Development and Validation of An Indoor Air Quality Assessment System Based on IoT Sensors

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complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

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ABSTRACT

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This study presents the development and validation of an Arduino-based Internet of Things (IoT) sensor system for continuous and real-time indoor air quality monitoring. Various sensors are examined and integrated into the IoT system to collect data on crucial air pollutants, including carbon dioxide (CO_2), particulate matter ($PM_{2.5}$), nitrogen dioxide (NO_2), and volatile organic compounds (VOCs). The collected data is transmitted to an online server and stored in a MySQL database, facilitating efficient data analyses and visualization. Two different validation studies were conducted at Concordia University and Qatar University to assess the system's accuracy and reliability. The Concordia University case study highlights the system's accuracy in measuring CO_2, $PM_{2.5}$, NO_2, and VOCs. Employing calibration and modification methods effectively reduces differences to less than 15% compared to well-established commercial monitoring instruments. The Qatar University case further reinforces consistent performance across various parameters and locations and has tested the remote access and management of the developed system. Comparing sensor readings with commercial instruments reveals strong positive correlations and minimal deviations, affirming the integrated device's efficacy in real-time air quality monitoring. Particularly, the developed Arduino-based IoT sensor system offers a user-friendly interface for real-time data visualization through online charts and tables. Additionally incorporating an indoor air quality index model into the developed IoT system allows users for real-time assessment of air cleanliness and to mitigate pollution. In summary, the developed Arduino-based air quality monitoring system presented herein underscores its potential as a cost-effective solution for sustainable environment.

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Table of Contents

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

AQI	Air quality index
ASHRAE	American society of heating, refrigerating and air-conditioning engineers
CO_2	Carbon dioxide
GSM	Global system for mobile communications
HCHO	Formaldehyde
IAQI	Indoor air quality index
IEEE	Institute of electrical and electronics engineers
IoTs	Internet of Things
MCU	Microcontroller unit
NO_2	Nitrogen dioxide
OSBSS	Open source building science sensors
PM	Particulate matter
PMV	Predicted mean vote
PNNL	Pacific northwest national laboratory
PPD	Predicted percentage dissatisfied
TVOC	Total volatile organic compounds
VOCs	Volatile organic compounds

CHAPTER 1: INTRODUCTION

This research aims to develop an Arduino-based IoT sensor system for indoor air quality monitoring. The system provides real-time continuous readings of pollutant levels online and offers a direct assessment of air quality suitability for indoor spaces. Additionally, the system's modularity allows multiple units to monitor various areas concurrently. The upcoming sections in this chapter will delve into the research's motivation, objectives, methodology, contributions, and the organization of this thesis.

1.1 Problem Statement and Motivation

The quality of indoor air in various environments, including working spaces and living spaces, plays a crucial role in public health. Pollutants such as PM, VOCs, and NO_2, which can originate from sources like inadequate ventilation, building materials, cleaning agents, and combustion processes, can significantly impact the well-being of individuals in these environments. Therefore, monitoring and maintaining optimal indoor air quality is vital for ensuring a healthy and safe environment for both work and living spaces (Saini et al., 2022). A summary of typical pollutants with their sources and health effects is provided in Table 1.

Table 1 Summary of indoor air pollutants (Saini et al., 2022)

POLLUTANTS	SOURCES	HEALTH EFFECTS
By-products of combustion (NO_X, CO_2, CO)	Tobacco smoke; unvented kerosene heaters; leaking chimneys; gas appliances; automobile exhaust.	Lung problems; respiratory diseases, flu-like symptoms.
Formaldehyde and VOCs	Building materials, chemical-rich cosmetic products, fireplaces, tobacco smoke, vehicle exhaust.	Respiratory issues; cancer; major damage to the central nervous system, liver, and kidney.
Particulate matter (PM)	Combustion processes, including cooking, heating, and the use of tobacco products; PM can also originate from outdoor air pollution sources that infiltrate indoors.	Respiratory illnesses such as asthma, bronchitis, and reduced lung function. It can also exacerbate existing respiratory conditions and increase the risk of developing cardiovascular diseases, including heart attacks and strokes.
Ozone	Ozone generators; some poor-quality air cleaners; printers and photocopiers.	Respiratory issues, lung diseases.

The significance of controlling indoor air quality cannot be overstated, given its direct impact on public health and well-being. The air we breathe within enclosed environments, whether they are workplaces or residences, has a profound influence on our physical comfort and long-term health. Substances such as PM, VOCs, NO_2, and by-products of combustion can pose serious health risks when present at elevated levels. It's imperative to recognize that individuals spend a significant portion of their time indoors, making the quality of indoor air a critical determinant of their overall health and productivity.

Particulate matter, for instance, originating from activities such as cooking, heating, and tobacco use, can have substantial adverse effects on respiratory health. These particles can exacerbate conditions like asthma and bronchitis, compromise lung function, and even elevate the likelihood of cardiovascular diseases such as heart attacks and strokes (Saini et al., 2022). Formaldehyde and VOCs, emitted from building materials, cosmetics, and other sources, can result in a range of health issues, from respiratory ailments to severe damage to vital organs like the central nervous system, liver, and kidneys. Furthermore, indoor ozone exposure can have detrimental effects on respiratory health, leading to symptoms such as coughing, throat irritation, chest discomfort, and shortness of breath. Chronic exposure to ozone may exacerbate pre-existing respiratory conditions and decrease lung function, increasing the risk of respiratory infections. The primary sources of indoor ozone include ozone generators, certain air purifiers with ozone functions, and outdoor air infiltration (Saini et al., 2022).

Inherited desertification along with rapid urbanization, industrialization in the Middle East (ME) demands a lookout for maintaining air quality standards (Lelieveld et al., 2025). Covering a larger area to monitor fine particulate matter ($PM_{2.5}$) and pollutants such as nitrogen dioxide (NO_2) and sulphur dioxide (SO_2) poses demands for a reliable IoT sensor network in the region (Awadh, 2023). It is interesting to note that the ME region has been monitoring air quality since the early 1990s such as sensor networks established by Bahrain in 1993 and Egypt in 1998 at city scale (Jasim and Coskuner, 2017). Similarly, Israel, Jordan, Morocco, Qatar, Saudi Arabia and UAE have also initiated working at a larger scale to monitor regional air quality (Negev, 2020; Fezari et al., 2015; Chirmata et al., 2017;

Yaacoub et al., 2013; Mofarrah et al., 2010; Omidvarborna et al., 2018). Qatar is expanding its network for air quality monitoring under the mandate of the Qatar Ministry of Municipality and Environment.

To carry out the monitoring and measurement, different techniques like passively collecting samples to be analyzed in a laboratory, sophisticated devices and professional instruments for daily measuring, or large and expensive monitoring stations that constantly sample the pollutants in fixed locations, are the strategies being used frequently. Passively collecting air samples for later laboratory analysis is a common method. However, this approach often provides delayed results and might not reflect real-time fluctuations in indoor air quality. Additionally, the accuracy of results can be influenced by the transportation and storage of samples, potentially leading to inaccuracies in the analysis. Using sophisticated devices for daily measurements can offer more immediate insights into indoor air quality. Yet, these devices may require regular calibration and maintenance to ensure accuracy. The expense of such instruments can also be a limiting factor for widespread adoption, particularly in smaller facilities or households. The deployment of large monitoring stations in fixed locations can provide continuous data collection. However, this approach is resource-intensive, requiring significant infrastructure and maintenance costs. Moreover, it may not capture the micro-scale variations in air quality that can occur in different areas of a building.

Consequently, there is a growing interest in developing air quality monitoring systems with IoT sensors. According to Kumar et al, IoT-based systems have emerged as a cost-effective and scalable solution for real-time environmental monitoring, offering benefits such as remote sensing, data transmission, and analysis capabilities (Kumar Sai et al., 2019). Punnet and Mamtaz presented an IoT-based PM monitoring system utilizing the PMS5003 sensor, NodeMCU ESP8266 12E Board as the microcontroller, and the ThingSpeak website as an open-source IoT platform for data recording and visualization (Kalia & Ansari, 2020). The implementation of IoT-based sensor monitoring systems for environmental management represents the future of air quality monitoring. These systems enable the efficient maintenance of fine air quality by monitoring and managing toxic gases such as HCHO, VOCs, and CO. With real-time data and automated responses, these systems provide timely information to make informed decisions and ensure a safe and healthy environment for individuals. The integration of IoT technology in environmental management holds great potential for enhancing air quality and improving the overall quality of life (Yang et al., 2019).

1.2 Research Objectives and Scope

The primary aim of this research is to create a cost-effective and efficient IoT sensor system utilizing Arduino as the central controller. This system is designed to enable continuous measurement, real-time monitoring, and comprehensive data analysis of air quality parameters in indoor environments. The research objectives encompass several key components that collectively contribute to the development of the IoT sensor system.

1. To develop an IoT-based sensor air quality monitoring system and integrate wireless communication capabilities into the Arduino-based IoT sensor system. This integration enables remote control and mobile measurement within indoor settings. By strategically placing sensors, the system collects air quality data and wirelessly transmits the readings to an online server database. This seamless data transmission is facilitated through a Wi-Fi connection, ensuring real-time storage and analysis of air parameter measurements.
2. To construct a user-friendly server webpage. This webpage serves as a visualization platform, enabling the real-time presentation of air quality data derived from the

database. The collected data can be conveniently displayed in either table or chart formats. This visualization mechanism provides immediate insights into air quality conditions, enhancing the system's usability and practicality.

3. To incorporate the Air Quality Index (AQI) model to provide a comprehensive assessment of air cleanliness or pollution levels, a critical feature of the IoT sensor system is the development of a mechanism to calculate and determine the AQI. This index is derived from the collected air quality data and offers a clear, easily understandable representation of the current air quality status. The AQI acts as a valuable tool for individuals to assess and respond to changing air quality conditions promptly.
4. To validate the developed IoT system through two field case studies on the Concordia University campus and the Qatar University campus to ensure the reliability and accuracy of the developed IoT sensor system, rigorous validation tests are conducted. These tests involve deploying the sensors across various locations within the Concordia University campus, encompassing both indoor and outdoor environments. The readings obtained from the IoT device are rigorously compared to those derived from established commercial instruments. This validation process guarantees the precision of the sensors' readings and reinforces the credibility of the system's capabilities.

In conclusion, the development of this Arduino-based IoT sensor system represents a pivotal advancement in air quality monitoring. By seamlessly integrating wireless communication, real-time visualization, AQI determination, and thorough sensor validation, this research endeavors to deliver a practical and efficient solution for continuous air quality assessment in indoor settings.

1.3 Thesis Organization

This thesis is structured into five chapters.

Chapter 1 serves as the introduction to the research, outlining its motivation and objective of creating an IoT sensor system with Arduino. It sets the context for the study and highlights the importance of investigating IoT sensor-based air quality monitoring.

Chapter 2 is the literature review of this study. It provides an overview of current practices in IoT sensor-based air quality monitoring, including microcontroller and micro-sensor options. In addition, it explores indoor air quality index model research and highlights existing limitations.

Chapter 3 details research methodologies and system components, encompassing MCUs, sensors, web servers, and the indoor air quality index model.

Chapter 4 presents case studies from Concordia University and Qatar University and engages in an in-depth discussion on sensors and the system, offering insights into their implications.

Chapter 5 synthesizes findings, highlights contributions, and suggests future research directions.

CHAPTER 2: LITERATURE REVIEW

This chapter begins by introducing the fundamental concept of the IoT. Afterward, it proceeds to discuss the present practices of IoT-based air quality monitoring systems. The review will emphasize prevalent techniques such as wireless communication and commonly employed hardware. Subsequently, the chapter will analyze the limitations of existing air quality monitoring systems, identifying gaps and providing a summary of the study's findings.

2.1 IoT Innovations in Environmental Research

IoT technology finds its primary applications in smart environments. Currently, this technology is extensively employed in urban areas, campuses, and various industries to oversee and integrate diverse functional tasks such as infrastructure management, ventilation systems, leakage monitoring, risk prediction, and more. The concept of smart environments existed in industrial contexts through supervisory control and data acquisition (SCADA) decades ago (Boyer, 1999). However, SCADA cannot be applied to IoT due to SCADA's adherence to specific standards, limited manufacturer diversity, and inadequate provisions for ensuring data security and confidentiality (Domínguez-Bolaño et al., 2022).

The construction of the IoT revolves around physical devices, usually sensors and command-receiving modules. These devices can exchange information within the network to facilitate communication, and they are all managed through a centralized system, often a server. A representative example of an IoT system employing sensors is an atmospheric quality detection system, where users directly access atmospheric data collected by the sensors. Another widespread application of IoT is in smart home systems, allowing residents to easily control or set various indoor appliances through a control interface on their smartphones (Figure 1).

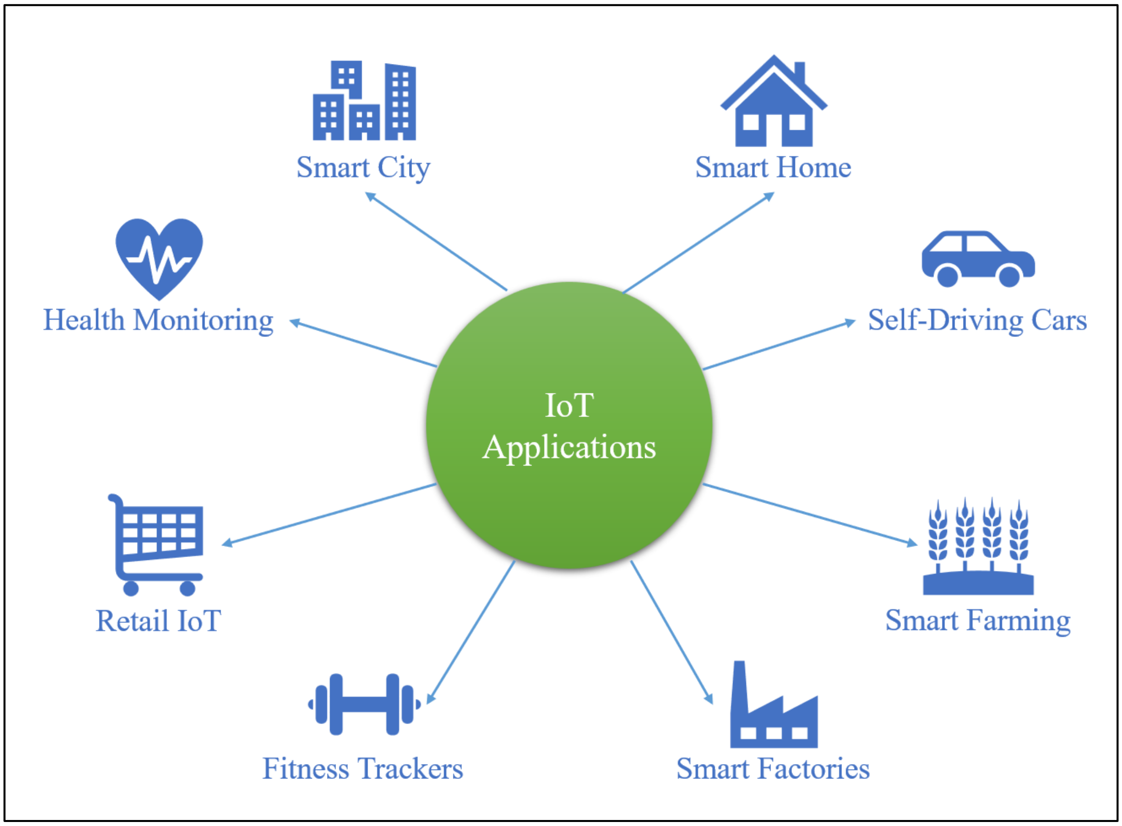
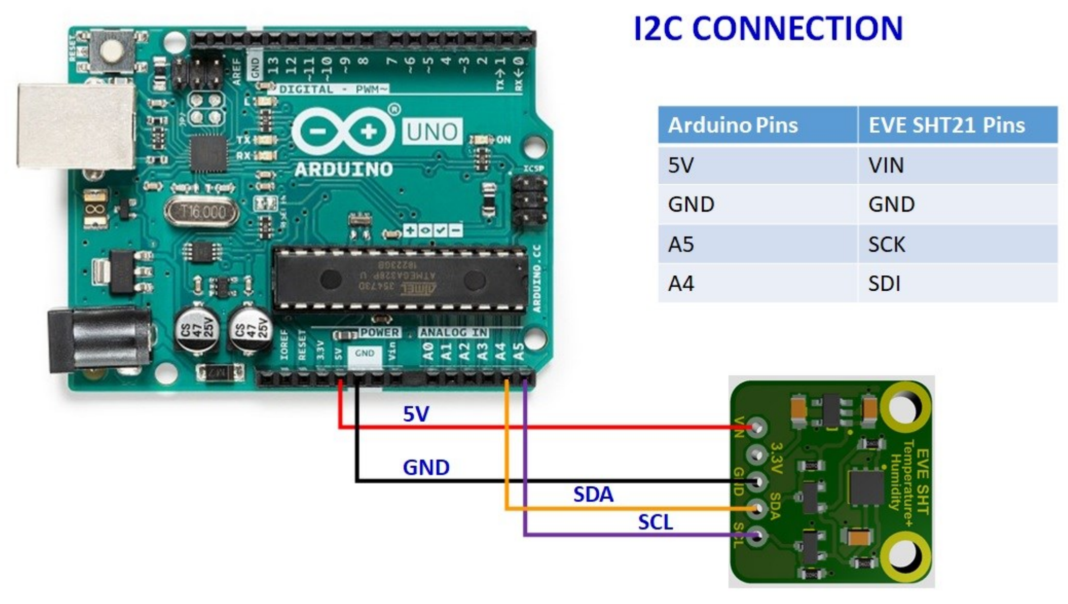


Figure 1 Applications of IoT technology

IoT systems encompass two key cores. The first core involves the interaction between users and end devices. Users can directly access data from all end devices and remotely control them to execute specific actions. The second core is the concept of "smart environment" mentioned earlier. This system not only facilitates the exchange of initial information among modules within the network but also encompasses various intelligent functions like data analysis, prediction, alerts, and auto-control. A typical example is the self-preservation mechanism that employs sensors to monitor temperature or other indicators, automatically halting system operations if necessary (Domínguez-Bolaño et al., 2022).

2.2 IoT Based Air Quality Monitoring

In recent years, there has been rapid technological development in the field of atmospheric parameter monitoring. New microcontroller Units (MCUs) and microsensors have become more user-friendly and efficient, making air quality monitoring increasingly convenient. For instance, the most widely used entry-level MCU, Arduino Uno, only requires a compatible sensor, a few jumper wires and a USB data cable to be connected to a computer. Then, with the Arduino IDE, it's possible to instantly start retrieving and displaying atmospheric data collected by the sensor. As shown in Figure 2, the sensor connection with Arduino Uno.



I2C CONNECTION

Arduino Pins	EVE SHT21 Pins
5V	VIN
GND	GND
A5	SCK
A4	SDI

Figure 2 SHT21 breakout I2C connections to Arduino (7semi sht21 humidity and temperature sensor breakout I2C 2022)

2.2.1 IoT-based system

Similar system architectures and usage approaches have become widespread. For example, Ali et al. (2016) utilized the Arduino Pro Mini, a small-size version of the Arduino MCU, along with temperature and humidity sensors to create a long-term indoor environmental data collection system called open source building science sensors (OSBSS). This system continuously gathers indoor temperature, humidity, and carbon dioxide concentration data, storing it on a microSD card. Yang et al. (2019) utilized an Arduino data logger and controller along with an MQ-4 sensor to detect methane in biogas. The design also incorporated a chamber to house the sensor and maintain optimal environmental conditions for its response, as well as a sample injection port. In a similar vein, Pedro (2022) aimed to assess the long-term efficacy of this low-cost design. They employed three different Arduino MCUs - Arduino Due, Arduino Pro Mini328, and Arduino MKR1000 - each connected to various functional sensors and a Micro SD card module for data storage. A testing period lasting 24 months was conducted to evaluate their performance.

However, the approach of storing data in a data logger comes with significant limitations. Firstly, users lack real-time access to the data. Moreover, the storage space on a security digital (SD) card is restricted, necessitating frequent data exports and SD card replacements. As a result, contemporary IoT systems predominantly incorporate wireless data transmission capabilities. The wireless communication technologies employed in IoT-based air quality monitoring systems will be systematically introduced in the subsequent sections.

2.2.2 Wireless communication technologies

Bluetooth technology stands as a mature short-range wireless data transmission technology at present. The majority of electronic devices are equipped with Bluetooth functionality, enabling wireless data transfer in close proximity as well as wireless connections to external devices. By leveraging Bluetooth technology, the system can transmit the collected data to smartphones or laptops wirelessly. Suárez et al. (2018) devised a wireless gas detection module employing Bluetooth technology. This system comprised an SHT21 sensor for measuring temperature and humidity, alongside five gas sensors to detect four distinct types of volatile organic compounds (VOCs). The collected data would be transmitted via Bluetooth to a home-developed smartphone application for display.

Zigbee is a wireless technology developed based on the Institute of Electrical and Electronics Engineers (IEEE) Standards Association's 802.15 specification. It utilizes the IEEE 802.15.4 wireless standard, which is intended for wireless personal area networks (WPANs) focused on control and sensor networks. It is tailored for machine-to-machine (M2M) and IoT applications with low data rates and low power consumption, and it operates as an open standard. Zigbee WPANs function on frequencies of 2.4 GHz, 900 MHz, and 868 MHz. One of the distinctive features of Zigbee is its support for mesh networking, where devices form interconnected networks for communication purposes. This mesh network architecture is a fundamental aspect of the Zigbee protocol (Sun & Zhang, 2009). Karami et al. (2018) introduced an Arduino-based Indoor Environmental Quality (IEQ) toolbox, that incorporates the Zigbee communication protocol. The system employed a wireless mesh network communication setup, facilitating the connection of sensors across different locations. It allowed the collection and storage of a variety of data, including dry bulb temperature, elevation temperature, relative humidity, horizontal illuminance, vertical illuminance, CO_2 levels, VOCs, $PM_{2.5}$ particulate matter, and human occupancy, all within a single location. Arduino Uno boards were equipped with XBee modules to collect data from the sensors. The received data was then transmitted through an XBee module functioning as a coordinator, which was linked to a computer. The data was subsequently conveyed to the software layer via a serial protocol. To serve as the IoT platform, the system utilized VOLTTRON, which is an open-source platform developed by the Pacific Northwest National Laboratory (PNNL) for distributed system control (Katipamula et al.,2016).

GSM, or the Global System for Mobile Communications, serves as a standardized protocol for digital cellular networks deployed by mobile devices such as mobile phones and tablets. To utilize GSM technology, devices must be equipped with GSM modules and SIM cards to establish connections with cellular networks. Presently, research efforts are exploring the application of GSM wireless communication technology in the context of air monitoring. Cheng et al. (2014) developed an innovative client-cloud system aimed at monitoring PM (particulate matter) concentrations in both indoor and outdoor environments. The front-end sensors positioned at specific points of interest were linked to the backend infrastructure through GSM technology. This allowed real-time PM concentration data from various locations to be transmitted to a cloud-based database, facilitating the development of emission models.

Wi-Fi is currently one of the most indispensable wireless technologies in daily life. Mobile phones, computers, tablets, and the majority of smart devices all possess the capability to connect to Wi-Fi networks. Wi-Fi involves the transmission of wireless radio signals emitted from a wireless router to nearby devices. The router serves as a central hub, disseminating the internet signal to all devices enabled with Wi-Fi connectivity. This ensures the convenience of staying connected to the internet within the network coverage area. Incorporating Wi-Fi technology into an IoT air quality monitoring system necessitates the inclusion of essential Wi-Fi modules. Currently, the widely used Wi-Fi modules belong to the ESP series, with the ESP32 and ESP8266 being popular choices (Figure 3). Both of these, the ESP32 and ESP8266, are programmable development boards equipped with all the required circuitries. They provide power to the chip and establish a connection to a computer, including a circuit for convenient code uploading, pins for peripheral connections, integrated power and control LEDs, and various other useful features.

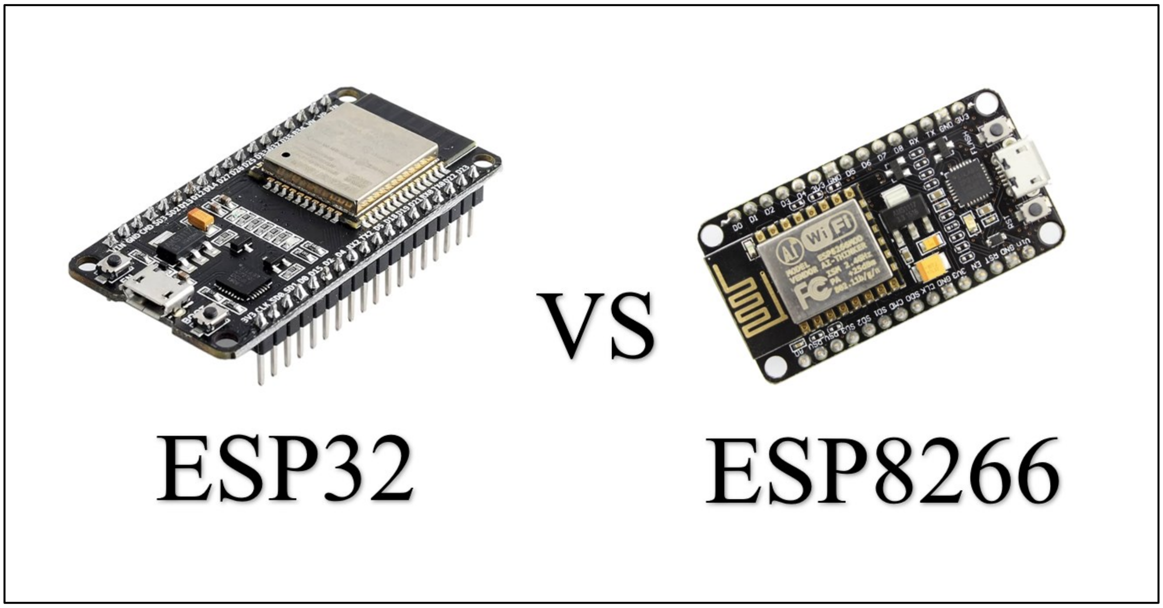


Figure 3 ESP32 & ESP8266 programmable development boards (ESP8266, 2023)

However, currently, only a handful of sensor products available in the market can be directly connected to ESP boards. The majority of sensors are designed to be compatible with basic MCUs like Arduino. As a result, ESP boards are more commonly used as standalone Wi-Fi connectivity modules, responsible for connecting to wireless networks and transmitting data to the cloud. For instance, in the work of Thiyaneswaran et al. (2023), an Arduino Nano, ESP8266, and sensors including MQ2, MQ3, MQ6, and MQ9 were employed to measure concentrations of CO, CO_2, NO_2, and CH_4 gases. The Arduino Nano was responsible for orchestrating data collection from the sensors and transmitting it to the ESP8266. The ESP8266, in turn, managed Wi-Fi connectivity and sent the gathered data to a cloud-based server. Similar frameworks are found in other cases as well. In the study conducted by Sridhar et al. (2023), an IoT node was designed, featuring multiple sensors to monitor various pollutants such as NH_3, NO_2, CO, and $PM_{2.5}$, along with air humidity and ambient temperature. The system utilized the Nucleo F401REtx, a 64-bit ARM microcontroller, along with semiconductor sensing elements to create compact nodes. These nodes transmitted and collected limited data to central control units or gateways (Raspberry Pi 3), facilitating internet connectivity. In this scenario, the Raspberry Pi 3 serves as the network device.

2.2.3 Sensors and MCUs

The backbone of the entire system operation rests on the MCU, while the fundamental aspect of ensuring the accuracy of system measurements undoubtedly lies in the selection of sensors. Despite several years of technological innovation for these microsensors, a significant portion of sensors still struggle to provide precise measurements. Apart from technical challenges, many sensors are designed for detection purposes, lacking the capacity for accurate measurements due to their intended applications. In the current field of air quality monitoring research, the MQ series of sensors (Figure 4) naturally stands out as the most widely applied (Thiyaneswaran et al., 2023; Yang et al., 2019; Sridhar et al., 2023; Kumar Sai et al., 2019, etc.). These sensors are extensively used to gauge gas concentrations and detect potentially explosive or hazardous gases. The range of gases they can identify includes alcohol, smoke, methane, LPG, hydrogen, ammonia (NH_3), benzene, and propane. These sensors are constructed with an electrode featuring a sensing material on its surface, which is heated to enhance reactivity and sensitivity. The MQ series' broad compatibility with a wide range of MCUs and its versatile options for gas detection contribute significantly to its popularity. However, the MQ series is predominantly utilized in industrial environments, which can lead to suboptimal performance in low-concentration indoor environments. Additionally, many of these products are designed to target multiple gas indicators, and there are few options available for precise measurement of a single gas.

Figure 4 MQ gas sensors

The SHT-series sensors are another popular choice in indoor environmental studies. This series specializes in measuring humidity and temperature levels, which is valuable for comprehending thermal conditions and aiding in the calibration of other gas measurements.

Apart from the common sensors mentioned, the range of available products is more diverse and intricate. Infrared gas sensors are engineered for the continuous detection of CO_2 and various hydrocarbon gases, including vapors within permanent systems. Metal oxide sensors operate on the principle that the presence of target gases causes a change in the resistance of the sensor's detecting layer. Resistance increases in the presence of oxidizing gases like ozone or nitrogen dioxide and decreases in the presence of reducing gases such as carbon monoxide or Volatile Organic Compounds (VOCs). Thermal conductivity sensors incorporate temperature-sensitive pellistors to detect and measure thermally conductive gases that significantly differ from a reference gas, typically air. Examples of thermal conductive gases are hydrogen, helium, and methane. Most PM (particulate matter) sensors utilize a laser scattering principle. This technique involves emitting a laser to interact with suspended particles in the air. The scattered light is collected at a specific angle, and changes in the scattering light curve over time are used to obtain data on particle concentration.

Once the sensors are chosen, selecting a suitable MCU to match becomes relatively straightforward. As mentioned earlier, the Arduino series of MCUs are highly popular due to their user-friendliness and extensive accessory support, making them a favorite among beginners. However, there are many other MCUs that have demonstrated impressive performance in research studies as well. Paithankar et al. (2023) opted for the STM32F103RC microcontroller unit as the central component of their system. They employed an LPWA-based IoT technique to manage the PMS5005 sensor for $PM_{2.5}$ measurement and the SHT20 sensor for temperature and humidity readings. Sridhar et al. (2023) combined the Nucleo F401REtx, a 64-bit ARM Microcontroller, with semiconductor sensing elements to create compact nodes. They also employed another MCU, the Raspberry Pi, as the network device.

In contrast to typical MCUs, the Raspberry Pi stands out with its extensive array of features and a notably potent processor. While conventional MCUs typically manage basic command operations, the Raspberry Pi can be better characterized as a miniature computer, proficient in executing a multitude of intricate instructions and even serving as a compact-scale server. Its impressive processing power extends to tasks like video and image processing. However, most sensor designs are not directly compatible with the Raspberry

Pi, and its higher price point compared to other basic MCUs limits its application in systems requiring multiple devices. As a result, the Raspberry Pi finds greater use in projects like building miniature robots.

2.3 Issues and Limitations of Existing IoT Systems

Up to this point, IoT-based air quality monitoring systems have been designed to provide real-time and automated measurements of indoor air quality. The effectiveness and efficiency of some systems have also been subjected to testing and validation. Nevertheless, certain deficiencies and shortcomings within air quality monitoring practices have been identified based on prior research studies.

a) Previous research has often focused solely on gathering data concerning CO_2 levels, temperature, and indoor humidity, which has resulted in a notable absence of data for other critical parameters. Additionally, some systems narrow their scope to a single parameter relevant to a particular gas-related application, rather than encompassing the entirety of indoor environmental factors.

b) The emphasis in most systems has been on structural design, with direct utilization of sensor data without thorough validations. Validations are often limited to CO_2, temperature, and humidity data. Consequently, advancements have been made in CO_2 and humidity sensors, while progress in other gas sensors remains limited.

c) Sensor selection is restricted. Currently, there is no gas sensor that offers 100.0% selectivity for a single gas (Sridhar et al., 2023). Most sensors are unable to accurately measure low-level concentrations.

d) A significant technical challenge is tied to the robustness and repeatability of current low-cost commercial sensors. Laboratory calibration falls short in correcting for real-world conditions, necessitating individual field calibrations for each sensor. Calibration parameters might change over time due to meteorological conditions and location, making it challenging to determine if deployed nodes overestimate or underestimate pollutant concentrations. Consequently, comprehensive evaluation of low-cost sensor platforms under various environmental conditions becomes imperative (Castell et al., 2017).

e) While most systems can effectively collect data, some still lack real-time capabilities and are limited to data log functions (Ali et al., 2016; Yang et al., 2019). Thus, wireless communication is necessary.

f) Limitations of Zigbee, Bluetooth, and GSM technologies in indoor environments have been identified. Bluetooth, operating on low radio frequencies, can encounter interference issues and has a limited range, often under 10 meters. Zigbee technology permits mesh network creation for communication between modules but lacks direct server data storage capabilities, necessitating wired connections. Constraints on data packet size and node distance reduce efficiency and transfer speed. GSM has higher power consumption than other communication technologies, and costs associated with GSM modules and SIM plans are concerning. In comparison, despite limited coverage, Wi-Fi is better suited for indoor environments due to its favorable cost, range, and data transfer speed.

g) A common limitation is that many systems only provide readings on web interfaces or apps, lacking proper analysis or indicators for decision-makers.

2.4 Review of Indoor Air Quality Index

Given that people spend more than 80% of their time indoors, encompassing residential buildings, vehicles, public transport, and public buildings, it becomes exceptionally important to recognize and address the consequences of IAQ on human health and overall well-being. The idea of IAQ is impacted by various factors which encompass indoor pollutant sources and the infiltration of pollutants from the outdoors, chemical transformations resulting in secondary pollutants, the processes of adsorption and desorption, rates of air exchange and ventilation, as well as the indoor and outdoor temperature along with relative humidity levels (Pourkiaei & Romain, 2023).

- Indoor Emissions: Various indoor sources can release pollutants, such as VOCs from building materials, furniture, cleaning products, and personal care items. Combustion appliances like stoves and heaters can emit particulate matter and gases like carbon monoxide.
- Outdoor Penetration of Pollutants: Pollutants from outdoor sources, such as vehicle emissions, industrial processes, and natural sources, can infiltrate indoor spaces through cracks, ventilation systems, and open doors/windows (Park et al, 2014).
- Chemical Reactions (Secondary Pollutants): Some pollutants emitted indoors or infiltrating from outdoors can undergo chemical reactions, producing secondary pollutants. For instance, ozone can form through reactions involving VOCs and sunlight.
- Sorption and Desorption Phenomena: Surfaces in indoor environments, such as walls, floors, and furnishings, can adsorb and release pollutants over time. This affects the concentration of pollutants in the air (Mora et al, 2014).
- Air Exchange Rates and Ventilation Characteristics: The rate at which indoor air is exchanged with outdoor air plays a crucial role in IAQ. Inadequate ventilation can lead to the accumulation of pollutants, while proper ventilation helps dilute and remove pollutants (ASHARE-62, 2001).

- Temperature and Relative Humidity: Temperature and relative humidity can influence the release of VOCs from materials, the growth of mold and bacteria, and the comfort of occupants. High humidity levels can lead to mold growth, while low humidity levels can exacerbate respiratory issues (ASHARE-55, 2010).

Diverse sets of keywords were used to encompass a wide range of literature concerning IAQ indicators and their connection to indoor constructed spaces, human health, overall well-being, work output, energy effectiveness, and HVAC systems (Pourkiaei & Romain, 2023). IEQ stands for Indoor Environmental Quality, which broadly encompasses the assessment of indoor environmental attributes encompassing air quality, as well as visual, thermal, and acoustic comfort. Multiple prominent organizations, each with distinct objectives and origins, have established definitions of IEQ. Notable among these are GSA (an American governmental agency), REHVA (a non-profit association in Europe), ASHRAE (a not-for-profit organization based in America), and NIOSH (a U.S. federal government agency) (Coulby et al., 2020). The EPA emphasizes that enhancing understanding and control of IAQ contributes to reducing potential health issues associated with indoor settings. This is underscored by their definition of IAQ (EPA, 2022), which characterizes it as "the standard of the air inside and around buildings and structures, especially with regard to the health and satisfaction of the individuals inhabiting these premises." Another description offered by ASHRAE Technical Committee (TC) 1.6 defines IAQ as the "qualities of the breathable air indoors (indoor environment), encompassing aspects like gaseous constitution, moisture levels, temperature, and pollutants." (ASHRAE Terminology, 2023)

While IAQ is a complex and multi-dimensional concept, there have been efforts to develop IAQ indices or indicators that attempt to simplify its assessment and provide a quantifiable metric for comparison. These indices aim to condense the various parameters that influence IAQ into a single value that can be easily understood by policymakers, researchers, and the general public. However, due to the complexity and variability of IAQ, creating a universally accepted and standardized IAQ index has proven challenging. Saravanan and Kumar (2022) presented an IoT-based hybrid model that integrates Factor Analysis (FA), Artificial Neural Networks (ANN), and Auto-Regressive Moving Average (ARMA) methods to predict the AQI. The study focuses on extracting polluting components from air quality data using FA, regressing the projected rate with ANN, and employing ARMA for prediction. The proposed model demonstrates improved accuracy, highlighting its potential for estimating the proportion of polluting components in the air (Saravanan & Kumar, 2022). C. Sun et.al (2022) proposed a new model for evaluating indoor air quality based on childhood allergic and respiratory diseases. The model incorporates data collected from residential buildings in Shanghai and employs logistic regression analyses to determine health-related pollutant indicators. The model predicts the state of indoor air using an adaptive neuro-fuzzy inference system (ANFIS) and discrete-time Markov chains (DTMC). The authors suggest the inclusion of specific pollutants like di(2-ethylhexyl) phthalate (DEHP) in IAQ standards based on their correlations with children's respiratory diseases (Sun et al., 2022).

2.5 Summary

In conclusion, this chapter has provided an in-depth exploration of IoT-based air quality monitoring systems. The fundamental concepts of the Internet of Things (IoT) and its applications in smart environments were introduced. It was demonstrated that IoT technology has evolved and found extensive use in various sectors, revolutionizing the way data related to air quality is collected, transmitted, and analyzed. The chapter then delved into the specific domain of IoT-based air quality monitoring, with an emphasis on the crucial role of microcontroller units (MCUs) and sensors. The significance of selecting the right wireless communication technology and the wide array of options available, including Bluetooth, Zigbee, GSM, and Wi-Fi, were discussed. Moreover, the role of different sensors in measuring air quality and the importance of choosing the appropriate MCU for specific monitoring applications were highlighted.

Previous research has often focused solely on gathering data concerning CO_2 levels, temperature, and indoor humidity, with an absence of data for other critical parameters. This study seeks to improve this limitation by expanding the range of sensors and parameters considered. By incorporating sensors for a broader spectrum of indoor environmental factors, the research aims to provide a more comprehensive and holistic view of indoor air quality, filling the data gaps left by previous studies. The emphasis in most systems has been on structural design, with limited validation of sensor data beyond CO_2, temperature, and humidity. A significant technical challenge is tied to the robustness and repeatability of current low-cost commercial sensors. this study addresses these limitations by conducting thorough validations for each sensor and parameter and exploring different calibration methods to minimize discrepancies. By thoroughly validating the accuracy and reliability of sensor data and developing calibration techniques that account for real-world conditions, your research contributes to a more trustworthy and robust monitoring system that extends beyond the limited focus on CO_2 and humidity sensors, thereby enhancing the precision and reliability of pollutant concentration measurements while overcoming calibration challenges associated with low-cost sensors.

While most systems can effectively collect data, some lack real-time capabilities and are limited to data log functions. A common limitation is that many systems only provide readings on web interfaces or apps, lacking proper analysis or indicators for decision-makers. This study addresses these limitations by designing a wireless IoT structure for real-time monitoring and applying an indoor air quality index model to the system.

Implementing real-time wireless communication ensures that real-time data is readily available for analysis and decision-making, overcoming the delays and limitations associated with data log functions. By incorporating advanced analytical tools, such as an indoor air quality index model, this research enhances the system's capability to analyze data and provide actionable insights to decision-makers, thus addressing the shortcomings of previous systems that primarily offered data without in-depth analysis.

In the following chapters, the foundational knowledge provided here will be built upon, with a focus on innovative solutions and addressing the identified limitations to contribute to the advancement of IoT-based air quality monitoring. This technology holds the potential to significantly impact the way air quality is understood and managed, ultimately benefiting human health and well-being.

CHAPTER 3: DEVELOPMENT OF WEB-BASED REAL-TIME SENSOR SYSTEM

3.1 Concept of IoT Sensor System

This chapter introduces the development of an Arduino-based IoT sensor system designed for the monitoring of indoor air quality. The system is engineered with the capability to perform continuous measurements, real-time monitoring, and data analysis. The primary objective of this system is to provide a comprehensive evaluation of indoor air quality across various locations, ensuring easily accessible and comprehensible results.

The significance of indoor air quality in relation to human health arises from a multitude of factors, including pollutant sources, human activities, stored objects, operational appliances, and even specialized installations within confined industrial spaces. Furthermore, since indoor environments typically consist of distinct zones or spaces, relying solely on a single monitoring unit is inadequate to represent the overall air quality of such complex settings.

Consequently, it is imperative for the developed system to embody specific attributes that enhance its effectiveness for users:

1. Cost-effectiveness and Efficiency: The system is designed to efficiently monitor multiple indoor air parameters while remaining cost-effective.
2. User-Friendly Interface: The system's interface is intuitively designed to facilitate ease of use for end-users, regardless of their technical proficiency.

3. Continuous Monitoring and Real-time Reporting: The system is engineered to maintain continuous monitoring and promptly display real-time air quality updates.
4. Advanced Data Visualization: The system employs variable data visualization techniques to aid in interpreting complex data patterns, enabling informed decision-making.
5. Immediate Air Quality Assessment: The system presents air quality status directly, allowing users to quickly determine whether indoor air quality meets acceptable standards or requires attention.

3.2 Design of the System

This research develops an Arduino-based IoT sensor system with the abilities of continuous measuring, real-time monitoring, and data analysis. It is an economic system with remote-controlled devices of small size which means they are appropriate for both fixed-location installation and mobile measurement. Sensors are installed in the system to acquire data from the air, which is then communicated to other modules to allow transmission of air parameter readings from the device to the online server database for saving and other applications. The data from the database could be visualized in real-time on the server webpage in either table or chart format, or it could be used to determine the Air Quality Index (AQI) to present a direct view of how clean or polluted the air is. The sensors and modules can be chosen and replaced with a wide variety of options, and this feature gives the system flexibility and adaptability which can be designed to fit specific environments based on factors like the air parameters, the communication methods, and the power source.

The core of this system relies on Arduino MCUs, which perform various essential tasks, including receiving commands, data collection from sensors, data processing, and wireless data transmission (Figure 5). To ensure accurate and comprehensive air quality monitoring, the system incorporates multiple sensors. The multichannel gas sensor module, equipped with GM-102B and GM-502B sensors, enables the detection of NO_2 and VOCs respectively. The SCD30 and SEN54 Sensor Module facilitate monitoring of CO_2 levels, $PM_{2.5}$ levels, temperature, and humidity. Data acquisition may be coordinated because the sensor modules and Arduino MCUs are smoothly coupled and integrated.

For wireless data transmission in outdoor scenarios, a Raspberry Pi micro-computer is employed as a wireless module, working in tandem with the Arduino Mega MCU. This configuration ensures reliable and efficient data transmission over long distances. In indoor scenarios, the Arduino UNO Wi-Fi Rev2, equipped with an inbuilt Wi-Fi module, serves as the Wi-Fi connection solution, enabling uniform communication with the server.

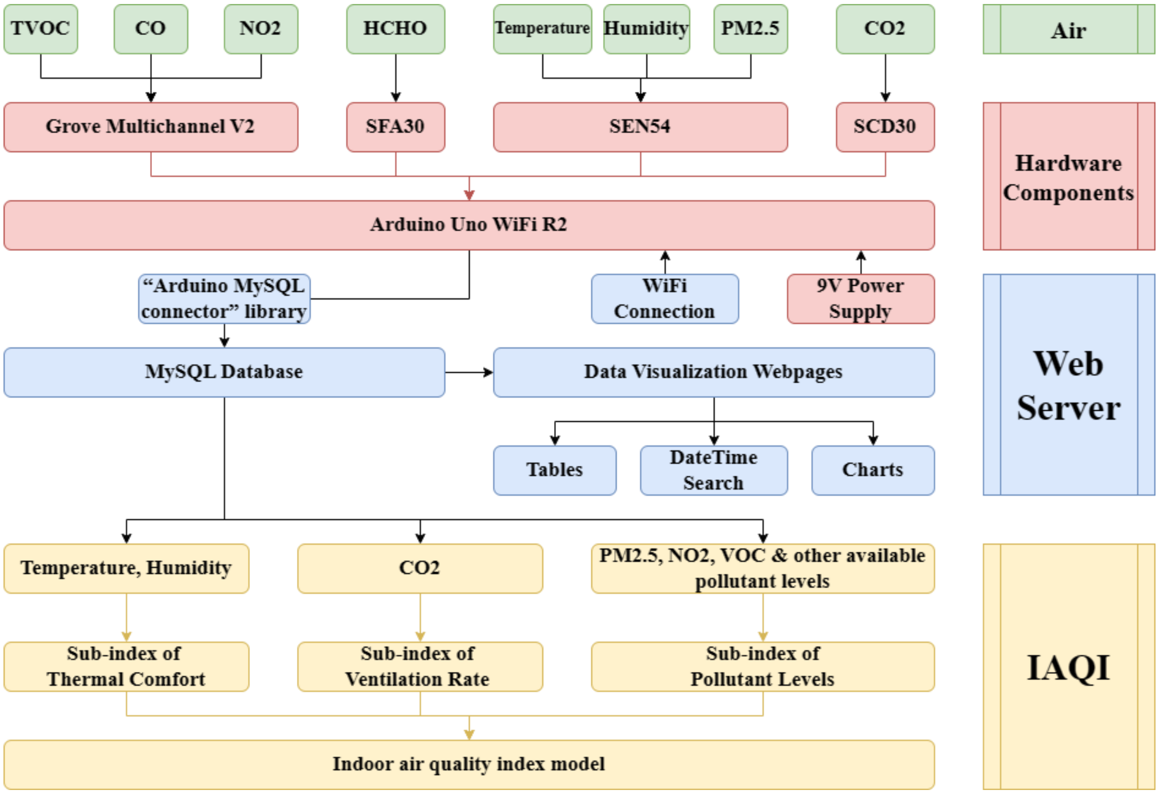


Figure 5 Flowchart of the Arduino Wi-Fi based indoor air quality monitoring system

To provide a compact and streamlined solution, a 3D-printed enclosure (Figure 6) with a mini-fan module is utilized to contain the sensors, Arduino MCUs, and wireless modules. The enclosure not only protects the components but also enhances the system's portability and ease of installation.

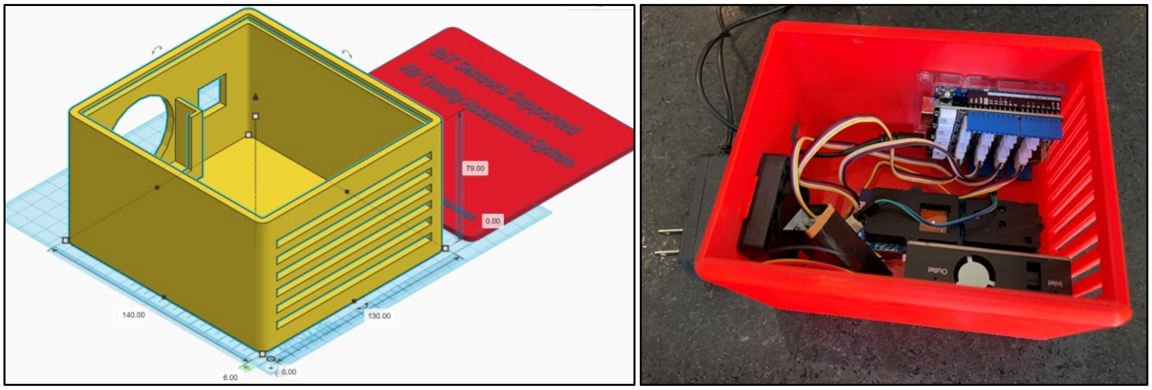


Figure 6 Device with 3D-Print enclosure

The collected air quality data is transmitted to a server database hosted on an online shared server. This online shared server provides a reliable and secure platform for storing, viewing, and analyzing sensor results. The integration of the "Arduino MySQL connector" library enables direct transmission of the collected data from the devices to the MySQL database. The web-based display interface allows users to access real-time air quality information, perform computations, and conduct further analysis. This comprehensive system facilitates informed decision-making and assists in identifying air pollution sources, thereby contributing to a healthier and sustainable environment.

In summary, it is an economic system with remote-controlled devices of small size which means they are appropriate for both fixed-location installation and mobile measurement. Sensors are installed in the system to acquire data from the air, which is then communicated to other modules to allow transmission of air parameter readings from the device to the online server database for saving and other applications. The data from the database could be visualized in real-time on the server webpage in either table or chart format, or it could be used to determine the Air Quality Index (AQI) to present a direct view of how clean or polluted the air is. The sensors and modules can be chosen and replaced with a wide variety of options, and this feature gives the system flexibility and adaptability which can be designed to fit specific environments based on factors like the air parameters, the communication methods, and the power source.

3.3 Hardware Components

The device unit within this system comprises the latest version of a microcontroller unit and micro-sensors, leveraging advanced technologies that enhance accuracy and communication capabilities. The subsequent section delineates the array of available options the system offers to cater to specific requirements, along with their distinctive features. Following this, a detailed and thorough deconstruction of the device's assembly, carefully implemented within this system, is provided with a focus on intricate particulars.

3.3.1 Sensors

In this IoT sensor system, several sensors are used for different pollutants and parameters as shown in Table 2.

Table 2 Sensors used in the system

Sensor module	Parameter	Range
SCD30	CO_2	0 ~ 40000 ppm
SEN54	$PM_{2.5}$, Temperature, Humidity	$PM_{2.5}$ 0 ~1000 µg/m^3
MULTICHANNEL V2	NO_2, CO, TVOC	NO_2 100 ~ 10000 ppb CO 5 ~ 5000ppm TVOC 10 ~ 20000 ppb

The sensors are essential components in air quality monitoring systems, particularly in Arduino-based IoT applications. The SCD30 CO_2 sensor is dependable for measuring carbon dioxide levels in indoor environments, offering a wide detection range and high accuracy. The SEN54 All-in-One sensor is versatile, detecting particulate matter, temperature, and humidity, making it ideal for both indoor and outdoor air quality assessments. The Multichannel V2 sensor detects harmful gases like NO_2, CO, and TVOC, crucial for monitoring industrial emissions and indoor air quality. The SFA30 HCHO sensor specifically measures formaldehyde levels in indoor spaces, ensuring occupant safety, while the MQ131 Low Concentration sensor is highly sensitive for detecting low levels of ozone in the air, suitable for precise environmental monitoring. These sensors collectively provide comprehensive data for assessing and managing indoor air quality in various settings, promoting healthier and safer living, and working environments. (SENSIRION, Datasheet, 2020)

3.3.2 Microcontroller units (MCUs)

Arduino Microcontroller Units (MCUs) are used as the core of this IoT system to collect air quality data. The Arduino MCUs are responsible for: 1. Receiving commands; 2. Let the sensors gather data; 3. Analyze and process the data then turn it into the level of pollutants; 4. Send the data that has been processed to the wireless module, then tell it to transmit the data to the server database.

In contemporary IoT applications, the dominant communication technologies encompass four primary types: Bluetooth, ZigBee, GSM/GPRS, and Wi-Fi. Bluetooth technology is constrained by its limited communication range and expandability, whereas ZigBee technology can transmit only restricted data packets. Given that this research centers on monitoring indoor air quality, where Wi-Fi connectivity is consistently accessible in the environment, Wi-Fi communication emerges as the ultimate selection to facilitate wireless data transmission for the system. Simultaneously, the selection of the microcontroller unit is contingent upon its capability to accommodate Wi-Fi connectivity, aligning with the system's requirements.

MCU with ESP8266: The Arduino Uno R3 and Arduino Mega 2560 (Figure 7) are popular microcontroller boards used for electronic prototyping and development, with the latter offering more I/O capabilities and memory.

Figure 7 Arduino Uno & Mega (Arduino)

These MCUs can work with the esp8266 module to enable a Wi-Fi connection (Figure 8). The ESP8266 stands as a budget-friendly Wi-Fi microchip, equipped with a comprehensive TCP/IP stack. This empowers microcontrollers to establish connections with Wi-Fi networks and establish uncomplicated TCP/IP connections through the utilization of Hayes-style commands (S. Muthukumar, 2018). In previous studies, researchers consistently opted for this strategy as the ESP module is the only option for Wi-Fi connectivity, but ESP8266 is restricted in its compatibility with a select range of sensors while Arduino boards can seamlessly integrate with most micro-sensors accessible in the market.

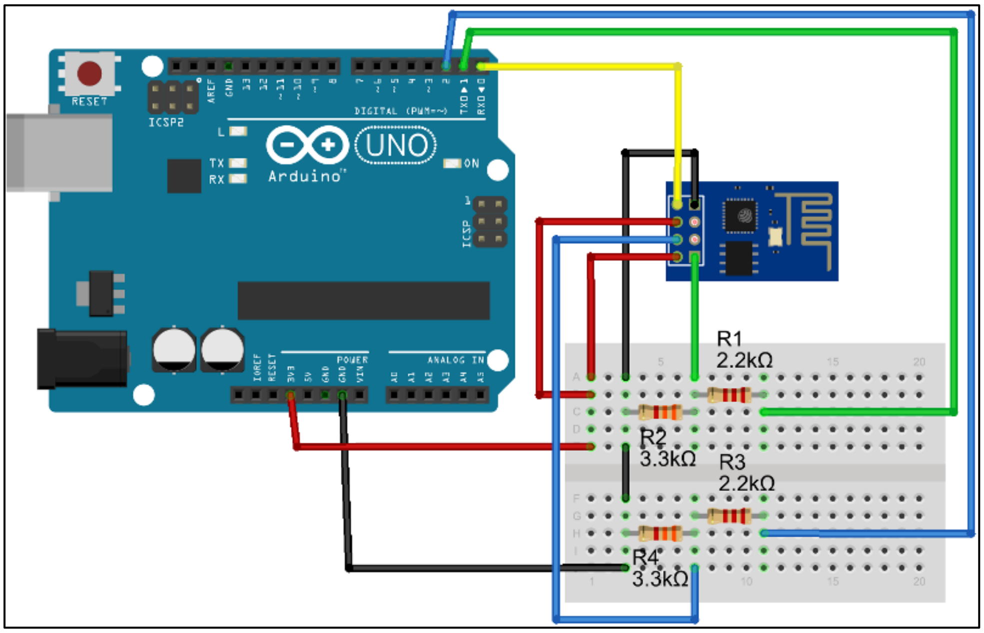


Figure 8 Connection of Arduino board and ESP8266

However, adopting this approach demands a skill set encompassing background knowledge in wire connections, soldering techniques, breadboard utilization, and resistor integration as Figure 8 shows. It is worth noting that these complexities not only deter entry for researchers without specialized skills but also escalate the risk of system failures due to intricate hardware setups. Furthermore, the reliance on wired connections or breadboards inevitably restricts the minimization of the device's overall size.

Raspberry Pi: The Raspberry Pi 4 is a powerful single-board computer that offers improved performance and enhanced features. It supports various operating systems, including Linux-based distributions, making it a versatile platform for both hobbyist projects and professional applications such as home automation, media centers, and IoT solutions (RaspberryPi, 2022). The Raspberry Pi micro-computer serves as a wireless module to assist the Arduino Mega MCU with data transmission in outdoor scenarios. Leveraging a Raspberry Pi introduces an additional dimension to the system's capabilities by incorporating camera functionality (Figure 9). The micro-computer's advanced processing capabilities empower the device to effectively handle image and video data, thereby equipping it with the potential to function as a wireless camera as well. This augmentation broadens the system's utility beyond conventional monitoring, enhancing its versatility to encompass visual data capture and transmission.

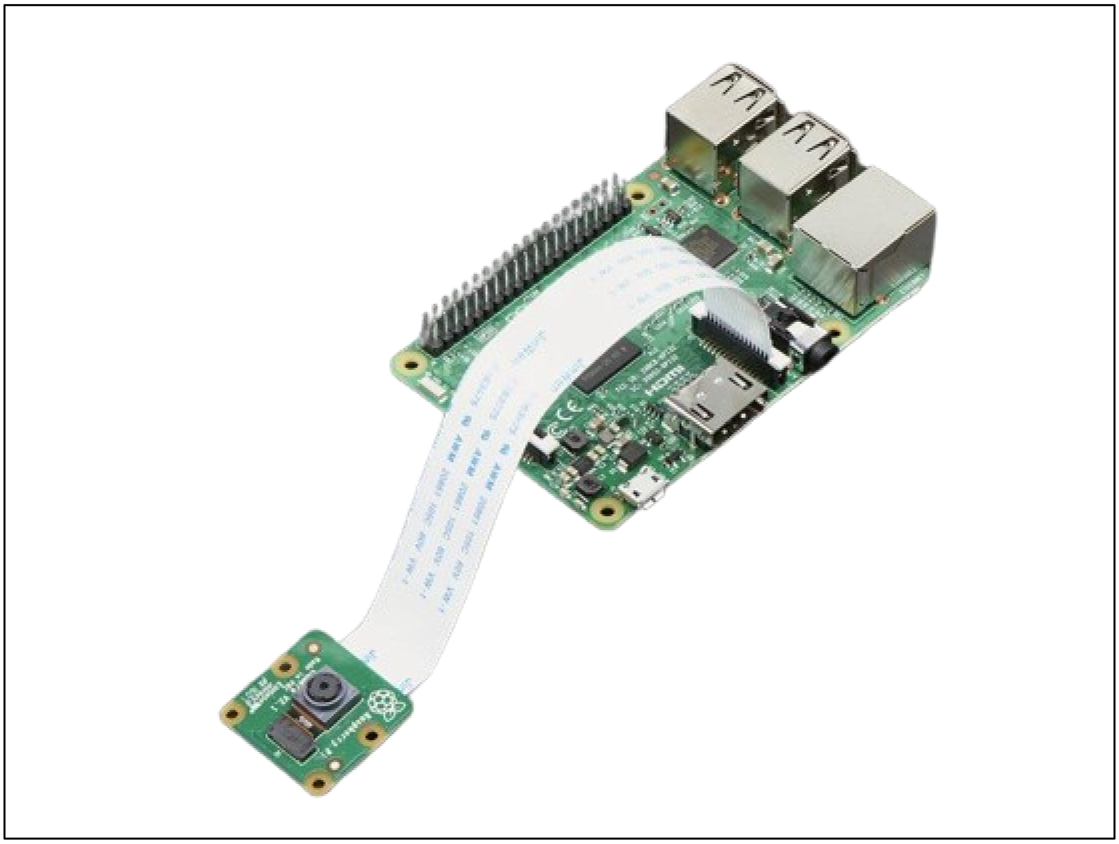


Figure 9 Raspberry Pi with Pi-Camera (Raspberry)

In this scenario, the Raspberry Pi microcomputer takes on a central role within the system, assuming the core responsibilities. Meanwhile, the Arduino board is tasked solely with data collection. The Raspberry Pi serves as the pivotal hub for both data collection and transmission, functioning not only as a central facility but also capable of operating as a compact server for data storage and comprehensive analysis.

Arduino Uno WiFi Rev2: The Arduino Wi-Fi Rev2 is an advanced development board that combines the functionality of the Arduino Uno with built-in Wi-Fi connectivity (Figure 10) (Arduino, 2021).

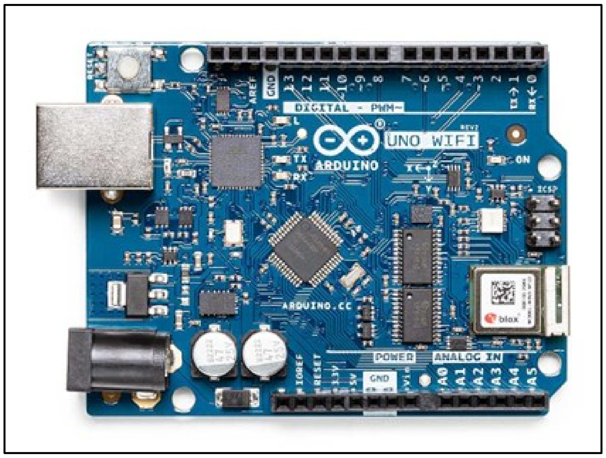


Figure 10 Arduino Uno Wi-Fi Rev2 (Arduino)

In contrast to previous methods, the Arduino Wi-Fi MCU possesses an integrated Wi-Fi module, obviating the necessity for an additional Wi-Fi connection module to facilitate wireless communication. This Wi-Fi enabled microcontroller unit boasts enhanced capabilities compared to the Arduino Uno while maintaining compatibility with the complete spectrum of sensors that are compatible with the Arduino Uno platform.

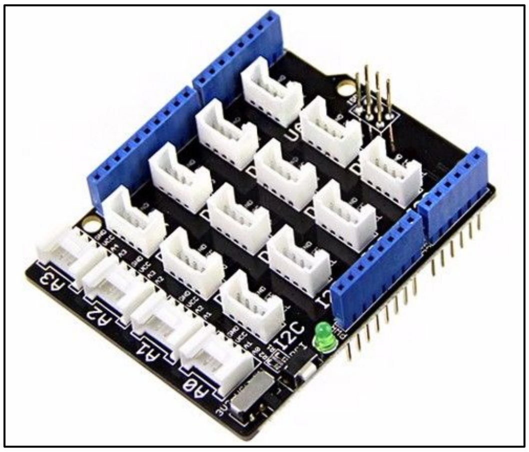


Figure 11 Base shield board (Base shield V2, 2023)

Facilitated by the base shield board as shown in Figure 11, which offers a streamlined means of connection with Arduino boards, the system dispenses with the need for breadboards and jumper wire setups. The amalgamation of these factors solidifies the Arduino Wi-Fi MCU as the ultimate and conclusive solution for our system.

3.3.3 Device construction

In general, the device unit is composed of sensors, the microcontroller unit (MCU), and a power supply, as visualized in the accompanying Figure 12. The microcontroller can derive power either from a 9V 1A AC DC 100V-240V Power Supply Adapter Cord, depicted in Figure 12 below, or through a USB connection to alternative power sources such as tablets or battery banks. Notably, for outdoor testing scenarios, a portable battery bank integrated with a solar charger is employed in this research. This configuration not only ensures portability but also yields promising outcomes for outdoor use.

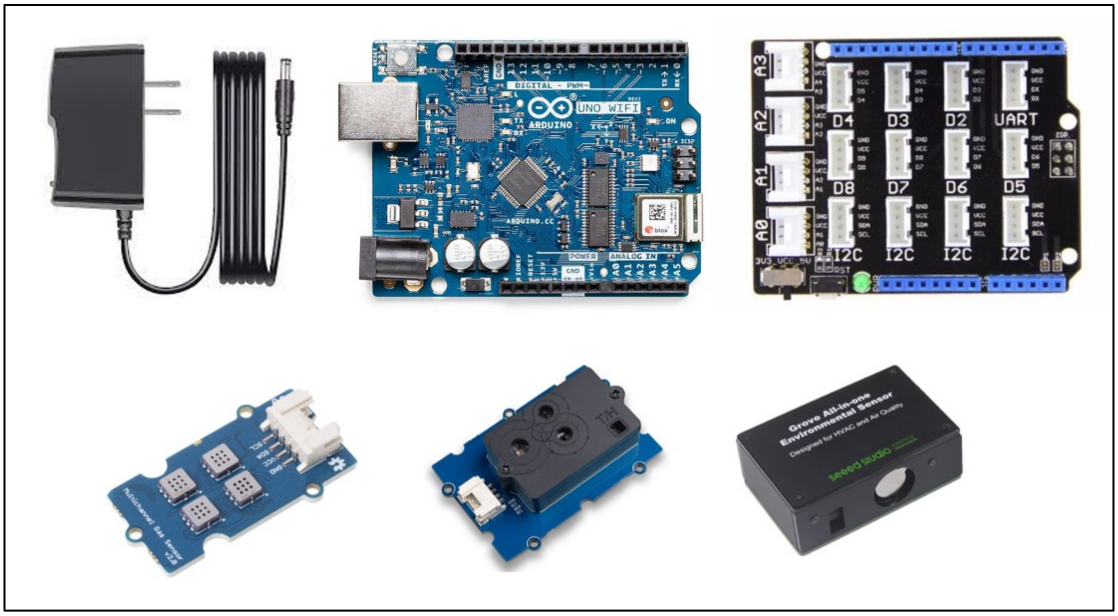


Figure 12 Parts in air monitoring unit

The provided Figure 13 displays the interconnected hardware components employed within the system. The microcontroller establishes I2C connections with sensors directly through the aid of the base shield. Both the power supply adapter and USB cable are linked to the MCU to ensure proper power provisioning. The device encompasses a range of sensor modules, including the SCD30 module for CO$_2$ measurement, the SEN54 module for PM$_{2.5}$ detection, and a multichannel sensor module catering to VOC and NO$_2$ measurements. Additionally, a sensor module for HCHO detection is integrated into the device. To facilitate effective ventilation inside the 3D-printed enclosure mentioned above, a mini-fan is also incorporated within the device's configuration.

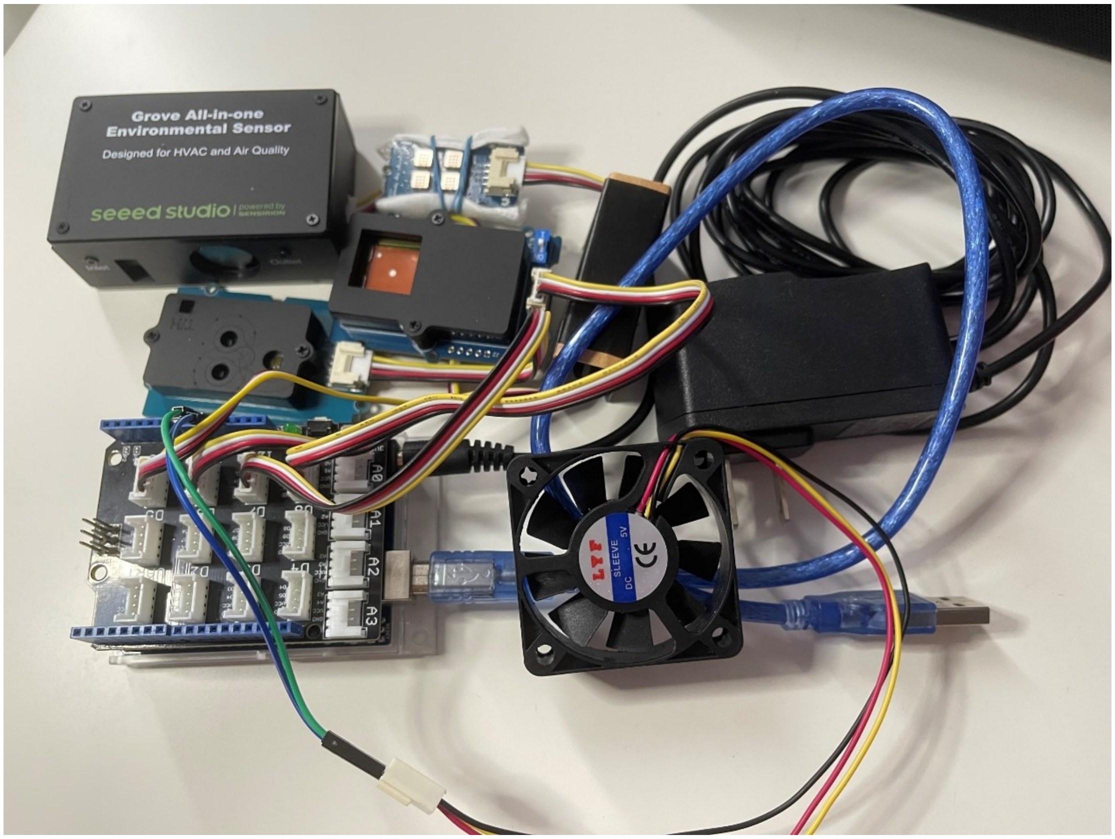


Figure 13 Connected device

3.4 Web Server

The web server is designed to effectively monitor and visualize the various parameters gathered by sensors within an indoor environment. The diagram in Figure 14 illustrates the step-by-step process of data transmission within the system. Sensor data is collected from multiple units situated in different rooms or spaces. These parameters are then transmitted through the local network to an online shared web server. Simultaneously, the data is automatically stored in a MySQL Database. To provide diverse perspectives on the collected data, multiple webpages have been created, each offering distinct visualization methods. The forthcoming sections will detail the step-by-step process of data transmission and storage, along with illustrative examples of data visualization.

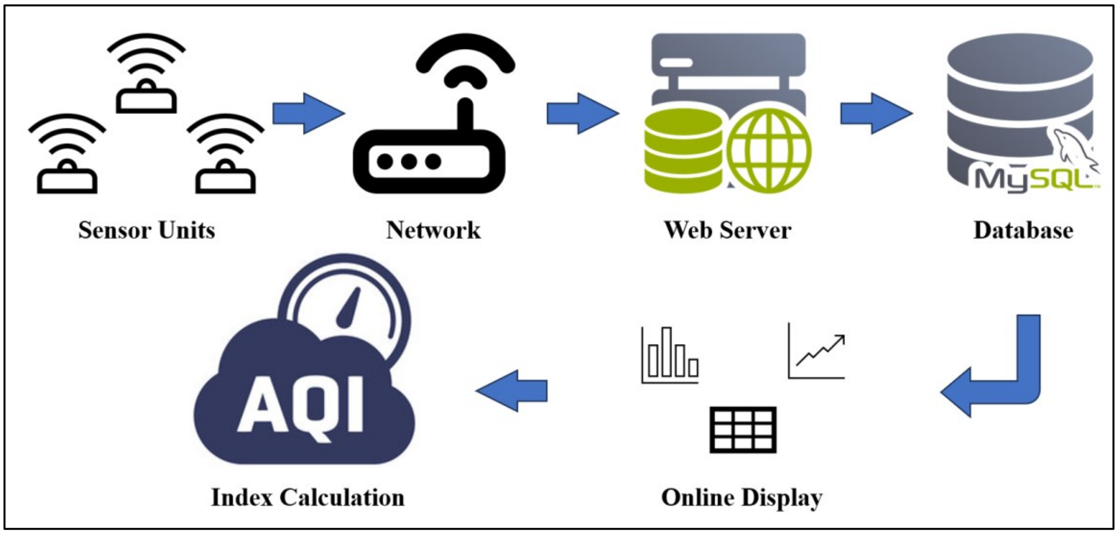


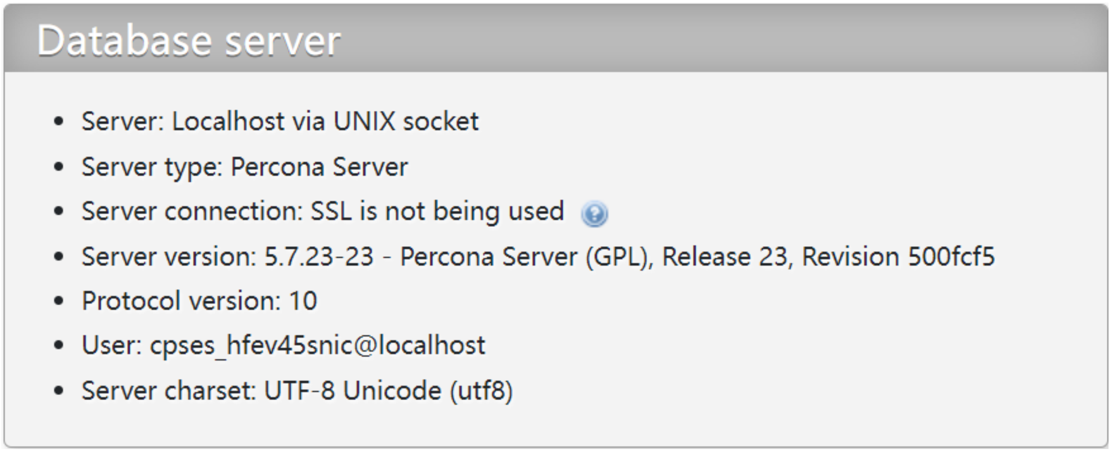
Figure 14 Architecture of air quality monitoring system

3.4.1 Server

Within this system, the choice of a reliable web hosting provider has led to the selection of an online shared server instead of a local self-made server to avoid power outage situations. An online shared server can offer a wide range of services to individuals, providing them with reliable hosting solutions for their websites. With its user-friendly control panel and website builder, users can easily manage their websites and create a professional online presence. Meanwhile, a robust database management capability is necessary, which allows users to efficiently store and access data.

3.4.2 Database

The MySQL database acts as a centralized storage facility for air parameter readings. MySQL is an open-source database management system which fast, reliable, scalable, and easy to use (Oracle, 2023). The web server is equipped with a pre-installed MySQL database (Figure 15), eliminating the need for additional setup. In the context of IoT applications, the “Arduino MySQL connector” library plays a vital role by facilitating the direct transmission of data from devices to the MySQL database via a Wi-Fi connection. By leveraging the online shared server, users can securely store and retrieve sensor data stored in the MySQL database.

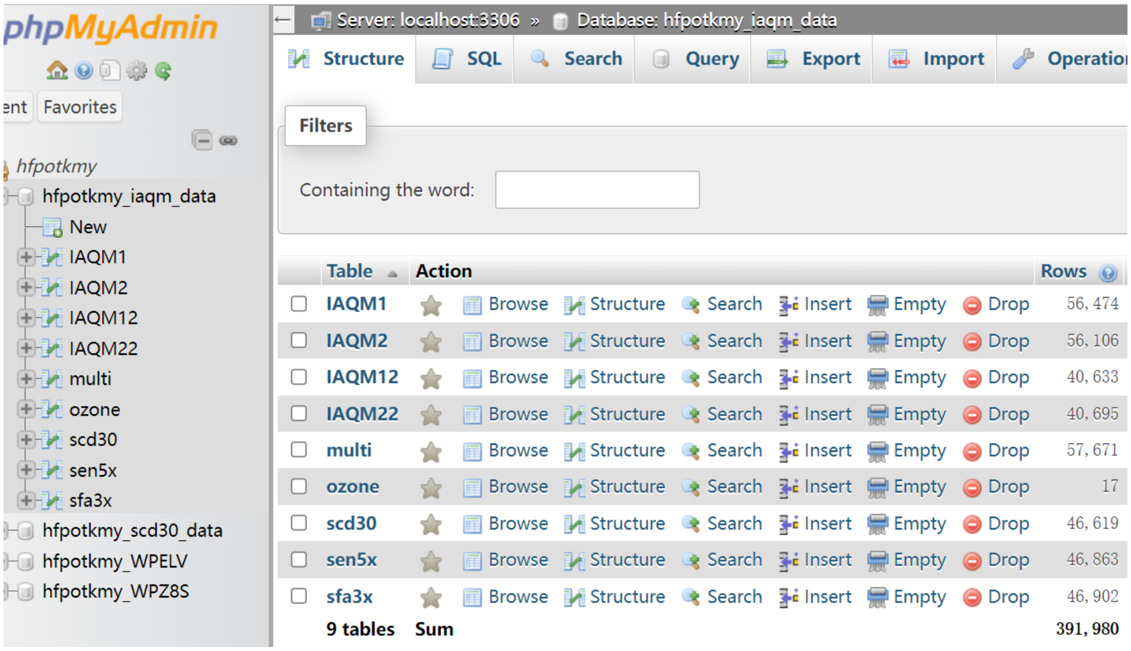


Database server

- Server: Localhost via UNIX socket
- Server type: Percona Server
- Server connection: SSL is not being used
- Server version: 5.7.23-23 - Percona Server (GPL), Release 23, Revision 500fcf5
- Protocol version: 10
- User: cpses_hfev45snic@localhost
- Server charset: UTF-8 Unicode (utf8)

Figure 15 MySQL database server information

The sensors operate in a continuous manner, consistently gathering real-time data and subsequently transmitting this data via the network. This transmission occurs when a Wi-Fi connection is available. The collected data is directed to predetermined tables within the database, as illustrated in Figure 16. These tables are specifically designated for individual sensor modules or the entire devices.

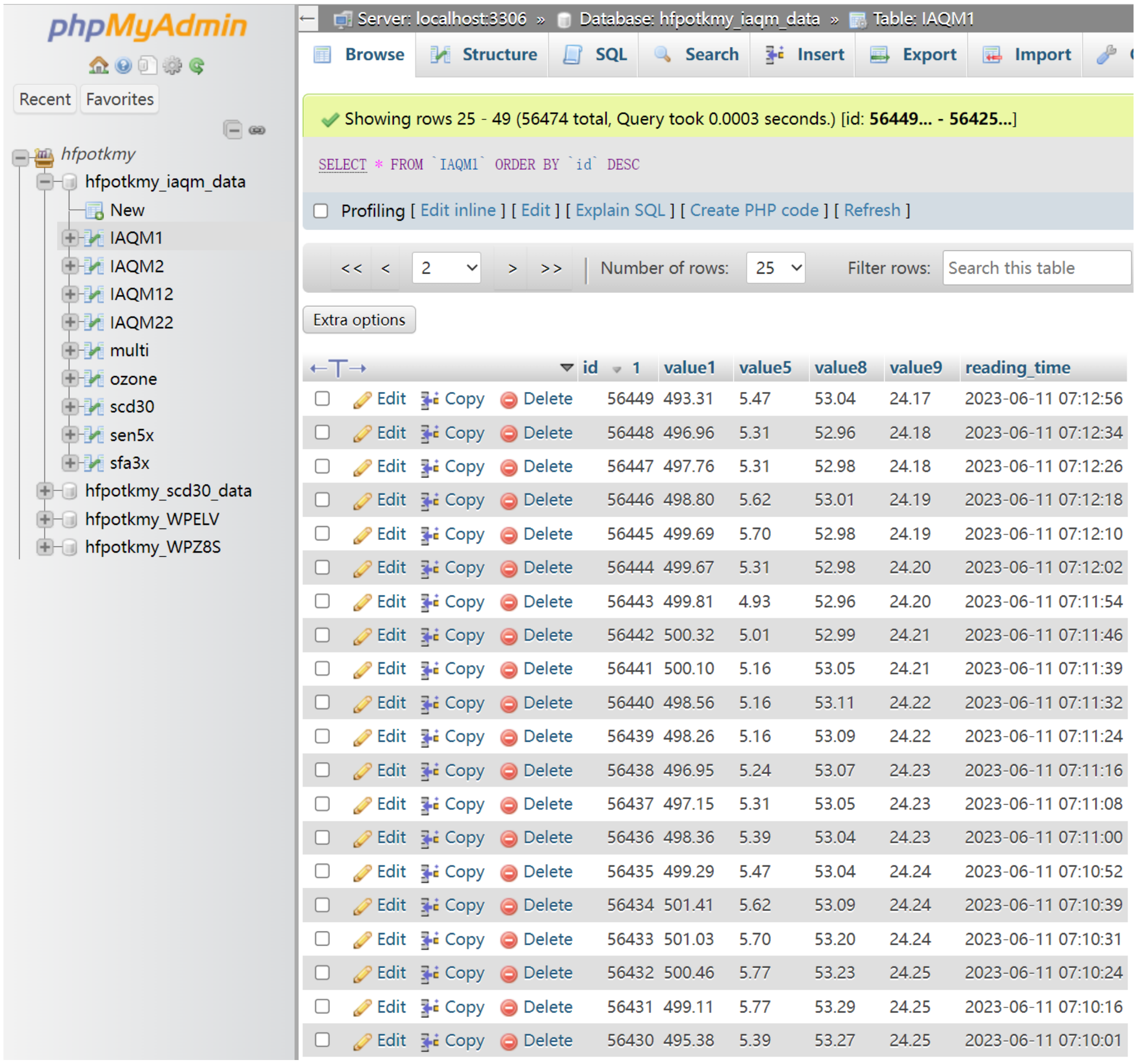


Containing the word:

	Table	Action							Rows
☐	IAQM1	☆	Browse	Structure	Search	Insert	Empty	Drop	56, 474
☐	IAQM2	☆	Browse	Structure	Search	Insert	Empty	Drop	56, 106
☐	IAQM12	☆	Browse	Structure	Search	Insert	Empty	Drop	40, 633
☐	IAQM22	☆	Browse	Structure	Search	Insert	Empty	Drop	40, 695
☐	multi	☆	Browse	Structure	Search	Insert	Empty	Drop	57, 671
☐	ozone	☆	Browse	Structure	Search	Insert	Empty	Drop	17
☐	scd30	☆	Browse	Structure	Search	Insert	Empty	Drop	46, 619
☐	sen5x	☆	Browse	Structure	Search	Insert	Empty	Drop	46, 863
☐	sfa3x	☆	Browse	Structure	Search	Insert	Empty	Drop	46, 902
	9 tables	Sum							391, 980

Figure 16 Table list in the database

In the case study, the unit being tested necessitates two tables to store the data. Table "IAQM1" is used to store CO$_2$, PM$_{2.5}$, humidity, and temperature values, along with the corresponding datetime when these values are collected. Table "IAQM2" is used to store CO, HCHO, NO$_2$, and VOC values. Figure 17 is table IAQM1. The column "reading_time" represents the date and time when each row of data is sent from the MCU (Microcontroller Unit) and received by the database. The recorded time in the database is based on the time zone of the webserver. However, for data display and presentation purposes, the system needs to modify the time zone to show the results accurately to the end-users.



Server: localhost:3306 » Database: hfpotkmy_iaqm_data » Table: IAQM1

✓ Showing rows 25 - 49 (56474 total, Query took 0.0003 seconds.) [id: **56449... - 56425...**]

```
SELECT * FROM `IAQM1` ORDER BY `id` DESC
```

☐ Profiling [Edit inline] [Edit] [Explain SQL] [Create PHP code] [Refresh]

<< < 2 > >> | Number of rows: 25 Filter rows: Search this table

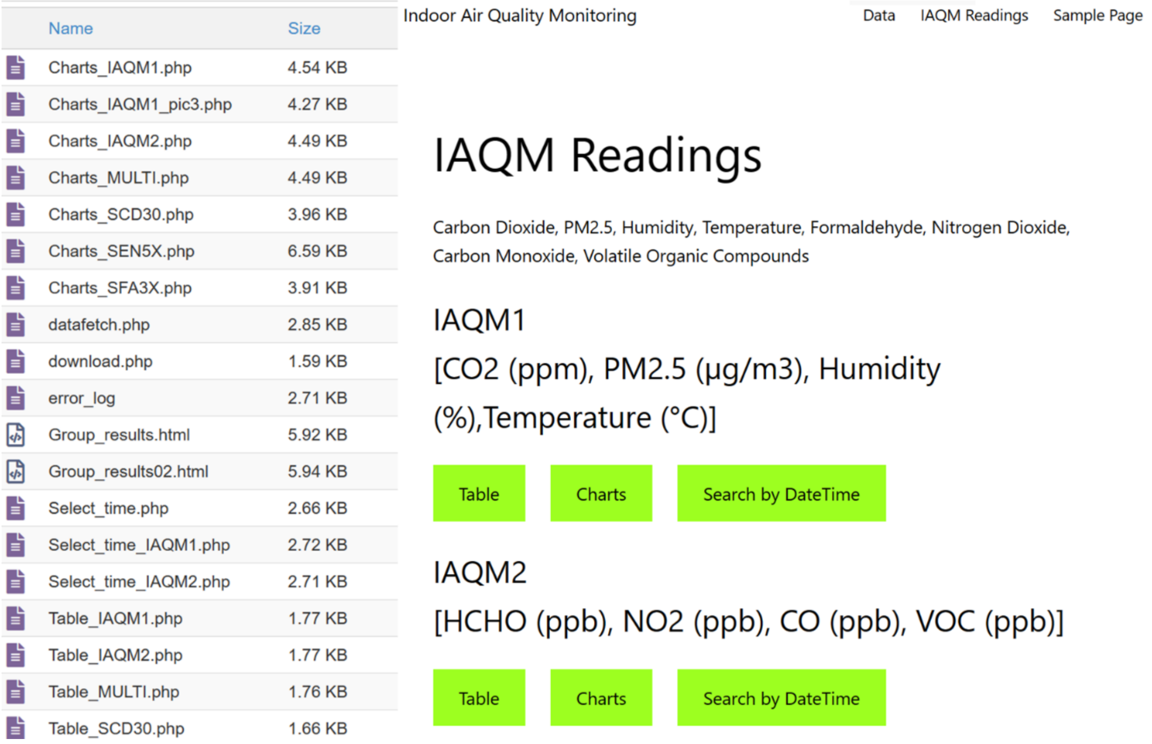
←T→				id ▾ 1	value1	value5	value8	value9	reading_time
☐	Edit	Copy	Delete	56449	493.31	5.47	53.04	24.17	2023-06-11 07:12:56
☐	Edit	Copy	Delete	56448	496.96	5.31	52.96	24.18	2023-06-11 07:12:34
☐	Edit	Copy	Delete	56447	497.76	5.31	52.98	24.18	2023-06-11 07:12:26
☐	Edit	Copy	Delete	56446	498.80	5.62	53.01	24.19	2023-06-11 07:12:18
☐	Edit	Copy	Delete	56445	499.69	5.70	52.98	24.19	2023-06-11 07:12:10
☐	Edit	Copy	Delete	56444	499.67	5.31	52.98	24.20	2023-06-11 07:12:02
☐	Edit	Copy	Delete	56443	499.81	4.93	52.96	24.20	2023-06-11 07:11:54
☐	Edit	Copy	Delete	56442	500.32	5.01	52.99	24.21	2023-06-11 07:11:46
☐	Edit	Copy	Delete	56441	500.10	5.16	53.05	24.21	2023-06-11 07:11:39
☐	Edit	Copy	Delete	56440	498.56	5.16	53.11	24.22	2023-06-11 07:11:32
☐	Edit	Copy	Delete	56439	498.26	5.16	53.09	24.22	2023-06-11 07:11:24
☐	Edit	Copy	Delete	56438	496.95	5.24	53.07	24.23	2023-06-11 07:11:16
☐	Edit	Copy	Delete	56437	497.15	5.31	53.05	24.23	2023-06-11 07:11:08
☐	Edit	Copy	Delete	56436	498.36	5.39	53.04	24.23	2023-06-11 07:11:00
☐	Edit	Copy	Delete	56435	499.29	5.47	53.04	24.24	2023-06-11 07:10:52
☐	Edit	Copy	Delete	56434	501.41	5.62	53.09	24.24	2023-06-11 07:10:39
☐	Edit	Copy	Delete	56433	501.03	5.70	53.20	24.24	2023-06-11 07:10:31
☐	Edit	Copy	Delete	56432	500.46	5.77	53.23	24.25	2023-06-11 07:10:24
☐	Edit	Copy	Delete	56431	499.11	5.77	53.29	24.25	2023-06-11 07:10:16
☐	Edit	Copy	Delete	56430	495.38	5.39	53.27	24.25	2023-06-11 07:10:01

Figure 17 Table IAQM1 (data for CO_2, $PM_{2.5}$, humidity and temperature with reading time)

3.4.3 Data visualization

The establishment of the web server setup introduces a crucial and innovative feature that revolves around the creation of dynamic data display webpages. This novel capability empowers users with the ability to harness the potential of the sensor data in a multitude of flexible and creative ways. By leveraging PHP, a versatile scripting language, users can craft visually engaging representations of the collected data, seamlessly translating raw numbers into meaningful insights through interactive tables and charts. This visual representation not only enhances the accessibility of the information but also provides a visual narrative that aids in comprehending trends and patterns.

Furthermore, the web server setup goes beyond mere static data representation, ushering in the era of real-time data visualization. Users are enabled to observe the data as it is generated, facilitating an instantaneous understanding of fluctuations and immediate reactions to changing conditions. This real-time aspect offers a dynamic layer to the data analysis process, allowing for prompt decision-making and the identification of anomalies or critical events.



Name	Size
Charts_IAQM1.php	4.54 KB
Charts_IAQM1_pic3.php	4.27 KB
Charts_IAQM2.php	4.49 KB
Charts_MULTI.php	4.49 KB
Charts_SCD30.php	3.96 KB
Charts_SEN5X.php	6.59 KB
Charts_SFA3X.php	3.91 KB
datafetch.php	2.85 KB
download.php	1.59 KB
error_log	2.71 KB
Group_results.html	5.92 KB
Group_results02.html	5.94 KB
Select_time.php	2.66 KB
Select_time_IAQM1.php	2.72 KB
Select_time_IAQM2.php	2.71 KB
Table_IAQM1.php	1.77 KB
Table_IAQM2.php	1.77 KB
Table_MULTI.php	1.76 KB
Table_SCD30.php	1.66 KB

IAQM Readings

Carbon Dioxide, PM2.5, Humidity, Temperature, Formaldehyde, Nitrogen Dioxide, Carbon Monoxide, Volatile Organic Compounds

IAQM1

[CO2 (ppm), PM2.5 (μg/m3), Humidity (%),Temperature (°C)]

IAQM2

[HCHO (ppb), NO2 (ppb), CO (ppb), VOC (ppb)]

Figure 18 User interface based on PHP files in server, webpage to display IAQM readings

The provided files in Figure 18 encompass two main categories: webpages accessible through web browsers and foundational code for data calculation and interpretation. The webpages are designed for easy access through standard web browsers, offering users an interactive gateway to engage with the data and insights. They can be directly navigated from the main website or accessed through specific link addresses. This ensures a seamless user experience on both PCs and mobile phones. Complementing these webpages are the PHP files, which serve as the backbone for data computation and interpretation. These files are essential for processing and presenting collected data in a coherent and meaningful manner. They provide the necessary logic and functionality to generate valuable insights. These PHP files offer versatile access, enabling users to harness their capabilities through web browsers on PCs or mobile phones. This contributes to a flexible and intuitive environment for exploration and analysis.

Data from the user interface can be fetched to display in terms of time series graphs in web page view displays (Figure 19). Within each chart, the x-axis is designated to depict both time and date parameters. Remarkably, these charts possess the capacity to dynamically access and display the most recent data entries stored within the database. For heightened adaptability, the quantity of data points exhibited can be customized to align precisely with specific requirements.

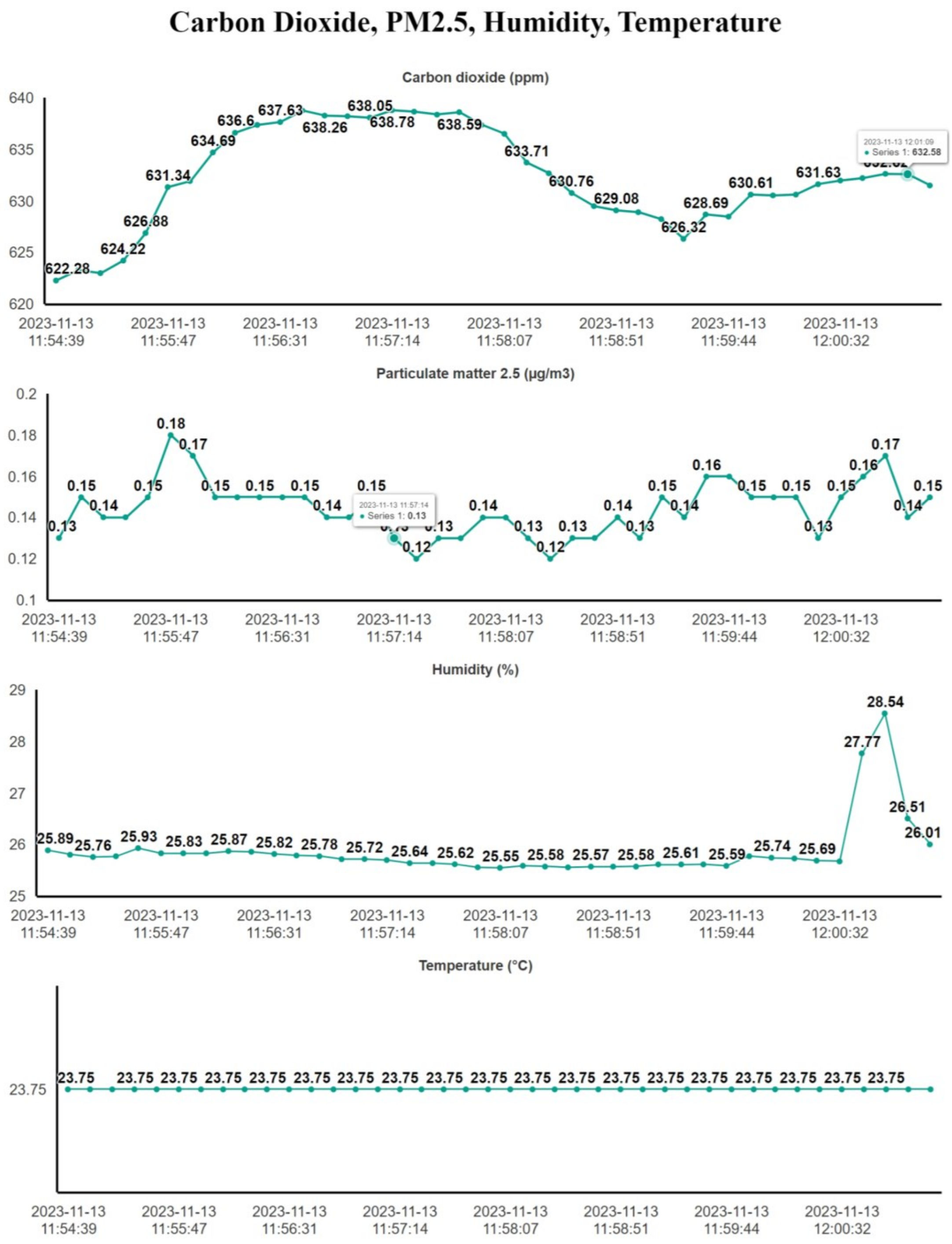
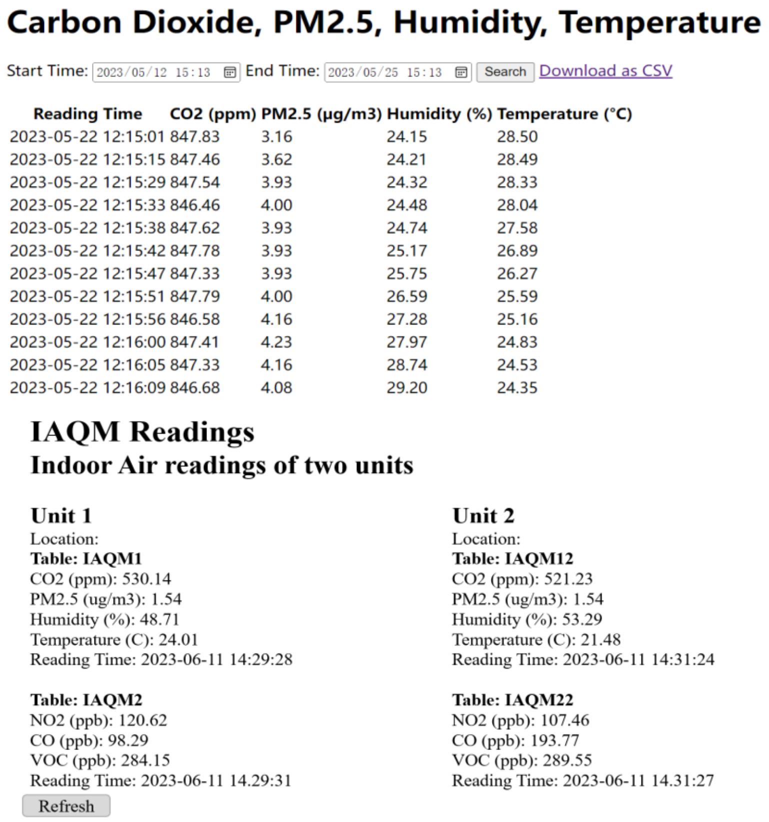


Figure 19 Graphical depiction of real-time measurements of CO_2, $PM_{2.5}$, humidity and temperature. The x-axis of each chart represents the time and date

The server's functionality includes specialized features tailored to enhance user experience. This encompasses the ability to search and retrieve data based on specific Date and Time parameters, as well as the capability to compare results across two or more units (Figure 20). These functions significantly enhance analytical precision and efficiency. By enabling users to extract data relevant to specific periods, the server streamlines in-depth analysis and historical review. Moreover, the comparative function provides a holistic perspective by presenting real-time data from multiple units concurrently. This empowers users to monitor various locations simultaneously, facilitating insights into performance variations and aiding informed decision-making.



Carbon Dioxide, PM2.5, Humidity, Temperature

Start Time: 2023/05/12 15:13 End Time: 2023/05/25 15:13

Reading Time	CO2 (ppm)	PM2.5 (µg/m3)	Humidity (%)	Temperature (°C)
2023-05-22 12:15:01	847.83	3.16	24.15	28.50
2023-05-22 12:15:15	847.46	3.62	24.21	28.49
2023-05-22 12:15:29	847.54	3.93	24.32	28.33
2023-05-22 12:15:33	846.46	4.00	24.48	28.04
2023-05-22 12:15:38	847.62	3.93	24.74	27.58
2023-05-22 12:15:42	847.78	3.93	25.17	26.89
2023-05-22 12:15:47	847.33	3.93	25.75	26.27
2023-05-22 12:15:51	847.79	4.00	26.59	25.59
2023-05-22 12:15:56	846.58	4.16	27.28	25.16
2023-05-22 12:16:00	847.41	4.23	27.97	24.83
2023-05-22 12:16:05	847.33	4.16	28.74	24.53
2023-05-22 12:16:09	846.68	4.08	29.20	24.35

IAQM Readings

Indoor Air readings of two units

Unit 1
Location:
Table: IAQM1
CO2 (ppm): 530.14
PM2.5 (ug/m3): 1.54
Humidity (%): 48.71
Temperature (C): 24.01
Reading Time: 2023-06-11 14:29:28

Table: IAQM2
NO2 (ppb): 120.62
CO (ppb): 98.29
VOC (ppb): 284.15
Reading Time: 2023-06-11 14.29:31

Unit 2
Location:
Table: IAQM12
CO2 (ppm): 521.23
PM2.5 (ug/m3): 1.54
Humidity (%): 53.29
Temperature (C): 21.48
Reading Time: 2023-06-11 14:31:24

Table: IAQM22
NO2 (ppb): 107.46
CO (ppb): 193.77
VOC (ppb): 289.55
Reading Time: 2023-06-11 14.31:27

Figure 20 Webpages of search function & two units' display

Delving into the benefits of this multifaceted functionality, it becomes evident that this web server setup introduces a structured and user-friendly avenue for analyzing and interpreting the data. Through the amalgamation of visual tools, real-time insights, and targeted data extraction, users are equipped to derive meaningful conclusions, thus facilitating informed decision-making and actionable insights. Furthermore, the inclusion of auxiliary features such as Email alerts ensures that users are promptly notified of critical developments, enhancing the system's utility in applications requiring swift responses.

3.5 Air Quality Index Model for Indoor Environments

The concept of the indoor air quality index is to assess and evaluate the quality of air within enclosed spaces, such as buildings or homes. It aims to provide a comprehensive measure of indoor air quality by considering several factors that contribute to the overall environment. According to Rastogi and Lohani (2022), an adaptive neuro-fuzzy inference system (ANFIS) was developed to assess IAQ in enclosed spaces, specifically focusing on classroom environments. The ANFIS model utilizes three key indicators—percent of dissatisfied people (PPD), ventilation rate (VR), and Air Quality Index (AQI) data—as sub-indices to evaluate IAQ. In this study, the methodology proposed by Rastogi and Lohani (2022) will be used, utilizing the three sub-indices, namely thermal comfort, ventilation rate, and pollutant concentrations, as the fundamental indicators for evaluating the air quality within enclosed spaces (Figure 21) (Rastogi & Lohani, 2022).

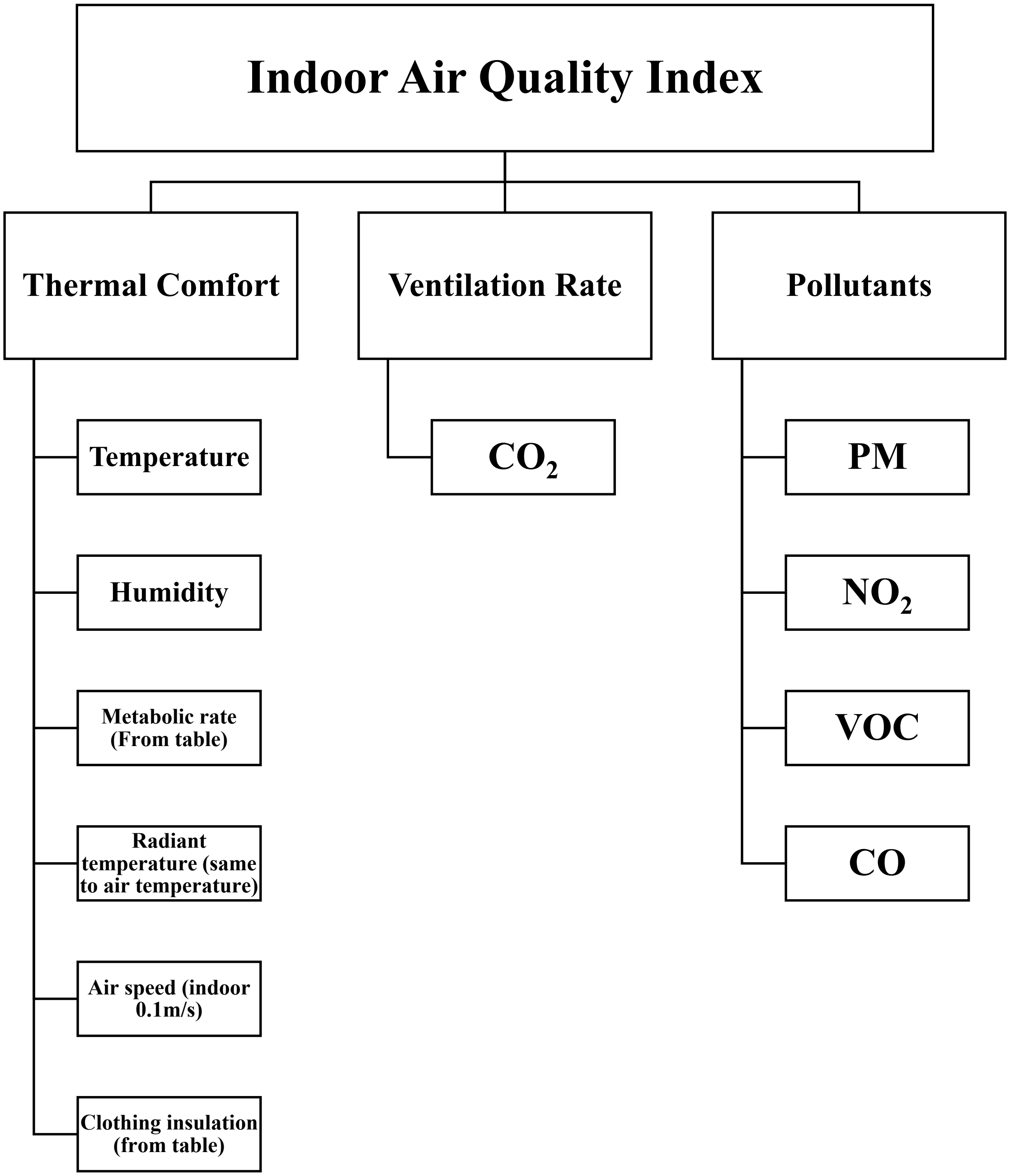


Figure 21 Indoor air quality index model

3.5.1 Thermal comfort

Thermal comfort refers to the condition of mind or sensation that indicates satisfaction with the thermal environment (ASHRAE Standard 55, 2010). This sub-index assesses the level of comfort experienced by predicted mean vote (PMV) and predicted percentage dissatisfied (PPD) (Figure 22), which are determined by two main factors: temperature and humidity.

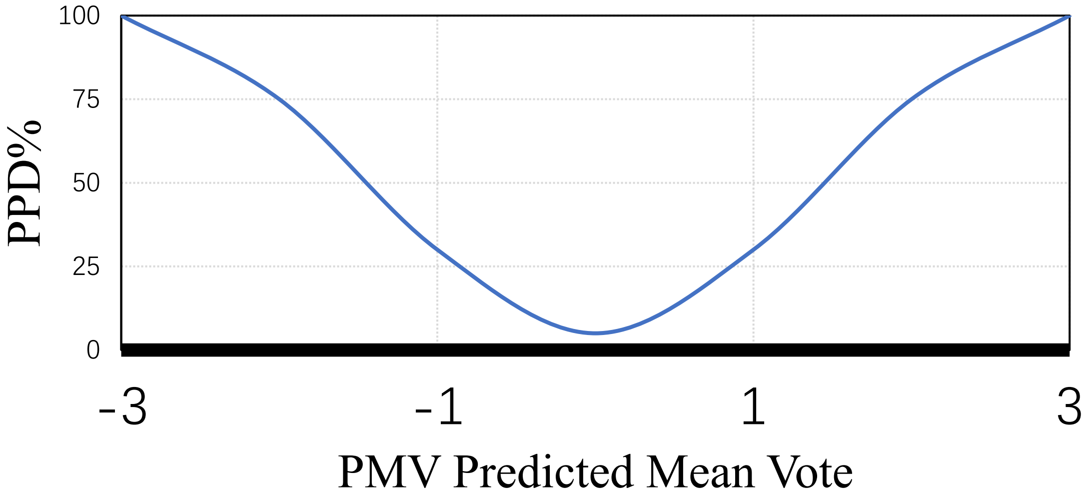


Figure 22 PMV & PPD

PMV is a measure of the average thermal sensation experienced by a group of individuals in a particular indoor environment (ASHRAE Standard 55, 2010). It considers numerous factors such as air temperature, mean radiant temperature, air velocity, humidity, and clothing insulation. The PMV scale ranges from -3 (feeling very cold) to +3 (feeling very hot) (Figure 22), with zero representing a thermally neutral state.

The equation for calculating PMV is as follows (ASHRAE Standard 55, 2010):

$$PMV = TS * (MW - HL1 - HL2 - HL3 - HL4 - HL5 - HL6) \quad (1)$$

In Equation (1), various parameters related to thermal comfort are used including clothing insulation (in m2·K/W), metabolic rate (in W/m2), external work (in W/m2), air Temperature (in degrees Celsius), mean radiant temperature (in degrees Celsius), relative air velocity (in m/s), relative humidity (in %), water vapour pressure (in Pa).

PMV represents the Predicted Mean Vote. TS is the thermal sensation transfer coefficient. MW stands for the internal heat production in the human body, calculated as the metabolic rate (MET) minus external work (WME). HL1 represents heat loss through the skin. HL2 represents heat loss by sweating, with different calculations for those with metabolic rates greater than or equal to 58.15 W/m² and those with lower metabolic rates. HL3 is the latent respiration heat loss. HL4 is the dry respiration heat loss. HL5 is the heat loss by radiation. HL6 represents the heat loss by convection.

The method for calculating the PMV involves several distinct steps. First, provide essential parameters related to thermal comfort, such as clothing insulation, metabolic rate, external work, air temperature, mean radiant temperature, relative air velocity, and humidity or water vapour pressure. Second, calculate saturated vapour pressure based on air temperature and subsequently calculate water vapour pressure if it's not provided. Then, convert the metabolic rate and external work into appropriate units and calculate the thermal insulation of clothing. The clothing area factor is determined next. Heat transfer coefficients for forced and natural convection are calculated, and an iterative process is employed to estimate the surface temperature of clothing.

Various components of heat loss are computed, such as heat loss through skin (HL1), heat loss by sweating (HL2), latent respiration heat loss (HL3), dry respiration heat loss (HL4), heat loss by radiation (HL5), and heat loss by convection (HL6). These components reflect different aspects of heat exchange with the environment. The thermal sensation transfer coefficient (TS) is a critical factor that represents an individual's perception of thermal comfort. The calculated PMV value indicates the overall thermal comfort level. A positive PMV suggests warmth, a negative value implies cold, and a value close to zero indicates comfort.

PPD represents the percentage of individuals within a group who are expected to feel dissatisfied with their thermal comfort conditions. The equation for calculating PPD is as follows (ASHRAE Standard 55, 2010):

$$PPD = 100 - 95 * e^{-0.03353*PMV^4 - 0.2179*PMV^2} \tag{2}$$

It is calculated based on the difference between an individual's thermal sensation vote (on a seven-point thermal sensation scale) and the PMV value. Table 3 shows the relationship between PPD and Thermal Comfort.

Table 3 ASHRAE thermal comfort index (ASHRAE Standard 55-2010, Thermal Environmental Conditions for Human Occupancy, 2010)

PPD	**Category**
0-10	Satisfactory
10-25	Moderate
25-50	Poor
50-75	Very Poor
75-100	Severe

3.5.2 Ventilation rate

As a comprehensive approach to assessing indoor air quality, incorporating ventilation rate as a sub-index offers a nuanced perspective that underscores the critical role of fresh air exchange. This method enhances the accuracy of indoor air quality evaluations and encourages a focus on maintaining optimal ventilation levels.

The utilization of indoor CO_2 concentrations serves as a widely adopted approach to estimate ventilation rates per person, achieved through the application of a single-zone CO_2 mass balance (Persily & de Jonge, 2017). The ASHRAE-62 standard delves into the connection between ventilation rates and CO_2 concentration in scenarios of steady-state conditions. By maintaining consistent values for generation rate, ventilation rate, and outdoor CO_2 concentration over the duration of mass balance analysis, the steady-state equation takes on the form:

$$Q_O = \frac{G}{C_{in,ss} - C_{out}} \tag{3}$$

The ASHRAE 62 standard, specifically ASHRAE Standard 62.1 and ASHRAE Standard 62.2, provides guidelines for ventilation rates in commercial and residential buildings, respectively. These standards aim to ensure adequate indoor air quality by specifying the minimum ventilation rates required to dilute indoor air pollutants and maintain a healthy environment. In indoor environments, the ASHRAE 62 standard recommends a ventilation air supply of fifteen cubic feet per minute (cfm) or greater, as indicated in Table 4.

Table 4 ASHRAE VR category (ASHRAE Standard 62-2001, Ventilation for Acceptable Indoor Air Quality, 2001)

Range	VR Category
>15	Satisfactory
13-15	Moderate
11-13	Poor
9-11	Very Poor
<9	Severe

3.5.3 Pollutant concentrations

The pollutant concentrations sub-index assesses the presence of diverse pollutants within indoor air. This index includes pollutants such as particulate matter, volatile organic compound (VOC), carbon dioxide (CO_2), nitrogen dioxide (NO_2) and other potentially hazardous gases like formaldehyde (HCHO) if present. By monitoring these pollutant levels, potential health hazards can be identified, facilitating the implementation of necessary measures to mitigate exposure and ensure safety.

Distinct pollutants necessitate diverse standards and methods for index calculation. For instance, the AQHI standard from the Canada National Standard may be employed to compute particulate matter and Nitrogen Dioxide (Canada, 2021), while VOC levels could be determined according to WHO standards. Post-establishing hazard levels for each pollutant, the sub-index value is derived from the highest index value attained, aligning with the most critical pollutant in the mix.

The AQHI from Canada National Standard (Canada, 2021) is :

$$PM_{2.5}AQHI = \frac{10}{10.4} \times \left\{100 \times \left[\left(e^{(0.000537 \times O_3)} - 1\right) + \left(e^{(0.000871 \times NO_2)} - 1\right) + \left(e^{(0.000487 \times PM_{2.5})} - 1\right)\right]\right\} \quad (4)$$

TVOC standards:

a) Indoor Air Quality Levels from German Federal Environmental Agency.

The German Federal Environmental Agency translates TVOC concentration, measured in parts per billion (ppb), onto a logarithmic scale, categorizing it into five distinct indoor air quality levels (IAQ), as demonstrated in Table 5.

Table 5 TVOC index - German federal environmental agency (Beurteilung von Innenraumluftkontaminationen mittels referenz- und Richtwerten., 2007)

Level	Hygienic Rating	Recommendation	Exposure Limit	TVOC
Unhealthy	Situation not acceptable	Use only if unavoidable / Intense ventilation necessary	hours	2.2 - 5.5
Poor	Major objections	Intensified ventilation / airing necessary Search for sources	< 1 month	0.66 - 2.2
Moderate	Some objections	Intensified ventilation / air recommended Search for sources	< 12 months	0.22 – 0.66
Good	No relevant objections	Ventilation / air recommended	no limit	0.065 – 0.22
Excellent	No objections	Target value	no limit	0 – 0.065

b) Air Quality Guidelines from the World Health Organization (WHO)

The World Health Organization (WHO) has issued indoor air quality guidelines specifically for Europe, categorizing them based on TVOC concentration values. Table 6 below enumerates various air quality classes along with their corresponding thresholds for TVOC concentration.

Table 6 TVOC Levels – WHO (Air quality guidelines for Europe – Second Edition; hg. v. World Health Organization – WHO, Copenhagen (2000). Directive for the assessment of the indoor air, published by the working group on indoor air in the Ministry of Sustainability and Tourism (BMNT) and the Commission for Clean Air of the Austrian Academy of Sciences (KRL). Vienna (2014).)

Level	Recommendation	TVOC [mg/m^3]	TVOC[ppm]
Outside quality classes	Greatly increased (not acceptable)	> 3.0	> 0.61
4	Significantly increased (only temporary exposure)	1.0 – 3.0	0.20 – 0.61
3	Slightly increased (harmless)	0.5 – 1.0	0.10 – 0.20
1	Target value	> 0.25	0 -0.05

3.6 Summary

In summary, this chapter provides a comprehensive outline of the envisioned IoT-sensor based air quality monitoring system. The system is composed of essential components: the hardware encompassing the MCU and sensors responsible for data collection, the web server accountable for data storage and visualization, and the indoor air quality index model designed to offer a clear assessment of air cleanliness. the system stands out with its attributes of cost-effectiveness, portability, and efficiency. Moreover, its adaptability and capacity for customization make it well-suited for addressing specific scenarios, thereby serving as a valuable tool for assessing indoor environments.

CHAPTER 4: RESULTS AND DISCUSSION

4.1 Calibration and Study Cases

Within this chapter, the system's performance will be detailed through the exploration of two distinct case studies as shown in Figure 23.

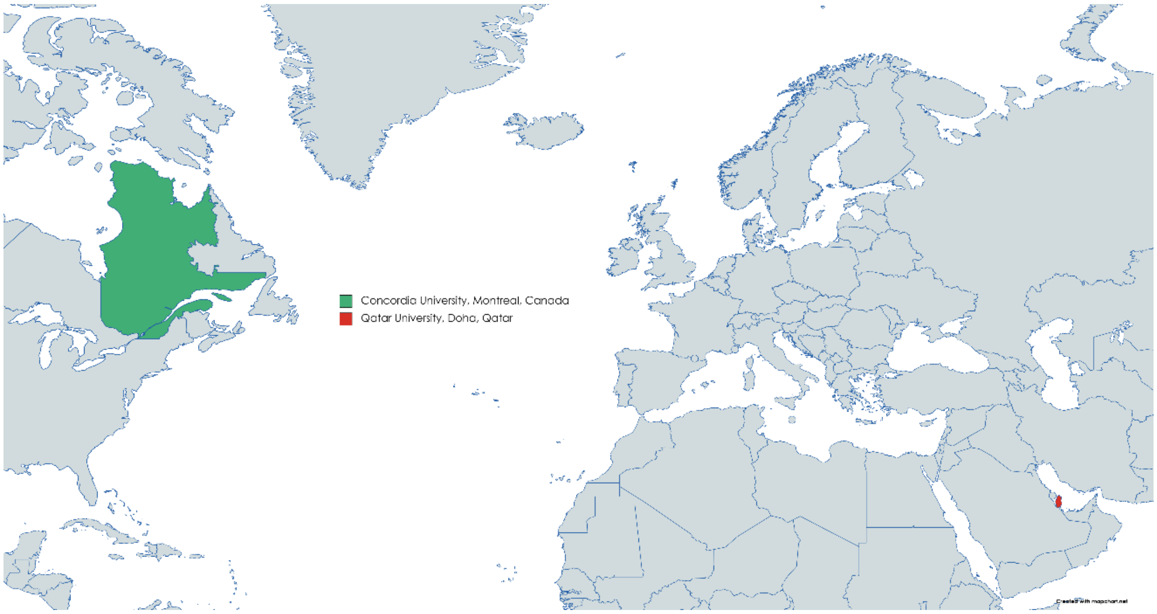


Figure 23 Locations of 2 field case studies of Concordia University, Montreal and Qatar University, Doha

Two case studies were conducted: one at Concordia University, Montreal, Canada and another at Qatar University, Doha, Qatar. At Concordia University, sensors underwent testing across a range of settings, such as offices, classrooms, garages, and outdoor spaces, to validate their adaptability. At Qatar University, two integrated units with sensors and an online display system were deployed. Multiple locations within the Qatar University Environment Science Center were assessed to evaluate sensor reading consistency and their alignment with commercial instrument measurements. Notably, the unique climates of these locations pose distinct air quality considerations. From Montreal's harsh winters to Doha's arid desert climate, both sites offer a diverse range of temperature variations and air compositions that will put the system to the test. Then, an example will illustrate the practical application of the indoor air quality index. The concluding section of the chapter will provide an in-depth discussion of the system's overall performance and functionality.

The results in Table 7 demonstrate the improvement achieved through proper calibration and modification. The enhanced accuracy results from the implementation of novel calibration methods, updated code, and refined data interpretation techniques applied to the sensors, as discovered through the case studies.

Table 7 Accuracy improvements

	Before calibration		After calibration	
Parameter	Absolute difference	Maximum deviation	Absolute difference	Maximum deviation
CO2	<35%	262 ppm	<10%	35 ppm
PM2.5	<54%	172 µg/m3	<10%	62 µg/m3
NO2	<38%	54 ppb	<15%	20 ppb
VOC	<25%	128 ppb	<15%	54 ppb

In two field case studies, data from all Arduino sensors were collected and thoroughly analyzed in comparison with readings from commercial instruments to assess sensor accuracy and identify avenues for further improvement. The analyses encompassed the following aspects.

First, similarities and major differences between sensor data and commercial instrument readings were sought to determine sensor performance and identify potential systematic errors. Second, the correlation and degree of correlation between system readings and commercial instrument readings were evaluated, contributing to the understanding of sensor reliability and suitability in real-world environments. Third, further analysis was conducted to understand the reasons for major differences between the datasets and explore methods to reduce these disparities.

For parameters with higher correlation, extensive data were utilized to obtain the distribution of reading differences. Based on these distributions, the main percentage range of reading differences was identified, and calibration methods and code corrections were tailored for the sensors. This involved providing simple multiplication factors or offering different calculation formulas for varying concentrations based on the identified range.

For parameters exhibiting lower correlation, a systematic evaluation of contributing factors is essential. Strategies are then formulated based on these identified factors. Subsequently, a comprehensive analysis of diverse data is employed to identify breakthroughs in alternative directions or necessitate fundamental modifications from the foundational program level. In this study, VOC readings were notably susceptible to temperature influences, resulting in substantial errors and weak correlation. However, extensive data comparisons revealed a close alignment between the predictive trend line of VOC and the readings from the commercial instrument. Therefore, enhancement strategies for this sensor include mitigating the impact of temperature variables and reducing errors through the generation of data-driven predictive trend lines or calculating averages over specific time intervals.

4.2 Field Case Study 1

4.2.1 Concordia University campus building

This case study focused on the validation of each sensor to see which parameter's reading is reliable and which sensor can be used in the system. Sensors have been tested in several locations near Concordia indoors and outdoors (Figure 23).

Figure 24 Locations to install air quality monitoring sensors for case study 1

Several tests were conducted to validate the functionality of sensors intended for use in a device. These sensors were designed to measure various air quality parameters, including NO_2, $PM_{2.5}$, TVOC, CO, CO_2, Temperature, and Humidity.

The validation process involved conducting tests in different environments, such as indoor and outdoor settings. For most parameters, direct measurements of indoor and outdoor concentrations were taken. However, since the concentrations of certain pollutants are typically too low under normal circumstances or fall within safe levels, additional tests were performed in specialized environments. For example, measurements were taken near traffic to capture higher levels of air pollutants, carbon monoxide (CO) readings were obtained in an underground garage to obtain elevated CO values and $PM_{2.5}$ measurements were conducted using lighting candles to increase $PM_{2.5}$ concentrations. Each parameter was assessed individually to compare the results with those obtained from commercial-grade instruments. This process helped evaluate the performance of different sensor modules available for each parameter.

4.2.2 Validation and results

***Carbon Dioxide (CO_2)*:** CO_2 readings were recorded at several locations to compare the real-time performances of sensors at three different locations in Concordia University (Figure 24).

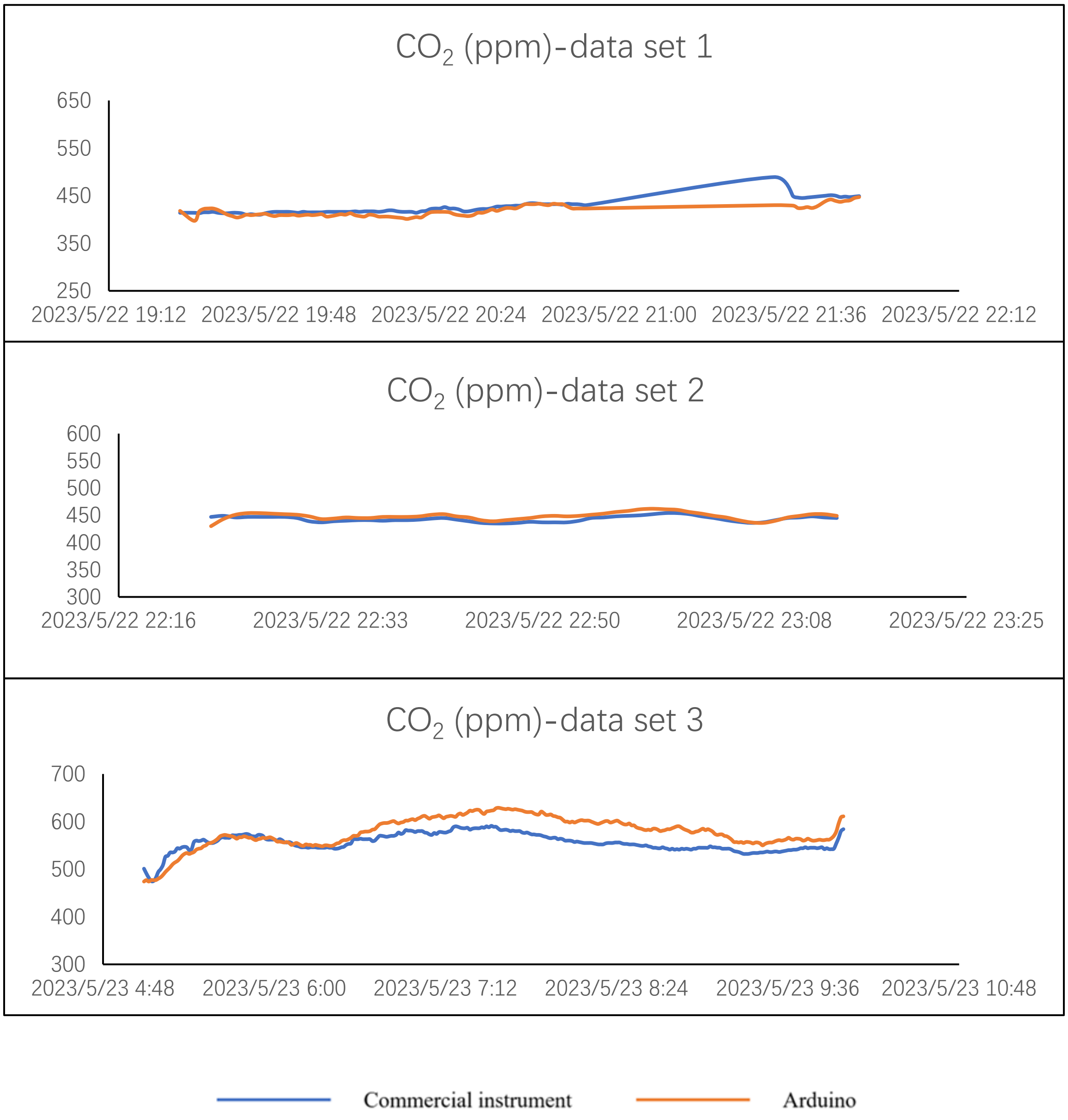


Figure 25 Charts showing the concentration of CO_2 – Concordia University building

CO_2 data set 1 was conducted to record CO_2 concentration on May 05, 2023, from 19:27 to 21:50 local time at Concordia University EV Building, Guy Street, Montreal. SCD30 CO_2 sensor (Arduino) was installed to compare with a commercial air detector. The average reading from the air detector was approximately 421.25 ppm, while the average reading from the Arduino sensor was around 414.92 ppm. The percentage difference between the two sensors' readings ranges from -1.5% to 3.6%, with the air detector showing slightly higher readings. A strong positive linear relationship was also observed between the two sensors, as indicated by a correlation coefficient of 0.87. Both sensors exhibit a similar increasing trend over time. However, there was a large spike in air detector readings from 21:00 to 21:36 local time. This spike was due to erroneous data at 21:33, and it had no impact on the Arduino sensor, which recorded accurate data throughout. At 21:33 and 21:34, the air detector recorded two sets of data that were significantly affected by nearby human respiration, registering at 2114.13 ppm. Given that these readings were clearly erroneous, they were not included in the comparative analysis. By 21:35, the air detector's readings gradually started to decrease, eventually returning to normal indoor concentrations. Consequently, during this period, the data diverged significantly from the readings recorded by the Arduino sensor. However, the tail of the time series data realigned with slightly raised readings by Arduino.

CO_2 data set 2 was conducted to record CO_2 concentration on May 22, 2023, from 22:23 to 23:14 local time at Concordia University EV Building, 9th-floor corridor, Montreal deploying the same devices. The average reading from the commercial air detector was approximately 442.69 ppm, while the average reading from the Arduino sensor was around 448.96 ppm. The percentage difference between the two sensors' readings ranged from -1.4% to 2.4%, with the air detector showing slightly higher readings. Again, a strong positive linear relationship was observed between the two sensors, as indicated by a correlation coefficient of 0.91. Both sensors mimicked the variations and trends of each other with a very small absolute deviation. Contrary to CO_2 data set 1, CO_2 data set 2 had a dissimilar start of time series with an offset of approx. + 15 ppm in air detector readings. This might indicate the need to consider or identify a zero-time period where the air detector may adjust its sensors during startup. However, no such adjustment functions were noticed in Arduino, which recorded stable or consistent variations.

CO_2 data set 3 was conducted to record CO_2 concentration on May 23, 2023, from 05:05 to 09:59 local time at Le 2100 Maisonneuve, Apartment, Montreal deploying the same devices. This location was a household apartment with possible domestic anthropogenic CO_2 emission sources other than human breathing. This test lasted 5 hours in an apartment with bad ventilation as depicted by the elevated levels of CO_2 consistently recorded by both sensors. The average reading from the air detector was approximately 555.75 ppm, while the average reading from the Arduino sensor was around 577.12 ppm. The percentage difference between the two sensors' readings ranged from -6.1% to 9.1%, with the Arduino showing higher readings. A strong positive linear relationship was observed between the two sensors, as indicated by a correlation coefficient of 0.81. Both sensors exhibited a similar trend over time. However, at 04:49 local time air detector started again with an elevated level of CO_2 than Arduino.

***Particulate Matter (PM$_{2.5}$)*:** PM$_{2.5}$ readings were recorded at several locations to compare the real-time performances of sensors at three different locations in Concordia University (Figure 25).

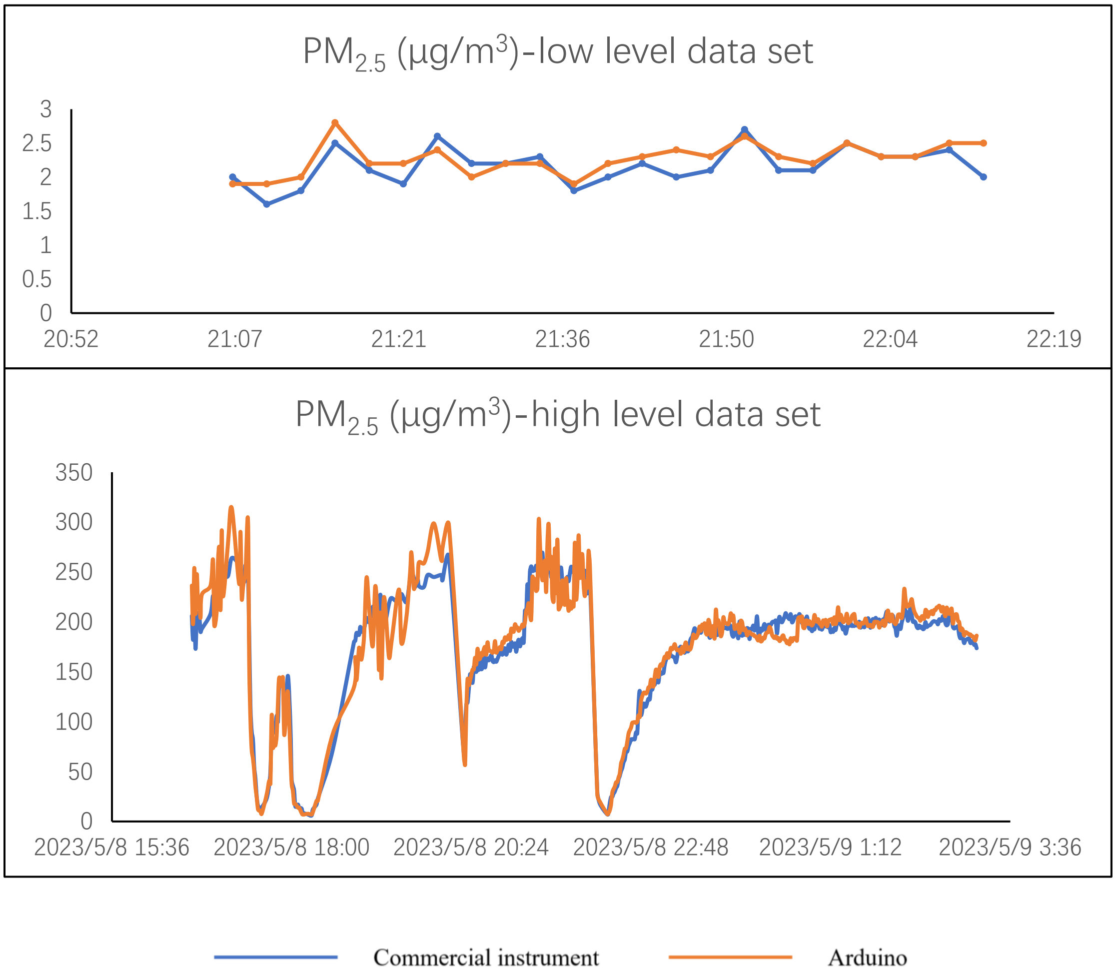


Figure 26 Charts showing the concentration of PM$_{2.5}$ – Concordia University building

PM$_{2.5}$ low-level data set was conducted to record PM$_{2.5}$ concentration on May 07, 2022, from 19:27 to 21:50 local time at one office room located in the EV Building. SEN54 PM sensor (Arduino) was installed to compare with a commercial air detector. Both recorded very low readings around 2 to 3 μg/m3 where room conditions were very clean and ventilated. Further, both sensors exhibited a very similar trend and variations over time.

However, as precious there was again a minute upper shift in the reading of the air detector at the very start.

$PM_{2.5}$ high-level data set was conducted to record $PM_{2.5}$ concentration on May 08, 2022, from 16:40 to 03:09 local time at an apartment located in Le 2100 Maisonneuve, Montreal deploying the same devices. In this scenario, the PM sensor was tested in the apartment. Because the outdoor space and the well-ventilated university office only had low-level readings of less than 5 µg/m3, the second test used a candle in a small room to create a higher PM-level environment. As shown in the charts, the PM level exhibited a volatile trend, fluctuating significantly over the observed period. This trend was due to the use of candles and several times ventilation by opening windows. The difference between the Arduino sensor and air detector was much more than normal, the percentage difference between the two sensors' readings ranges from -45% to 22%. However, the distribution of percentage differences showed 97% of the data had differences of less than 20%, and 86% of the data had differences of less than 15%. Meanwhile, a strong positive linear relationship was observed between the two sensors, as indicated by a correlation coefficient of 0.96. Overall, Arduino exhibited higher sensitivity to transient variations in PM reading compared to air detector.

***Nitrogen Dioxide (NO_2)*:** NO_2 readings were recorded on the 6th floor of the EV Building on Apr 11, 2023, from 09:24 to 21:24 local time to compare the real-time performances of sensors (Figure 26). Around 400 observations were collected during this time. The commercial instrument recorded steady readings between 115.00 and 135.00 ppb whereas Arduino sensor readings were not stable with average readings of approximately 125.68 ppb and 129.56 ppb respectively. The absolute percentage difference between the two sensors' readings was less than 25%.

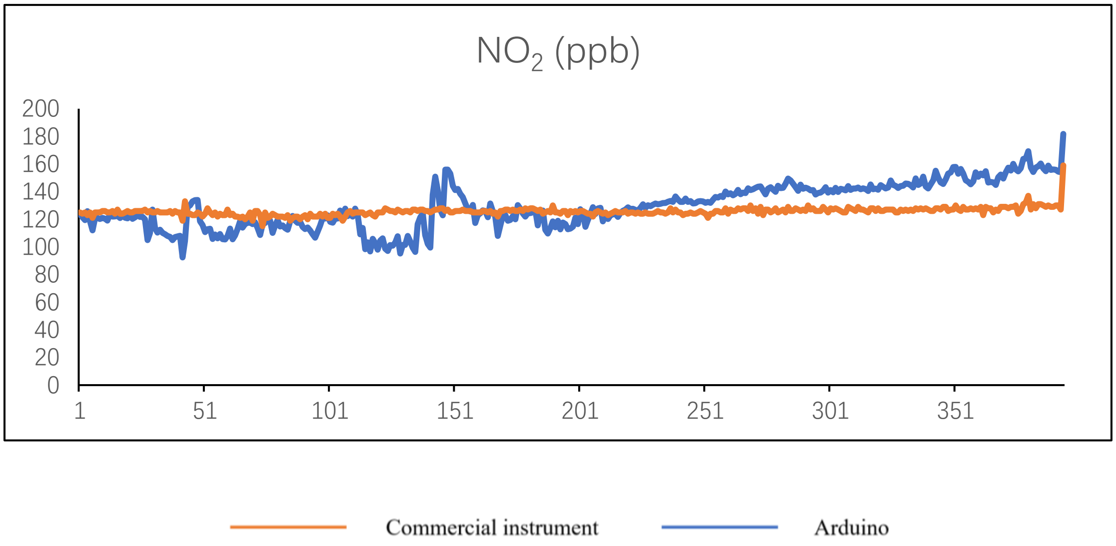


Figure 27 Chart showing the concentration of NO_2 – Concordia University building

***Volatile Organic Compounds (VOCs)*:**

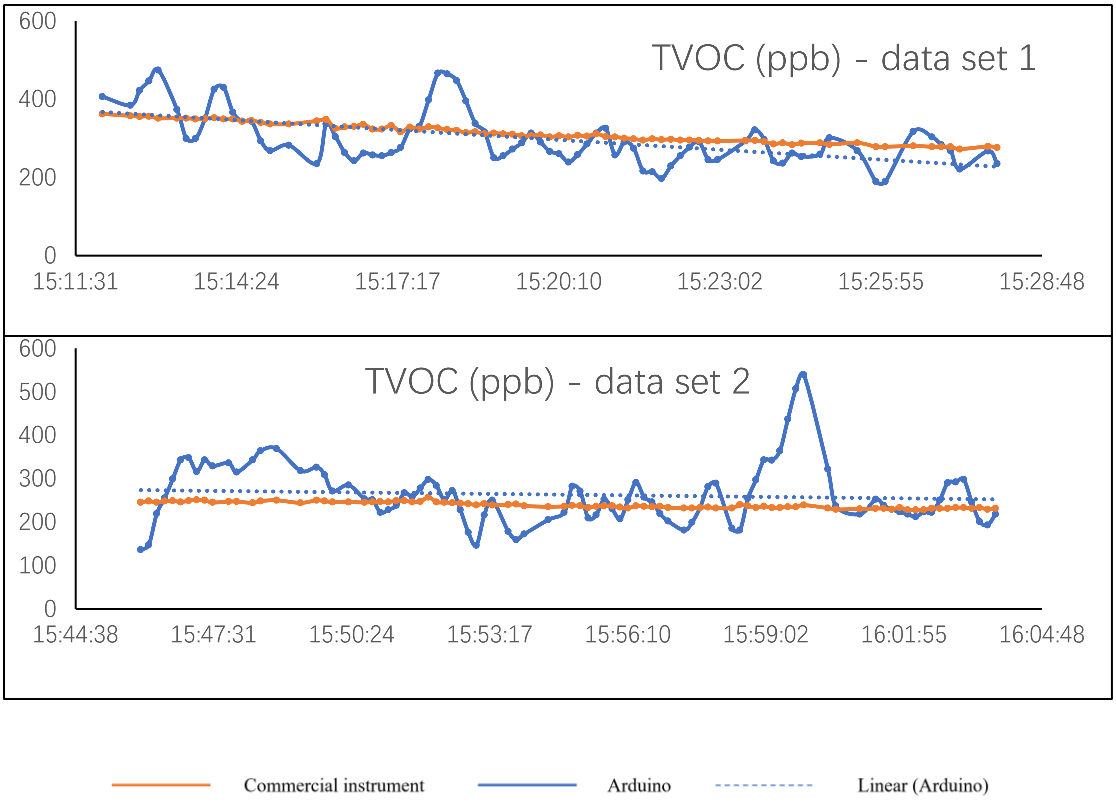


Figure 28 Charts showing the concentration of TVOC (SGP30) – Concordia University building

TVOC data sets 1 and 2 were conducted to record TVOC concentration on May 15, 2023, from 15:11 to 16:04 local time outside Concordia University GM Building, Montreal. SGP30 TVOC sensor (Arduino) was installed to compare with a commercial TVOC instrument (Figure 27). The readings of the Arduino sensor exhibited a cyclic pattern of unequal magnitude and period as a recurring rise and fall pattern. Whereas commercial sensors did not show any variations and kept a declining trend as of Arduino. However, it was observed that the linear trend of the Arduino results closely aligns with the instrument readings. The average of Arduino was 236.86 ppb, while the commercial VOC detector had an average of 228.35 ppb with a difference of 3.73%. The differences between Arduino and commercial instrument ranged from 15% to 30%.

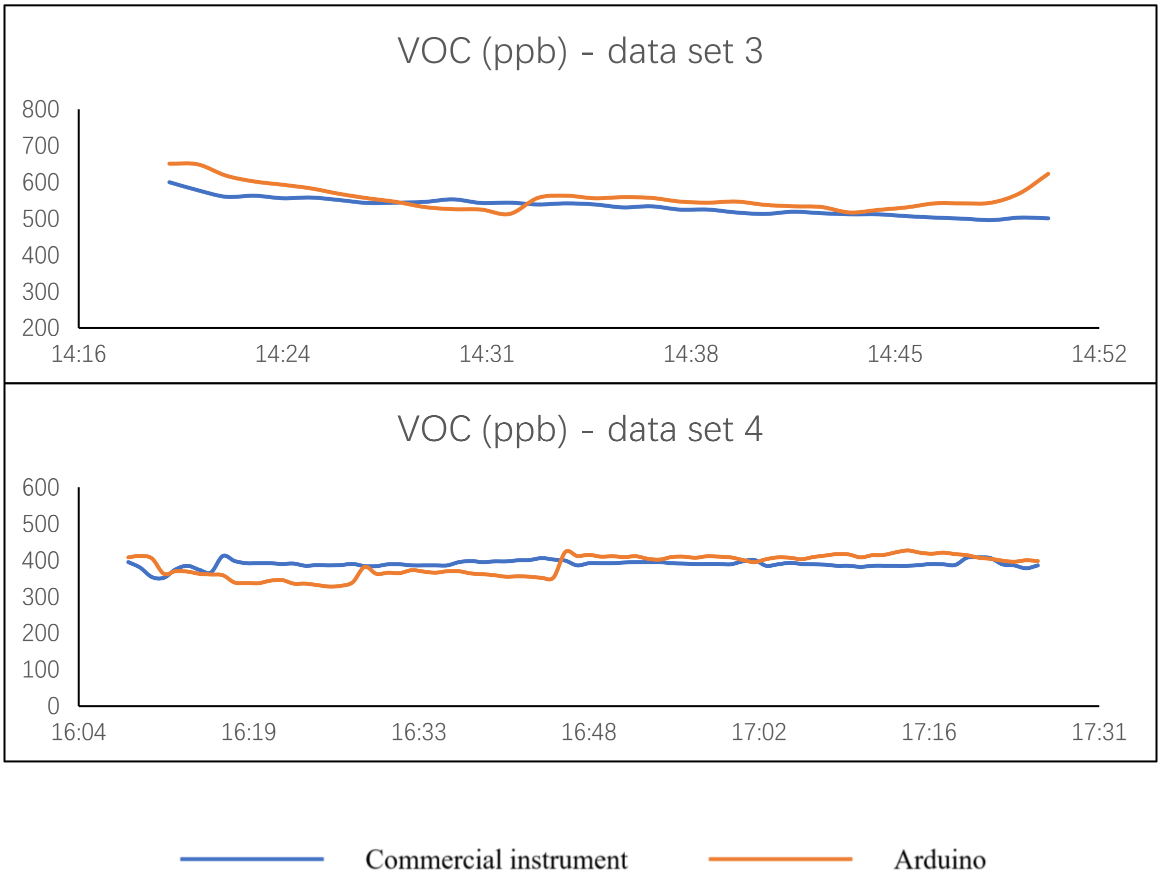


Figure 29 Charts showing the concentration of TVOC (GM502B) – Concordia University building

For indoor scenarios, TVOC data sets 3 and 4, the GM502B sensor module was used on May 22, 2023. A commercial TVOC instrument along with Arduino was deployed on the EV building's 6th floor from 14:20 to 17:20 local time (Figure 28). The TVOC instrument consistently recorded values ranging from 500 to 600 ppb during the time. The Arduino sensor recorded values ranging from 325 to 650 ppb during the given time. There was a wider range of values recorded by the Arduino sensor compared to the TVOC instrument. The values exhibited more variability and fluctuations compared to the TVOC instrument. The Arduino sensor recorded higher values than the TVOC instrument, with occasional spikes of up to 650 ppb. The average reading from the TVOC instrument was 533.53 ppb, while the average reading from the Arduino sensor was 559.03 ppb. In data set 4, the average reading from the TVOC instrument was 389.54 ppb, while the average reading from the Arduino sensor was 385.91 ppb. The absolute percentage difference between the two sensors' readings was less than 15%.

Temperature and Humidity**:** Temperature and humidity readings were recorded to compare the real-time performances of sensors in one office room on the 15th floor of the EV Building office in Concordia University on May 22, 2023, from 21:00 to 22:00 local time using a commercial air detector and Arduino sensor SEN54 (Figure 29).

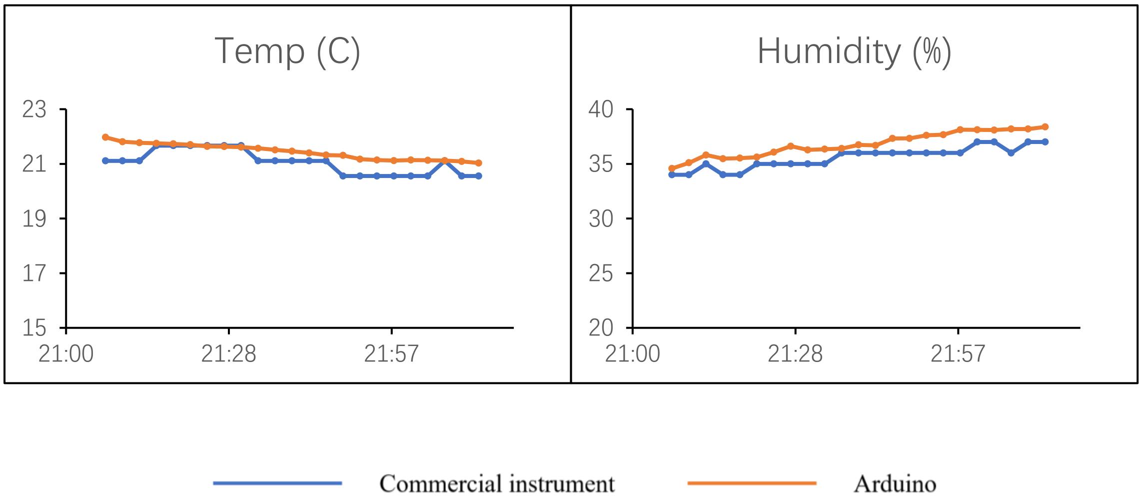


Figure 30 Charts showing the result of temperature and humidity – Concordia University building

The temperature and humidity were collected during every PM test. The data in these two charts was randomly picked from long-time observation. Arduino sensor significantly overestimated the temperature and humidity. In most tests, the temperature difference was less than 2 degrees Celsius, humidity difference was less than 5%. Further air detector can only record temperature and humidity in integers (round values) while Arduino sensors give readings with two decimal places, but the same increasing trend of temperature and decreasing trend of humidity still can be observed from the charts.

4.3 Field Case Study 2

4.3.1 Qatar University campus building

Deployment of the integrated sensor device at Qatar University validated the performance of the system in completely different climatic conditions. The integrated sensor device contains all sensors which were tested in the Concordia case study. Two devices were assembled (unit 1 & unit 2) to monitor CO_2, $PM_{2.5}$, NO_2, VOC, temperature and humidity at the same time at indoor locations in the Environment Science Center (ESC), at Qatar University on Jun 10, 2023 (Figure 30). These locations include the main entrance of the ESC, the cafeteria, and the main lobby of the Research Complex (H10) in Zone 3. Real-time results of two devices were collected at the same location from the webpage and compared with commercial instruments.

Figure 31 Locations to install air quality monitoring sensors for case study 2

The following charts illustrate the average value of each parameter at 3 locations for two devices and instruments.

4.3.2 Validation and results

Carbon Dioxide (CO$_2$)**:**

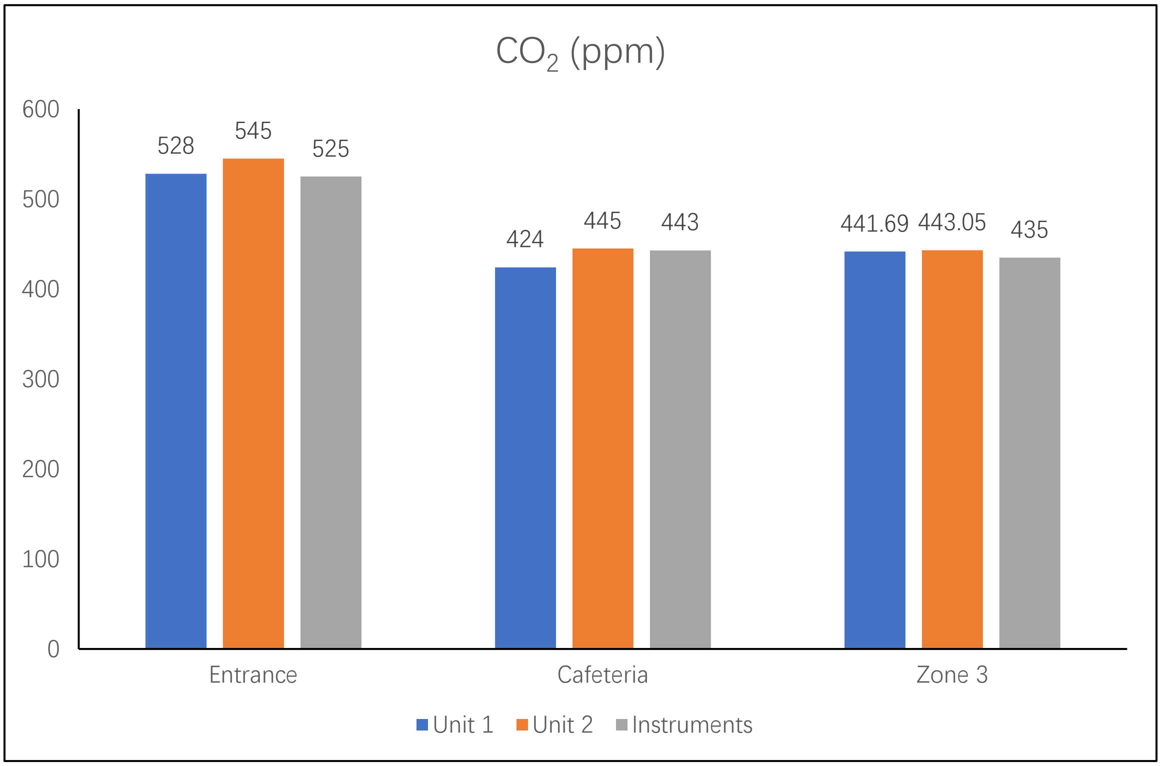


Figure 32 Chart showing concentrations of CO$_2$ in 3 locations – Qatar University building

The chart (Figure 31) compares the CO$_2$ average values in ppm obtained from units and the instrument. Overall, the data reveals minor differences between the two units, with Unit 2 consistently recording slightly higher CO$_2$ values. The largest difference observed between the unit and the instrument was 4.15%. However, despite these variances, there was a strong positive correlation coefficient of 0.97, indicating a high degree of similarity in the CO$_2$ readings obtained from both units and commercial instruments.

***Particulate Matter (PM2.5)*:**

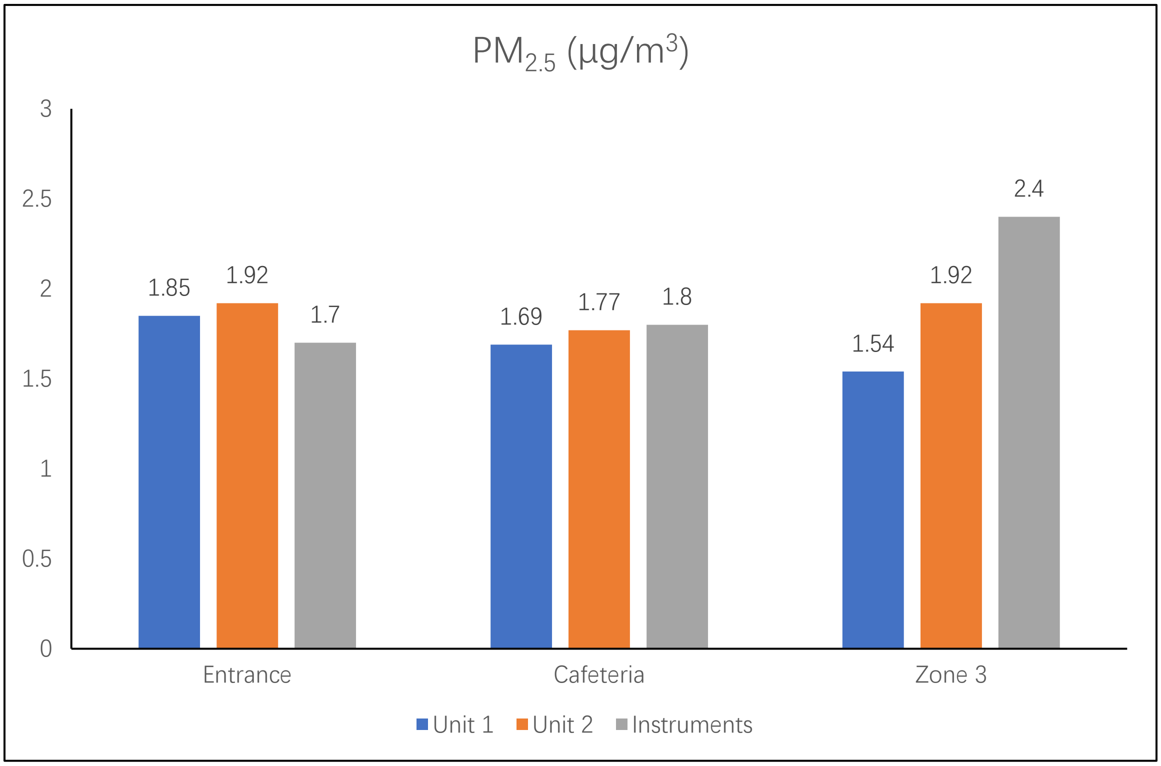


Figure 33 Chart showing concentrations of $PM_{2.5}$ in 3 locations – Qatar University building

The chart (Figure 32) compares the $PM_{2.5}$ data in µg/m3 obtained from units and the instrument. The data shows varying levels of $PM_{2.5}$ concentrations between the units and instruments. Unit 2 consistently recorded higher $PM_{2.5}$ values compared to Unit 1, with the largest difference between unit and instrument observed being 18%. In 3 locations where room conditions were clean and well-ventilated, two devices and instrument only had low-level $PM_{2.5}$ readings, the percentage difference increased. The major differences between Unit 1 and Unit 2 ranged from 1.67% to 15%. The correlation coefficient was 0.93.

Nitrogen Dioxide (NO_2):

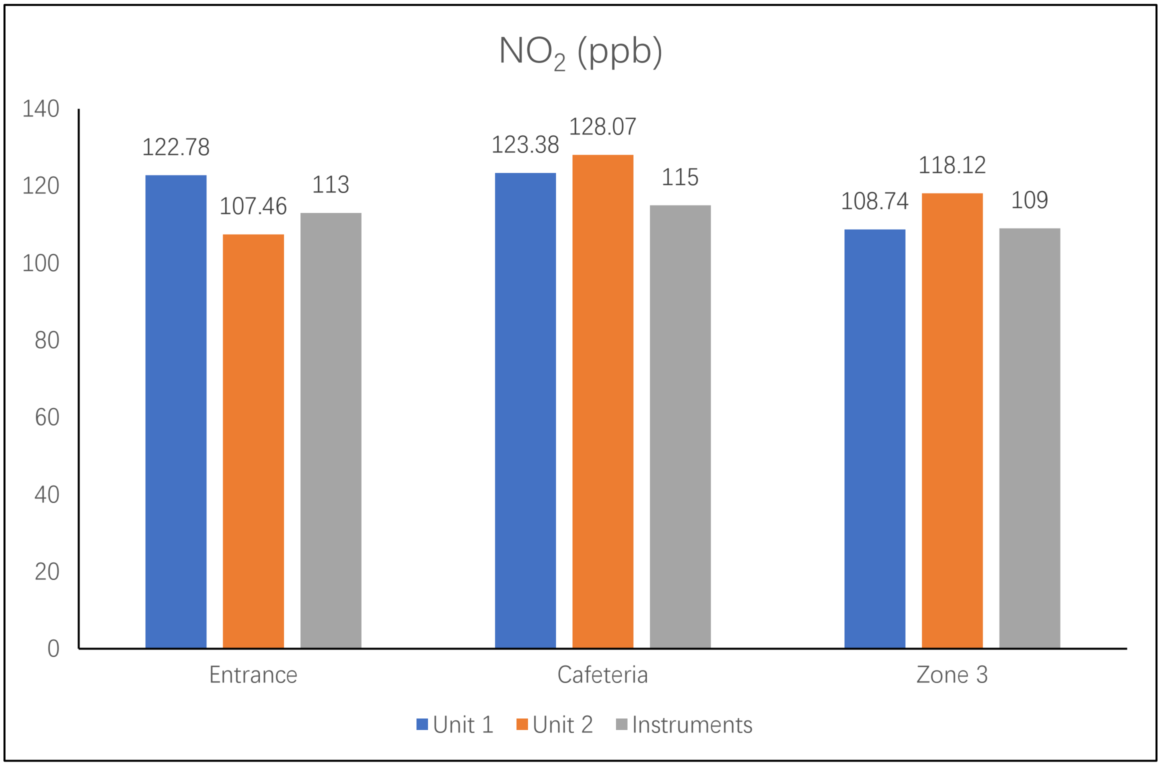


Figure 34 Chart showing concentrations of NO_2 in 3 locations – Qatar University building

The chart (Figure 33) presents the NO_2 data in ppb obtained from units and the instrument. The major differences between Unit 1 and Unit 2 ranged from 0.45% to 7.81%, which suggested some discrepancies in their readings. The primary source of the observed difference appeared to be the influence of temperature. The correlation coefficient was 0.70.

***Volatile Organic Compounds (VOCs)*:**

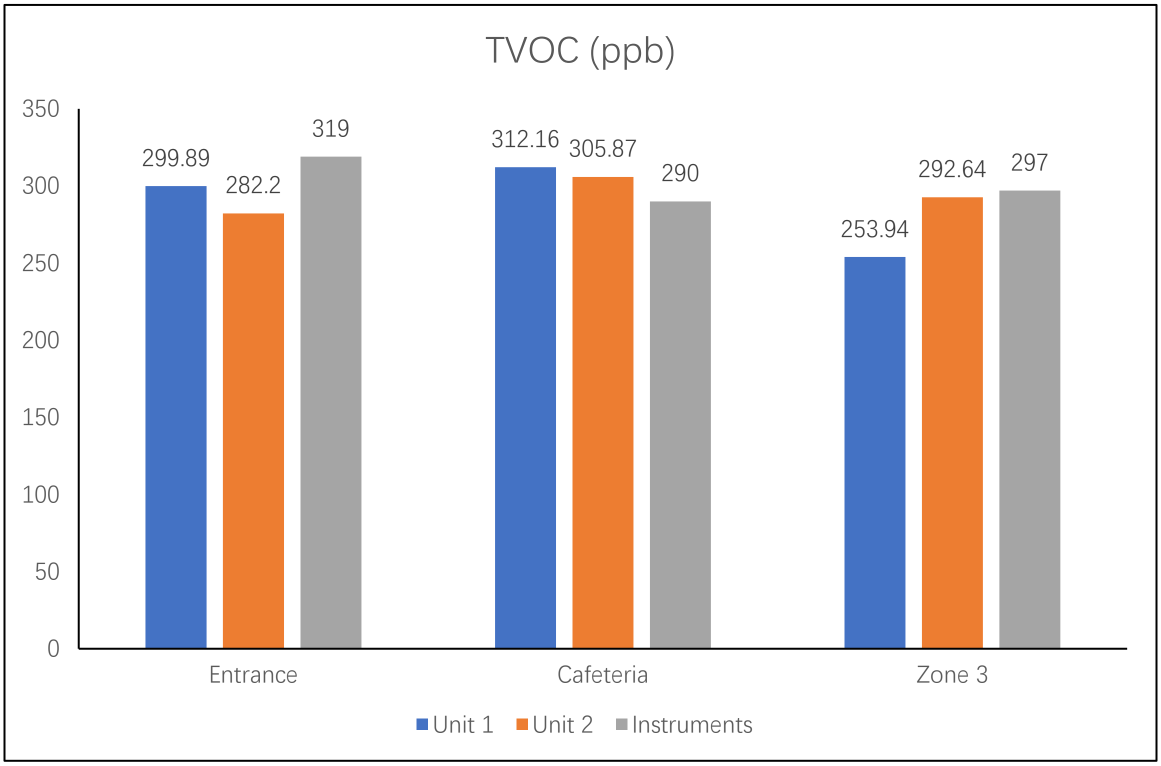


Figure 35 Chart showing concentrations of TVOC in 3 locations – Qatar University building

VOC readings of two units were close to the instrument in the main entrance and cafeteria (Figure 34). In zone 3, the results of Unit 1 were lower than Unit 2 and the TVOC instrument, the observed difference might be due to the influence of temperature or potential errors in the sensor calibration process. The largest difference between units and the instrument was observed to be 20%. The major differences ranged from 1.47% to 14.5%. The correlation coefficient was 0.62. Although, there is a similarity in the performance of the instruments, the significant variations under the influence of temperature as indicated by the low correlation coefficient.

***Temperature and Humidity*:**

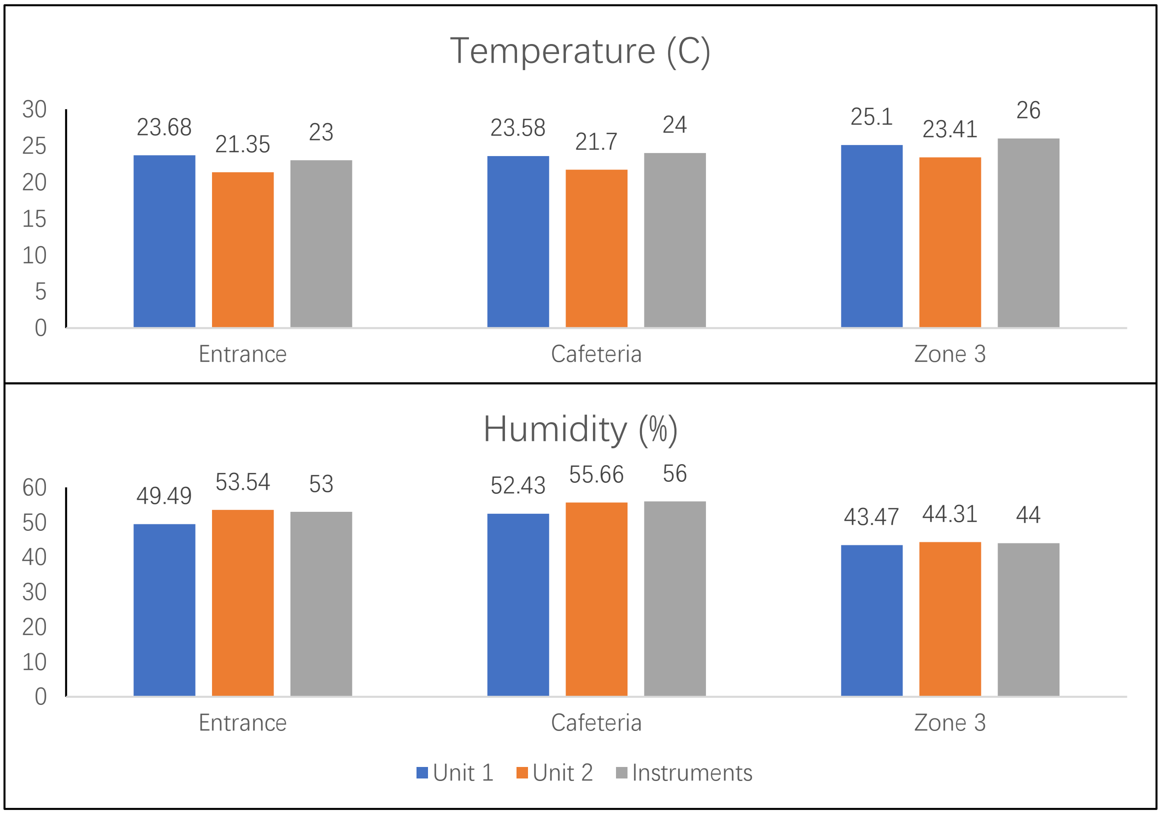


Figure 36 Charts showing results of temperature and humidity in 3 locations – Qatar University building

As shown in Figure 35, in terms of temperature, Unit 2 was much lower than Unit 1 and the instrument, this may be due to the different impact-resistant material used in the two units, maybe the new sensor in Unit 2 still needs time for the pre-heat and calibration process. Humidity still had a difference of less than 5%.

4.4 Indoor Air Quality Index Model – Case Study

4.4.1 IAQI case study

In this particular case, air data was gathered from a confined space to provide a tangible demonstration of the index model's functionality. The intention was to showcase both the operation of the index model as a whole and the individual calculation of each sub-index. The Thermal Comfort sub-index and the Ventilation Rate sub-index adhere to the ASHRAE Standard, while the Pollutant sub-index aligns with the parameters integrated into the system and associated protocols.

The index model was extended to incorporate the Air Quality Health Index (AQHI) from the Canada National Standard and the Volatile Organic Compound (VOC) index level as defined by the World Health Organization (WHO) as shown in Table 7, ensuring their compatibility to be applied for the building in Canada.

Table 8 AQHI and VOC level (Canada, WHO)

AQHI (Canada)	VOC (WHO)	Category
1 – 2	0 to 200 ppb	**Satisfactory**
2 – 5	200 to 400 ppb	**Moderate**
5 – 7	400 to 800 ppb	**Poor**
7 – 10	800 to 2200 ppb	**Very Poor**
Above 10	2200 to 30000 ppb	**Severe**

To provide a concrete example, the data was collected on June 4, 2023, in one office room with occupancy of only one person at EV building, Concordia University, from 16:26 to 16:30 local time (Table 8).

Table 9 Measured data for the study office room

Time	Pollutants					
	CO_2 (ppb)	$PM_{2.5}$ ($\mu g/m^3$)	Humidity (%)	Temp (℃)	NO_2 (ppb)	VOC (ppb)
16:26	427	1.6	35	24	42	253
16:27	467	1.1	35	24	50	245
16:28	419	0.8	35	25	43	247
16:29	449	1.2	35	25	54	242
16:30	434	1.3	35	25	56	251

4.4.2 Results of IAQI

Sub-index thermal comfort: The temperature was measured at 25℃, and relative humidity was 35% as shown in Table 8. This data was collected in the office room with one person inside working in front of a computer, so the metabolic rate, airspeed and clothing insulation are set. As shown in Table 9, other values were obtained from the ASHRAE – 55 Standard (ASHRAE standard 55, 2020).

Table 10 Parameters used in PMV calculation

Clothing insulation (in $m^2 \cdot K/W$)	0.61
Metabolic rate (in W/m^2)	1 met
External work (in W/m^2)	0 met
Air Temperature (in degrees Celsius)	25
Mean Radiant Temperature (in degrees Celsius)	25
Relative air velocity (in m/s)	0.1
Relative humidity (in %)	35
Water vapor pressure (in Pa)	1109.185

To Calculate the PMV value, Equation (1) is used:

PMV = -0.28, which indicated a neutral sensation.

To Calculate the PMV value, Equation (2) is used:

$$\begin{aligned} PPD &= 100 - 95 * e^{-0.03353*PMV^4 - 0.2179*PMV^2} \\ &= 100 - 95 * e^{-0.03353*(-0.28)^4 - 0.2179*(-0.28)^2} \\ &= 7.99 \end{aligned} \tag{5}$$

PPD = 7.99, based on Table 3, the PPD value is between 0 and 10, which indicates a satisfactory condition.

Sub-index ventilation rate: The room area is around 800 ft^2, ceiling height is around 10 ft. One person nearly 30 years old working in front of the desktop. The average CO_2 was 439.20 ppm. The recorded average outdoor CO_2 level on the same day was 401.75 ppm.

$$\begin{aligned} Air\ changes\ per\ hour &= \frac{Clean\ air\ rate(ft^3/hour)}{Room\ volume(ft^3)} \\ &= \frac{Cubic\ feet\ per\ hour}{Room\ length * width * height(ft)} \end{aligned} \tag{6}$$

The air changes per hour was 1.98 based the Equation (6) for this study case. The ventilation rate is 33 cfm per person. Based on Table 4, the ventilation rate can be categorized as satisfactory.

Sub-index pollutant concentrations: As the collected results include NO_2, $PM_{2.5}$ and VOC, the index was determined by these 3 values, with the measured data using the IoT system for this study room (Table 8): NO_2 49 ppb, $PM_{2.5}$ 1.2 µg/m^3 and VOC 248 ppb, and ozone is below the detection limit, which is taken as zero. Then, the AQHI from Canada National Standard is:

$$PM_{2.5}AQHI = \frac{10}{10.4} \times \left\{100 \times \left[\left(e^{(0.000871 \times NO_2)} - 1\right) + \left(e^{(0.000487 \times PM_{2.5})} - 1\right)\right]\right\}$$
$$= \frac{10}{10.4} \times \left\{100 \times \left[\left(e^{(0.000871 \times 49)} - 1\right) + \left(e^{(0.000487 \times 1.2)} - 1\right)\right]\right\}$$
$$= 4.25 \tag{7}$$

AQHI = 4.25, when multiple parameters were utilized to determine this sub-index, the higher value takes precedence. It is evident that the air quality level is classified as moderate based on Table 7.

4.4.3 Summary of IAQI model

In this case, three separate sub-indices have been calculated to indicate the severity of air quality concerns within the office environment. These sub-indices correspond to different categories, as outlined in Table 10:

Table 11 Indoor air quality index category

Category	**PPD**	**VR**	**Pollutants (AQHI)**
Satisfactory	0-10	>15	1 – 2
Moderate	10-25	13-15	2 – 5
Poor	25-50	11-13	5 – 7

Very Poor	50-75	9-11	7 – 10
Severe	75-100	<9	Above 10

Using the gathered data, the PPD value of 7.99 signifies that the thermal comfort level falls under the “satisfactory” category. Furthermore, with an ACH value of 33 cfm per person, there appears to be enough ventilation within the room. The pollutant index of 4.25 is a moderate condition in air quality.

A preliminary analysis reveals air conditions within the room:

1. Thermal Comfort: The PPD value of 7.99 falls under the "Satisfactory" category, indicating that the thermal comfort level is generally comfortable for most individuals. However, it's essential to consider the specific requirements and expectations of occupants. If some individuals are sensitive to temperature variations, adjustments may be needed to ensure comfort for all.
2. Ventilation: The ventilation rate of 33 cfm per person indicates that the room's ventilation is at a satisfactory level, meeting the recommended standard of 15 cfm per person. Sufficient ventilation is essential for preserving air quality and creating a fresh and comfortable environment for occupants. A higher ventilation rate helps prevent the accumulation of indoor pollutants and promotes overall indoor air quality.
3. Air Quality: The Pollutant Index of 4.25, categorized as "Moderate" on the AQHI scale, indicates a moderate level of pollutants in the indoor air. While this is not in the "Severe" category, it does suggest that there is room for improvement in maintaining air quality. Identifying the specific pollutants and their sources is essential for addressing this issue.

The analysis of the index values can provide insight into the necessary actions to enhance air quality in the office. In this case, the focus lies on reducing the pollutant level, particularly NO2 and VOC, as the PM2.5 levels are already within an acceptable range. If consider new readings of NO2 at 20 ppb and VOC at 185 ppb. With these updated values, the sub-index for pollutant level reaches 1.75, indicating a 'satisfactory' air quality level.

In conclusion, the gathered data indicates that the indoor air quality in this room falls within the "Moderate" category. Although the situation is not critical at the moment, there is still room for progress and improvement. It's important to address these issues promptly to create a healthier and more comfortable indoor environment for occupants. Prolonged exposure to less-than-optimal air quality conditions may have health implications, including potential respiratory discomfort, allergies, and reduced overall well-being. Therefore, taking proactive steps to improve ventilation and manage indoor pollutants is advisable to ensure the well-being of individuals working or residing in the space.

4.5 Discussion

This study focused on comparing indoor air quality measurements for CO_2, NO_2, VOC, $PM_{2.5}$, and temperature and humidity between consumer-grade sensors (Arduino-based) and commercial-grade instruments. Here is the discussion of the findings and implications of this study.

4.5.1 Sensors

Table 12 Salient features of performance measurements for each sensor and parameters

Parameter	Sensor	Performance
CO_2	SCD30	The CO_2 readings closely matched those of the air detector device. The correlation coefficient is very close to 1. A new sensor may have a large difference but can be calibrated by mitigating the difference simply. However, the difference may increase when the CO_2 level increases, after the CO_2 level reaches 700 ppm. This can be modified by a calibration code set with several stages with several equations.
$PM_{2.5}$	SEN54	$PM_{2.5}$ readings from SEN54 closely resembled those of the air detector. The correlation coefficient is very close to 1. After verification, the calibration of the sensor is simple.
Humidity	SEN54	Humidity difference less than 5%
Temperature	SEN54	Temperature difference less than 1 degrees

NO_2	GM-102B	The Multichannel sensor, as observed in this study, performed notably better in indoor settings. At fixed locations, readings are close to commercial instruments with most of the difference between 10% to 20%. The sensor is strongly influenced by temperature. It takes more than 2 days for the first setting and every time it needs a long-time heat-up process which may take 2 to 6 hours until it gets a stable reading. The potential reason is most of the gas sensors are specified only for a certain temperature. Further improvements like a temperature-control module only for this sensor may be tested and validated.
VOC	GM-502B	

a) CO_2

The Arduino device generally recorded higher values compared to the air detector device, suggesting a dissimilar standard of calibration or sensitivity of the sensors used in each device. Despite this variation, a strong correlation of 0.971 signified that the two devices generally provide consistent results and can be considered reliable for air quality monitoring purposes. Furthermore, when examining the overall range of values recorded by the two devices, it was observed that the Arduino device had a wider range compared to the air detector device. This broader range of values captured by the Arduino device implies its ability to detect a wider spectrum of air quality variations. The air detector device consistently recorded lower values compared to the Arduino device, the observed differences in readings could arise from varying calibration methods, distinct sensitivities to CO_2 levels, or disparities in sensor quality and manufacturing, all contributing to discrepancies in measurement accuracy between the two devices. In most prior studies, the system utilized a different variant of the CO_2 sensor, specifically the K30 model, owing to its detection range spanning from 0 ppm to 5000 ppm (Brown et al., 2020; Pereira & Ramos, 2022). Nevertheless, given the focus on indoor environments in this study, the monitoring of sub-atmospheric concentrations is unnecessary. The SCD30 model suffices with its minimum detection threshold of 400 ppm and has demonstrated favorable outcomes. Despite the minor differences between the Air Detector and Arduino devices, most of the recorded measurements show a minimal difference of less than 10% between the two sensors. This indicates a high level of agreement and consistency between the two devices, further validating the availability and reliability of Arduino-based air quality sensors.

b) $PM_{2.5}$

The $PM_{2.5}$ measurements were compared between the SEN54 sensor and the commercial air detector. At lower $PM_{2.5}$ levels, the readings from the consumer-grade sensor were in close agreement with the Air Detector instrument. However, at higher $PM_{2.5}$ levels, the differences increased, with most results showing less than a 20% difference. In case study 1, the PM values changed with time due to ventilation in the room which also showed better performance of the Arduino sensor. The correlation coefficient of 0.94254 indicated a strong relationship between the two sensors, although some discrepancies were observed. These findings suggest that the consumer-grade sensor can provide reasonable estimates of $PM_{2.5}$ concentrations but may exhibit limitations in accurately capturing higher levels.

c) NO_2

The results indicated that, following calibration, the consumer-grade Arduino sensor provided NO_2 readings within a 20% difference compared to the commercial instrument. The commercial instrument recorded NO_2 concentrations ranging from 110ppb to 135ppb.

However, it's worth noting that the Arduino sensor exhibited sensitivity to temperature influences, potentially affecting its accuracy. Therefore, caution should be exercised when interpreting readings from the consumer-grade sensor.

d) VOC

The outdoor VOC measurements conducted using the consumer-grade SGP30 sensor module were compared to those obtained from a commercial-grade VOC Gas Detector. The results indicated that the consumer-grade sensor had an average VOC value difference of approximately 3.73% compared to the commercial-grade instrument. The long-term differences ranged from 2.46% to 5.34%, showing a consistent linear trend.

However, the real-time readings from the SGP30 sensor were less stable due to weather influences and the self-calibration program within the module. The differences in readings ranged from 15% to 30%. Based on the provided data, the VOC Detector consistently recorded VOC values within a specific range with relatively low variability. On the other hand, the Arduino sensor, which presumably served a similar purpose of measuring VOC, exhibited wider fluctuations and higher values. These observations raised concerns about potential issues or inconsistencies with the functionality of the Arduino sensor. The higher values and greater variability compared to the VOC Detector bring into question the accuracy and reliability of the Arduino sensor's VOC measurements. Likewise, in line with previous research findings, relying solely on the absolute values of VOCs for analysis is not recommended. This is attributed to the absence of a universally standardized definition, consistent measurement methodology, or well-defined acceptable ranges for VOC concentrations (Karami et al., 2018). Hence, for indoor air quality analysis, it is advisable to consider the relative fluctuations in VOC levels instead.

e) Temperature and Humidity

The comparison of temperature and humidity measurements between the consumer-grade Arduino sensor and the commercial instrument, the Indoor Air Pollution Detector, revealed minimal differences. The temperature difference was less than 1 degrees, and the humidity difference was less than 5%. These findings suggest that the consumer-grade Arduino sensor is capable of providing reliable measurements of temperature and humidity in indoor environments.

4.5.2 Web server

A reliable web hosting provider ensured a stable environment for hosting the system. The user-friendly control panel and website builder simplified the process of website management, enabling users to effortlessly control their online presence and efficiently interact with their data. Integration with the MySQL database enabled efficient data storage and retrieval, a crucial aspect, especially for IoT applications dealing with vast amounts of sensor data that needed secure storage and easy access.

The web server setup allowed for the creation of dynamic data display webpages. This empowered users to visualize sensor data through tables and charts, aiding in the analysis and interpretation of collected data. However, due to limitations in the data transmission capabilities of the MCU, Wi-Fi, and server, the system required multiple tables in the database, each with a maximum of 6 columns. This restriction imposed limitations on the volume and format of data transmitted in a single command.

While data visualization was a strong feature, the complexity of data interpretation might have varied depending on the user's familiarity with PHP and data analysis concepts. Additionally, the recorded time in the database was based on the time zone of the web server. While the system could adjust for accurate data presentation, managing time zone differences for global users may have required additional consideration.

In summary, whether it was using cloud servers to establish the framework as done in this study or resorting to pre-existing IoT platforms like the ThingSpeak as seen in most previous research, these approaches had their own limitations (Katushabe et al., 2023; Parashar & Parashar, 2021). The ideal solution would be to set up an independent physical server and design a suitable server architecture from scratch. This would ensure meeting constraints on data transmission and accommodating specific requirements. However, the corresponding downsides are evident as well: the cost and maintenance of building servers are substantial, and it demands a high level of expertise in the field for researchers. The choice of the most suitable approach for constructing this system should be determined based on the actual circumstances.

4.5.3 Indoor air quality index model

In the case study of IAQI, the process utilized to determine these sub-indices demonstrates the application of an indoor air quality index model to the system. Each sub-index can be used independently or collectively. Users may choose to rely on the worst sub-index as an indicator of air quality or assign weights or importance values to each sub-index based on their specific requirements. For instance, spaces situated in relatively clean air environments may prioritize thermal comfort, while industrial settings may place greater emphasis on pollutant levels in unmanned areas.

4.5.4 Limitations and uncertainties

While microsensors offer tremendous potential for advancing air quality monitoring, it's essential to recognize the inherent limitations and uncertainties associated with them. These challenges include sensor variability, environmental factors, sensor drift, limited sensor lifespan, and data interpretation complexities. To ensure reliable and accurate data, it's crucial to address these issues proactively. Sensor Variability, resulting from differences in accuracy and sensitivity among sensor models. Integrating multiple sensor models within a single network could result in measurement discrepancies. Therefore, meticulous sensor selection and validation are imperative (Karami et al., 2018). Furthermore, environmental conditions such as temperature, humidity, and exposure to pollutants can influence sensor performance over time. Sensor drift and degradation can lead to inaccurate readings, necessitating frequent maintenance to ensure reliability (Pereira & Ramos, 2022). Moreover, the sensor Lifespan. Comparable to sensors found in laboratory or commercial-grade instruments, these sensors typically have a lifespan of around 1 year. Regular calibration and maintenance routines are essential to uphold measurement accuracy.

Microsensors, especially those utilizing metal-oxide semiconductor (MOS) technology, require a period to reach a stable operating temperature before delivering precise measurements. This heat-up time can vary, spanning from hours to days. The time interval at which sensors measure air quality can impact data representativeness. Brief sampling times might miss transient spikes in pollution levels, while extended sampling times could average out fluctuations. Calculated air quality indices rely on algorithms and models that might not perfectly mirror real-world conditions. Interpreting these indices can be intricate due to intricate interactions between various pollutants and environmental factors (Ferrer-Cid et al., 2022).

Effectively addressing these challenges involves leveraging technical expertise, conducting careful sensor selection, prioritizing maintenance and calibration, and fostering a deep understanding of sensor limitations and environmental influences. It is also crucial to communicate these limitations to ensure accurate data interpretation and informed decision-making. By focusing on enhancing sensor calibration techniques, refining data processing, and embracing advanced IoT infrastructure to overcome these limitations, the improvement involves three major areas of development.

Firstly, there's an emphasis on advancing Sensor Calibration Techniques. The investigation into sophisticated calibration methods for consumer-grade sensors holds the potential to enhance accuracy and reduce sensitivity to environmental conditions. The formulation of robust calibration approaches tailored to specific sensor types could substantially improve the consistency and reliability of measurements (Ferrer-Cid et al., 2022). Secondly, the focus lies on enhancing Data Processing Methodology. While current data processing algorithms are embedded within the MCU, a promising avenue for the future involves transmitting raw data directly from the sensors and relocating algorithm enhancements to cloud-based processing. This strategy seeks to streamline system adjustments and modifications through network-based updates, significantly reducing the need for physical equipment manipulation and operation. Lastly, the study recognizes the significance of Advanced IoT Infrastructure. By delving into innovations within IoT infrastructure, like edge computing and cloud-based analytics, the potential to elevate data processing capabilities is substantial (Katushabe et al., 2023). These advancements could facilitate real-time data analysis, anomaly detection, and predictive modelling, thereby propelling the efficacy of sensor systems in the domain of air quality management.

The case studies demonstrate the valuable insights that consumer-grade sensors can provide into indoor air quality parameters. However, they also reveal certain limitations, including sensitivity to environmental factors, instability, and comparatively lower accuracy when compared to commercial-grade instruments. These findings underscore the significance of considering sensor quality and reliability during air quality assessments. For situations requiring precision and accuracy, particularly in critical applications, commercial-grade instruments are still recommended.

It is worth mentioning that the case studies are specific to the Concordia University EV Building and the Qatar University Environment Science Center, and the results may not be directly applicable to other environments. Further studies and validations are necessary to establish the generalizability of the findings.

CHAPTER 5 CONCLUSION

This chapter begins with the conclusion of this study. Following that, the contributions of the developed systems in this study are provided. Lastly, the chapter presents the findings, recommendations, and potential directions for future research.

5.1 Conclusion

This system is designed to enable continuous measurement, real-time monitoring, and comprehensive data analysis of air quality parameters in indoor environments. The research aims to design a cost-effective and efficient IoT sensor system utilizing Arduino for continuous air quality assessment. The objectives of this study encompass several crucial aspects:

Wireless Communications: The research integrates wireless communication into the Arduino-based IoT sensor system, allowing remote control and mobile measurements. The system collects air quality data through strategically placed sensors and transmits readings to an online server database via Wi-Fi. This real-time data transmission ensures timely storage and analysis. **Real-Time Data Visualization:** An essential facet of the research involves the development of a user-friendly server webpage for real-time presentation of air quality data. This visualization platform enables data display in both tabular and chart formats, enhancing usability and insights into air quality conditions. **Air Quality Index (AQI) Determination:** The IoT sensor system calculates and determines the Air Quality Index (AQI), offering a clear representation of air quality status. This feature aids individuals in promptly assessing changing air quality conditions and responding effectively. **Sensor Accuracy Validation:** Rigorous validation tests ensure the reliability of the IoT sensor system. Deploying sensors across varied locations within the Concordia

University campus and comparing their measurements with established instruments validate the precision of the sensors' readings.

In conclusion, this study developed an Arduino-based IoT sensor system for automatic air quality monitoring. The system offers continuous measuring, real-time monitoring, and data analysis capabilities. It is a cost-effective and convenient solution that can be used for both fixed-location installation and mobile measurements. The sensors and modules in the system can be chosen and replaced with various options, providing flexibility and adaptability to fit specific environments. It highlighted that consumer-grade sensors can serve as effective tools for gaining insights into indoor air quality trends. However, their accuracy and reliability can be influenced by factors such as sensor variability, sensitivity to environmental conditions, and calibration requirements. The case study's exploration of web server integration underscored the importance of robust data hosting and visualization mechanisms while acknowledging potential complexities in data transmission and interpretation. The system utilizes an online server and a MySQL database to store and access the sensor results. The data can be visualized in real-time on a server webpage in table or chart format, and it can also be used to calculate the Air Quality Index (AQI) for a direct assessment of air cleanliness or pollution.

The limitations and uncertainties discussed in the paper provide critical insights for future research and development. The proposed areas for future study, including sensor calibration techniques, data processing methodology, and advanced IoT infrastructure, offer promising avenues for enhancing sensor accuracy, real-time analysis, and overall air quality management efficiency.

As a result of this case study, it is evident that consumer-grade sensors can contribute meaningful data to indoor air quality assessments. However, the study also underscores the necessity of careful consideration when selecting sensors for specific applications. For situations that demand high precision and accuracy, especially in critical environments, the use of commercial-grade instruments remains advisable. Overall, the Arduino-based air quality monitoring system presented in this study demonstrates its potential as a cost-effective and versatile solution for monitoring air quality in various indoor and outdoor environments. Further improvements and calibration can enhance the accuracy and reliability of the measurements, making it a valuable tool for individuals, organizations, and policymakers to make informed decisions regarding air quality management.

5.2 Contributions

This research makes substantial contributions to the field of indoor air quality monitoring and assessment, offering innovative solutions and methodologies that advance the understanding and management of indoor environments. These contributions can be distilled into three major aspects.

Development of an IoT-Based Indoor Air Quality Monitoring System:

1. Designed a real-time IoT system with multiple sensors capable of monitoring a variety of parameters, including CO2, PM2.5, NO2, TVOC, temperature, and humidity.

2. Featured multi-unit monitoring capability, allowing simultaneous assessment across different locations for a monitoring network, validated in Montreal and Doha.

3. Empowered users with access to online data visualization tools, the system offers immediate insights through interactive charts, tables, and search functionalities.

4. Incorporated an IAQI model into the system to ensure comprehensive analysis.

Contributions to incorporate an Indoor Air Quality Index Model into the IoT air quality monitoring system:

1. The IAQI model categorizes indoor air quality into five categories with index values, giving a clear assessment of whether it is satisfactory or poor. This contribution simplifies the understanding of indoor air quality conditions, aiding both practitioners and occupants in making informed decisions.

2. The IAQI model accounts for multiple critical factors, including thermal comfort, ventilation, and pollutants. The IAQI model factors in thermal comfort, ventilation rate and pollutants, providing a well-rounded understanding of air quality and enabling targeted efforts for improvement.

3. The IAQI model's flexibility allows for customizable sub-index ratios, enhancing adaptability to different indoor environments and specific considerations. This adaptability enhances the model's applicability across various contexts, enriching its utility for diverse users.

Contributions During the Research Process:

1. The Montreal field case study validated each sensor of the developed IoT monitoring system, ensuring accuracy and reliability.

2. The Doha field case study further validated the performance of the integrated sensor unit and real-time online displays through two identical units, confirming the system's effectiveness in varied environments using multiple units for a regional monitoring network.

3. Innovative sensor calibration and integration methodologies were devised, optimizing data quality and successfully reducing the difference.

4. Integrated a new wireless communication method with a new model of the microcontroller unit, not only ensuring reliable data but also reducing the size of the device by half.

5. Built a robust web infrastructure that enables seamless real-time data collection, presentation, and analysis.

6. The improved codes and calibration methods, achieved a remarkable reduction in differences in CO2 and PM2.5 readings to less than 10% and in NO2 and VOC readings to less than 15%.

In addition, the selection and interchangeability of sensors and modules offer a wide array of options, empowering the system to be tailored to specific environments. This dynamic feature enables customization based on critical factors such as air parameters, communication methods, and power sources.

The ability to select and replace sensors and modules not only enhances the system's versatility but also optimizes its performance in varying settings. This adaptability ensures that the system can be finely tuned to meet the unique demands of different indoor environments. As a result, the research yields a solution that is not only innovative but also highly responsive to the nuanced requirements of diverse scenarios.

The IoT sensor system integrates various components to create a holistic solution for indoor air quality assessment. Sensors collect data from the air, which is then communicated to other modules for transmission to an online server database. The real-time visualization of data in table or chart formats, along with the determination of the Air

Quality Index (AQI), enhances the system's ability to convey air quality information to users. The system's flexibility, adaptability, and integration of IoT technologies enable it to cater to diverse indoor environments and specific monitoring needs. **Sensor and Microcontroller Units:** The system's effectiveness relies on the integration of sensors and microcontroller units (MCUs). A range of sensors, including those for CO_2, $PM_{2.5}$, humidity, temperature, VOCs, NO_2, and formaldehyde, collect comprehensive air quality data. Various MCUs, such as Arduino Uno, Arduino Mega, Raspberry Pi, and Arduino Uno WiFi Rev2, are strategically employed to ensure wireless data transmission, data processing, and communication with the web server. The choice of MCUs is based on factors such as Wi-Fi connectivity, compatibility with sensors, and the system's intended application. **Data Transmission and Visualization:** The establishment of an online server, database, and web-based display interface plays a crucial role in the system's functionality. Sensor data is collected, transmitted through the local network, and stored in a MySQL database hosted on the online shared server. The web-based interface allows users to access real-time air quality information and engage with interactive tables and charts. The system's real-time data visualization empowers users to comprehend fluctuations, make informed decisions, and identify anomalies promptly. **Indoor Air Quality Index (IAQI) Model:** The incorporation of an Indoor Air Quality Index (IAQI) model enhances the system's assessment capabilities. By considering factors such as thermal comfort, ventilation rate, and pollutant concentrations, the IAQI model provides a comprehensive evaluation of indoor air quality. This model aligns with established standards and methodologies, enabling users to gauge the air quality status based on recognized indicators.

The contributions of this study are multifaceted and can be categorized into three distinct dimensions. The IoT-Based Indoor Air Quality Monitoring System itself presents a paradigm shift in monitoring practices. It offers a cost-effective means of real-time monitoring, effectively accommodating multi-unit monitoring scenarios, and enhancing user experience through online data visualization. The integration of an advanced Indoor Air Quality (IAQ) model further elevates the system's capabilities, enabling accurate interpretation of air quality data and facilitating informed decision-making.

The contributions of the Indoor Air Quality Index (IAQI) model extend beyond numerical representation. By enabling a direct assessment of air cleanliness and considering a comprehensive range of factors including thermal comfort and pollutants, the IAQI model simplifies the complex landscape of indoor air quality assessment. Its adaptability, reflected in flexible sub-index ratios, enhances the model's applicability across various contexts, enriching its utility for diverse users.

Lastly, the research process itself yielded contributions that fortified the system's integrity. Rigorous sensor validation, innovative calibration methodologies, advanced wireless communication integration, and establishment of a reliable web infrastructure collectively underscore the robustness of the system. Notably, the system's versatility through sensor and module interchangeability not only caters to a wide array of environments but also ensures its responsiveness to varying requirements.

5.3 Recommendations and Future Work

In conclusion, while this research has yielded valuable insights and contributions to the field of indoor air quality monitoring, it is important to acknowledge the inherent limitations and uncertainties that come with the use of sensor-based systems. Variability among different sensor models, sensor drift, and degradation due to environmental conditions, limited sensor lifespan, and challenges related to data interpretation all underscore the complexity of working with sensor-based data.

Looking towards future studies, several areas of development present themselves. Firstly, there is a pressing need to advance Sensor Calibration Techniques. As consumer-grade sensors become more integral to air quality monitoring, sophisticated calibration methods must be explored. These methods have the potential to enhance accuracy and reduce sensitivity to changing environmental conditions, thereby improving the overall reliability of measurements. Secondly, enhancing Data Processing Methodology is a critical aspect of future research. While current data processing algorithms reside within the microcontroller unit, shifting towards cloud-based processing by transmitting raw data from sensors opens up new avenues for improvement. This transition could streamline system adjustments and updates, reducing the reliance on physical equipment manipulation and operation. Lastly, the study emphasizes the significance of Advanced IoT Infrastructure. Innovations in IoT infrastructure, including edge computing and cloud-based analytics, hold the promise of elevating data processing capabilities. By enabling real-time data analysis, anomaly detection, and predictive modelling, these advancements have the potential to significantly enhance the effectiveness of sensor systems in the realm of air quality management.

In summary, while this research has brought us closer to efficient and cost-effective indoor air quality monitoring, there remains a rich landscape of possibilities for further refinement and advancement. Addressing the limitations and delving into these recommended areas of focus will undoubtedly contribute to the ongoing evolution of sensor-based systems and their applications in ensuring healthier indoor environments.

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