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Development of a Particulate Matter Sensor Network for Air Quality Monitoring in Indoor Settings and in Mines

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DEVELOPMENT OF A PARTICULATE MATTER SENSOR NETWORK FOR AIR QUALITY MONITORING IN INDOOR SETTINGS AND IN MINES

by

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ABSTRACT

The importance of indoor air quality (IAQ), especially concerning particulate matter (PM), has become increasingly recognized due to its substantial impact on public health. Individuals spend a significant portion of their time indoors, where PM concentrations can exceed that of outdoors, leading to potential adverse health effects ranging from immediate irritation to long-term respiratory and cardiovascular diseases. The dynamic nature of indoor environments, combined with the diversity of PM sources, presents considerable challenges for effective IAQ monitoring and management. Traditional approaches to IAQ assessment often fall short, lacking the granularity and immediacy required to address these challenges adequately.

This abstract proposes the development and deployment of advanced sensor networks as a transformative solution for real-time PM monitoring in indoor settings. These low-cost, high-sensitivity sensors enable continuous, high-resolution monitoring of PM concentrations, providing critical data for identifying pollution sources and taking timely action to mitigate exposure. The integration of sensor networks with building management systems allows for automated adjustments to ventilation and air purification strategies, directly responding to real-time IAQ data. Such an approach not only promises to enhance the health and well-being of indoor occupants by minimizing exposure to harmful PM but also contributes to energy efficiency by optimizing the operation of HVAC systems based on actual air quality conditions. Future advancements in sensor technology and smart building integration are anticipated to further refine IAQ monitoring capabilities.

ACKNOWLEDGMENTS

Completing this thesis has been one of the most challenging yet rewarding endeavours of my academic journey, and it would not have been possible without the unwavering support and guidance of several key individuals.

First and foremost, I am immensely grateful to my advisor, Yang Wang, for his invaluable mentorship, patience, and encouragement throughout this process. His expertise and insights have been crucial in shaping both the direction and success of my research.

To my family, who have been my foundation and a constant source of strength and encouragement: thank you. To my parents, your endless love, sacrifices, and belief in my abilities have been the driving force behind my achievements. Your example has instilled in me the value of hard work, perseverance, and humility.

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1. INTRODUCTION

1.1. AIR QUALITY

Air quality refers to the condition or cleanliness of the air in our environment and is determined by the amount and types of pollutants it contains. Good air quality is characterized by low levels of pollutants, making the air safe to breathe and posing minimal risks to human health and the environment. The relationship between air quality and human health has been underscored by extensive research (Anderson. et al, 2011), highlighting the profound impact of particulate matter (PM), on various health outcomes. PM is a complex mixture of tiny particles and droplets in the air, composed of acids, organic chemicals, metals, and soil or dust particles. Among the various sizes of particulate matter, $PM_{2.5}$—particles with an aerodynamic diameter of 2.5 micrometers or smaller—are of significant concern due to their ability to penetrate deep into the respiratory tract and enter the bloodstream, posing serious health risks (WHO guidelines, 2021). The World Health Organization estimates that PM air pollution contributes to approximately 800,000 premature deaths annually, ranking it as a leading cause of mortality worldwide. Populations exposed to high levels of PM over long periods exhibit a significantly higher incidence of cardiovascular events. (Anderson et al, 2011). Figure 1.1 categorizes the Air Quality Index (AQI), breaking down the ranges of air quality into categories that signify their effects on human health (EPA).

AQI Category	Index Values	Previous Breakpoints (1999 AQI) (µg/m³, 24-hour average)	Revised Breakpoints (µg/m³, 24-hour average)
Good	0 - 50	0.0 - 15.0	0.0 – 12.0
Moderate	51 - 100	>15.0 - 40	12.1 – 35.4
Unhealthy for Sensitive Groups	101 – 150	>40 – 65	35.5 – 55.4
Unhealthy	151 – 200	> 65 – 150	55.5 – 150.4
Very Unhealthy	201 – 300	> 150 – 250	150.5 – 250.4
Hazardous	301 – 400	> 250 – 350	250.5 – 350.4
	401 – 500	> 350 – 500	350.5 – 500

Figure 1.1. EPA PM25 standards

1.2. AIR QUALITY MEASUREMENT

The measurement of air quality, particularly the concentration of PM, is a critical aspect of environmental and occupational health monitoring. Recent advancements have shifted towards leveraging low-cost, light-scattering particulate matter sensors for more widespread and real-time surveillance of PM concentrations, including respirable particles such as coal dust in mining environments. These sensors, exemplified by the Plantower PMS7003, offer a promising solution to the limitations posed by traditional, bulky, and expensive monitoring equipment, making it feasible to monitor different environments and settings. The calibration of low-cost sensors for coal dust monitoring in underground mines emphasizes the need for precise calibration to harness their high spatiotemporal resolution for characterizing PM concentration. Linear regression models are used to calibrate the sensors. This approach not only confirmed the potential of low-cost sensors in accurately monitoring coal dust but also revealed the minimal influence of environmental factors such as temperature and relative humidity on sensor performance (Amoah. et al, 2022). The broader applications of low-cost PM sensors are detailed, including the evaluation methods used to ascertain compliance with ambient air quality standards for suspended particles. This encompasses diverse methodologies available for assessing the accuracy, precision, and reliability of these sensors under various environmental conditions, including comparisons with Federal Equivalent Methods (FEMs) or research-grade instruments. This method of measurement offers a comprehensive framework for the calibration and deployment of low-cost sensors in monitoring air quality, paving the way for their application in diverse settings beyond industrial environments (Judith et al, 2012).

1.3. LOW-COST SENSOR NETWORKS

A low-cost PM sensor network consists of a distributed array of inexpensive, often compact sensors designed to measure concentrations of particulate matter in the air. These sensors can detect various sizes of particulate matter, commonly $PM_{2.5}$ and PM_{10}.

The term low-cost differentiates these sensors from traditional, high-precision air quality monitoring equipment used by governmental and research institutions, which can be prohibitively expensive and typically result in sparse monitoring networks due to budgetary constraints. Low-cost sensors, on the other hand, are affordable enough to deploy in much higher densities, thereby providing more detailed spatial coverage and the ability to capture localized pollution events that might be missed by fewer, widely spaced high-end monitors.

Recent studies have highlighted the potential of these sensors in environmental monitoring, providing a solid foundation for their application in IAQ management (Zaid et al, 2024). Similarly, (Thangavel et al, 2022) further justified the need for advanced monitoring technologies. The adoption of such sensor networks for IAQ management is poised to enable the ease of air quality monitoring, making it accessible to a broader population segment and enhancing awareness of the importance of maintaining healthy indoor air standards. The study by (Thangavel et al, 2022) also integrates findings from pivotal studies to emphasize the role of innovative sensor networks in advancing our understanding and management of IAQ, particularly concerning the particulate matter.

The advent of low-cost sensor networks has opened new avenues for air quality monitoring enabling dense spatial coverage. An example of low-cost networks are networks that leverage advancements in sensor technology, the Internet of Things (IoT), and low-power wide-area networks (LPWAN) such as LoRaWAN, enable a detailed and dynamic understanding of air pollution patterns at a fraction of the cost of traditional monitoring systems. The potential of integrating low-cost PM sensors with IoT devices for city-scale air quality monitoring is significant. The feasibility of using these sensors to monitor PM concentrations across the city offers valuable data for environmental health studies (Johnston et al., 2018). The employment of LPWAN technologies further underscores the scalability and efficiency of low-cost PM sensor networks. LoRaWAN’s long-range and low-power communication capabilities ensure that sensors can transmit data over extensive urban areas without the need for frequent maintenance, making it an ideal choice for large-scale air quality monitoring networks.

A significant section of our study is the use of the PM sensor network in the Missouri University of Science and Technology (MS&T) mine. The conventional approach for measuring Diesel Particulate Matter (DPM) exposure in underground metal and nonmetal mines aims to calculate the mean concentration over a full work shift. This process generally involves gathering air samples during the shift. However, this approach could be problematic because, although it reports the correct data, it cannot do so in real-time (Noll. et al, 2013).

In this context, the proposed development and deployment of advanced sensor networks offer a transformative solution for real-time PM monitoring in indoor environments. This initiative, grounded in the employment of low-cost, high-sensitivity sensors, aims at facilitating continuous, high-resolution monitoring of PM concentrations. Such an approach is critical for identifying sources of indoor pollution and implementing timely measures to reduce exposure. Moreover, the integration of these sensor networks with building management systems enables the automation of adjustments in ventilation and air purification strategies, thereby enhancing the health and well-being of indoor occupants.

2. METHODS AND MATERIALS

2.1. THE SENSOR UNIT

This study focuses on the development and deployment of a network of particulate matter sensors in various settings including indoor and in-mine settings, the goal of this network of sensors is to offer a way to measure particulate matter in a passive low-cost alternative to the traditional ways to collect particulate matter data. To achieve this goal, a low-cost sensor was developed, which consists of a PCB board with an ESP8266 chip, a temperature and humidity sensor along with a PMS7003 $PM_{2.5}$ by Plantower sensor these sensors report data in ($\mu g/m^3$), and finally the power source of AiBOCN power banks. This is the first step towards establishing a network of particulate matter sensors. The production of the sensors has been upscaled to approximately ten units. These sensors will be interconnected through a developed mesh network, for catalysing the connectivity between particulate matter sensors.

Figure 2.1 The sensor unit.

This setup will enable efficient and accurate data collection across a large area, as well as inside the MS&T mine. The sensor units were calibrated using the GRIMM 11-D Advanced Real-Time Dust Monitor. 4 sensors were placed in a chamber with a small fan, and two inlets one to introduce particles into the chamber and another to enable the GRIMM unit to collect readings from withing the chamber. The readings of the GRIMM were graphed against the sensors, the rest of the sensors were calibrated using the sensors that were calibrated using the GRIMM. overall, the sensors positively correlated with GRIMM.

Figure 2.2. Calibration of sensors

2.2. THE SENSOR NETWORK

The sensor network comprises two main categories which are the hardware and the software made to work together to create a mesh network of sensors that connect to-enable the coverage of a large area.

Figure 2.3. Sensor components

2.2.1. Hardware. The development of a mesh network for monitoring particulate matter, specifically $PM_{2.5}$ levels, involves a carefully selected assembly of hardware-components. This section outlines the materials chosen for the project and the process of integrating the following components.

ESP8266 Module: The core of each sensor node, the ESP8266 module, was selected for its Wi-Fi capabilities, compact size, and compatibility with the Arduino development environment, making it ideal for IoT projects. LoRa Module (E32-433T20DT): For long-range communication across the mesh network, LoRa modules were chosen. These modules are known for their low power consumption and long-distance communication abilities, essential characteristics for remote sensor nodes.

PMS7003 Particulate Matter Sensors: The PMS7003 sensor was specifically chosen for its ability to accurately measure $PM_{2.5}$ levels. Its small form factor and UART interface make it well-suited for integration with the ESP8266 modules. Power Sources: Considering the deployment in potentially remote areas, power sources such as battery packs or solar panels were evaluated for their suitability to ensure uninterrupted operation, the AiBOCN power banks. Connectors and Cables: A variety of connectors and cables were prepared to facilitate the physical connections between the ESP8266 modules, LoRa modules, and PMS7003 sensors, including USB to UART converters for sensor data communication.

2.2.2. Assembly of the Network. The following is the assembly process of the hardware components. The ESP8266 modules were flashed with the latest firmware and configured to be programmed using the Arduino IDE, setting the foundation for the software development phase. Connecting the LoRa Modules: Utilizing SPI communication, the LoRa modules were connected to the ESP8266. Special attention was given to the wiring configuration to ensure reliable communication for data transmission across the mesh network. Integrating the PMS7003 Sensors: The PMS7003 sensors were connected to the ESP8266 modules via UART. Adapters were used where necessary to match the logic levels and connectors, ensuring accurate and reliable data communication. Power Management solutions were implemented, focusing on efficiency and reliability, leading to the choice of the Aibcon power banks.

2.2.3. Software. Upon establishing a robust hardware foundation, the focus shifted towards developing the software to control the sensor nodes, manage data collection, and handle communication across the mesh network. Software development environment, Arduino IDE, the primary tool for programming the ESP8266 modules, the IDE's wide support for libraries and straightforward programming model facilitate rapid development and testing. Combined with the Arduino libraries, key libraries included the LoRaWAN library for Arduino, providing an abstraction layer for handling LoRa communication, and the Software Serial library, enabling UART communication with the PMS7003 sensors on the ESP8266's digital pins. Software implementation, sensor Data Collection Custom Arduino sketches were written for the ESP8266 modules to manage data collection from the PMS7003 sensors. The sketches utilize the Software Serial library to read $PM_{2.5}$ concentration levels, process the data, and prepare it for transmission. This custom sketch also enabled the connection to the private server that was set up for the data collection and transmission. LoRa module communication, and the implementation of the LoRaWAN protocol via the Arduino LoRa library allowed for efficient configuration of the LoRa modules. Scripts were developed to package the $PM_{2.5}$ data and manage its transmission across the network, ensuring data integrity and optimizing for power consumption. Mesh network configuration and software routines were developed to enable mesh networking capabilities, allowing sensor nodes to communicate directly or relay data. Algorithms for dynamic routing and network health monitoring were integrated to maintain network reliability and data accuracy. The main source of the internet is a hotspot that is connected to the mother node. A Private server, a private server was set up through Python that connects to the sensor network, enabling the sensors to upload data to the private server and have tables that show the collection of the data in time. Data analysis**:** A MATLAB code was developed to digest and graph the PM2.5 data as a time series plot.

2.3. SENSOR DEPLOYMENT

The deployment of particulate matter sensors plays a crucial role in the comprehensive monitoring and assessment of air quality in different environments. This section details the deployment strategies and insights gained from deploying sensors in three distinct settings: on campus, in residential areas, and within mining operations. Each environment presents unique challenges and opportunities for understanding and mitigating particulate matter exposure.

2.3.1. On-Campus Deployment. The experiment conducted on September 22^{nd}, 2021, involved deploying sensors in the lobby of Butler Carlton Hall (BCH). This was the first experiment conducted with the sensors. The start was to make sure that the sensors work in this environment and report data accurately, the sensors were deployed near chairs where students frequent in the lobby. The sensors were also deployed in a classroom in a BCH classroom from March 3^{rd}, 2022, to March 8^{th}, 2022, where the sensors were set at different heights. The reason behind this setup is to observe the $PM_{2.5}$ vertical distribution which will help with identifying sources of $PM_{2.5}$ and estimate the health impacts of this distribution.

2.3.2. In-House Deployment. The in-house sensor deployment was conducted from November 25^{th}, 2023, to November 26^{th}, 2023, and aimed to assess indoor air quality and identify sources of particulate matter within residential settings. Sensors were placed in various rooms, including a kitchen, a bedroom, and a living room/office space. The purpose of this experiment is to report data from a day-to-day living basis such as cooking, or lighting candles among other activities that come with daily living. In this-step, another sensor was added to make it a total of 4 as a means of scaling up to the next step.

Figure 2.4. Classroom sensor deployment

Figure 2.5. In-house sensor deployment

2.3.3. In Mine Deployment. The final experiment that was conducted from March 5th, 2024, to March 11th, 2024, using the sensors is the mine experiment where 9 sensors were deployed near the entrance of the MS&T mine. In this step, the mesh network was also introduced to enable the connectivity between sensors the Raspberry Pi and the mother node to be able to share the internet and allow the sensors to upload the data to the private server.

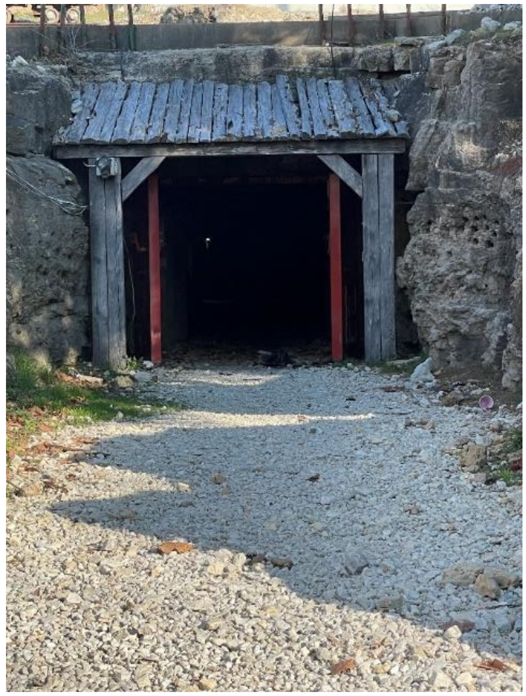

Figure 2.6. Mine entrance

Figure 2.7. Sensor deployed in the mine.

3. RESULTS AND DISCUSSION

3.1. ON CAMPUS DEPLOYMENT RESULTS

Figure 3.1 provides a time-series representation of $PM_{2.5}$ concentrations, tracked by three distinct sensors between 15:00 and 18:30 on September 22, 2021. The readings are smoothed averages of every 500 measurements (50 seconds) to reduce noise. At the onset, the sensor 1 at 68 cm above the ground records the highest $PM_{2.5}$ levels, initiating at concentrations just above 220 $\mu g/m^3$. Sensor 2 at 102 cm begins slightly lower, under 200 $\mu g/m^3$, while Sensor 3 at 170 cm starts at approximately 160 $\mu g/m^3$. The initial divergence between the sensors could be attributed to spatial differences in particulate matter distribution, or variable sensitivities. Shortly after the recording period commences, all sensors show a peak in $PM_{2.5}$ concentration followed by a general decline. The peak is most pronounced in Sensor 1, suggesting a localized spike in particulate matter, which is progressively less evident in Sensor 2 and minimal in Sensor 3, hinting at the possibility of a spatially confined particulate source or differing sensor responses. The trend continues with a consistent decrease in $PM_{2.5}$ levels for all sensors. This decline may reflect changes in environmental conditions, effectiveness of ventilation, or the resolution of a localized particulate emission. The downward trend across all sensors post-peak indicates a shared environmental influence or a collective response to an event, pointing toward a systemic change in the area’s air quality. The gradual descent in $PM_{2.5}$ concentrations suggests that the particles dissipate slowly, providing insight into air purification or circulation effectiveness within the area.

Sensor 1 showed a mean value of 169 μg/m³ which is already higher than the EPA recommendation. Sensor 2 shows a mean value of 148 μg/m³, finally, sensor 3 showed an average of 153 μg/m³. The $PM_{2.5}$ levels recorded by all sensors exceeded the WHO's recommended safe thresholds, implying a persistent health risk. This is a significant concern, particularly in the context of the roof construction, that was taking place during the time of this experiment. The reported values all fall in the range that is considered unhealthy for sensor 2 and very unhealthy for sensors 1 and 3. The area that this experiment was conducted in was undergoing some construction maintenance which could explain the high reported values of $PM_{2.5}$.

The data underscores the importance of real-time environmental monitoring, especially in scenarios involving construction or other particulate-generating activities. Continuous monitoring allows for the immediate identification of potential hazards and the swift implementation of corrective actions to minimize health risks. Future analyses should consider correlating specific construction activities with observed $PM_{2.5}$ trends, further calibration of sensors, and a detailed assessment of the health implications for individuals exposed to such particulate levels during similar events. The height at which sensors are positioned can lead to significant differences in readings, which is particularly important because people of different heights may be exposed to varying levels of pollution, especially in relation to $PM_{2.5}$. This variation is significant as the distribution of particulate matter within a given environment can be uneven, with concentrations potentially varying at different heights due to factors such as airflow, source of pollution, and physical barriers. Therefore, understanding how sensor height affects readings is crucial for accurately assessing exposure levels.

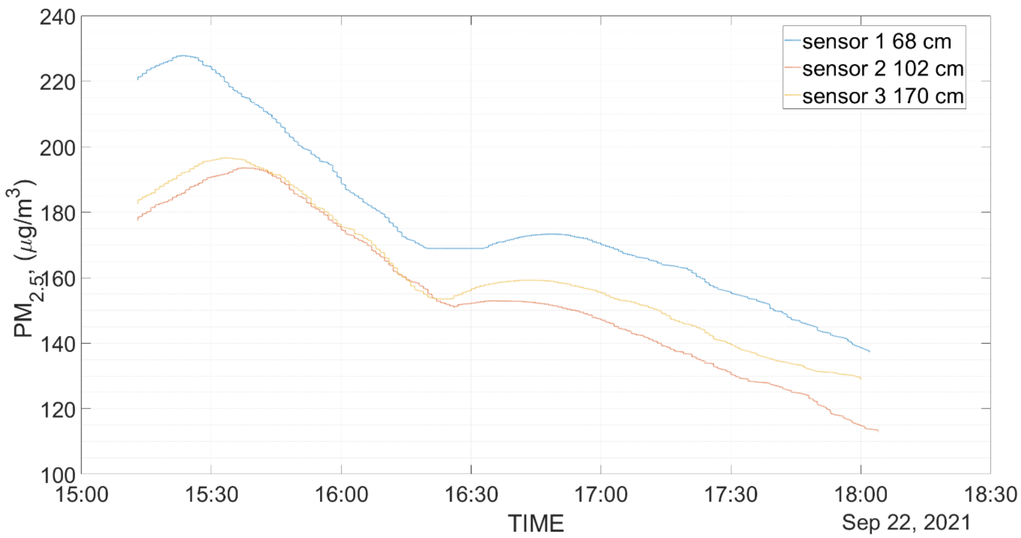

Figure 3.1. On-campus deployment 1

Figure 3.2 is tracking $PM_{2.5}$ levels over several days in March 2022, with the addition of the height variability. The sensors' heights are given as 68 cm, 70 cm, 102 cm, 136 cm, and 170 cm. The concentration of $PM_{2.5}$ particles. The scale reaches up to 140 µg/m3, indicating that the sensor detected higher levels of $PM_{2.5}$ particles at some points compared to the previous graph, where the scale only reached 40 µg/m³.

There is an extreme spike for Sensor 2 on March 3rd, where the $PM_{2.5}$ concentration shoots up above 120 µg/m³. This is a significant outlier compared to the other readings and might suggest an event that caused a high level of particulates near the floor or a sensor malfunction. The rest of the data points for Sensor 1 are close to zero, which, together with the spike, might indicate an intermittent source of pollution or error in measurement. Sensor 2, which is at a similar height to Sensor 1, does not show this extreme spike, suggesting that the event on March 3rd was very localized or that there was a problem with Sensor 1. On March 6th and 7th, all sensors detect increases in $PM_{2.5}$

levels, with the higher sensors (136 cm and 170 cm) generally recording higher concentrations. This could suggest that certain activities or environmental factors affected the entire room but had a greater impact at higher elevations.

The mean value for sensor 1 was analysed to be 8 $\mu g/m^3$, sensor 2 showed a 10 $\mu g/m^3$ mean, sensor 3 average is 6 $\mu g/m^3$, sensor 4 showed an average of 9 $\mu g/m^3$, and finally sensors 5 and 6 both showed an average of 7 $\mu g/m^3$. All these values were found to be below the WHO's standard for the 24-hour mean sensor 2 showed the highest average which was the closest to the WHO's 24-mean of 15 $\mu g/m^3$. These values would be categorized in the good category according to the EPA standard. (Figure 1.1).

Across the days, $PM_{2.5}$ levels rise and fall which could correlate with the daily use of the classroom, possibly indicating that the particulates are associated with occupancy and activities. If this classroom's ventilation system is more active at higher levels, it might not be as effective in clearing particulates at lower levels. Alternatively, if there are windows or other sources of air entry at higher levels, this could explain why sensors placed higher show higher $PM_{2.5}$ levels. When compared to the previous on-campus deployment, it's notable that the scales of the two graphs are different, with this one showing much higher peak values. This points out the differences the change in deployment achieves.

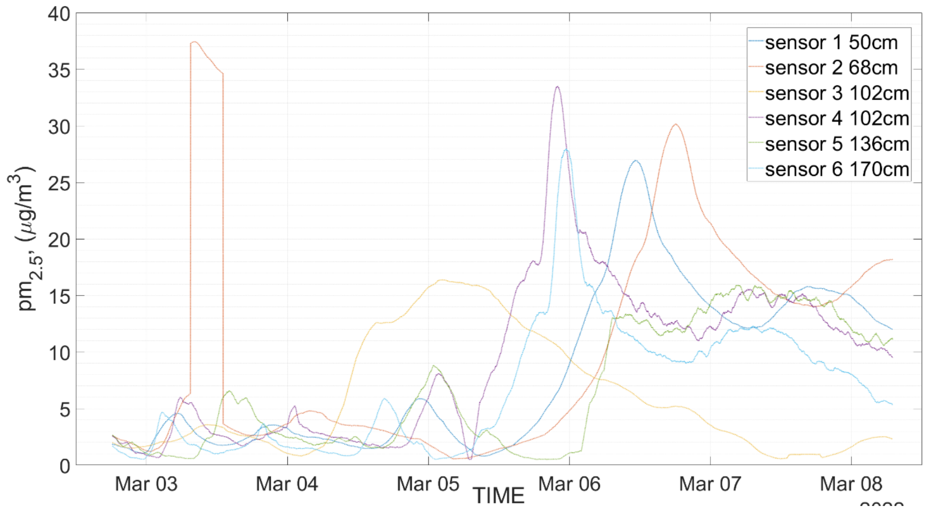

Figure 3.2. On-campus deployment 2

3.2. IN-HOUSE DEPLOYMENT RESULTS

A time series analysis of $PM_{2.5}$ concentrations within a residential setting was conducted, using data collected from four sensors located in different rooms of a house on November 26, 2023. Figure 3.2 indicates distinct particulate matter profiles for each location within the home. Sensor 1, located in the kitchen, shows two significant peaks, one just after midnight and another in the early afternoon. These peaks are indicative of activities typically associated with high particulate matter production, such as cooking. Sensors 2 and 3, both positioned in the living room, exhibit a different pattern, with sensor 2 displaying a small peak in the early hours and sensor 3 showing a gradual rise in $PM_{2.5}$ levels before a sharp increase around midday. The variance between these two sensors might suggest different proximities to the particulate matter source or varied sensitivities.

Sensor 4, placed in a bedroom, records relatively stable and low $PM_{2.5}$ concentrations throughout the day, with a slight increase in the evening. The stability of this sensor suggests fewer particulate matter sources in the bedroom, as expected in an area typically associated with rest and low activity levels. The peaks observed in the kitchen (Sensor 1) can likely be correlated with meal preparation times, where activities such as frying or sautéing can significantly increase particulate matter concentrations. The peaks' magnitude suggests either intense cooking activities or inadequate ventilation.

In the living room, the difference between the readings from Sensors 2 and 3 could result from their locations within the room. If one sensor is closer to a source of particulate matter, such as a doorway, a window, or a heavily trafficked area, it could explain the higher readings compared to the other sensor. The data from the bedroom sensor (Sensor 4) implies that it is a low-PM environment for most of the day, with the evening rise possibly attributed to activities like changing clothes or nighttime routines that can stir up particulates.

For sensor 1 the mean value was calculated to be 14 $\mu g/m^3$, while for sensor 2 it was reported to be 15 $\mu g/m^3$ for the mean value, Sensor 3 Produced a mean value of 15 $\mu g/m^3$, and lastly sensor 4 recorded a mean value of 48 $\mu g/m^3$. Sensors 1, 2 and 3 and in this deployment are at a level that is considered good by the EPA (Figure 1.1), however, the mean values for sensor does put it at the unhealthy for sensitive people.

The data collectively demonstrates the dynamic nature of indoor air quality and how it can be affected by routine domestic activities. It also underscores the necessity of sensor placement strategy when monitoring particulate matter in a residential setting to capture a comprehensive picture of air quality. The patterns observed here provide valuable insights that could be used to advise on the placement of air purifiers or to encourage behavior that minimizes particulate matter emissions indoors.

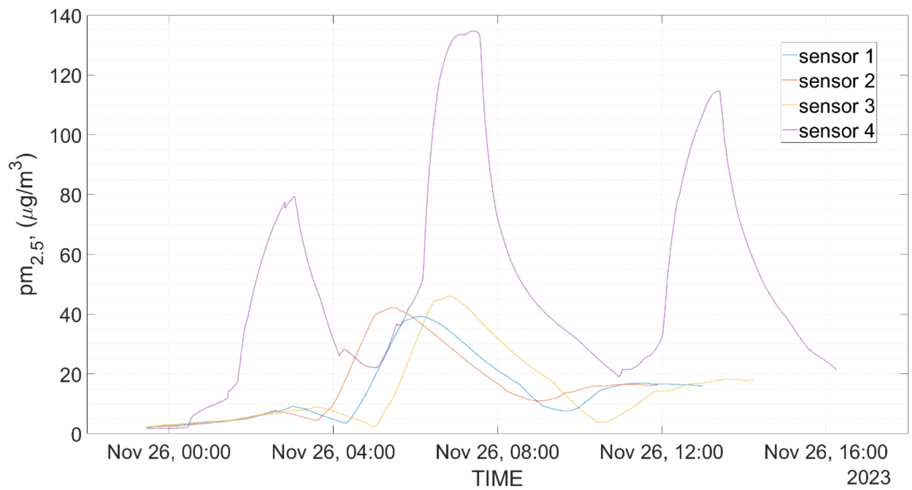

Figure 3.3. In house deployment

3.3. IN MINE DEPLOYMENT RESULTS

The highlighted areas on the mine map indicate the measurement area for these sensors. Figure 3.5 is the zoomed-in version of the mine map, where the sensors were deployed. The locations of the sensors are marked on the map of the mine 1-3 where 1 is the closest to the door, 2 is the one in the middle and 3 is the furthest one in the middle. While sensors 4-6 are on the right side on the map where sensor 4 is the one closest to the entrance, sensor 5 is the one in the middle right after 4 and sensor 6 is the furthest one in on the right side, sensors 7-9, the sensors are placed similarly to the sensors on the right side. Where sensor 7 is the one closest to the main mine entrance, sensor 8 is in between sensor 7 and sensor 9 is the furthest one in on the left side of the mine deployment area.

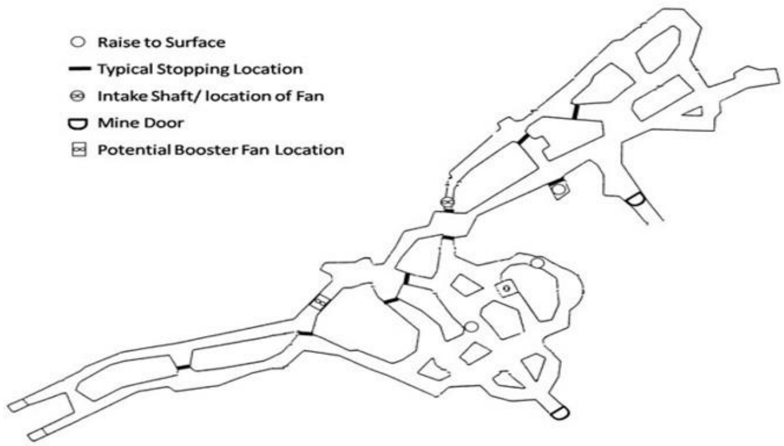

Figure 3.1. Mine map

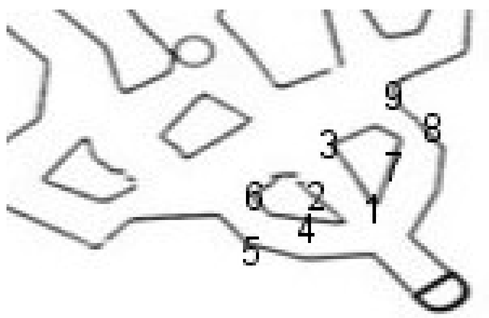

Figure 3.2. Mine map zoomed in

While sensors 4-6 are on the right side on the map where sensor 4 is the one closest to the entrance, sensor 5 is the one in the middle right after 4 and sensor 6 is the furthest one in on the right side, sensors 7-9, the sensors are placed similarly to the sensors on the right side. Where sensor 7 is the one closest to the main mine entrance, sensor 8 is in between sensor 7 and sensor 9 is the furthest one in on the left side of the mine deployment area.

Sensors 1, 2, and 3 are associated with Figure 3.6, which shows $PM_{2.5}$ levels that are generally below 200 µg/m³. Sensors 1, 2, and 3 are placed in the middle of the mine walkway. These sensors had lower $PM_{2.5}$ readings compared to the others, suggesting this area may have better air quality or is further from direct pollution sources.

The mean values calculation for the mine deployment of sensors 1,2 and 3 was conducted to report the following mean values. Sensor 1's mean value 78 µg/m³, while sensor 2's mean was identified to be 111 µg/m³, next the mean for sensor 3 was found to be the same as sensor 2 at 111 µg/m³. all the reported averages place this deployment in the unhealthy category according to the EPA standards (figure 1.1)

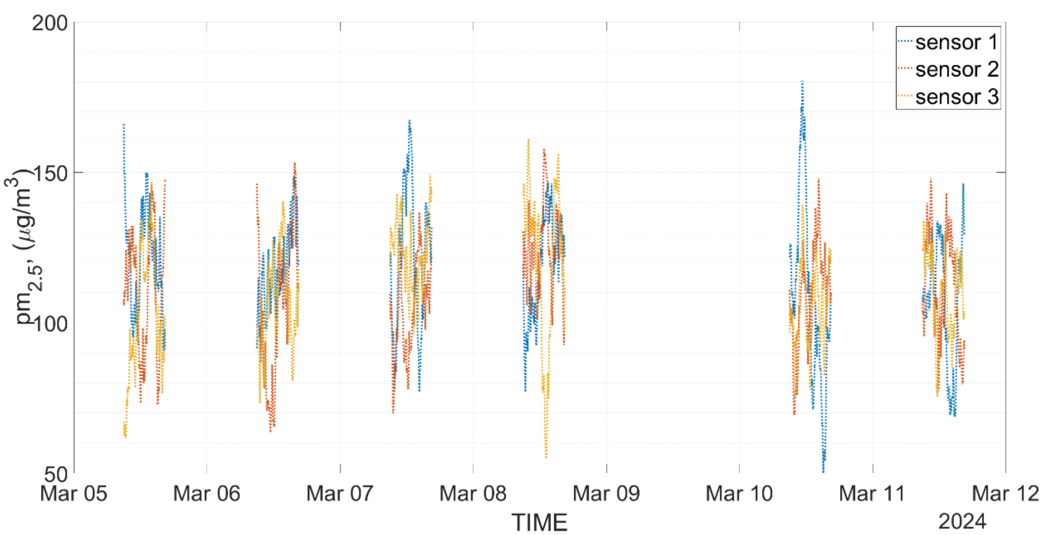

Figure 3.6. Sensors 1,2,3

Sensors 4, 5, and 6 correspond to Figure 3.7, with $PM_{2.5}$ levels reaching up to about 350 µg/m³. Sensors 4, 5, and 6 are placed on the right side of the main mine walkway. The readings from these sensors were higher than the first group of sensors, indicating more exposure to particulate matter. Calculation of the mean values provided the following values for each sensor. Sensor 4 presented a mean value of 211 µg/m³, sensor 5 showed a value of 201 µg/m³, and finally sensor 6 showed a mean value of 203 µg/m³. The reported values would be considered unhealthy by the EPA standards (figure 1.1).

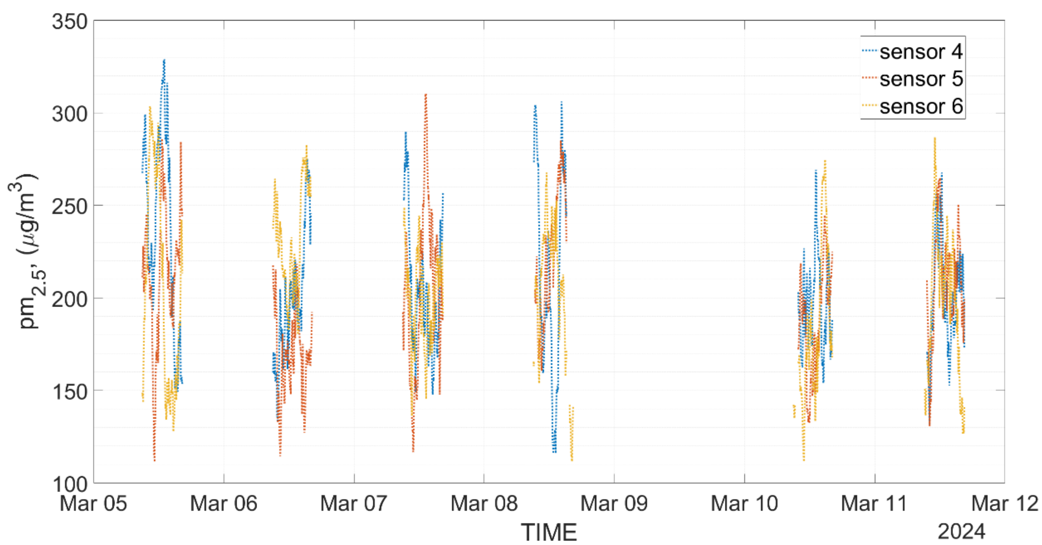

Figure 3.7. Sensors 4,5,6

Sensors 7, 8, and 9 are related to Figure 3.8, showing $PM_{2.5}$ levels peaking near 400 µg/m³. Sensors 7, 8, and 9 are placed on the left side of the main mine walkway. These sensors recorded the highest $PM_{2.5}$ levels, which could suggest proximity to the pollution source or less efficient air circulation. For the final set of sensors that were deployed in the mine. The mean values were calculated to be 228 μg/m³ for sensor 7, while sensor 8 showed a mean value of 231 μg/m³. and lastly sensor 9 showed a mean value of 227 μg/m³. Following the EPA standards for air quality shows that all the sensors fall within the category that would be considered unhealthy (figure 1.1).

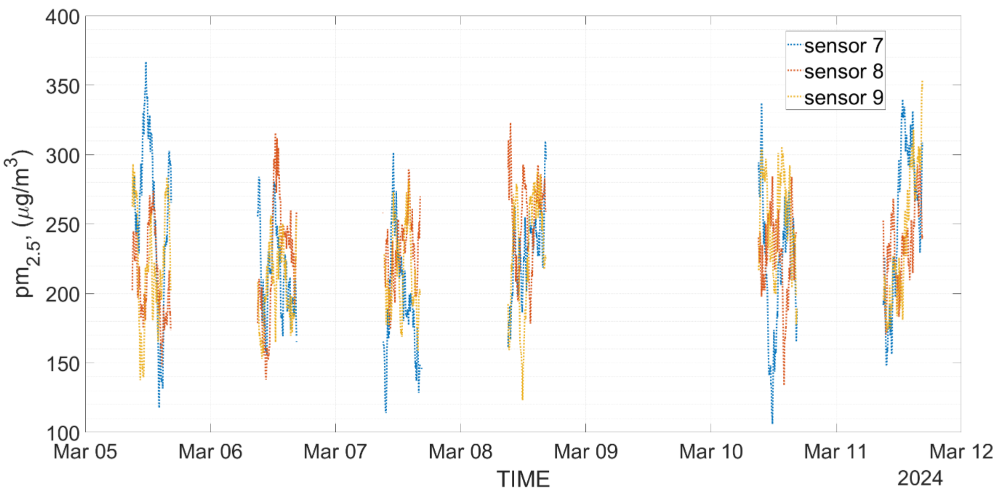

Figure 3.8. Sensors 7,8,9

The middle walkway of the mine might be more ventilated or could be an area where less dust-generating activity occurs. The Left walkway of the mine indicates moderate exposure to particulate matter, which could mean some activity is happening there that generates $PM_{2.5}$, but there is still some form of ventilation or air purification. The right walkway area indicates a zone with high $PM_{2.5}$ levels, which may be due to insufficient ventilation, proximity to dust-generating operations, or ineffective air filtration. The calibration method was not used to correct the sensor outputs for the results of the experiments.

A problem that seems to be occurring in the mine measurements, is that there are periods of time where the sensors were not reporting data or were reporting data that was unusable as it was reporting constant values. That can also indicate a problem with the sensor units where they are reporting false data. This illustrates the need for more research and more opportunities for development. Deploying sensors at higher densities within mines to capture a more detailed spatial resolution of air quality. This could involve placing sensors at different heights and locations that are representative of where workers spend their time. Enhanced Frequency of Data Transmission, by improving the frequency of data transmission between sensors and the central data collection system. This could involve optimizing the mesh network for more robust connectivity or exploring alternative communication technologies that are more reliable underground. Power Management Innovations by exploring innovations in power management for sensors, such as energy harvesting technologies or simply long-life batteries, to extend the operational life of the sensors and reduce the need for maintenance. Expanding research by deploying low-cost sensor networks across a variety of mine settings, including different types of mines (e.g., coal, metal, non-metal) and various geographical locations. This diversity can provide a broader data set for understanding sensor performance across different environmental conditions.

4. CONCLUSION

In conclusion, the study illustrates the significant potential of implementing a low-cost particulate matter (PM) sensor network within a mining environment, highlighting its flexibility and adaptability across various conditions and scenarios. The data acquired from the network is invaluable, providing insights into the spatial distribution of PM concentrations and identifying areas that might require attention due to higher levels of pollutants.

The consistency of measurements obtained is crucial, reflecting the sensor network's reliability within the specific deployment settings. The sensor placement strategy, considering factors such as proximity to potential pollution sources and ventilation efficiency, plays a vital role in capturing an accurate representation of the air quality within the mine.

However, while the study underscores the utility of such a network, it also uncovers several areas for improvement and challenges that need to be addressed in future deployments. The discrepancies in data integrity due to incorrect timestamps represent a critical issue that can impair data analysis and decision-making processes. This calls for a more robust data management system that ensures synchronization and accuracy in reporting. The mine experiments show this the most where it is illustrated that there are timestamps where the sensors were not gathering data.

Additionally, the communication infrastructure utilized for the sensor network, particularly the frequency for sensor interconnectivity, poses limitations. The study suggests that relying solely on a private server for data collection might be insufficient in today's context, where real-time monitoring is increasingly vital. The adoption of a webbased platform could offer a more reliable and accessible means of data aggregation and visualization. Such a platform would be beneficial not just for data collection but also for the analysis, enabling remote monitoring and timely interventions.

Moreover, the study indicates the necessity of an offline data storage solution as a backup to safeguard against data loss due to network outages or server downtime. This dual approach to data storage ensures continuity and integrity, which are critical for long-term monitoring and analysis.

The insights gleaned from deploying the sensor network demonstrate its advantages in providing environmental monitoring at a lower cost compared to traditional methods. However, the “growing pains” experienced, such as the need for enhanced data management and improved communication protocols, are reminders of the need for ongoing development in this field.

Overall, the study is a testament to the efficacy of low-cost sensor networks in environmental monitoring and the potential improvements that can amplify their impact. The lessons learned pave the way for future advancements, indicating a shift towards more sophisticated, resilient, and user-friendly monitoring systems. The continued evolution of these networks will undoubtedly contribute to a better understanding and management of occupational health risks and the creation of safer work environments.

APPENDIX A

THE SENSOR COMPONENTS AND NETWORK

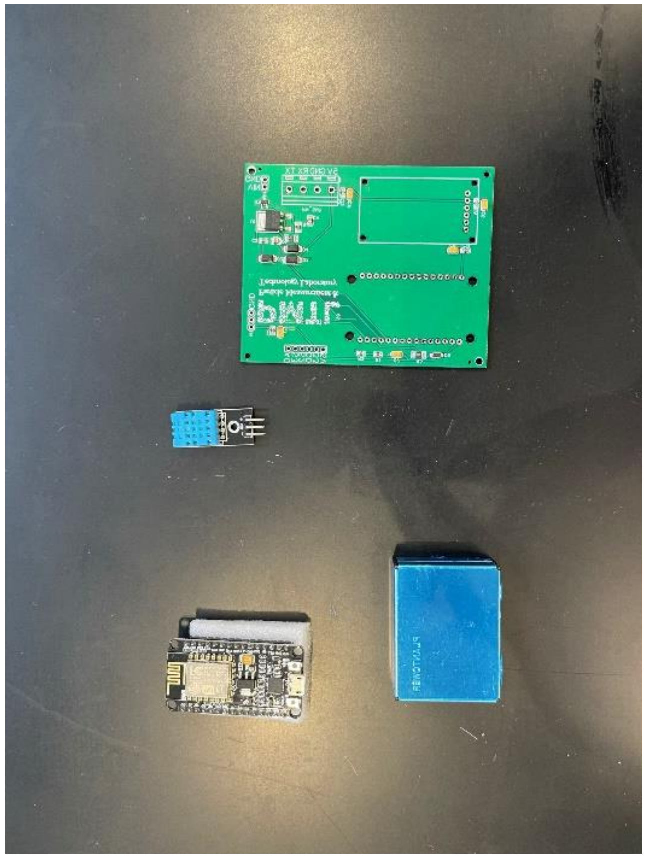

Figure A.1. Sensor components 1

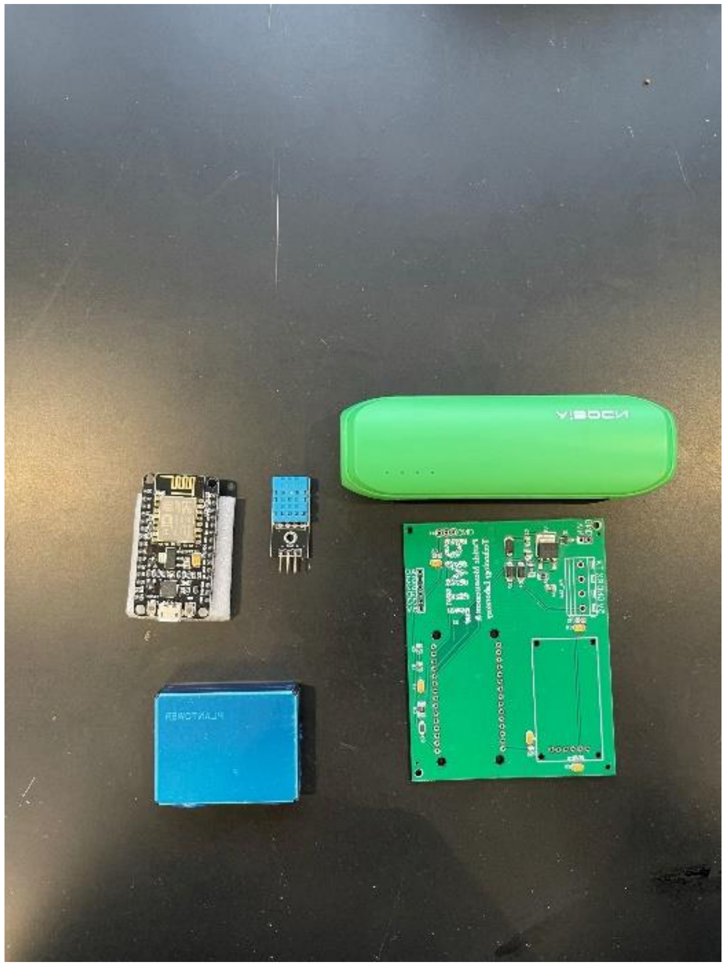

Figure A.2. Sensor components 2

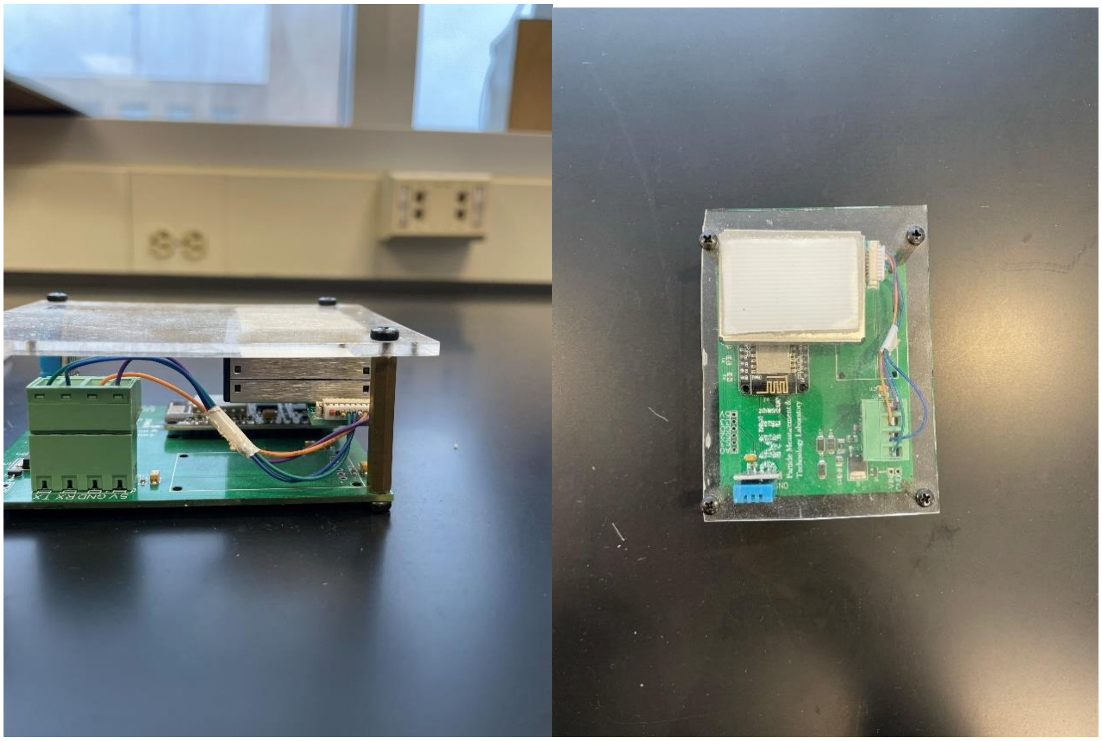

Figure A.3. Sensor components 3 the completed sensors

SensorID	Location	Temperature	Humidity	Timestamp	particles03	pm10	pm25	pm100
PMTL_Sensor1	55108	21.00	43.00	Mon, 13 Nov 2023 04:05:00 GMT	999.99	8.00	10.00	12.00
PMTL_Sensor1	55108	21.00	43.00	Mon, 13 Nov 2023 04:05:01 GMT	999.99	7.00	9.00	11.00
PMTL_Sensor4	55108	24.70	43.00	Mon, 13 Nov 2023 04:05:01 GMT	999.99	8.00	12.00	15.00
PMTL_Sensor3	55108	22.10	51.00	Mon, 13 Nov 2023 04:05:01 GMT	999.99	8.00	12.00	15.00
PMTL_Sensor3	55108	22.10	51.00	Mon, 13 Nov 2023 04:05:02 GMT	999.99	7.00	11.00	15.00
PMTL_Sensor4	55108	24.70	43.00	Mon, 13 Nov 2023 04:05:02 GMT	999.99	8.00	12.00	15.00
PMTL_Sensor2	55108	22.00	52.00	Mon, 13 Nov 2023 04:05:02 GMT	999.99	7.00	9.00	10.00
PMTL_Sensor1	55108	21.00	43.00	Mon, 13 Nov 2023 04:05:03 GMT	999.99	7.00	10.00	13.00
PMTL_Sensor3	55108	22.10	51.00	Mon, 13 Nov 2023 04:05:03 GMT	999.99	8.00	12.00	16.00
PMTL_Sensor4	55108	24.70	43.00	Mon, 13 Nov 2023 04:05:03 GMT	999.99	8.00	12.00	15.00
PMTL_Sensor2	55108	22.00	52.00	Mon, 13 Nov 2023 04:05:03 GMT	999.99	7.00	9.00	10.00
PMTL_Sensor4	55108	24.70	43.00	Mon, 13 Nov 2023 04:05:04 GMT	999.99	8.00	12.00	15.00
PMTL_Sensor2	55108	22.00	52.00	Mon, 13 Nov 2023 04:05:04 GMT	999.99	7.00	9.00	10.00
PMTL_Sensor3	55108	22.10	51.00	Mon, 13 Nov 2023 04:05:05 GMT	999.99	8.00	13.00	15.00
PMTL_Sensor2	55108	22.00	52.00	Mon, 13 Nov 2023 04:05:05 GMT	999.99	7.00	9.00	10.00
PMTL_Sensor1	55108	21.00	44.00	Mon, 13 Nov 2023 04:05:07	999.99	8.00	10.00	12.00

Figure A.4. Sensor components 3 the private server interface

A.1. ARDUINO SENSOR CODE

```
#include "DHT.h"
#include "PMS.h"
#include <ESP8266WiFi.h>
#include <WiFiClient.h>
#include <ESP8266HTTPClient.h>
#include <SoftwareSerial.h>
#define DHTPIN D1
#define DHTTYPE DHT11

SoftwareSerial pmsSerial(D4, D3);

const char *ssid = "Bani - WiFi";
const char *password = "5736129023";
const char *serverName = "http://192.168.0.35:5000/upload-data";

// String apiKeyValue = "tPmAT5Ab3j7F9";

String sensorName = "PMTL_Sensor3";
String sensorLocation = "55108";
String httpRequestData;

DHT dht(DHTPIN, DHTTYPE);
WiFiClient wifi;

PMS pms(pmsSerial);
PMS::DATA data;

void setup()
{
  Serial.begin(9600);
  pmsSerial.begin(9600);
  dht.begin();
  WiFi.enableInsecureWEP(true);
  WiFi.begin(ssid, password);
  while (WiFi.status() != WL_CONNECTED)
  {
    Serial.println("Waiting");
    delay(500);
  }
```

```
  Serial.println("Connected!!");
}

void loop() {
  Serial.println("Output!!");
  float h = dht.readHumidity();
  float t = dht.readTemperature();
  if (WiFi.status() == WL_CONNECTED) {
    Serial.println("Output123!!");
    if (pms.read(data)) {
      HTTPClient http;
      http.begin(wifi, serverName);
      http.addHeader("Content-Type", "application/json");
      String payload = "{";
      payload += "\"SensorID\":\"" + sensorName + "\",";
      payload += "\"location\":\"" + sensorLocation + "\",";
      payload += "\"temp\":" + String(t) + ",";
      payload += "\"humidity\":" + String(h) + ",";
      payload += "\"pm10\":" + String(data.PM_AE_UG_1_0) + ",";
      payload += "\"pm25\":" + String(data.PM_AE_UG_2_5) + ",";
      payload += "\"pm100\":" + String(data.PM_AE_UG_10_0) + ",";
      payload += "\"particles03\":" + String(data.P_03);
      payload += "}";

      int httpResponseCode = http.POST(payload);
      Serial.println("HTTP Response code: " + String(httpResponseCode));
      http.end();
    }
  }
}
```

A.2. PRIVATE SERVER NETWORK CODE

```
from flask import Flask, jsonify, request, render_template
from database import DataBase
import logging
import datetime

app = Flask(__name__)  # Create a Flask instance

# Configure logging
logging.basicConfig(level=logging.INFO)


@app.route(“/fetch-data”, methods=[“GET”])
def fetch_data():
    draw = request.args.get(“draw”, type=int)
    start = request.args.get(“start”, type=int)
    length = request.args.get(“length”, type=int)
    sensor = request.args.get(“sensor”, None)
    start_date_str = request.args.get(“start_date”, None)
    end_date_str = request.args.get(“end_date”, None)

    db = DataBase()
    db.connect()

    if start_date_str and end_date_str:
        start_date = datetime.datetime.strptime(start_date_str, “%Y-%m-%d %
H:%M:%s”)
        end_date = datetime.datetime.strptime(end_date_str, “%Y-%m-%d
%H:%M:%s”)
        data = db.fetch_sensor_data(sensor, start, length, start_date, end_date)
    else:
        data = db.fetch_sensor_data(sensor, start, length)

    records_total = db.get_total_record_count()
    records_filtered = db.get_filtered_record_count(
        sensor, start_date_str, end_date_str
    )

    db.close()
```

```
    return jsonify(
        {
            "draw": draw,
            "recordsTotal": records_total,
            "recordsFiltered": records_filtered,
            "data": data,
        }
    )


@app.route("/upload-data", methods=["POST"])  # Define a route to upload data
def upload_data():
    # Log the receipt of a request
    logging.info("Received request to /upload-data")
    data = request.json  # Get JSON data from request
    logging.info(f"l;ksdfagl;ksdfj {str(data)}")
    if not data:
        # Log warning if no data provided
        logging.warning("No data provided in request")
        # Return error if no data provided
        return jsonify({"error": "No data provided"}), 400

    # Create DataBase instance and upload data
    db = DataBase()
    db.connect()

    try:
        # Construct SQL query and parameters
        query = (
            "INSERT INTO sensordata "
            "(SensorID, location, temp, humidity, pm10, pm25, pm100, particles03, timestamp) "
            "VALUES (%s, %s, %s, %s, %s, %s, %s, %s, %s)"
        )
        params = (
            data["SensorID"],
            data["location"],
            data["temp"],
            data["humidity"],
            data["pm10"],
            data["pm25"],
            data["pm100"],
```

```
            data[“particles03”],
            datetime.datetime.utcnow(),
        )

        db.execute_query(query, params)
        db.cnx.commit()  # Commit the transaction
        # Log successful data upload
        logging.info(“Data uploaded successfully”)
    except Exception as e:
        db.close()
        # Log error if exception occurs
        logging.error(f”Error occurred: {str”€}")
        # Return error if exception occurs
        return jsonif“({"er”or": €(e)}), 500

    db.close()
    # Return success message
    return jso“ify({"m”ss“ge": "Data uploaded succes”fully"}), 201


@app.“o”te("/")  # Define a route for the home page
def home():
    # Render the home page using index.html
    return render_tem“late("inde”.html")


if __name“_ == "__”ain__":
    app.run”host="0”0.0.0", debug=True)
```

A.3. DATABASE CODE

```
import typing
import mysql.connector
from mysql.connector import errorcode
import datetime
import csv
import pandas as pd
import os
from dotenv import load_dotenv

load_dotenv()

class DataBase:
    def __init__(self):
        self.username = os.getenv("DB_USERNAME")
        self.password = os.getenv("DB_PASSWORD")
        self.endpoint_url = os.getenv("DB_ENDPOINT")
        self.db = os.getenv("DB_NAME")
        self.cnx = None
        self.cursor = None

    def connect(self):
        try:
            self.cnx = mysql.connector.connect(
                user=self.username,
                password=self.password,
                host=self.endpoint_url,
                database=self.db,
            )
            self.cursor = self.cnx.cursor()
        except mysql.connector.Error as err:
            if err.errno == errorcode.ER_ACCESS_DENIED_ERROR:
                raise ValueError("Invalid username or password") from err
            elif err.errno == errorcode.ER_BAD_DB_ERROR:
                raise ValueError("Database does not exist") from err
            else:
                raise err

    def close(self):
        if self.cursor:
```

```
            self.cursor.close()
        if self.cnx:
            self.cnx.close()

    def execute_query(self, query, params=None):
        if not self.cursor:
            raise ValueError("Database not connected")
        try:
            self.cursor.execute(query, params)
        except mysql.connector.Error as err:
            raise err

    def get_total_record_count(self):
        query = "SELECT COUNT(*) FROM sensordata"
        self.execute_query(query)
        return self.cursor.fetchone()[0]

    def get_filtered_record_count(self, sensor, start_date_str, end_date_str):
        query = "SELECT COUNT(*) FROM sensordata WHERE 1=1 "
        params = []

        if sensor:
            query += "AND SensorID = %s "
            params.append(sensor)

        if start_date_str and end_date_str:
            query += "AND timestamp BETWEEN %s AND %s "
            params.extend([start_date_str, end_date_str])

        self.execute_query(query, params)
        return self.cursor.fetchone()[0]

    def fetch_sensor_data(self, sensor=None, start=0, page_size=10,
start_date=None, end_date=None):
        datetime_format = "%Y-%m-%d %H:%M:%S"
        if start_date:
            start_date = start_date.strip()
            try:
                start_date = datetime.datetime.strptime(start_date, datetime_format)
            except ValueError as e:
                raise ValueError(f"Start date is not in the correct format: {e}")
```

```
        if end_date:
            end_date = end_date.strip()
            try:
                end_date = datetime.datetime.strptime(end_date, datetime_format)
            except ValueError as e:
                raise ValueError(f"End date is not in the correct format: {e}")

        query = "SELECT * FROM sensordata WHERE 1=1"
        params = []

        if sensor:
            query += " AND SensorID = %s"
            params.append(sensor)

        if start_date and end_date:
            query += " AND timestamp BETWEEN %s AND %s"
            params.extend([start_date, end_date])

        query += " ORDER BY timestamp ASC LIMIT %s OFFSET %s"
        params.extend([page_size, start])

        self.execute_query(query, params)
        rows = self.cursor.fetchall()
        column_names = [desc[0] for desc in self.cursor.description]
        data = [dict(zip(column_names, row)) for row in rows]
        return data

    def export_to_csv(self, file_name, data):
        file_loc = os.path.join(os.getcwd(), file_name)
        with open(file_loc, mode="w", newline="") as sensorfile:
            fieldnames = [
                "SensorID",
                "location",
                "temp",
                "humidity",
                "pm10",
                "pm25",
                "pm100",
                "particles03",
                "timestamp",
            ]
            sensor_write = csv.DictWriter(sensorfile, fieldnames=fieldnames)
```

```
            sensor_write.writeheader()

            for row in data:
                sensor_write.writerow(row)
if __name__ == "__main__":
    db_info = DataBase()
    try:
        db_info.connect()
        data = db_info.fetch_sensor_data(
            sensor="PMTL_sensor4",
            start_date="2024-03-04 23:00:00",
            end_date="2024-03-05 05:30:00",
            start=0,
            page_size=500000)
  db_info.export_to_csv("03_04_PMTL_sensor4.csv", data)
    except Exception as e:
        print(f"An error occurred: {e}")
    finally:
        db_info.close()
```

APPENDIX B

EXPERIMENTS DEPLOYMENT

Figure B.1. On campus (in classroom)

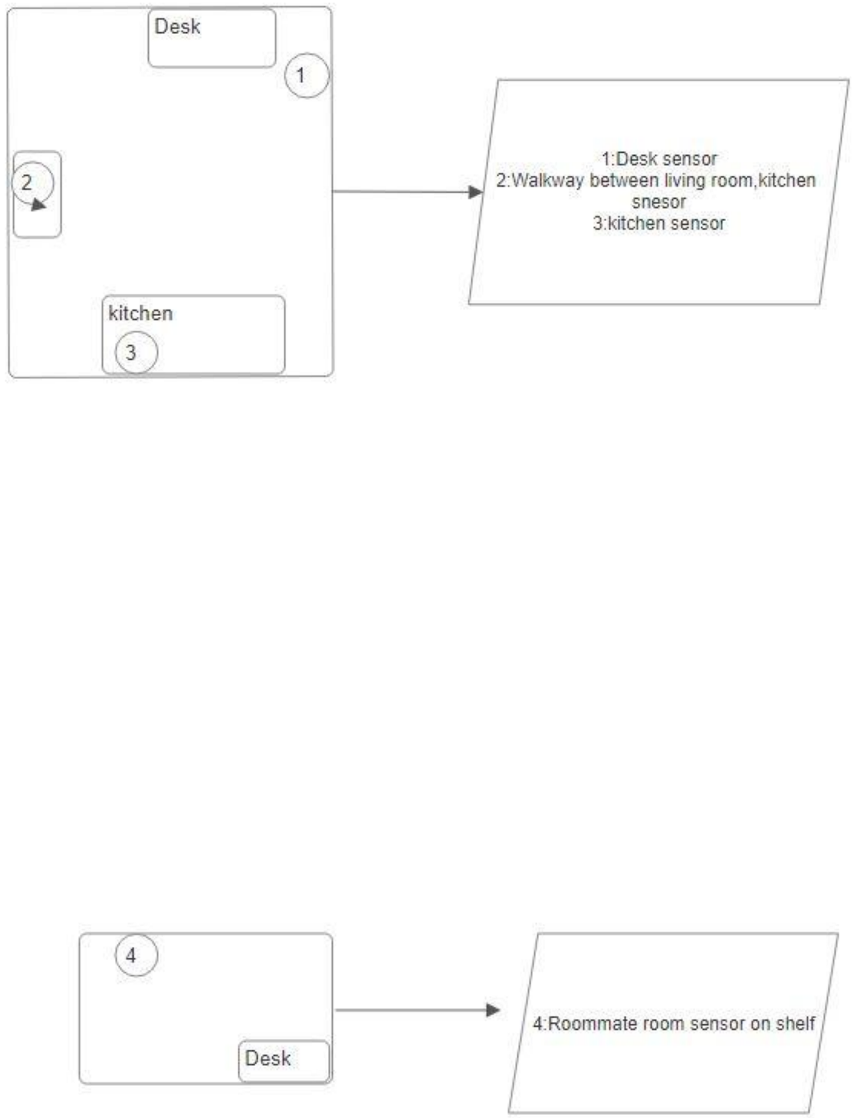

Figure B.2. Schematic of house deployment

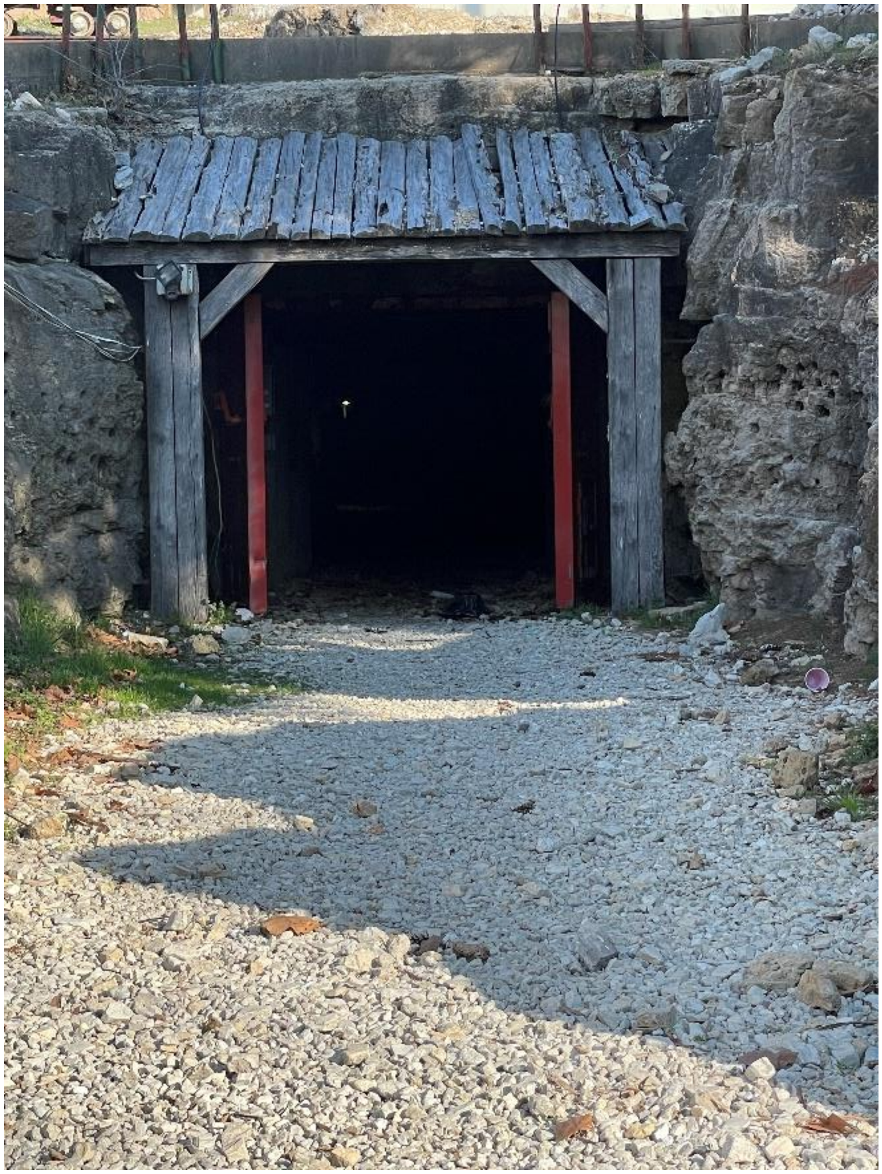

Figure B.3. Mine entrance 1

Figure B.4. Sensor 7 right side 2

Figure B.5. Sensor 8 right side 1

Figure B.6. Sensor 9 right side 2

Figure B.7. Sensor 1 middle 1

Figure B.8. Sensor 2 middle 2

Figure B.9. Sensor 3 middle 3

Figure B.10. Sensor 4 right side 1

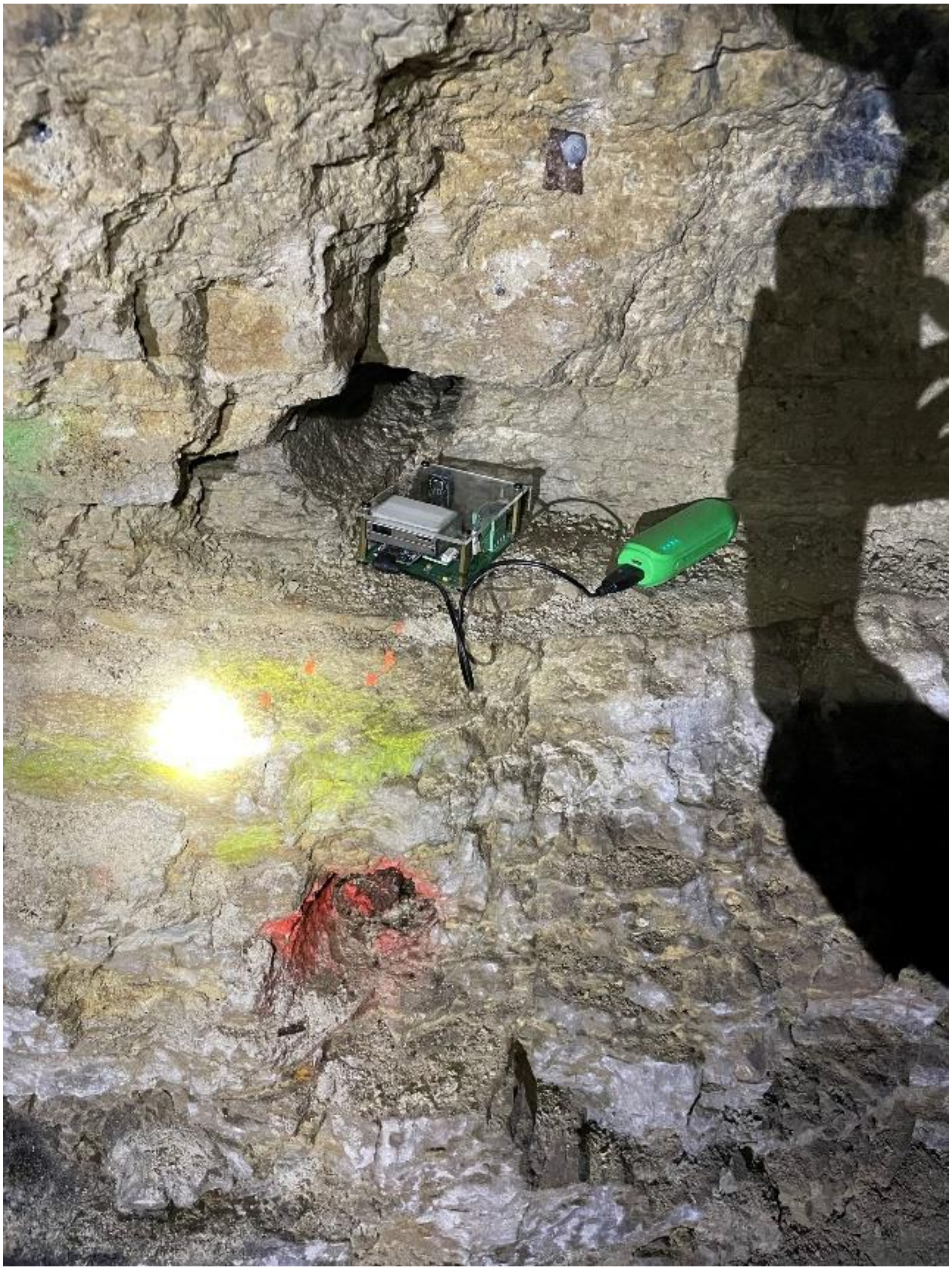

Figure B.11. Sensor 5 right side 2

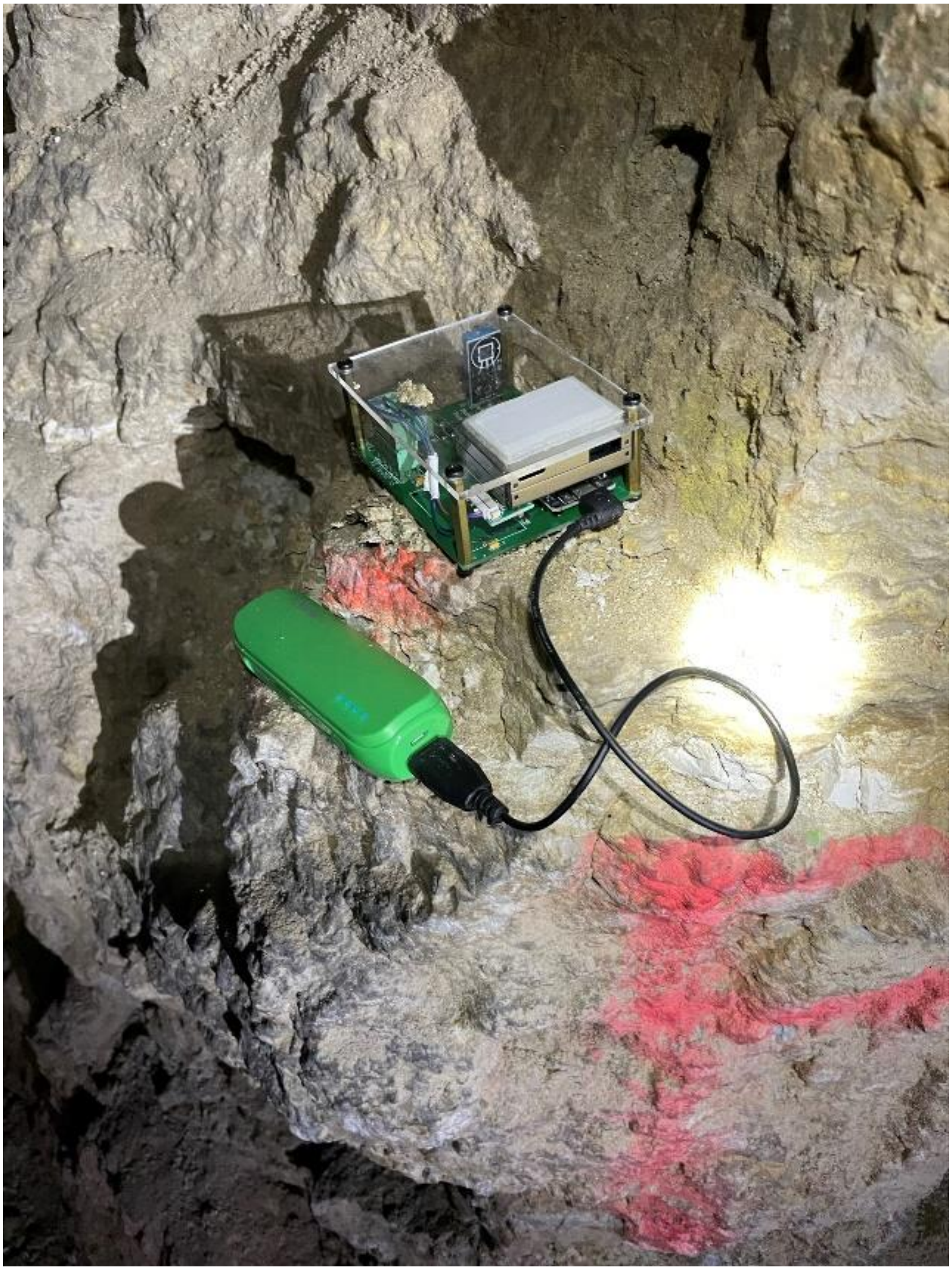

Figure B.12. Sensor 6 right side 3

Figure B.13. LoRa Module in mine building

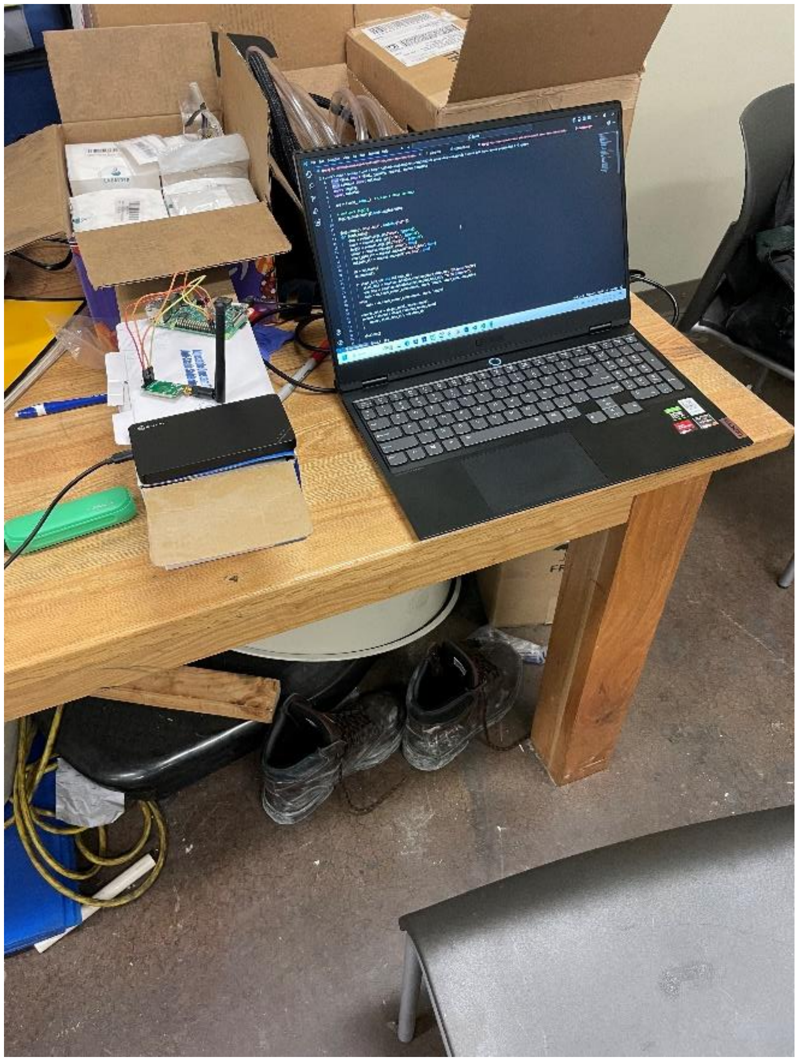

Figure B.14. Data collection monitoring station with the Raspberry Pi

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VITA

Abdulrahman Bani was born and raised in Tripoli, Libya in 1996. Abdulrahman graduated from Missouri University of Science and Technology in the fall of 2019 with a Bachelor of Science degree in Environmental Engineering. He began his Master of Science program in Environmental Engineering at Missouri S&T in the Summer of 2021. He received his Master of Science degree in Environmental Engineering from Missouri University of Science and Technology in May 2024.