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Monitoring of climatic and environmental indicators in crowded areas based on internet of things and wireless sensor networks

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ABSTRACT

Significant environmental and climatic challenges are being faced worldwide due to increasing urbanization, extensive traffic and industrial development. The rising levels of vehicular emissions and industrial waste have led to concerning levels of air pollution, which significantly impact public health, including respiratory conditions. Given that air pollutants are often imperceptible to the naked eye, there is a critical need for an efficient and reliable monitoring system to assess air quality in real-time. To contribute to the efforts being performed for mitigating pollution drastic consequences, the current paper focuses on the following primary objectives. First, design and implement a cost-effective IoT-enabled air quality monitoring system. Second, establish a reliable wireless sensor network using long-range (LoRa) technology for extended coverage. Third, develop an interface for data visualization in real time, and finally, validate the system's effectiveness in both indoor and outdoor environments over crowded areas. This research presents several novel contributions, including the integration of low-cost sensors with LoRa technology for enhanced range and reliability, the development of an energy-efficient monitoring solution, and the implementation of a scalable architecture suitable for dense urban environments. The system comprises multiple sensor nodes, each equipped with a microcontroller, LoRa communication module, and an array of environmental sensors that measure key parameters including temperature, humidity, air quality index, particulate matter, and harmful gas concentrations. These smart nodes transmit data to an IoT platform (Thing Speak), which processes and shows them through an intuitive, user-friendly dashboard featuring real-time visualization of air quality metrics. Although this study is an early-stage investigation of the feasibility of the expected monitoring system, its initial deployment in crowded city (Jeddah, Saudi Arabia) results indicate reliable performance in various environmental conditions, making it a promising solution for urban air quality monitoring. This research contributes to the development of sustainable smart city infrastructure and public health management systems in Jeddah and may be extended to larger urban environments, while offering a cost-effective alternative to existing expensive monitoring solutions. The system's adaptability and scalability make it especially valuable for developing regions seeking to implement comprehensive environmental monitoring systems..

Keywords: air pollution, internet of things, wireless sensor networks, long-range, cloud platform.

INTRODUCTION

Air pollution is known to be one of the leading causes of death and respiratory diseases worldwide [1]. Therefore, environmental and healthcare authorities as well as people at the community level, are asked to implement efficient measures to mitigate the spread of pollution and to limit the concentration of dangerous pollutants in the atmosphere. Efficient monitoring and assessment of pollution indicators is the primary step in a mitigation process, since the dynamics of air pollution should be carefully understood. Traditionally, air pollution monitoring was taken into account by environmental authorities by establishing a few stations equipped with high-quality sensor technologies to obtain precise pollutant concentrations. Although their reasonable relative accuracy, these conventional stations are huge, inflexible, and expensive to deploy on a community scale. In addition, traditional stations are usually installed in remote locations, which can make their maintenance and calibration a challenging task. In general, the existence of a few stations installed throughout large urban areas makes it difficult to assess pollution levels with fine spatial and time granularity. Moreover, traditional air quality monitoring systems are facing the problem of storage space since they are programmed to continuously record pollution and climatic, data even in the case of non-significant changes in the collected values [2, 3]. These inherent limitations have created an urgent need for affordable real-time monitoring solutions that can offer granular time-space measurements of air quality while being cost-efficient and scalable. The emergence of Internet of Things (IoT) [4, 5] and long-range (LoRa) technologies has offered an opportunity to overcome the previous challenges by enabling the development of affordable, long-range, and energy-efficient monitoring systems suitable for urban and developing regions. In the air pollution monitoring field, the research gap lies in the lack of cost-effective, scalable systems that integrate low-cost sensors with long-range communication technologies to offer real-time, neighborhood-level air quality monitoring. As a contribution to address this research gap, this study proposes an IoT-based air quality monitoring system leveraging LoRa technology, which combines affordability, extended coverage, and user-friendly real-time visualization. The main novelties of the present study include a comprehensive approach integrating diverse environmental sensors, energy-efficient design, and scalability for both indoor and outdoor applications. Scalability is a key consideration in the design of our monitoring system. Leveraging LoRa technology, which supports long-range communication with low power consumption, enables the deployment of a large number of sensor nodes distributed across urban areas without the need for extensive infrastructure. The modular architecture allows additional sensor nodes to be integrated seamlessly, facilitating expansion to cover larger geographic regions or higher spatial resolution as needed. While the current prototype utilizes two nodes for initial validation, the system is architected to accommodate tens or even hundreds of nodes by employing LoRaWAN's capability for managing multiple devices through adaptive data rate, duty cycle management, and network server coordination. In addition, this study investigates recent advancements in air pollution monitoring systems by lever- aging various sensors, microcontrollers, and communication technologies to enhance the accuracy, accessibility, and cost- effectiveness of environmental monitoring. The integration of IoT with low-cost sensors and microcontrollers like Arduino, ESP8266, and ESP32 has been pivotal in developing efficient air quality monitoring systems.

BACKGROUND

During the previous few years, the design and implementation of air pollution monitoring systems have interested researchers and environmental issues practitioners worldwide. Several aspects including the used technologies, the targeted air pollution indicators, the used sensors and microcontrollers, were considered. Although different scales of monitoring accuracy were reached, the designed systems didn't cover all the aspects mainly the time and space scales. For instance, this section provides a review of some recent related works concerning air pollution monitoring and focuses on the above-cited aspects in order to later well-situate the contributions of the current paper. For instance, in [6], the authors have used wireless sensor network (WSN) technology to create a self-sustaining air quality monitor for usage in metropolitan settings, with only two sensors to detect carbon monoxide (CO) and particulate matter (PM). The main limitation of this study lies on the fact that other important pollutants were disregarded although they are dangerous for human health. Reference [7] included a real-time standalone air quality monitoring system reported to be able to address a variety of parameters, including $PM_{2.5}$, CO, CO_2, temperature, humidity, and air pressure. In this study again, dangerous pollutants such as PM_{10} and NO_2 were not considered. Moreover, because the sensor node was wired to the gateway, the system was constrained in terms of complexity and the use of new wireless technologies. Using the NodeMCU microcontroller, paper [8] presented a standard solution based on IoT technology. Pollutant gases (CO and NO_2), as well as temperature and humidity, were the main emphasis, however PM were overlooked. Wi-Fi, a short-range wireless communication technology, was used for sending data. With the improvement of wireless sensing, new study fields on smartphone-based air pollution monitoring have arisen [9]. In [10], the authors created the first sensing framework for high-volume corridor deployment on public transportation infrastructure such as buses. Many of the applications have benefited from dust or PM sensors, however low-cost sensors produced erroneous and inaccurate results, especially when temperature and humidity values are subject to fluctuations. In addition, sensors would frequently fail to properly capture data and give the timestamps needed to synchronize data collection. Most of these studies have the limitation of collecting data over long periods of time in stationary environments [11]. Under such conditions, the monitoring operation covers the unique locations where the stations are deployed. However, the dynamics of air pollution are rapidly changing even at nearby locations. Therefore, Wired stationary sensors could be ineffective for remote monitoring. Furthermore, verifying the effectiveness of those devices in an indoor context is insufficient. Papers [12] and [13] used Raspberry Pi operating almost 40 times faster than Arduino in terms of clock speed. However, Pi as powerful hardware requires a continuous power supply reflecting difficulty in its operation for long periods of time with sufficient amounts of energy. Paper [14] has used the Arduino Uno microcontroller and six sensors, namely, gas sensors (MQ135, MQ136, MQ9, and MiCS4514), a temperature and humidity sensor (DHT11), and a dust sensor. It used also one of the most recent LPWAN (low-power wide area network) technologies for data transfer and communication, namely, LoRa for the physical layer and LoRaWAN for the Medium Access Control layer. The main limitation of this work is the high cost of the LoRa gateway used. Existing research on air pollution surveillance systems exhibits significant limitations. For example, while systems such as [6–8] effectively measure a subset of air quality parameters, they lack holistic integration of key variables such as particulate matter, harmful gases, and humidity. Further- more, most rely on short-range communication technologies like Wi Fi, limiting their scalability in urban contexts. In contrast, LoRa-based solutions [14] address the range issue but are constrained by high gateway costs. Finally, the studies referenced in [15–18] primarily concentrated on the analytical aspects of air pollution data rather than the practical implementation of hardware for monitoring systems. These works delve into advanced data analysis methods, comprising machine learning algorithms and statistical models, to interpret air quality measurements and predict pollution levels. While their contributions to understanding pollution dynamics and enhancing predictive capabilities are significant, they often overlook the hardware component necessary for real-time data acquisition and monitoring. Consequently, these studies highlight a critical gap in the research landscape, emphasizing the need for integrated systems that combine robust data analysis with effective hardware deployment to create comprehensive air quality monitoring solutions. To contribute in filling the above-cited research gaps, this study presents a novel approach for monitoring climatic and environmental indicators in crowded urban areas using an integrated internet of things (IoT) and WSN framework. The main contributions include the design and deployment of cost-effective, scalable sensor node architecture; the implementation of a real-time data acquisition and transmission system; and the development of visualization tools to display air quality and environmental conditions in real-time which may support decision-making in the field of pollution control and management. More explicitly, the current research builds on the previous efforts by integrating low-cost sensors with LoRa, offering a versatile, energy-efficient, and affordable solution, thus filling a critical gap in the current landscape of air quality monitoring technologies. Table 1 below provides a comparative summary of the different air quality monitoring systems discussed above and highlights some key design choices made in each of the systems. To clarify, dust in our system represents PM2.5 levels, as measured by the Optical Dust Sensor (GP2Y1010AU0F), which detects fine particulate matter in the air. Smoke is the reading obtained from the MQ-2 gas sensor, which is designed to detect combustible gases, including smoke particles. Pollution refers to the air quality index (AQI) measurement derived from the MQ135 sensor, which detects harmful gases such as ammonia, sulfur dioxide, benzene, and other volatile organic substances.

As shown in Table I, compared to previous works, our system provides a more comprehensive approach, integrating multiple sensor types, using a low power and long-range communication protocol and a user-friendly cloud dashboard. It also supports both indoor and outdoor operation for a greater range of real-world scenarios including crowded urban areas. Although several air quality monitoring systems have been proposed in the literature, many suffer from critical limitations that hinder their scalability and practical deployment in urban environments. In addition to relying on high-cost or pollutant-specific sensors, existing solutions often exhibit limited communication range, non-availability of internet connection, high power consumption, and lack of interoperability between sensor nodes. Many systems depend on short-range protocols such as Wi-Fi or Bluetooth, which are unsuitable for wide-area deployment without extensive infrastructure. Moreover, real-time data visualization and remote accessibility are often overlooked, especially in low-resource or developing regions. These gaps highlight the need for an energy-efficient, long-range, and low-cost IoT-based monitoring system that integrates affordable sensing hardware with reliable wireless communication protocols and cloud-based analytics. In this context, our research presents an innovative approach to environmental monitoring that takes advantage of the power of IoT and LoRa technology to create a robust, scalable and cost-effective solution. By developing a network of smart sensors capable of measuring various environmental parameters, our aim is to provide real-time information on air quality in urban areas using Jeddah (Saudi Arabia) as a benchmark, since it involves a diverse urban landscape with variable air pollution features at the city level in addition to a high level of crowd mainly caused by transportation. The system designed and implemented in this study serves as an efficient tool for environmental monitoring and represents a significant step toward creating smart cities of the future that are sustainable and health-conscious.

MATERIALS AND METHODS

Methodology

After conducting a comprehensive review of existing air pollution and environmental monitoring systems, we selected the most suitable components for developing a smart air quality monitoring solution tailored to urban deployment. The system's design incorporated considerations such as technical performance, cost-efficiency, adaptability, and maintainability. The implementation process began with the wiring and integration of the chosen sensors onto an Arduino based microcontroller, followed by the development of the corresponding software and communication protocols. Each hardware and software component was tested individually to verify its functionality, with particular attention given to sensor-to-sensor consistency to enhance measurement accuracy. Once assembled, the system was programmed to collect data from four environmental sensors, DHT22, MQ-135, MQ-5, and the GP2Y-1010AU0F optical dust sensor, and transmit this

Table 1. Summary of related studies

Parameter	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]	[15]	[16]	[17]	[18]	Our System
Temperature	✗	✓	✓	✓	✓	✗	✗	✓	✓	-	-	-	-	✓
Humidity	✗	✓	✓	✓	✓	✗	✗	✓	✓	-	-	-	-	✓
Dust	✓	✗	✗	✗	✓	✓	✓	✗	✓	-	-	-	-	✓
Harmful gazes	✗	✓	✓	✓	✓	✓	✓	✓	✓	-	-	-	-	✓
Smoke	✗	✗	✗	✗	✓	✗	✗	✗	✗	-	-	-	-	✓
AQI	✗	✗	✗	✗	✗	✗	✓	✗	✓	-	-	-	-	✓
Arduino	✗	✗	✗	✓	✓	✗	✗	✓	✓	-	-	-	-	✓
NodeMCU	✓	✓	✓	✗	✗	✗	✗	✗	✗	-	-	-	-	✓
Raspberry	✓	✗	✗	✗	✗	✗	✓	✗	✗	-	-	-	-	✓
Wi-Fi	✓	✓	✓	✗	✗	✗	✗	✓	×	-	-	-	-	✓
Lora	✗	✗	✗	✓	✓	✓	✓	×		-	-	-	-	✓
Dashboard	✗	✓	✓	✗	✗	✓	✗	✓	✓	-	-	-	-	✓
Forecasting	✗	✗	✗	✗	✗	×	✗	✗	✗	✓	✓	✓	✓	✗
Indoor	✓	✓	✓	✓	×	✓	✗	✓		-	-	-	-	✓
Outdoor	✗	✗	✗	✗	✓	✗	✓	✗	✓	-	-	-	-	✓

information via LoRa modules to a centralized gateway. The collected data was processed and visualized through the Thing Speak IoT platform, which enabled real-time dashboard monitoring and applied smoothing algorithms to reduce noise measurement. To evaluate system performance in real-world conditions, sensor nodes were deployed in two distinct locations within Jeddah, Saudi Arabia (AshShati and AlBasatin), and tested over distances of up to 12–13 km from the gateway. The system operated reliably across varied environmental conditions, demonstrating robust data transmission and monitoring capabilities. The evaluated specific metrics included:

1. Communication range – deploy sensor nodes at incremental distances from the gateway, up to 13 kilometers. In our case, as specified in the LoRa module's datasheet, the system can achieve a maximum transmission range of 15 km under optimal conditions.
2. Accuracy of measurements – compare sensor readings to similar sensors co-located at the same place (referred to as sensor-to-sensor measurement) for parameters such as temperature, humidity, and air quality index (AQI). An aggregated average value was calculated and adopted.
3. Latency – measure the time delay between data transmission from the nodes and its visualization on the dashboard.

Materials

This section presents an overview of the tools used during the development of our smart monitoring system. The most important electronic components such as microcontrollers and sensors are presented. For the two transmitter circuits (Sensor Nodes), we needed a microcontroller to operate the system. We selected Arduino Uno because of its simplicity and efficiency. For communication, we selected LoRa, which is a long range, low power communication technology. We also needed sensors for temperature, humidity, dust, smoke, and gas to measure air pollution and meteorological parameters. Finally, we selected a breadboard and jumper wires to connect all the components and a battery to provide the required power. The selection of sensors was guided by their cost-effectiveness, compatibility with IoT systems, and suitability for detecting key air quality parameters. The DHT22 sensor was chosen for its reliability in measuring temperature and humidity, offering ±0.5 °C and ±5% RH accuracy, respectively. The MQ2 and MQ135 sensors were selected to detect harmful gases due to their wide detection range and high sensitivity. The ”GP2Y1010AU0F” Sharp optical dust sensor, while providing satisfactory accuracy for particulate matter measurements, has limitations in distinguishing particle sizes, which may affect the granularity of the data. To mitigate these limitations, future iterations of the system could incorporate more advanced sensors with higher specificity and accuracy.

Overview of LoRa technology

LoRa was chosen according to the comparative analysis shown in the communication technology spectrum (Figure 1) where LoRa [19] emerges as the optimal choice for our air quality monitoring system. The diagram (Figure 1) clearly illustrates that LoRa occupies a good spot in the trade-off between range and bandwidth, offering long-range capabilities while maintaining reduced power usage and cost- effectiveness. Unlike cellular networks that require higher power consumption and Wi-Fi that has limited range, LoRa provides an ideal balance for outdoor environmental monitoring applications. Although Bluetooth low energy (BLE) offers energy efficiency, its short range makes it unsuitable for city- wide deployment. The mission-critical nature of air quality monitoring requires reliable long-range communication, and LoRa's ability to transmit data over several kilometers while operating on minimal power makes it particularly well suited for our sensor network. Furthermore, since our application does not require high-bandwidth transmission of video or voice data, but rather focuses on periodic sensor readings, LoRa's moderate bandwidth capacity is sufficient, making it a practical and affordable solution for our system.

System architecture

Figure 2 depicts the overall architecture of our wireless IoT network for air quality monitoring. The designed system included a LoRa-based air quality monitoring network implemented in Jeddah City, Saudi Arabia. The system consists of two LoRa nodes (as an early-stage prototype) scattered throughout the area, each equipped with necessary sensors like the DHT22 for temperature and humidity measurements, MQ2 and MQ135 for detecting various gases along with

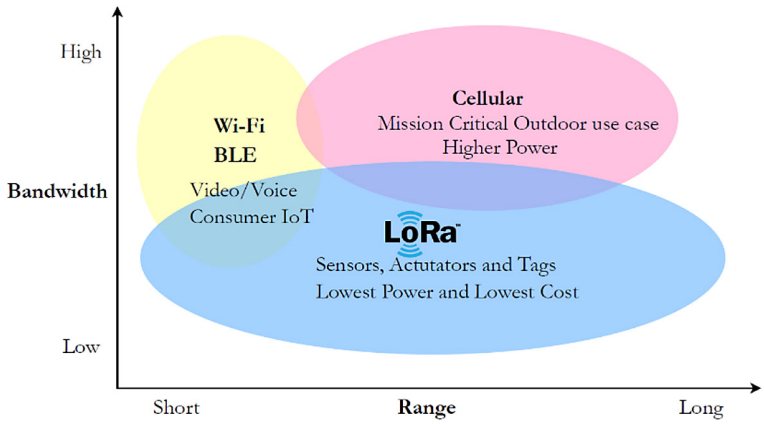

Figure 1. Comparison between different Communication technologies [20]

their concentrations, and a dust sensor for particulate matter collection. The data from these nodes are ransferred to a LoRa gateway, which acts as bridge, relaying information to a centralized cloud server. The cloud server's main role is to process and analyze the data. The dashboard therefore provides an intuitive visual representation of air quality metrics across different locations of the city. The integration of NodeMCU and LoRa modules at each node facilitates seamless sender/receiver communication, highlighting a robust and scalable network design that is pivotal for effective environmental monitoring in urban areas. It should be noted here that this study presents an early-stage prototype and proof-of-concept deployment of the monitoring system using two sensor nodes communicating via LoRa technology. Due to resource and budget constraints, a larger-scale deployment or simulation involving 30–50 sensor nodes was not conducted at this

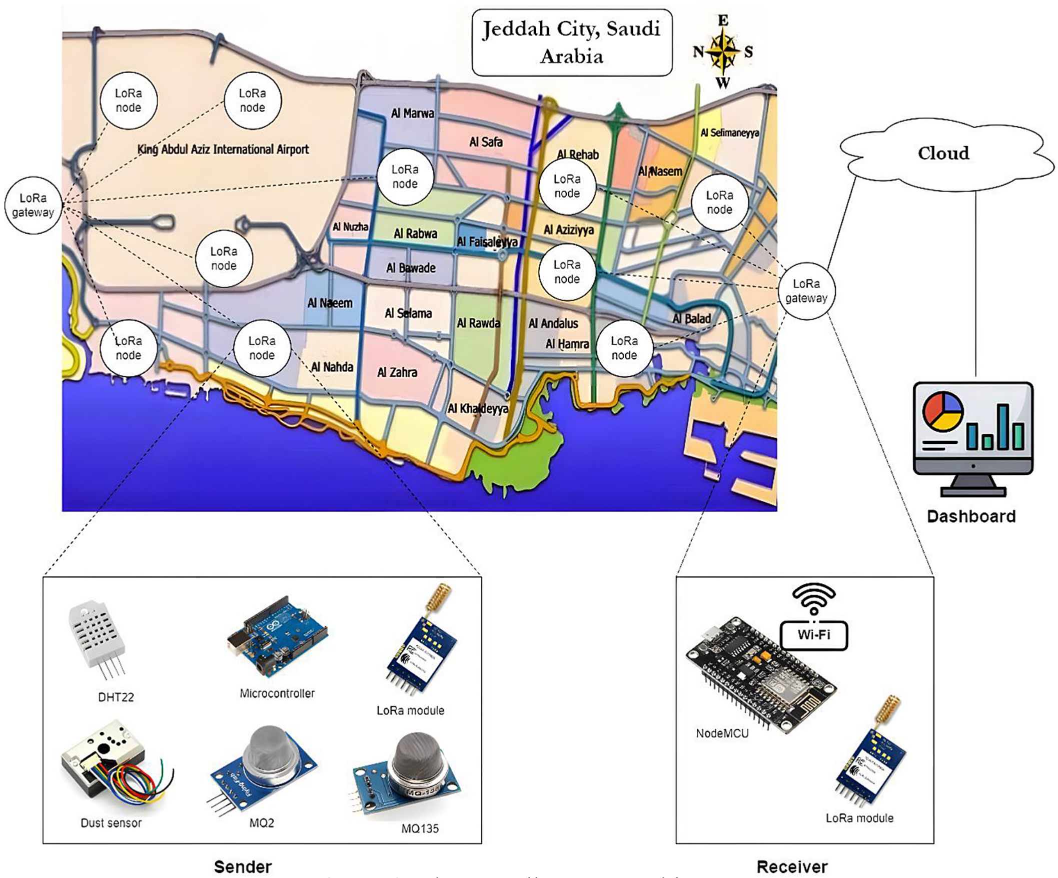

Figure 2. The overall system architecture

stage. The current setup focused on validating core functionalities and sensor agreement under real conditions. Future work will include comprehensive simulations and field deployments with a greater number of sensor nodes to evaluate network scalability, data throughput, and system robustness in more complex urban environments.

Block diagram

The next step of the system design and implementation consists of the establishment of the block diagram that represents its workflow and the relevant units/modules through blocks (Figure 3).

Circuits

To ensure system operation before investing in practical implementation, a common practice in engineering design consists of conducting extensive simulations of the individual components and the whole system. In our study, Fritzing [21] (an open-source software) was used to verify the circuit design and evaluate its capabilities. To provide a clearer understanding of the circuit design process, screenshots of the Fritzing simulations for each circuit (sensor nodes and gateway) have been included. These simulations illustrate the wiring and component connections (Table 2), ensuring that the designs can be reproduced or further optimized by other researchers and practitioners.

Figures 4 and Figure 5 incorporate these simulation results, highlighting the layout and functionality of the circuits. The main idea behind the simulation task is to save time and reduce the risk of component deterioration during practical implementation. In our system, we have two sensor nodes which will be located in two different monitored areas, and one gateway node which will receive data from both sensor nodes. Therefore, three circuits for the three units of the system were extensively simulated prior to the final implementation. Figure 4 shows the circuit of one sensor node. Although a detailed experimental power consumption analysis was not conducted due to logistical limitations, energy efficiency was considered during hardware selection. All components, including the microcontroller (ESP32), LoRa transceiver (SX1278), and environmental sensors (DHT22, GP2Y1010AU0F), were chosen based on their low power consumption characteristics as specified in their respective datasheets. Future work will include experimental energy profiling under varied operational conditions to validate these assumptions. The circuit of the gateway node (the receiver) is shown in Figure 5.

Hardware specifications

The most important electronic components such as microcontrollers and sensors are shown in Table 3. Each component was selected to meet the technical requirements of the system. The Arduino Uno microcontroller serves as the central processing unit, offering compatibility with the LoRa module and sufficient input/output pins to accommodate multiple sensors. The DHT22 sensor is connected to the analog pin to capture temperature and humidity readings. The MQ2 and MQ135 gas sensors are integrated via analog inputs to detect harmful gases, while the optical dust sensor is wired to the digital input for particulate matter detection. The LoRa module connects to the microcontroller's universal asynchronous receiver / transmitter (UART) pins, facilitating long-range wireless communication. Power is supplied through a

Table 2. Pinouts of the sensors connection

Sensor	Sensor Pin Name	Arduino Uno Pin	Components/ Notes
DHT22 (Temp/Humidity)	VCC DATA GND	5V D3 GND	Power supply D3 is an analog pin Ground connection
GP2Y1010AU0F (PM)	V-LED LED- GND LED Control Vo (Signal Output) VCC GND	5V GND D7 A0 5V GND	LED power LED ground LED control via digital pin Analog input. A typical value like 220 μF is connected between the sensor output pin (Vo) and ground. Without this capacitor, the sensor output might be noisy and cause erratic or unstable readings. Sensor power Signal ground

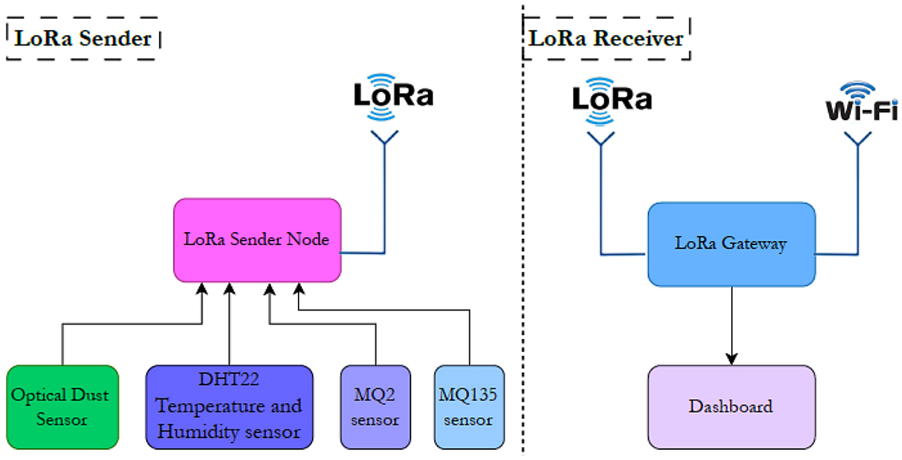

Figure 3. Block diagram

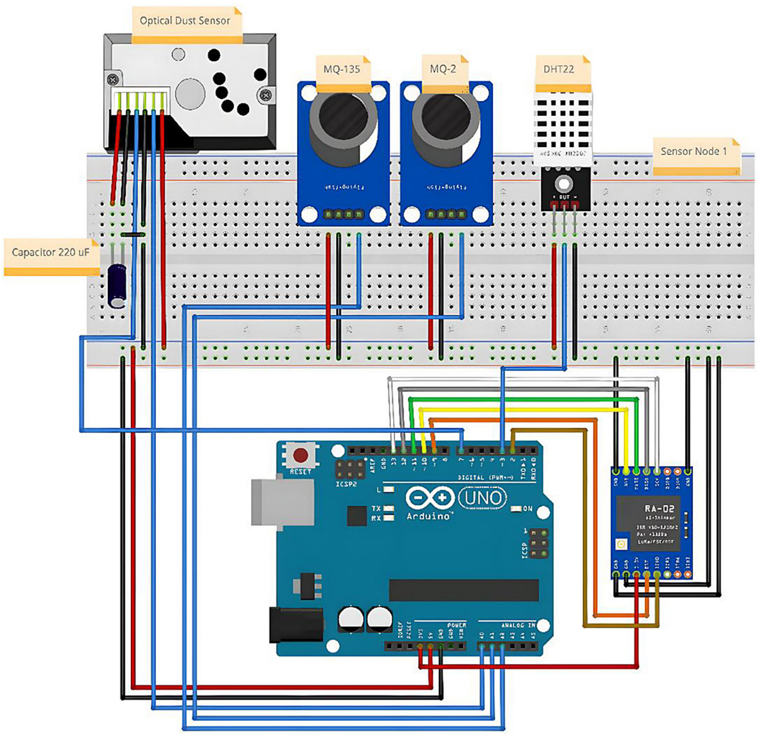

Figure 4. Fritzing simulation and wiring diagram for Sensor Node, showing connections for the DHT22, MQ2, MQ135, and dust sensors integrated with the LoRa module and Arduino Uno

9V battery with a voltage regulator to ensure stable operation. The gateway node, which features a LoRa receiver module, is designed to aggregate data and transmit it to the cloud platform, ensuring efficient integration with the monitoring system.

Software specifications

Table 4 summarizes the main characteristics of the software tools utilized in this research paper, along with their references.

Sensor readings

In this paper, sensor to sensor measurement, often referred to as ”inter sensor” or ”cross measurement”, is an alternative technique used when high precision reference instruments for sensor calibration are unavailable or impractical due to cost or logistical constraints. This approach involves deploying multiple low-cost sensors, ideally of the same model and with similar baseline accuracy to measure the same environmental parameter (such as temperature, humidity,

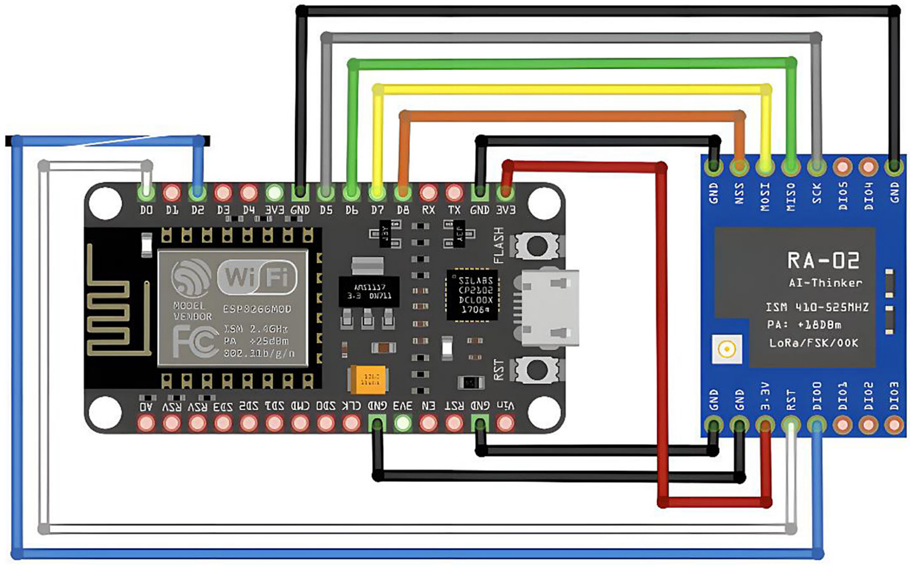

Figure 5. Fritzing simulation and wiring diagram for the Gateway node, detailing the integration of the LoRa receiver module and its connection to the centralized processing unit

Table 3. Main characteristics of selected electronic components

Component	Main Characteristics
MQ2 [22]	Gas sensor designed to detect LPG, smoke, alcohol, propane, hydrogen, methane, and carbon monoxide. It features fast response and recovery times, with adjustable sensitivity, ideal for gas leakage detection systems.
MQ135 [23] DHT22 [24]	Gas sensor capable of detecting alcohol, benzene, smoke, and other harmful gases. It offers high sensitivity and stability, making it suitable for air quality monitoring applications. A digital temperature and humidity sensor with a calibrated digital signal output. It offers high reliability and long-term stability, measuring temperature from -40 to 80 °C (±0.5 °C accuracy) and humidity from 0 to 100% RH (±2-5% accuracy).
Optical Dust Sensor (GP2Y1010AU0 Sharp) [25]	Measures particulate matter (e.g., PM2.5) in the air using an infrared emitting diode (IRED) and a phototransistor. It detects dust particles as small as 0.5 µm, providing analog voltage output corresponding to dust concentration, useful for air purifiers and air quality monitors.
LoRa Module (RYLR896) [26]	A long-range, low-power wireless communication module operating in the ISM bands (e.g., 868 MHz, 915 MHz). It enables data transmission over distances up to 15 km in rural areas, with low data rates, making it suitable for IoT applications requiring extended range and battery life.
Arduino Uno [27]	A microcontroller board based on the AT- mega328P, featuring 14 digital I/O pins (6 capable of PWM output), 6 analog inputs, a 16 MHz quartz crystal, USB connection, power jack, and reset button. It operates at 5V and is widely used for prototyping and educational purposes.
NodeMCU (ESP8266) [28]	An open-source IoT platform integrating the ESP8266 Wi-Fi module. It includes GPIO, PWM, I²C, 1-Wire, and ADC functionalities, operating at 3.3 V. Suitable for IoT applications requiring Wi-Fi connectivity.

particulate matter, or gas concentrations) simultaneously. By statistically comparing their output over time, it is possible to detect outliers, quantify systematic biases, and improve overall measurement reliability through aggregation. A common strategy is to compute the average (or sometimes a weighted average if prior sensor performance is known) of the measurements from the group, under the assumption that random errors across individual sensors will cancel out, while true environmental signals will reinforce. This technique can significantly enhance the precision of a network without relying on expensive reference instruments. If all sensors share a common systematic bias, simple averaging will not be correct for it. Additionally, environmental factors like temperature or humidity may affect the sensors differently, especially if slight manufacturing differences exist, which can introduce variability not fully resolved by aggregation alone. The proposed

Table 4. Main characteristics of utilized software

Software	Main Characteristics
Fritzing [21]	Purpose: Open-source hardware initiative for designing and prototyping electronics. Features: Visual breadboard layout, schematic capture, PCB layout, parts library, ability to document and share prototypes. License: Open-source.
Adobe XD [29]	Purpose: Vector-based user experience design tool for web and mobile apps. Features: Wire-framing, prototyping, user interface design, collaboration tools, integration with other Adobe products ,responsive resize. License: Proprietary with free starter plan and subscription options.
Arduino IDE [30]	Purpose: Integrated Development Environment for writing, compiling, and up- loading code to Arduino boards. Features: Supports multiple program ming languages (C, C++), extensive library management, serial monitor for debugging, cross-platform compatibility. License: Open-source.
Thing Speak [31]	Purpose: IoT analytics platform service for aggregating, visualizing, and analyzing live data streams in the cloud. Features: Real-time data collection, MATLAB integration for data analysis, RESTful API for data access, support MQTT and HTTP protocols. License: Proprietary with free and paid tiers.
Firebase [32]	Purpose: Platform developed by Google for creating mobile and web applications. Features: Real-time NoSQL database, authentication, cloud storage, hosting, cloud functions, analytics, cross-platform sup- port. License: Proprietary with free and paid tiers.
Visual Studio [33]	Purpose: Integrated Development Environment from Microsoft for developing computer programs, websites, web apps, web services, and mobile apps. Features: Code editor supporting IntelliSense, debugger, GUI design tools, sup- ports multiple programming languages, extensions for additional functionalities. License: Community (free), Professional, and Enterprise editions.

measurement technique can enhance data quality in large scale deployments, particularly in projects focused on spatial variability rather than absolute accuracy (like in our case study). Since purchasing and maintaining reference-grade instruments was financially unfeasible, we relied on sensor-to-sensor measurement to ensure reasonable data quality. As an illustration of a sensor-to-sensor measurement in practice, we conducted an urban environment experiment (Figure 6) by co-locating two temperature-humidity sensors (DHT22 1 and DHT22 2) and two air quality index sensors (MQ135 1 and MQ135 2). The sensor network was deployed alternately indoors and outdoors. The sensor network was connected to the cloud using a Wi-Fi ESP32 Arduino microcontroller and a cloud platform (Thing Speak). As a result, a total of 1272entries were collected and visualized through the platform channels. For the operational phase, we aggregated the measurements from each two sensors using simple averaging techniques, assuming that random errors would offset each other and the averaged value would better represent the true parameter. Although the system could not achieve the absolute accuracy of a reference-grade monitor, this measurement strategy significantly improved measurement consistency, allowed for the detection of relative pollution/temperature/humidity hotspots, and offered a cost-effective method for air quality and climatic parameters sensors readings.

The steps of the measurement process can be summarized as follows. The first step consists of the outliers' removal using the Interquartile technique. The interquartile range (IQR) technique [34] is a common method for identifying and removing outliers from the pollution and climatic datasets, namely, the temperature, humidity and air quality index. This technique operates by calculating the first quartile (Q1) and the third quartile (Q3), which represent the 25th and 75th percentiles, respectively. The IQR is the difference between Q3 and Q1. Outliers are then defined as any data points that fall below a lower limit or above an upper limit. By removing these extreme values, the dataset becomes cleaner and more representative of the underlying trend, improving the reliability of statistical analyses and model performance. The concept of IQR is mathematically described by the following equations:

$$Q1 = 25\text{th}\, percentile\ of\ the\ dataset \quad (1)$$

$$Q3 = 75\text{th}\, percentile\ of\ the\ dataset \quad (2)$$

$$IQR = Q3 - Q1 \quad (3)$$

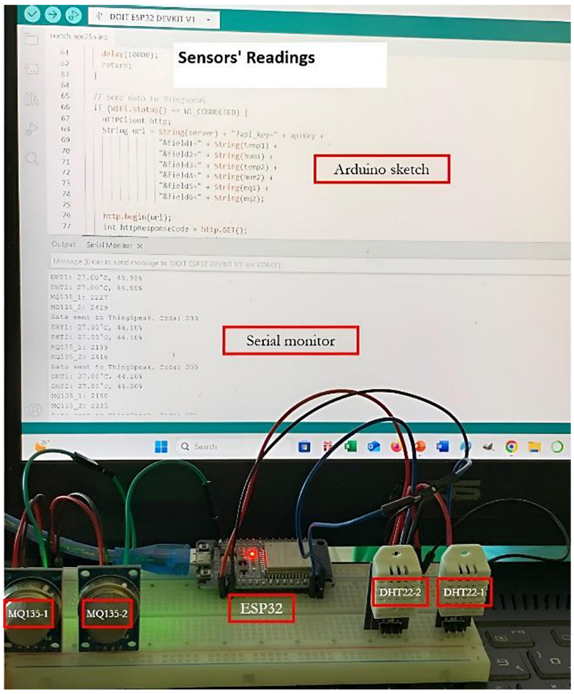

Figure 6. Sensors 'calibration

$$Outliers = \{x \mid x < Q1 - 1.5 \times IQR \text{ or } x > Q3 + 1.5 \times IQR\} \quad (4)$$

By applying this technique, 25 rows from the collected dataset were removed, and the analysis was conducted using the remaining 1247 records. The cleaned dataset is shown in Figure 7.

The second step consists of comparing each of the two sensors by calculating the correlation coefficients as well as the linear regression model for each parameter [35]. The results of this comparison are shown in Figure 8. As shown in Figure 8, the correlation coefficients are respectively of 1 (between the two temperature sensors), 0.91 (between the two humidity sensors) and of 0.84 (between the two AQI sensors). The three calculated correlation coefficients suggest a strong similarity between each of the two sensors and a certain level of stability of the obtained measurements.

In addition, the respective scatter plots show the distribution of the measurements of each of the two sensors as being close to the line Y=X (First bisector) which corresponds to the ideal similarity. Although the similarity is almost perfect in the temperature, it is high for the humidity and less but always good for the AQI. At the final step, the adopted measurements were calculated using the simple aggregation method (aggregated average) [36]. The plots of respectively, the calibrated temperature, humidity, and AQI are shown in Figure 9.

To evaluate the agreement between the readings of two paired sensors (temperature, humidity and AQI), we use three statistical metrics: root mean square error (RMSE), mean absolute error (MAE), and standard deviation (SD). These metrics help quantify the consistency and spread between measurements from two sensors.

Let x_i and y_i represent the readings from Sensor 1 and Sensor 2 respectively, for i = 1, 2,..., n. Root mean square error (RMSE):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2} \quad (5)$$

Mean absolute error (MAE):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|x_i - y_i| \quad (6)$$

Standard deviation of differences (SD):

$$SD = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left((x_i - y_i) - \bar{d}\right)^2} \quad (7)$$

where: $\bar{d} = \frac{1}{n}\sum_{1}^{n}(x_i - y_i)$ s the Mean of the differences between paired observations. The results obtained are summarized in Table 5.

As shown in Table 5, the sensor agreement metrics provide quantitative insight into the consistency between paired sensors measuring temperature, humidity, and air quality index (AQI). The temperature sensors exhibit a low root mean square error (RMSE) of 0.301 °C, mean absolute error (MAE) of 0.190 °C, and standard deviation (STD) of 0.286 °C, indicating strong agreement and precise measurements. Humidity sensors show slightly higher variability, with an RMSE of 1.302%, MAE of 0.347%, and STD of 1.292%, yet the errors remain within acceptable bounds for typical environmental monitoring. The AQI sensors display larger discrepancies, with an RMSE of 173.282 ppm, MAE of 141.504 ppm, and STD of 121.085 ppm, reflecting greater variation likely due to sensor sensitivity or environmental heterogeneity. These metrics confirm the reliability of temperature and humidity sensors for accurate environmental assessment, while highlighting the need for further calibration or

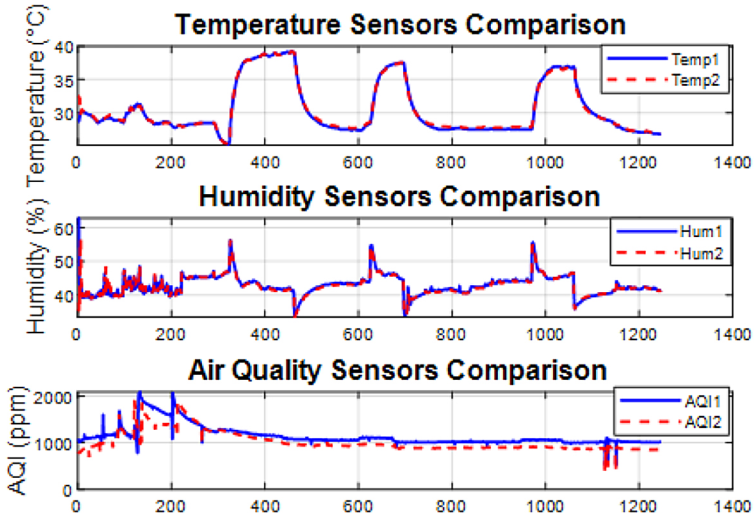

Figure 7. Time variation of the temperature, humidity, and AQI of each of the two sensors

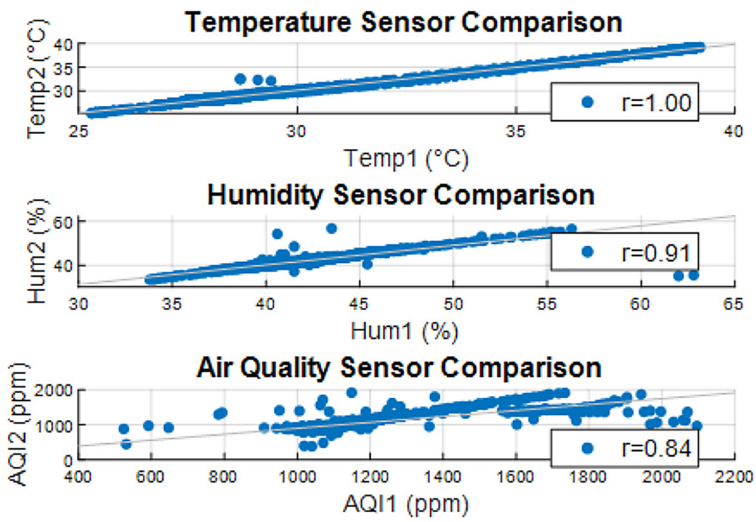

Figure 8. Correlation and regression analysis of the three parameters

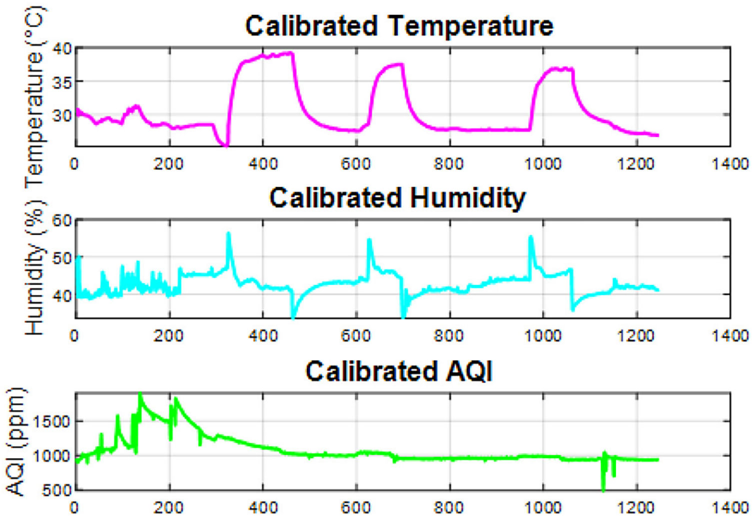

Figure 9. Plots of the aggregated average (three parameters)

Table 5. Main characteristics of selected electronic components – sensor to sensor agreement metrics (RMSE, MAE, and standard deviation) for temperature, humidity, and AQI measurements

Parameter	RMSE	MAE	Std. Dev
Temperature	0.301 °C	0.190 °C	0.286 °C
Humidity	1.302%	0.347%	1.292%
AQI	173.282 ppm	141.504 ppm	121.085 ppm

data processing to improve AQI sensor agreement. To complement the quantitative agreement metrics, visual analysis of the sensor data was conducted through timeseries plots, boxplots, and histograms. The time-series plots illustrate the temporal behavior of each sensor pair, showing how measurements evolve over the sampling period. The temperature sensors exhibit closely aligned trends, confirming the strong agreement indicated by low RMSE and MAE values. Humidity sensor readings demonstrate more variability but maintain consistent relative patterns. The AQI sensors display greater fluctuations and occasional spikes, consistent with their higher error metrics. Boxplots (Figure 10) summarize the distributions of sensor measurements, highlighting central tendencies, variability, and potential outliers. Temperature sensor data are tightly distributed with minimal outliers, supporting their reliability. Humidity sensors show a wider spread, reflecting natural environmental changes and sensor response differences.

The AQI boxplots reveal broader ranges and outliers, suggesting intermittent high pollutant levels or sensor noise. Histograms of pairwise sensor differences (Figure 11) provide insight into the frequency and magnitude of measurement discrepancies.

Temperature differences cluster tightly around zero, confirming high inter-sensor consistency. Humidity differences have a moderate spread with some asymmetry, while AQI differences are broadly distributed, reinforcing the need for enhanced calibration or noise reduction techniques. The data acquisition campaign was intentionally designed to alternate between indoor and outdoor environments in order to introduce variability and test sensor reliability under different conditions. These alterations aimed to simulate real-world deployment scenarios where environmental factors such as temperature

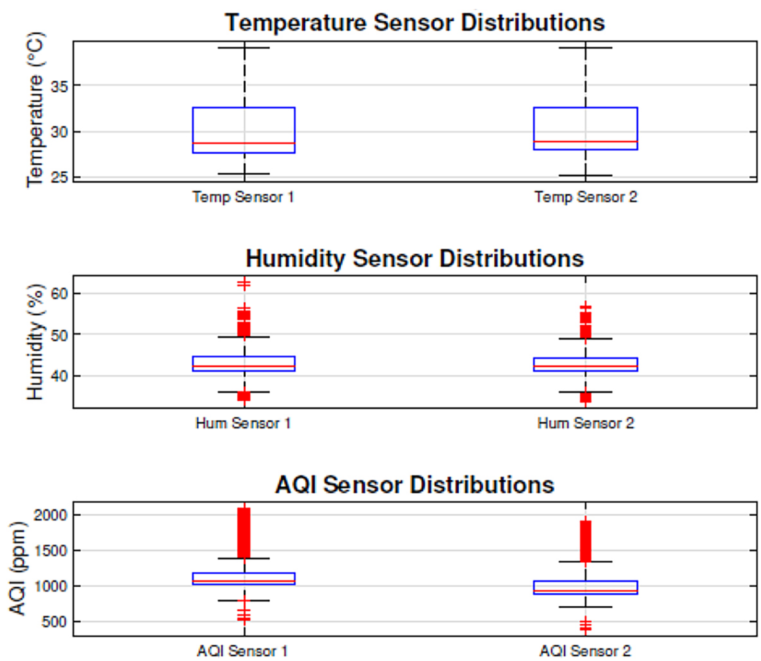

Figure 10. Boxplot visualization of the sensor readings, showing the distribution and variability across temperature, humidity, and AQI measurements

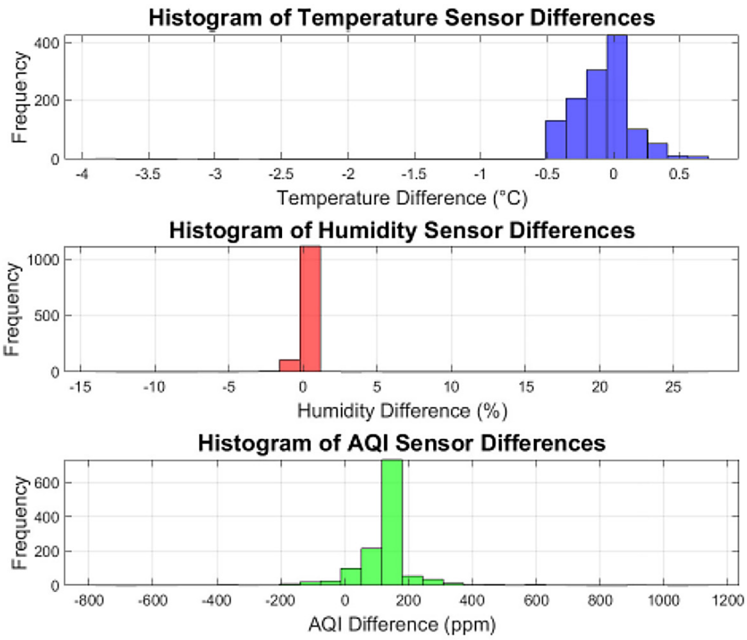

Figure 11. Histogram of sensor-to-sensor measurement differences, illustrating the distribution of discrepancies across temperature, humidity, and AQI readings

fluctuation, humidity variation, and air pollutant exposure differ significantly. However, the transitions between indoor and outdoor conditions were not systematically logged, resulting in a dataset where measurements from both environments are interleaved without clear segmentation. This mixture introduces natural variability into the dataset, particularly evident in the AQI readings, which exhibit higher error metrics due to more volatile outdoor pollutant levels and sensor sensitivity to external disturbances. Despite this, the temperature and humidity sensors demonstrate relatively consistent agreement, suggesting their robustness across different environments. Future studies will implement systematic labeling of measurement contexts to enable a more precise analysis of sensor behavior under controlled indoor and outdoor conditions. While this study focused on evaluating the consistency between pairs of identical low-cost sensors, no direct validation against certified reference-grade equipment was conducted. This decision was driven by the high cost and limited accessibility of such instruments, especially in the context of an early-stage prototype and proof-of-concept. The primary goal at this phase was to develop and demonstrate a functional and scalable sensing system, rather than to achieve high-precision calibration. Nonetheless, the sensor agreement metrics (e.g., RMSE, MAE, and standard deviation), along with the variability visualizations, offer useful insights into the internal reliability of the system. Future work will include a formal validation campaign using laboratory-grade instruments to establish absolute accuracy and further improve the system's calibration fidelity.

Prototype

The exterior views of the three circuits and their locations are shown. Sensor node 1 placed in AlShati district, sensor node 2 placed in Al-Basatin district, and the LoRaWAN gateway are shown in Figure 12. It is important to note that while the selected sensors, such as the DHT22, are low-cost and not typically rated for prolonged industrial outdoor use, all sensing components in our system were carefully enclosed in weatherproof boxes to protect them from direct sunlight, rain, and other environmental factors. This protective casing ensured the sensors' reliable operation during the testing period. The choice of hardware was driven by cost constraints and the goal of developing an early-stage proof-of-concept prototype. Our primary objective was to demonstrate the feasibility of integrating and communicating environmental sensor data through a scalable and energy-efficient IoT-based framework. From this perspective, the use

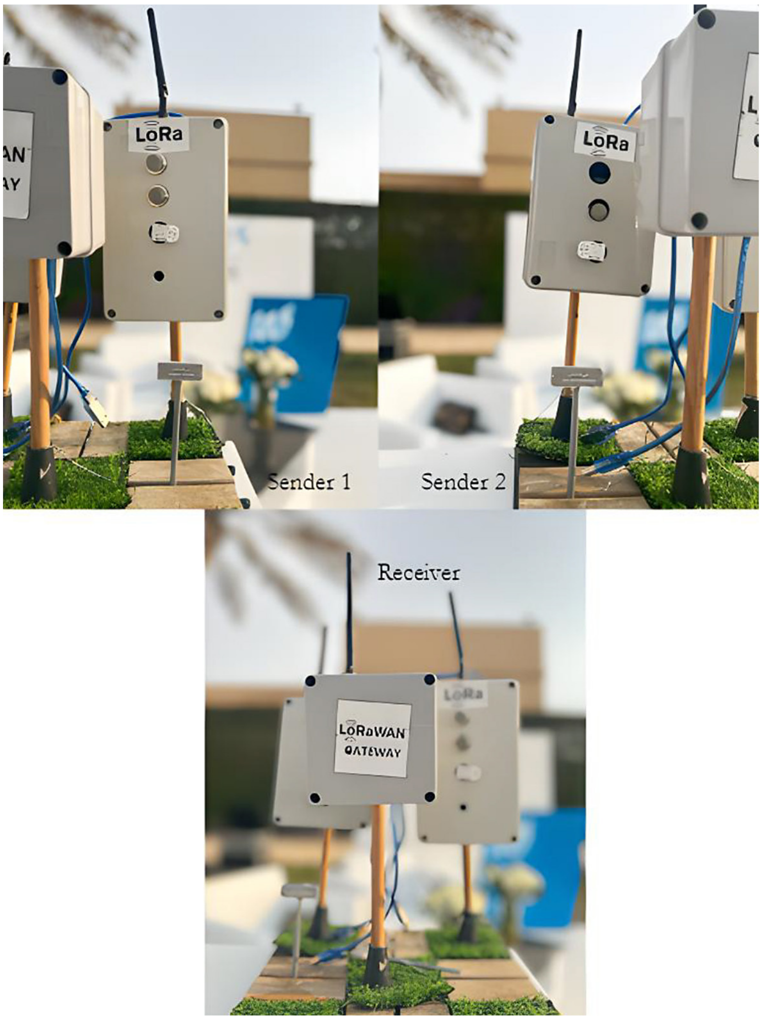

Figure 12. Sensor Node#1, Sensor Node#2 and Gateway node

of low-cost and readily available components remains fully appropriate and justified.

Cost analysis

To analyze the cost of our proposed monitoring system, we conducted a detailed comparison of our system with two selected systems found in the literature. The detailed comparison is provided in Table 6.

As can be seen from Table 6, our system demonstrates a cost-effective and integrated approach to air quality monitoring compared to the other two referenced systems. It is significantly more affordable than [37] (250 USD) and [38] (166USD, excluding sensors). Unlike [37], which uses separate and partially uncalibrated sensors, our design directly provides the air quality index (AQI) through the judiciously selected appropriate sensor (MQ-135), enhancing reliability and reducing calibration complexity. Compared to [38], which employs an indoor-only Dragino LPS8v2 gateway in an outdoor application, our system features a flexible gateway setup using two LoRa modules, one at the sensor node and one at the gateway, allowing for adaptable deployment in various environments. Furthermore, our integration of Arduino Uno and NodeMCU offers both modularity and scalability at a reduced cost, making it ideal for low-budget or proof-of-concept projects while maintaining core functionality.

RESULTS AND DISCUSSION

In this section, the results of the air pollution monitoring system tested in Jeddah city (Saudi Arabia) are presented and commented on. To validate and test the system, we placed the sensor nodes in two different areas (Alshati, Albsatin), and moved the nodes away from the gateway with a distance that may reach approximately 12–13 km

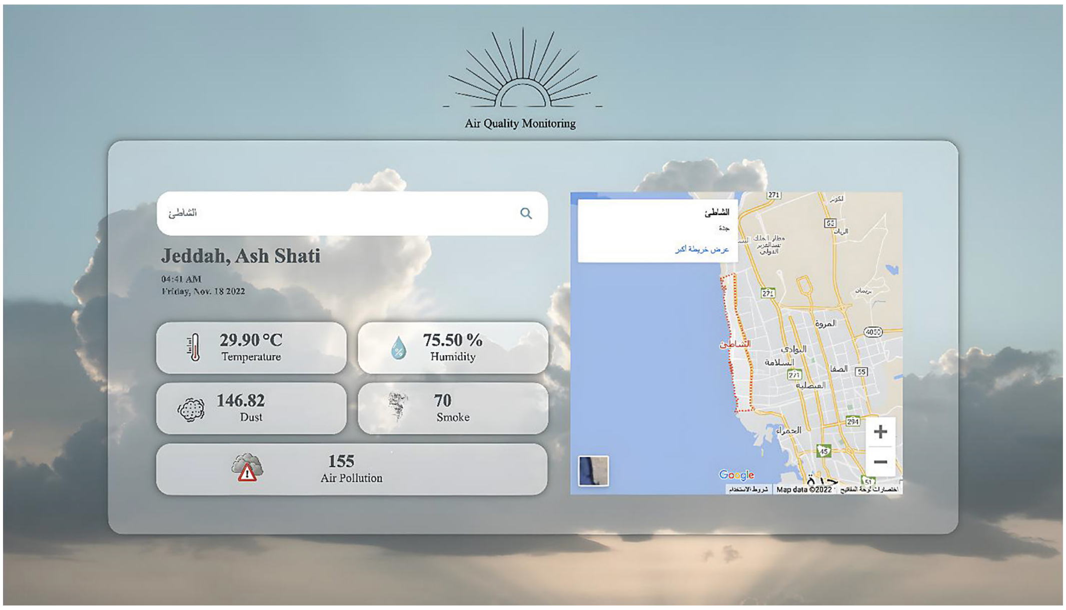

Figure 13. Real-time air quality monitoring dashboard displaying sensor readings from Node#1 (AlShati district)

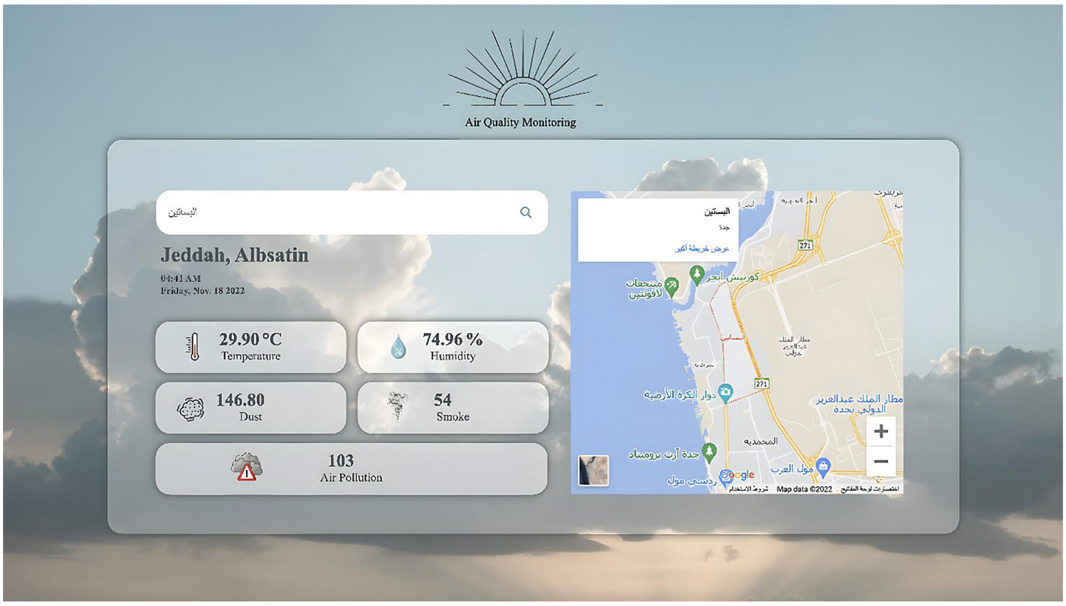

Figure 14. Real-time air quality monitoring dashboard displaying sensor readings from Node#1 (AlBasatin district)

to test the connection between the nodes. Figure 13 and Figure 14 show the values that appeared on the dashboard when searching for AlShati and AlBasatin at the same time. Figure 13 and Figure 14, which display real-time dashboard outputs for AlShati and AlBasatin, have been included to validate the system's data visualization capabilities. These figures highlight air quality metrics such as temperature, humidity, levels of particulate matter and harmful gas concentrations in a user-friendly format. The dashboards demonstrate the system's ability to aggregate and display data accurately, with dynamic updates reflecting changes in environmental conditions. This visual confirmation reinforces the reliability of the system's data collection and presentation. The proposed IoT-based air quality monitoring system was successfully deployed and evaluated in two urban locations to validate its functionality and performance. The system demonstrated excellent coverage, with LoRa communication effectively transmitting data over distances of up to 13 km.

Figure 15. Thing Speak Node#1

This capability ensures robust connectivity, making it suitable for widespread urban applications. The real-time data collected by the sensors were transmitted to the Thing Speak IoT platform and visualized on a user-friendly dashboard (Figure 15 and Figure 16). Figure 15 and Figure 16 illustrate the real-time air quality monitoring dashboard, displaying sensor readings collected from different environmental parameters. The legend provides a detailed explanation of each data set, including temperature, humidity, particulate matter (PM2.5), and gas concentrations.

The graphical representation enables users to track the variations in air quality over time, facilitating easy interpretation of pollution trends. Although the system provided reliable performance under optimal conditions, occasional delays in dashboard updates were observed if the Wi-Fi signal is relatively weak. The delays observed in dashboard updates were mainly attributed to fluctuations in Wi-Fi signal strength and network congestion during peak usage periods. These issues affected the transmission of sensor readings from the gateway to the cloud platform, resulting in a delay of 5–10 seconds per update. To address this limitation, potential solutions include the integration of backup communication protocols, such as cellular or Ethernet connections, and the implementation of data buffering at the gateway level to minimize the impact of temporary connectivity issues. Furthermore, optimizing data packet size and transmission intervals could further reduce latency, ensuring more consistent real-time updates, particularly during peak network usage. Despite these minor lags, the dash- board provided clear insights based on which suitable actions to assess and make decisions on air quality may be taken by the responsible authorities. In particular, the system's affordability, which is approximately 110 USD (including the sensors, LoRa modules and the Gateway), highlights its potential as a cost- effective alternative to

Figure 16. Thing Speak Node#2

Table 6. Cost-based comparative analysis of our monitoring system with other similar systems

Ref	Sensors/Gateway	Cost	Comment
Ref[37]	CO, NO_2, PM10, temperature, and humidity sensors + LoRaWAN gateway	250 USD	Use of separate sensors without calibration of some of them
Ref[38]	NO_2, SO_2, CO_2, CO, PM2.5, temperature, and humidity sensors + LoRaWAN Gateway (Dragino LPS8v2 – Indoor LoRaWAN Gateway	166 USD (Not including the sensors) [39] the sensors) [39]	The used gateway is designed to operate indoor.
Our system	DHT22, Optical Dust Sensor- GP2Y1010AU0F Sharp, MQ-5, and MQ-135 + Lora modules (sender+receiver)+ Arduino Uno microcontroller + NodeMCU	Price of the gateway (NodeMCU+ Lo Antenna) was 50 USD (Prices from a local shop) [40]	This DIY LoRa gateway (low- cost NodeMCU andLoRa rantenna) significantly reduces expenses while offering full control over network configuration and data routing

traditional monitoring solutions, which are often expensive. In addition, based on the cost, the designed system may be deployed at larger scales, including indoor and outdoor applications. The reliance on low-cost sensors, while advantageous in terms of affordability, results in a moderate level of accuracy compared to high-end alternatives. For further improvement, future iterations could incorporate advanced calibration techniques or integrate higher precision sensors to reduce error margins, particularly for particulate matter detection. Furthermore, the system's dependency on Wi-Fi for data transmission introduces occasional latency, which could be mitigated by adopting

Table 7. Comparison of air quality monitoring systems

Feature	Proposed system	[41]	[42]	Traditional Station [43]
Cost	Low (110 $)	Medium	High	Very high
Communication range	13 km (LoRa)	¡ 1 km (Wi-Fi)	10 km (Cellu- lar)	Stationary only
Scalability	High	Medium	Low	Low
Real-time wUpdates	Yes	Yes	No	Yes

hybrid communication protocols, such as LoRaWAN coupled with cellular backup. Enhancing the robustness of data transmission during peak network congestion will further solidify its applicability in dense urban environments.

The study highlights the transformative potential of IoT technology in making environmental monitoring easier. Be- yond air quality monitoring, the architecture of the system could be adapted to monitor other environmental parameters, such as water quality or noise pollution, further contributing to sustainable urban development. The combination of low-cost sensors, robust communication technology, and user-friendly data visualization tools positions this system as a model to address environmental challenges in developed and developing regions. To further show the contribution of the system, a detailed comparison with existing air quality monitoring systems is presented in Table 7. This table highlights key aspects such as sensor integration, communication range, cost, scalability, and real-time capabilities. Compared to traditional fixed monitoring stations, the proposed system excels in affordability, scalability, and versatility, making it suitable for large-scale deployment. Unlike other IoT-based solutions that rely on short-range communication technologies, the use of LoRa extends coverage to 13 kilometers, bridging a critical gap for urban applications. Although this study was presented as a proof-of-concept to demonstrate the feasibility of deploying an IoT-based environmental monitoring system using LoRa communication and real-time dashboards, the efficient deployment of the proposed system requires deeper experimentation and analysis. While the dashboards effectively visualize sensor data, no formal user experience evaluation was conducted at this stage. Additionally, although LoRa connectivity was functionally confirmed, a detailed performance analysis, including metrics such as packet loss, message frequency, signal strength under varying urban densities, and transmission reliability, was beyond the scope of this phase. These aspects are recognized as critical and are planned for comprehensive investigation in future extended deployments.

CONCLUSIONS

In this paper, an IoT and WSN-based air quality monitoring system was designed and implemented practically. The developed system has demonstrated its effectiveness, affordability, and scalability in collecting real-time data related to air pollution and environmental conditions in urban crowded areas. The system included two sensor nodes and a gateway communicating through LoRa devices. During the design step, several technical requirements including power consumption and cost were considered. The successful application in two distinct areas of Jeddah city (Saudi Arabia) highlights the system's adaptability and potential for broader application. The implemented system has provided real-time air quality monitoring with an average delay of less than 10 seconds, covering a range of up to 13 kilometers. Moreover, the system's affordability, with a total cost of approximately 110 USD, positions it as a viable solution for resource-constrained regions seeking cost-effective environmental monitoring.

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