. It aligns that warmer air can hold more water vapor. When temperatures drop in the afternoon and evening, they sometimes reach saturation, creating a daily cycle that highlights the close connection between temperature and humidity.

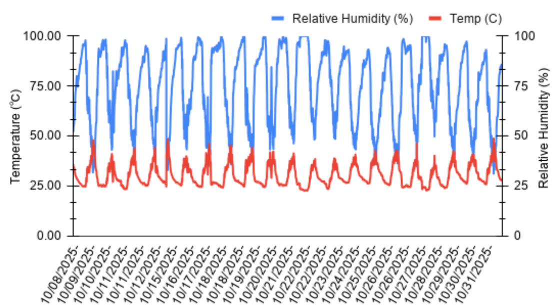

Fig. 5 Temporal variation of air temperature and relative humidity during the selected observation period.

The temperature was fairly stable. It was fluctuating between 23.3°C and 48.3°C, with its highest point during the day because of sunlight and local weather. According to Table 3, during the monitoring period, air temperature averaged 30.41°C, with a range of 22.60–48.70°C and a standard deviation of 5.23°C. The average daily temperature ranged from 26.51°C to 34.35°C. It indicated significant meteorological variation during the observation period. While Relative humidity (RH) averaged 75.09%, with a minimum of 31.10% and a maximum of 100.00%. The standard deviation was 18.61%. This indicates moderate temporal variation. This variation aligns with changing weather conditions and the inverse relationship between temperature and humidity. The temperature decreased as the sun set and heat dissipated through surface cooling at night. The humidity at night can make the air feel uncomfortable and might lead to condensation in lecture halls, which could affect air quality.

4.4 The concentration of CO, CO_2, and NO_2, and threshold analysis

CO, CO_2, and NO_2 concentrations are fundamental elements in the environmental monitoring network, serving as key indicators of air quality. The gas concentration monitoring was conducted in the outdoor lecture building, as shown in Fig. 6.

The CO graph displays concentration fluctuations from approximately 168.67 to 286.72 ppm, with an average of 254.56 ppm. This suggests relatively stable conditions over the observation period. Despite CO being a significant local pollutant and a byproduct of vehicle emissions, its levels in open areas around the campus remain fairly steady. This aligns with research indicating that outdoor CO levels tend to be lower than those in enclosed spaces or near direct emission sources. [2].

Meanwhile, the CO_2 concentration profile shows sharp spikes above 1500 ppm at certain times. CO_2 concentrations exhibited very high temporal variation. The average value was 199.80 ppm, with a range of 0–1937 ppm and a standard deviation of 330.29 ppm. The daily average CO_2 varied from 6.73 ppm to 585.40 ppm, indicating periods of significant increases in concentration compared to normal conditions. These values may be associated with human activity and the buildup of exhaled CO_2 in specific areas. Such brief peaks are especially noticeable during busy campus hours, when more pedestrians and vehicles are around the lecture buildings. The high CO_2 levels indicate that the local air exchange might not be enough to effectively dilute the emissions during these times.

The NO_2 parameter had a mean of 5.40 ppm, a minimum of 0 ppm, a maximum of 104.30 ppm, and a standard deviation of 13.59 ppm. The daily average ranged from 0.63 ppm to 24.63 ppm. It indicates episodic events that caused spikes in NO_2 concentrations at specific times. The most common sources of NO_2 are combustion sources, broadly represented by vehicle engines and traffic. NO_2 concentrations in off-campus data suggest that the vehicle traffic area might play a role in the measurement area. Additionally, exposure to NO_2 is linked to respiratory irritation and inflammation.

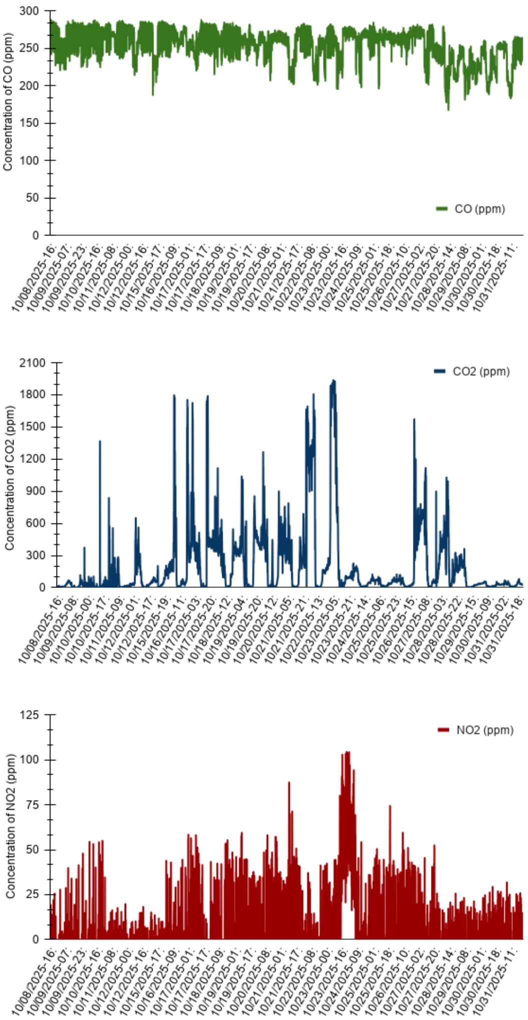

Fig. 6 Temporal variation of CO, CO_2, and NO_2 concentration during the observation period.

4.5 The concentration of $PM_{2.5}$

From Fig. 7, the average $PM_{2.5}$ concentration was 1.46 µg/cm³, with a minimum of 0 µg/cm³ and a maximum of 50.72 µg/cm³. The standard deviation 4.31 µg/cm³. The daily average $PM_{2.5}$ varied between 0 and 6.44 µg/cm³, which indicates that the air was relatively clean most of the time, but with occasional significant increases in particulate matter. It indicated short-term fluctuations in particulate matter within the monitored outdoor campus environment [3]. Although these concentrations are relatively moderate levels when compared to international air quality thresholds, their occurrence still needs significant concern from a health perspective. Over time, the particulate matter can bypass the upper respiratory tract's natural filtration mechanisms.

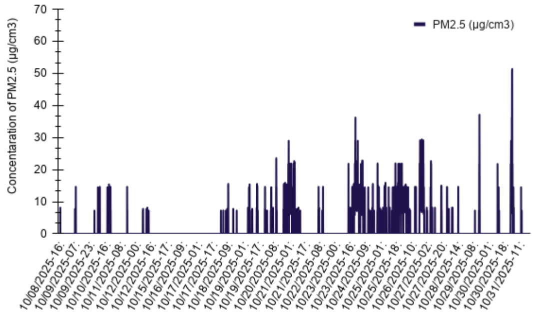

Fig. 7 Temporal variation of $PM_{2.5}$ concentration during the observation period.

4.6 Assessment Relative to Air Quality Standards

In terms of air quality hazards, it should be discussed and expanded to contextualize measured values within health risk frameworks. The $PM_{2.5}$ levels measured stayed below the WHO's 24-hour guideline of 15 µg/m³, as indicated in Table 4. The highest recorded concentration was 14.49 µg/m³. It showed that particulate pollution mostly stayed within safe limits. However, some short-term peaks approached the guideline threshold, indicating nearby emission sources and underscoring the need for ongoing monitoring.

The measured NO_2 levels stayed below the internationally recognized safety guidelines for short-term exposure. While there were a few brief spikes from time to time, overall air quality remained good, with no indication of a serious decline. This suggests that campus emissions do cause some short-term changes in air quality, but these changes weren't strong enough to lead to ongoing exceedances during the observation period.

Meanwhile, the measured CO concentrations remained substantially below regulatory limits established for short-term human exposure. The CO levels observed suggest relatively low pollution from combustion during the monitoring period. Nonetheless, occasional spikes aligned with traffic activity, showing that the system is responsive to emissions in the campus area.

Several CO_2 peaks went over 1,000 ppm, a level commonly used as an indicator of insufficient ventilation in occupied environments. Although these concentrations are still well below safety limits

Table 4. Air quality threshold classification applied in this study [1]

Parameter	Category			
	Good	Moderate	Unhealthy (sensitive)	Unhealthy
CO_2 (ppm)	< 200	200–400	400–800	> 800
CO (ppm)	< 600	600–1000	1000–1500	> 1500
NO_2 (ppm)	< 20	20–40	40–80	> 80
PM2.5 (μg/m³)	< 12	12–35	35–55	> 55

for workers, the rises we saw hint at a short-term buildup of human-made emissions from campus activities and passing cars.

While CO and $PM_{2.5}$ levels remained below toxicity thresholds, exposure to moderate CO_2 (>1000 ppm) has been associated with reduced decision-making performance and feeling sleepy in academic settings [28]. So, it is one of the causes the student felt unfocused in class. On the other hand, intermittent NO_2 spikes at certain times may trigger asthma symptoms for any sensitive students, particularly when combined with high humidity and poor ventilation. Although outdoor measurements do not directly equal indoor exposure, the data in rooftop trends correlate with infiltration potential through natural ventilation pathways. Therefore, continuous monitoring serves as an early-warning mechanism for campus facility managers to use as a foundation to adjust ventilation schedules, implement traffic calming near lecture zones, or issue health advisories during haze episodes.

Moreover, even though the measurements were taken outdoors, they indicated that small regions can be prone to localized pollution spikes despite well-meaning regulatory efforts by authorities. So, it is important that continuous real-time monitoring be retained. This allows us to rapidly detect short-term trends that might be missed with sporadic manual reviews. Changes in air quality give insight into how human practices and small-scale atmospheric dynamics balance each other outdoors in college. Hence, it is crucial to monitor air quality in academic buildings because it directly affects the health and wellness of students, faculty, and staff. Air quality has a direct relationship with human health and ultimately impacts the learning outcomes, which is why it becomes necessary to comprehend air conditions and respond appropriately to provide a healthy and safe environment. High concentrations of these gases can affect human health and significantly impact the environment [29], [30], [31].

5. CONCLUSION

This study presented the design and field using a low-cost IoT-based air-quality monitoring platform integrating temperature, relative humidity, CO_2, CO, NO_2, and $PM_{2.5}$ sensors with Google Spreadsheet as cloud-based data acquisition and visualization. During the observation period, temperature, relative humidity, CO, CO_2, NO_2, and $PM_{2.5}$ were observed. It showed several fluctuations appearing during periods of increased campus activity. However, the analysis indicated that pollutant concentrations generally remained within the air-quality categories adopted in this study, although several short-term concentration peaks were observed. On the other hand, by using a 20-WP solar panel and a battery, the system operates continuously without needing grid electricity. Throughout the monitoring period, the system proved to be stable, reliable, and consistent in capturing data and transmitting it using the internet. Thus, the results confirm that the proposed system successfully demonstrated continuous environmental monitoring under field conditions. Also, the system shows potential for broader deployment following additional validation and long-term evaluation.

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