Implementation of a Low-Cost IoT Indoor Air Quality Monitor in Dynamic Public Environments

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***Abstract*—We implement an affordable Internet of Things (IoT) device for evaluating indoor air quality (IAQ) in dynamically changing public environments, such as transportation buses and shopping centers in San Luis Potosi, Mexico. An ESP32 microcontroller integrates the monitor with a DS18B20 temperature sensor and a PMS5003 particulate matter (PM) sensor to measure PM2.5 and PM10. The monitor uses the fifth generation mobile network to transmit this information to the IoT platform ThingSpeak for storage and further analysis. Over six days, we measured three bus routes during the morning and afternoon and four shopping centers in the afternoon, as experienced by an ordinary user. Results show that PM2.5 and PM10 levels can achieve 116 and 121 $\mu g/m^3$, respectively, which are dangerous for human health, thus demonstrating the potential of communication technologies and low-cost IoT devices for implementing IAQ monitoring in resource-constrained scenarios, highlighting the need for adequate ventilation policies and compliance in such dynamic public spaces.**

***Index Terms*—air pollution, data collection, environmental monitoring, Internet of Things, public health, wireless sensors.**

I. Introduction

The Internet of Things (IoT) facilitates data exchange between a vast network of devices and systems by integrating various advanced technologies [1], [2], enabling the deployment of low-cost, scalable solutions for real-time monitoring and decision-making across diverse domains. IoT technologies, which include embedded systems, wireless technologies, and data processing frameworks, collectively form the backbone of this interconnected ecosystem [3]. As these technologies evolve, they are integrated into next-generation innovative systems, supported by the advancements in fifth generation (5G) networks [4]. The development and rapid prototyping of IoT-based indoor and outdoor monitoring systems are essential in deploying effective solutions [5]. These advancements have led to practical applications in sectors such as environmental monitoring, where low-cost IoT devices are increasingly used to track air quality, especially in indoor scenarios. In [6], the authors developed a low-cost IoT-based system to monitor indoor air quality, tracking pollutants and environmental conditions in real-time to maintain healthy indoor environments. Moreover, in [7], the authors integrated cloud computing with IoT, creating an intelligent monitoring system for residential environments that enhances data processing and control capabilities. Likewise, [8] focused on multi-point indoor air quality (IAQ) monitoring systems based on IoT, thus showing the potential for widespread adoption of these technologies in various indoor environments. Recent studies have demonstrated the effectiveness of IoT in monitoring air quality in public transportation systems. In [9], authors investigated commuter exposure to particulate matter (PM) in urban public transportation, revealing significant PM levels in buses and subways, highlighting the critical need for robust air quality monitoring. In [10], authors developed an IoT prototype for air quality monitoring in public transport vehicles, proving vital for maintaining safety during epidemiological crises like coronavirus disease (COVID) in 2019. Similarly, [11] designed an environmental monitoring system for buses, measuring pollutants and environmental factors to enhance public health and passenger comfort. Traditional IAQ monitoring systems can be expensive and lack the flexibility required for deployment in resource-constrained settings. This paper presents the design and implementation of an IAQ monitor tailored explicitly for public transportation (buses) and shopping centers in San Luis Potosi, Mexico. Similar to the framework outlined in [12], our approach leverages readily available IoT components to create a scalable and adaptable solution capable of real-time data collection and analysis. This experimental study integrates a portable, low-cost IoT device and available communications technologies to evaluate air quality in the targeted scenarios as experienced by regular users. The monitor is equipped with PM2.5 and PM10

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sensors, which transmit readings to the ThingSpeak[1] platform for remote visualization, storage, and analysis. Measurements were conducted during peak hours across different urban bus routes with high occupancy, often exceeding the maximum allowed, representing potential pollution sources. The results indicate that PM2.5 and PM10 concentrations can reach high levels in the analyzed scenarios, showing the need for further long-term measurements. This work focuses on affordability and ease of deployment, aiming to provide a low-cost, practical tool for implementing IAQ monitoring and ensuring compliance in environments with economic constraints. The main contributions of this study are as follows:

- We deployed a low-cost IoT IAQ monitor in Mexico's dynamic, high-traffic environments (buses and shopping centers) and validated its functionality.
- We confirmed the sensor's suitability for consistent IAQ monitoring in resource-constrained settings.
- We demonstrated the potential of budget-friendly devices to support IAQ monitoring in frequently occupied public spaces, many of which are often overlooked in public health initiatives. This study emphasized the value of such monitoring, particularly in contexts where attention to these areas may be limited.

II. Measurement Setup

A. Measurement Environments and Scenarios

In this study, we present the implementation of a low-cost IoT device for monitoring air quality in environments where people are exposed to air pollution daily. We performed the measurements in San Luis Potosi, Mexico, over six days at different times. We captured data from two primary dynamic scenarios in which users are frequently exposed to varying air pollutants: public transportation buses and shopping centers. The former was selected to represent typical commuting patterns in places where buses often lack air conditioning and can become extremely crowded, especially during peak hours, as in Mexico. Measurements were taken along three bus routes (9, 11, and 36) during the morning and afternoon to capture the variations in pollution levels throughout the day. Interestingly, each route presented different conditions regarding passenger density and ventilation. Route 9 had medium (bus's seating capacity $< 70\%$) and high (bus's seating capacity $> 70\%$) passenger densities with medium and good ventilation, respectively. Route 11 had medium (bus's seating capacity $> 60\%$) and low (bus's seating capacity $< 50\%$) passenger densities with good and low ventilation, respectively. Route 36 consistently had low (bus's seating capacity $< 50\%$) passenger density with good ventilation. These routes reflect the typical exposure experienced by a regular user in their daily transport routine. The measurement setup is illustrated in Fig. 1. In contrast, the shopping centers are located in the historical city center and are housed in old, large buildings repurposed to accommodate multiple small businesses. These centers vary in size, leading to differences in the number of people present at any given time, particularly during peak hours. They are characterized by poor ventilation, often having a single main entrance and a concentration of people within confined interior spaces, especially in the afternoons when foot traffic peaks. The lack of proper ventilation, combined with varying occupancy levels, makes these environments particularly relevant for evaluating the effectiveness of low-cost sensors. The measurements were taken by a person who walked through the shopping centers, emulating a typical visit to these spaces. These frequently overlooked everyday scenarios provide valuable insights for public health interventions.

[1]ThingSpeak is an IoT platform for collecting, visualizing, and analyzing real-time data in the cloud. For more information, visit https://thingspeak.com/.

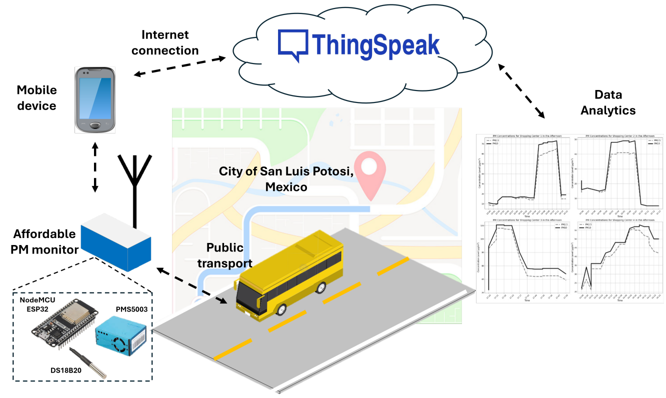


Fig. 1: Implementation of IoT-Based air quality monitoring system in buses.

B. IoT Device Setup and Data Collection

The data collection process involved using a custom-developed IoT monitoring portable device incorporating an ESP32 microcontroller, a DS18B20 temperature sensor, and a PMS5003 PM sensor. We selected the DS18B20 sensor for its ability to measure temperatures ranging from -50°C to 125°C with high precision. The PMS5003 sensor can measure PM1.0, PM2.5, and PM10 concentrations. We equipped the IoT monitoring device with an OLED display to visualize sensor readings *in situ*, updated every 32 to 33 seconds. This interval was chosen to ensure that sensor readings were frequent enough to capture variations in air quality in dynamic environments, such as buses and shopping centers.The monitor is connected via Bluetooth to a smartphone to facilitate data transmission, which sends the data to a next-generation node B (gNB), i.e., the functional counterpart of a base station in a conventional cellular network. Then, the data is transmitted to the ThingSpeak platform every 90 seconds. This transmission interval was selected to address the trade-off between real-time data availability and network efficiency, thus allowing data transfer without overwhelming the smartphone data consumption. The data collection involved recording start and stop times for each measurement session to calculate the total duration of each monitoring period. We designed the device for portability and powered it with a battery, making it suitable

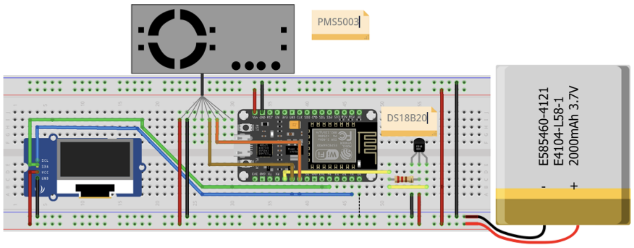


Fig. 2: Circuit diagram for ESP32-based indoor air quality IoT monitor.

for bus passengers and pedestrians in a shopping center. Fig. 2 illustrates the connection diagram of the IoT air quality monitor.

C. Data Processing and Analysis Techniques

We downloaded the collected data from the ThingSpeak platform for processing and evaluation. Several steps were taken to clean and structure the data, enabling the analysis of PM levels under different conditions. We stored the initial dataset in a CSV file and processed it using Python's Pandas library. The 'Date' and 'Time' columns were standardized into a unified datetime format to facilitate time-based operations and analyses. Then, we applied a function to categorize the measurements into different parts of the day (morning, afternoon, and evening) based on the measurement time. Subsequently, the 'Time' column was converted back to a datetime format to enable the calculation of time differences. The data was grouped by 'Scenario,' 'Route or Shopping Center Number,' 'Date,' and 'Day Period' to determine the start and stop times of measurements, total duration, and statistical measures of PM2.5 and PM10 concentrations. Then, the processed data, including calculated PM statistics and periods, was saved for further analysis and presentation.

III. Statistical Analysis of Air Quality Data

The World Health Organization (WHO) air quality guidelines (AQG) presented in [13] are the global benchmarks for the maximum concentrations of PM2.5 and PM10 that should be observed in periods of 24 hours and one year. According to the guidelines, the annual AQG levels for PM2.5 and PM10 are $5\mu g/m^3$ and $15\mu g/m^3$, respectively. In contrast, the 24-hour AQG levels PM2.5 and PM10 are $15\mu g/m^3$ and $45\mu g/m^3$, respectively. In both periods, WHO set interim targets at progressively higher levels to guide incremental improvements in air quality, as presented in Table I. In our study, however, the measurements are taken from the perspective of a regular user of public transportation and shopping centers to evaluate their exposure to PM2.5 and PM10 concentrations in these dynamic environments. Therefore, the measurement periods vary between 10 and 36 minutes, representing a short walk inside a shopping center or an urban bus trip. Furthermore, the National Air Quality Information System (SINAICA) is a governmental program

TABLE I: Air Quality Guidelines for PM2.5 and PM10

Pollutant	Averaging time	Interim target				AQG level
		1	2	3	4	
PM2.5 ($\mu g/m^3$)	Annual	35	25	15	10	5
	24-hour	75	50	37.5	25	15
PM10 ($\mu g/m^3$)	Annual	70	50	30	20	15
	24-hour	150	100	75	50	45

in Mexico that systematically collects and disseminates air quality data across the country[2]. It provides real-time and historical measurements of various air pollutants using a network of monitoring stations strategically located in urban and rural areas. SINAICA's data is regarded as a reliable and authoritative source for assessing air quality. It is an essential reference for studies related to Mexico's environmental health and pollution management. By comparing the measurements from our IoT device with SINAICA's data, we can validate the accuracy and effectiveness of our low-cost monitoring system, ensuring that our findings are aligned with established national standards. San Luis Potosi had one active monitoring station (i.e., *Biblioteca* in the SINAICA platform) during the measurement period, providing data on PM10 per hour each measurement day, against which we compared the experimental results. The overall information of the measurements is concentrated in Table II, which includes the scenario, i.e., bus route (BR) or shopping center (SC), the date and day period (morning or afternoon), the start and stop times and the total duration of the measurements, the minimum, maximum, and average values for PM2.5 and PM10, and the PM10 values from the SINAICA's monitoring station, thus offering a detailed snapshot of the air quality levels experienced in the studied environments.

Moreover, we present the histograms and corresponding density plots for PM2.5 and PM10 concentrations in Fig. 3. On the one hand, the histogram of PM2.5 concentrations is a right-skewed distribution with most values concentrated between 10 and 50 $\mu g/m^3$. The density plot shows a peak around 20 $\mu g/m^3$. A smaller peak around 35 $\mu g/m^3$ is observed, suggesting occasional higher pollution levels. On the other hand, the distribution of PM10 concentrations also exhibits a right-skewed pattern, with the majority of values ranging from 10 to 60 $\mu g/m^3$. The density plot highlights a primary peak near 30 $\mu g/m^3$ and a secondary peak around 50 $\mu g/m^3$, reflecting variability in the measurements and the presence of higher pollution episodes.

In addition, we generated box plots to compare PM2.5 and PM10 concentrations across the studied scenarios and present the results in Fig. 4. The PM2.5 levels varied significantly among the bus routes. Bus Route 9 exhibited a relatively wide interquartile range (IQR). Bus Route 11 showed lower variability. Bus Route 36 displayed the highest PM2.5 levels, with a median concentration around 30 $\mu g/m^3$ and an upper quartile extending to nearly 50 $\mu g/m^3$. The average PM2.5 concentration across all bus routes and all the measured peri-

[2]For more information, visit https://sinaica.inecc.gob.mx/.

TABLE II: Scenario Data for Routes and Shopping Centers

Scenario	Date	Day Period	Start Time	Stop Time	Total Time	PM2.5 ($\mu g/m^3$) Min. - Max.	Avg. PM2.5 ($\mu g/m^3$)	PM10 ($\mu g/m^3$) Min. - Max.	Avg. PM10 ($\mu g/m^3$)	SINAICA PM10 ($\mu g/m^3$)
BR 9	2024-06-24	afternoon	14:24:14	14:38:31	00:14:17	17 - 54	36.636364	24 - 58	43.909091	14
BR 9	2024-06-25	morning	07:46:52	08:05:41	00:18:49	6 - 33	26.160000	6 - 37	28.960000	28 - 24
BR 11	2024-06-25	afternoon	12:01:25	12:27:25	00:26:00	17 - 52	25.838710	17 - 62	28.612903	43
BR 11	2024-06-25	morning	07:04:23	07:16:12	00:11:49	21 - 35	26.777778	22 - 38	28.888889	28
BR 36	2024-06-25	morning	08:07:30	08:26:25	00:18:55	10 - 41	31.038462	11 - 49	35.884615	24
BR 36	2024-06-28	afternoon	17:05:59	17:33:31	00:27:32	10 - 54	34.090909	14 - 66	42.848485	39
SC 1	2024-06-24	afternoon	13:49:56	14:14:11	00:24:15	21 - 56	42.185185	22 - 58	45.629630	19 - 14
SC 2	2024-07-05	afternoon	13:40:02	14:15:46	00:35:44	8 - 65	26.566667	10 - 73	30.366667	55 - 54
SC 3	2024-07-08	afternoon	14:56:04	15:13:14	00:17:10	5 - 41	21.818182	5 - 49	25.136364	No data
SC 4	2024-07-09	afternoon	17:20:02	17:50:50	00:30:48	24 - 116	68.100000	24 - 121	76.550000	27

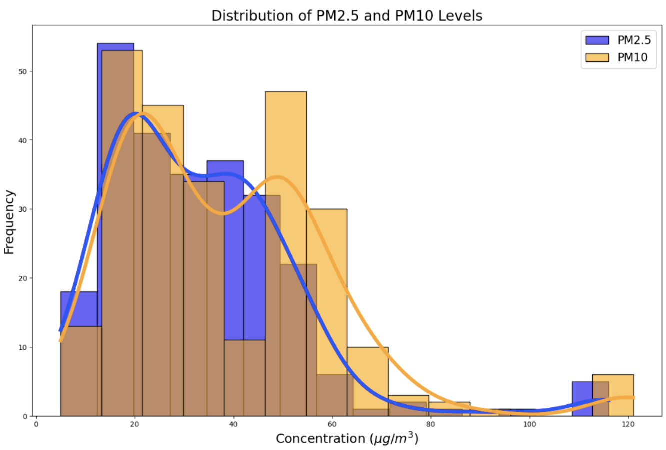


Fig. 3: Distributions of PM2.5 and PM10 levels in bus routes and shopping centers.

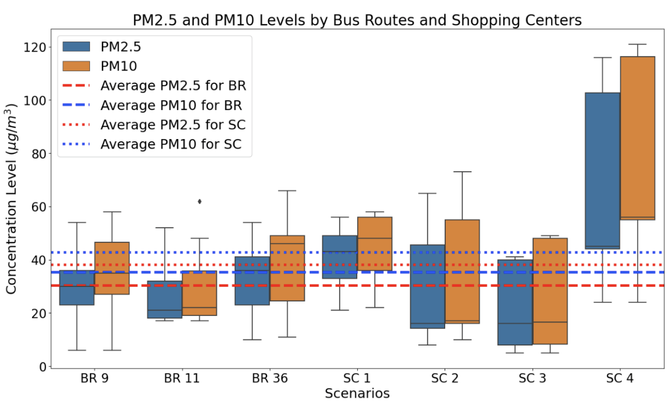
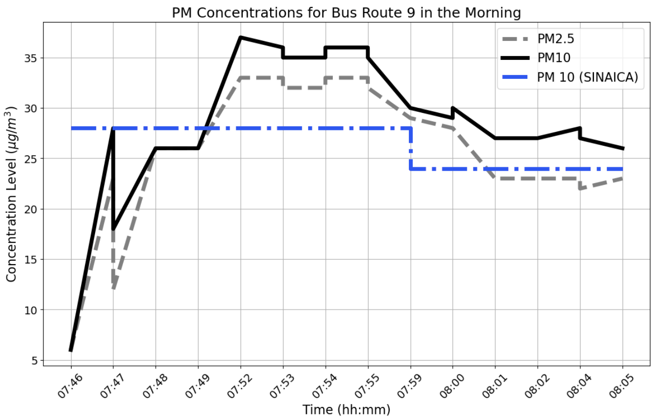


Fig. 4: Boxplots of PM2.5 and PM10 levels in bus routes and shopping centers.

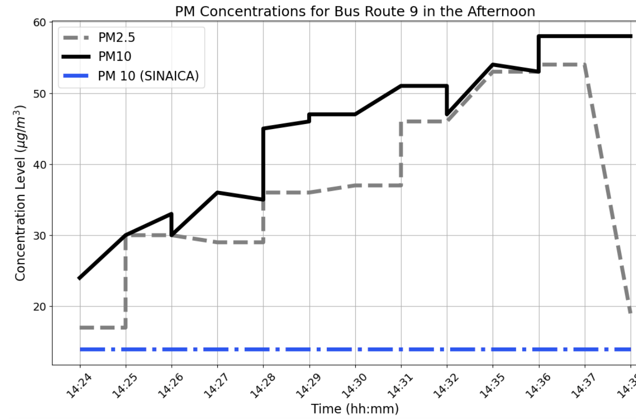
ods was 30.23 $\mu g/m^3$. PM10 levels on bus routes exhibited patterns similar to PM2.5. The average PM10 concentration across all bus routes was 35.21 $\mu g/m^3$. The PM2.5 levels in shopping centers showed significant differences. The overall average PM2.5 concentration for shopping centers was 38.16 $\mu g/m^3$. The overall average PM10 concentration for shopping centers was 42.70 $\mu g/m^3$.

IV. Results

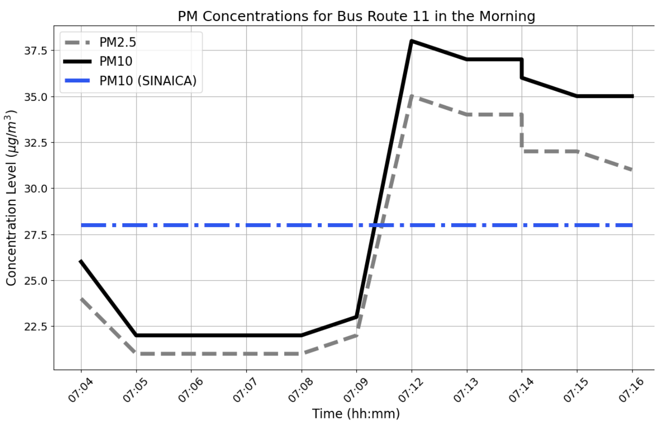
In all the results, we included the PM10 values reported from SINAICA's station during the corresponding days and times as a reference, except for shopping center 3, on whose measurement day the monitoring station did not report data. Next, we present the results of the PM measurements in bus routes 9, 11, and 36 during morning and afternoon periods. The figures show temporal variations in PM2.5 and PM10 levels for each bus route. Fig. 5 (a) shows the morning PM2.5 and PM10 concentrations for Bus Route 9. The recorded PM2.5 concentrations ranged from 6 to 33 $\mu g/m^3$ with an average of 26.16 $\mu g/m^3$, and PM10 concentrations from 6 to 37 $\mu g/m^3$ with an average of 28.96 $\mu g/m^3$. In the afternoon, PM2.5 levels ranged from 17 to 54 $\mu g/m^3$ with an average of 36.64 $\mu g/m^3$, while PM10 levels ranged from 24 to 58 $\mu g/m^3$ with an average of 43.91 $\mu g/m^3$, as it is shown in Fig. 5 (b). PM2.5 and PM10 concentrations increased sharply at around 07:49, reaching peak values before gradually declining. Fig. 5 (c) illustrates the morning measurements on Bus Route 11. The PM2.5 concentrations range from 21 to 35 $\mu g/m^3$ with an average of 26.78 $\mu g/m^3$, and PM10 concentrations from 22 to 38 $\mu g/m^3$ with an average of 28.89 $\mu g/m^3$. The data shows a sharp increase in concentrations starting at 07:09, with PM10 peaking at 07:12 before stabilizing. Fig. 5 (d) shows afternoon measurements on this route showed PM2.5 levels from 17 to 52 $\mu g/m^3$ with an average of 25.84 $\mu g/m^3$, and PM10 levels from 17 to 62 $\mu g/m^3$ with an average of 28.61 $\mu g/m^3$. The concentrations peaked early in the measurement period at around 12:01 before declining sharply and stabilizing for the remainder. Fig. 5 (e) presents the results on Bus Route 36 in the morning. Measurements showed PM2.5 concentrations from 10 to 41 $\mu g/m^3$ with an average of 31.04 $\mu g/m^3$, and PM10 concentrations from 11 to 49 $\mu g/m^3$ with an average of 35.88 $\mu g/m^3$. The concentrations gradually increased with multiple peaks, reaching the highest values around 08:23. For the afternoon, the results can be seen in Fig. 5 (f). The PM2.5 levels ranged from 10 to 54 $\mu g/m^3$ with an average of 34.09 $\mu g/m^3$, while PM10 levels ranged from 14 to 66 $\mu g/m^3$ with an average of 42.85 $\mu g/m^3$. The data indicates a steep increase in PM10 concentrations at the beginning of the period, followed by fluctuations and an overall upward trend. The results for Shopping Center 1, presented in Fig.6



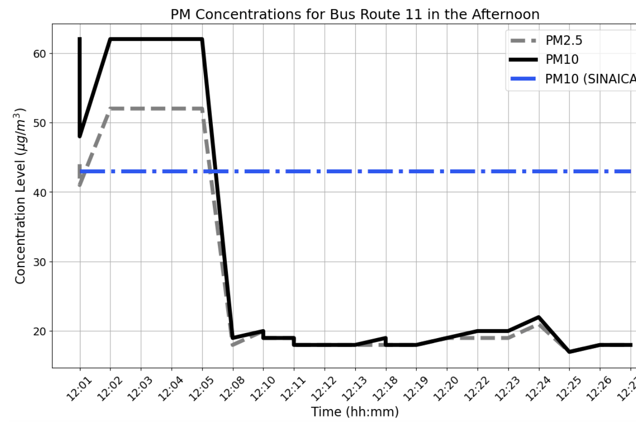
(a) PM2.5 and PM10 results for bus route 9 in the morning.



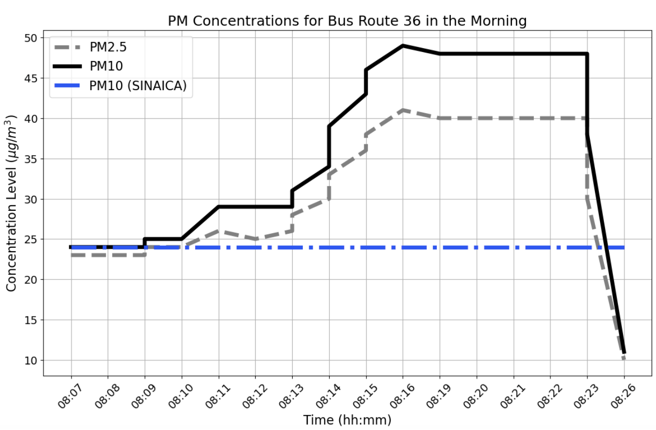
(b) PM2.5 and PM10 results for bus route 9 in the afternoon.



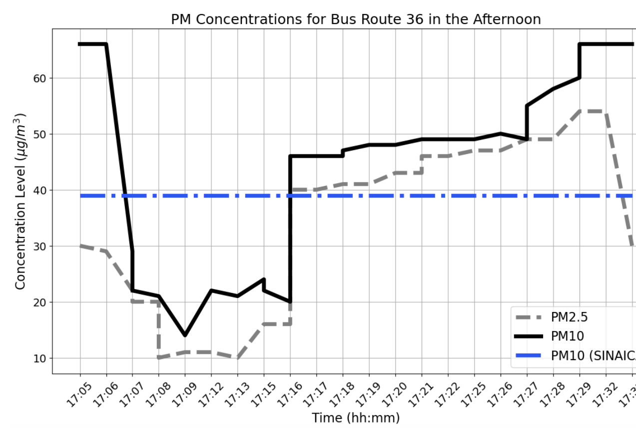
(c) PM2.5 and PM10 results for bus route 11 in the morning.



(d) PM2.5 and PM10 results for bus route 9 in the afternoon.



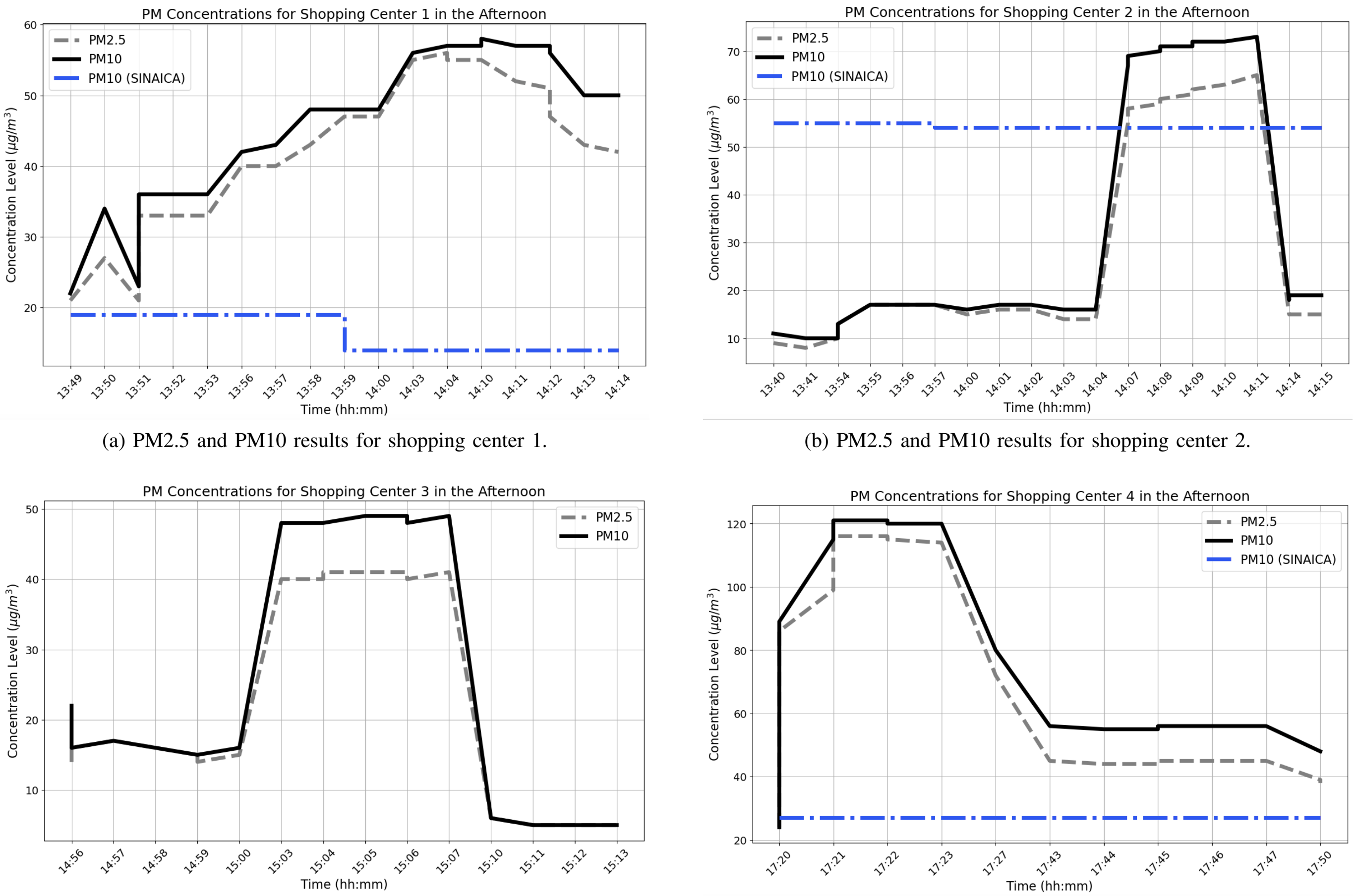
(e) PM2.5 and PM10 results for bus route 36 in the morning.



(f) PM2.5 and PM10 results for bus route 36 in the afternoon.

Fig. 5: PM2.5 and PM10 results for bus routes during morning and afternoon.

(a), recorded PM2.5 concentrations from 21 to 56 $\mu g/m^3$ with an average of 42.19 $\mu g/m^3$, and PM10 concentrations from 22 to 58 $\mu g/m^3$ with an average of 45.63 $\mu g/m^3$. Shopping Center 2 showed PM2.5 levels from 8 to 65 $\mu g/m^3$ with an average of 26.57 $\mu g/m^3$, and PM10 levels from 10 to 73 $\mu g/m^3$ with an average of 30.37 $\mu g/m^3$, as is shown in Fig.6 (b). In Fig.6 (c), the results for Shopping Center 3 show PM2.5 levels from 5 to 41 $\mu g/m^3$ with an average of 21.82 $\mu g/m^3$, and PM10 levels from 5 to 49 $\mu g/m^3$ with an average of 25.14 $\mu g/m^3$. Notably, Shopping Center 4 exhibited the highest pollution levels, as can be seen in Fig.6(d) with PM2.5 concentrations ranging from 24 to 116 $\mu g/m^3$ and an average of 68.10 $\mu g/m^3$, and PM10 concentrations ranging from 24 to 121 $\mu g/m^3$ with an average of 76.55 $\mu g/m^3$.



(a) PM2.5 and PM10 results for shopping center 1.

(b) PM2.5 and PM10 results for shopping center 2.

(c) PM2.5 and PM10 results for shopping center 3.

(d) PM2.5 and PM10 results for shopping center 4.

Fig. 6: PM2.5 and PM10 results for shopping centers during the afternoon.

A. *Factors Influencing Data Variability*

The variability observed in our PM measurements could be partially attributed to environmental factors, such as humidity and atmospheric conditions, which are known to influence the accuracy of low-cost sensors. In [14], the authors noted that high humidity and fog could cause low-cost PM sensors, like the PMS1003, to register artificially elevated particle concentrations due to hygroscopic growth and detect water droplets as particles. This effect is particularly pronounced above relative humidity levels of approximately 75%, where particles begin to absorb water, thus increasing their apparent mass. Given these insights, our study's dynamic scenarios, which include high-traffic environments like buses and shopping centers, may intensify these impacts on sensor readings due to frequent fluctuations in air exchange, human movement, and variable temperature and humidity conditions. This variability highlights the need to interpret the data cautiously and consider environmental controls when feasible. Future work could explore methods to mitigate these effects by employing sensors with inlet drying mechanisms or post-processing techniques to account for humidity effects.

V. Conclusions

We integrated IoT and advanced communication technologies to monitor environmental conditions in dynamic public spaces in San Luis Potosi, Mexico, focusing on public transportation and shopping centers. The study captured the dynamic nature of these environments, with fluctuating passenger densities and varying ventilation, adding context to the sensor data. Contextualizing low-cost sensors in real-world scenarios offered a practical and effective approach for air quality monitoring in resource-constrained settings. Significant temporal and spatial variability in PM levels was observed, with the highest concentrations on Bus Route 36 and Shopping Center 4, highlighting interesting areas to improve air quality. The findings underscore the need for continuous, long-term monitoring, supported by robust IoT and wireless systems, to ensure effective pollution mitigation strategies. Future research should expand the study's scope, incorporate additional sensors, and enhance connectivity to build an IoT network. Moreover, integrating machine learning optimizes air quality monitoring by enabling predictions and proactive interventions.

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