BIM-integrated Path Planning for Semi-autonomous Robots: Remote Real-time Ambient Data Collection in Indoor Spaces

Fahad Iqbal[1] and Shayan Mirzabeigi[1,2*]

[1]Department of Sustainable Resources Management, State University of New York College of Environmental Science and Forestry, Syracuse, NY, United States
[2]Department of Mechanical and Aerospace Engineering, Syracuse University, Syracuse, NY, United States
fiqbal@esf.edu, smirzabeigi@esf.edu

Abstract

Rising global temperatures and more frequent extreme weather events have made air conditioning systems essential for maintaining indoor thermal comfort. Building engineers often rely on real-time data to optimize energy retrofits that can also help improve building thermal resilience against these extreme climate events. However, older buildings often lack the automation commonly found in new structures with wired/wireless sensory networks, making retrofitting both costly and labor-intensive. Therefore, this paper introduces a novel framework that combines Building Information Modeling (BIM) with semi-autonomous mobile robots for efficient real-time indoor ambient data collection. BIM serves as a centralized knowledge base for spatial maps and navigation plans for unmanned ground mobile robot (UGR) equipped with sensors. These robots use advanced navigation and drift-correction algorithms to efficiently collect indoor environmental data, including temperature, humidity, and CO_2 levels, in complex indoor environments. The collected data is visualized on a web-based platform, enabling facility managers to make informed decisions and remotely control HVAC systems for greater operational flexibility. This framework was implemented in a case study demonstrating its capability for collecting spatial and temporal ambient data and visualizing them to support human-centered energy-efficient building operations. The results emphasize the framework's scalability, cost-effectiveness, and use case in various building types.

Keywords:

BIM; IoT; Mobile Robot; UGR; Indoor Environmental Quality

1 Introduction

The growing global demand for energy-efficient indoor environments highlights the critical need for innovative approaches to managing Heating, Ventilation, and Air Conditioning (HVAC) systems, which are among the most energy-intensive components of buildings. With individuals spending nearly 80% of their time indoors [1], buildings account for 40% of total global electricity use [2]. According to the International Energy Agency (IEA), 3.6 billion cooling appliances are currently in use worldwide. This number is projected to surge to 14 billion by 2050 if equitable access to cooling is provided [3]. Additionally, the frequency of extreme weather events is expected to rise and there is a need to address thermal resilience in buildings against these climate events through new construction and retrofitting. These highlight the urgent need for more innovative approaches in the built environment and more efficient and adaptive active and passive building systems. In this context, there is an opportunity to explore technologies that can optimize building energy performance and occupant thermal comfort through advanced monitoring and data-driven control strategies.

The effective optimization of building energy use and thermal comfort requires a holistic understanding of various interconnected systems, including the building's mechanical and electrical components, occupant behaviors, as well as external factors like weather patterns. To achieve this, a significant amount of data must be continuously gathered, analyzed, and managed at different scales (e.g., granular levels such as individual rooms and floors). Prior research has shown that whether in real-time, near real-time, or through batch processing, data-driven insights can enhance energy efficiency and occupant comfort [4]. However, the challenge lies in the efficient collection of high-quality spatial and temporal data, particularly in existing buildings where constraints on system retrofitting can limit the implementation of modern energy management strategies.

The use of wired and wireless sensor technologies has revolutionized data collection in building [5]. Traditionally, inspectors manually collected data through time-intensive processes that yielded limited information. With the integration of wired and wireless sensors into Building Automation Systems (BAS), the need for manual inspections has been greatly reduced. In newly constructed buildings, sensors are often pre-installed and integrated into the operational infrastructure. However, for older buildings, retrofitting such systems is challenging due to high installation costs, labor-intensive processes, and limitations on building closure for such retrofitting [6]. Wired systems, commonly used in applications like video surveillance, are particularly costly and less feasible for larger structures such as dormitories and office complexes, where extensive wiring and installation efforts are required [7]. These challenges necessitate innovative and technological solutions for cost-effective and flexible data collection. UGR provides a promising alternative, offering a versatile and cost-effective approach to collect real-time data without the need for extensive building updates in existing buildings to understand the existing conditions to make informed decisions. By navigating through building interiors autonomously, these robots can gather critical environmental data, overcoming the constraints of traditional wired systems and manual inspections.

2 Background

The use of sensors for indoor environmental data collection is a fundamental approach to improving energy efficiency and thermal comfort in buildings, particularly in regions with extreme climates. In tropical regions, where the adoption of air conditioning systems is on the rise due to the increase in extreme heat events, sensor networks are essential for optimizing HVAC operations. Sensors such as temperature, humidity, Particulate Matter (PM), Carbon Dioxide (CO_2), and occupancy detectors enable real-time monitoring of indoor environmental conditions, allowing for more precise control of air conditioning systems [8], [9]. Research has demonstrated that sensor-based systems can significantly reduce energy consumption by providing actionable data for adjusting HVAC settings based on actual environmental conditions rather than static, user-determined settings [10]. However, in tropical climates, a common issue is that users tend to "over-control" temperature settings, leading to inefficiencies such as excessive compressor operation, which increases power consumption without necessarily improving comfort [11]. The integration of more intelligent sensor systems can help mitigate such over-control by providing data-driven insights and optimizing temperature regulation.

Building Information Modeling (BIM) combined with robotics is an emerging approach for real-time ambient data collection in buildings, especially in complex or older environments where traditional sensor installation might be challenging due to cost, labor, or installation time requirement [12]. UGR, equipped with sensors, can autonomously navigate indoor spaces to collect data on temperature, humidity, and air quality, feeding this information into BIM and Building Energy Modeling (BEM) tools for analysis and optimization. This integration allows for the creation of detailed, dynamic simulation models that provide accurate spatial and environmental insights, which can then be used to tune building operations (e.g., operation of HVAC systems) [13]. Additionally, UGR can access areas that are difficult or impractical for human intervention, making data collection more efficient and comprehensive. Studies have shown that this approach not only improves thermal comfort but also supports energy-efficient building management, particularly in older structures that lack required levels of automation.

The integration of BIM, sensors, and robotics has the potential to revolutionize building management by offering a holistic solution to the challenges of ambient data collection and energy optimization. Recent studies highlight the interactions between these technologies, where BIM provides a comprehensive spatial framework, sensors deliver real-time environmental data, and robotics ensure efficient and flexible data collection in difficult-to-reach areas [14]. Hu et al. developed "AirScope," a robotic system using distributed deep Q-learning to monitor indoor air quality, effectively reducing data latency and optimizing cooperative route planning [15]. Cao et al. proposed an intelligent construction robot system using BIM-based navigation maps, camera calibration, and A* and TEB algorithms for autonomous navigation and obstacle avoidance, demonstrating its feasibility for advancing construction automation [16].

This paper presents a novel framework integrating BIM with UGR for real-time indoor environmental data collection in indoor spaces, particularly addressing the challenges of retrofitting in older buildings that do not have modern Building Management System (BMS). In this study, spatial maps and navigation plans are generated from the building's BIM model for UGR equipped with lightweight sensors. These UGRs efficiently navigate complex environments to collect critical data such as temperature, humidity, PM and CO_2 levels. The collected data is processed and visualized on a web-based platform, providing facility managers with actionable insights for optimizing HVAC systems. An experimental case study demonstrates the framework's effectiveness, showcasing its scalability, cost-efficiency, and suitability for diverse building types. The results highlight the framework's potential to transform building operation management practices in existing buildings with minimal infrastructure investments, contributing to global sustainability goals.

3 Research Methodology

This section outlines the conceptual framework and methodology of the study, detailing different phases and system implementation. The study integrates BIM, Internet of Things (IoT) sensors, and semi-autonomous robotics in a case study. BIM semantic data is used for navigation, allowing the UGR to move autonomously. The robot, equipped with IoT sensors, collects environmental data, which is stored in a cloud database and visualized on a web-based BIM platform.

3.1 Framework

The framework begins with the extraction of data from an Industry Foundation Classes (IFC) file, which represents the building's geometry and structure within BIM. This data is processed to create a spatial map of the building, defining key building components such as walls, doors, and rooms. The spatial map enables a semi-autonomous robot equipped with IoT sensors to navigate through the building and collect environmental data, including temperature, humidity, PM, and CO_2 levels. This information is stored in a cloud-based database and accessed via a REST API for visualization on the BIM web platform, allowing facility managers to make real-time adjustments to HVAC systems in order to improve energy efficiency, occupant thermal comfort, and indoor air quality. Figure 1 provides an overview of the framework.

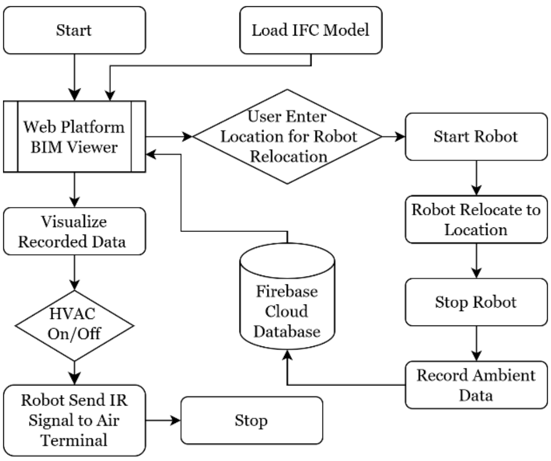


Figure 1. Overview of the proposed framework.

The process begins with loading an IFC file onto the web platform. The user then specifies the robot's starting location, from which it autonomously moves through the building, collecting and uploading data to the Firebase Cloud database. The retrieved data is displayed on the platform in a user-friendly interface, enabling informed, data-driven decisions to enhance building operations and indoor environmental quality.

3.2 Web Platform

The web platform for data visualization and control is built with IFC.js, a JavaScript library that enables the visualization of IFC data in web applications. It displays building geometry, sensor data, and system performance in an intuitive and user-friendly interface. The backend is powered by a Node.js server that runs Python scripts for processing navigation maps and retrieving sensor data from the cloud database to the web platform. For cloud data storage, the platform uses Firebase's Database, a cloud-based NoSQL solution. Firebase's real-time data syncing capabilities ensure instant updates across all connected devices, critical for real-time monitoring applications. Using a combination of TypeScript and Python, the platform offers a scalable solution for monitoring building conditions, allowing facility managers to optimize HVAC operations and remotely control the robot. Figure 2 shows a snapshot of the web platform with two windows: one for visualizing sensor data and controlling HVAC operations, and the other one for robot control and navigation plan.

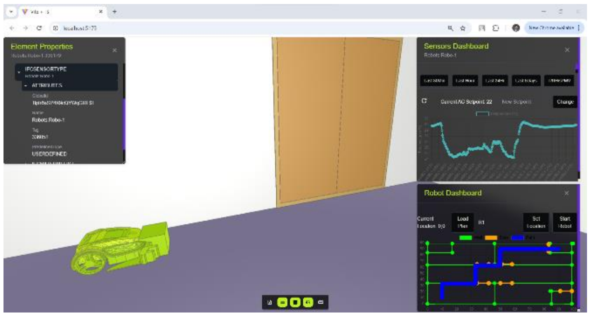


Figure 2. User interface for developed web platform for robot control and ambient data visualization.

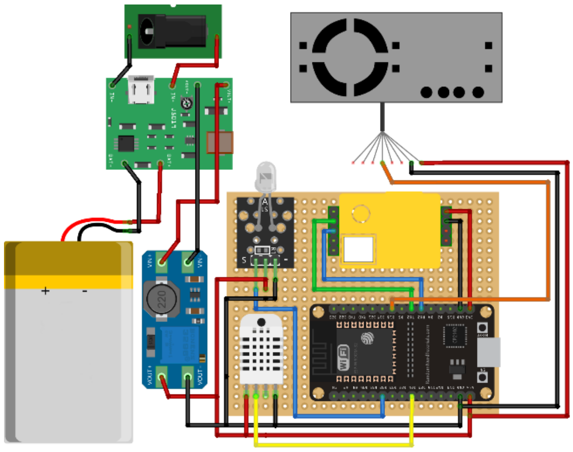
3.3 UGR and Sensor Module Development

A. UGR Robot Development

The UGR is a compact and efficient platform for autonomous ambient data collection. It features a 256 × 150 × 2 mm chassis with a 500 g load capacity, ensuring a lightweight and durable build. Equipped with 65 mm wheels, it offers smooth mobility across indoor surfaces. The robot is powered by a 3.7V, 5000mAh lithium-ion battery with a step-up converter to supply the required voltage for motors and sensors, providing a runtime of up to 4 hours on a full charge. ESP32-WROOM microcontroller enables wireless communication and real-time sensor data processing, making it an effective solution for environmental monitoring and smart automation applications.

B. Sensing Module Development

The framework includes IoT-based sensors installed on a UGR for ambient data collection. It includes a DHT22 for temperature and humidity recording, PMS5003 for particulate matter measurement, and the MH-Z19B sensor for CO_2 measurement. The DHT22 sensor provides high accuracy for temperature and humidity measurements, with a temperature accuracy range of ±0.5°C and a humidity accuracy of ±2-5%. This makes it ideal for indoor climate monitoring [17]. The PMS5003 sensor delivers real-time particulate matter (PM2.5 and PM10) data with an accuracy of ±10 µg/m³, ensuring a healthy indoor environment [18]. The MH-Z19B is a reliable sensor for measuring CO_2 concentrations, offering an accuracy of ±50 ppm in the range of 400-5000 ppm, contributing to comprehensive indoor air quality monitoring [19]. These sensors are connected to an ESP32-WROOM microcontroller, which interfaces with a Wi-Fi network. Data recorded by the sensors is first stored locally on the ESP32 and then transmitted to a Firebase database via HTTP POST requests, ensuring efficient and reliable data management. Figure 3 illustrates the circuit diagram of the sensor setup and their installation locations on the UGR, providing a clear overview of the system's hardware integration.



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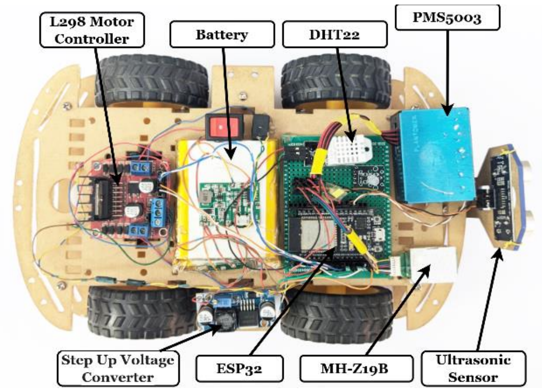


(b)

Figure 3a. Circuit diagram of the sensors installed on UGR; b. Sensors configuration on UGR.

3.4 Navigation Algorithms

The navigation of the UGR adopted in this study is based on the study by Chen et al. [20], which employs the A* algorithm, a widely applied pathfinding method in robotics. A* combines the strengths of Dijkstra's Algorithm and Greedy Best-First Search, enabling efficient navigation in complex environments [21]. This approach allows the robot to balance exploring the shortest paths while considering a heuristic to direct movement toward a target location. The process begins when a user uploads an IFC file to the platform, where different components (e.g., walls, doors, and furnishing) are extracted from the building model. Walls and furnishing are treated as obstacles, while doors are identified as access points, crucial for allowing the robot to navigate between different rooms and spaces.

When the user inputs the target room or location on the developed web platform, the target coordinates are sent to a Python script via a HTTP POST request. The algorithm then calculates the optimal path from the robot's current location to the target destination, ensuring that obstacles are avoided and that the robot can efficiently move to the target point. Once the path is identified, the Python code computes the distances and angles required for navigation. The path is displayed on a 2D graph for the user's review. Upon user acceptance of the path, the path data is uploaded to the cloud database. This data includes the distance the UGR needs to traverse and the angles at which it must turn. Once the path data is successfully stored, the robot initiates its movement towards the targeted location, which may be a space, room, corridor, or other predefined area. Upon arrival at the target location, the robot begins recording relevant data, which is subsequently stored in the cloud database for further analysis and processing. Figure 4. provided shows a building plan where walls are represented as obstacles and doors as access points. The robot's path is illustrated with blue lines, highlighting the optimal route calculated by the A* algorithm from the starting location to the target room. The figure highlights how the robot navigates around obstacles and through access points, offering a clear representation of its motion path within the building layout.

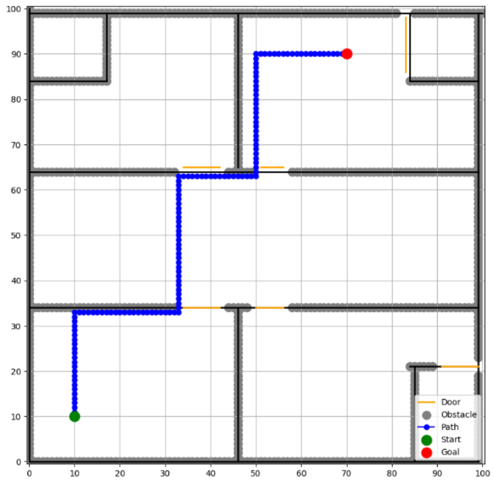
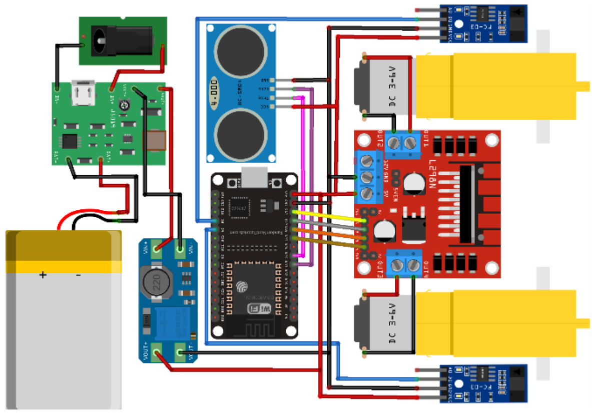


Figure 4. UGR Navigation Path in a 2D Building Layout with Obstacles and Access Points.

3.5 Robot Working

The UGR used for data collection is a four-wheel-drive vehicle powered by gear motors with speed encoders and is controlled via an LM298 motor driver [22], [23]. The robot's movements are managed by the motor driver and an ESP microcontroller. In addition to motor control, an ultrasonic sensor is employed in front of the robot for obstacle detection, ensuring the robot can avoid unexpected objects and navigate safely in dynamic environments [24]. Given the low-cost nature of the prototype, the dynamic obstacle avoidance approach is simple yet effective. When an obstacle appears in the robot's path, it initially pauses and waits for the obstruction to clear. If the obstacle remains stationary, the UGV adjusts its path by turning left or right to navigate around it, ensuring continued movement without complex real-time mapping. Once the A* algorithm sets the path, the distance and angle the robot needs to cover are stored in a cloud database. When the user clicks the "Start Robot" button on the platform, the ESP retrieves this data and directs the robot to travel the specified distance and angle. The speed encoder counts the wheel revolutions to ensure the robot stops after covering the required distance. The LM298 motor driver enables bidirectional control, allowing the robot to move forward, backward, or rotate, while the speed controller ensures smooth and precise movement.

This cost-effective setup allows the robot to navigate complex indoor environments and collect environmental data efficiently, with minimal disruption. Figure 5a shows the circuit diagram of the developed UGR, illustrating the connections between the ESP, LM298 motor driver, motors, speed encoders, and the power circuit, while Figure 5b displays images of the developed robot, highlighting the configuration of all sensors and hardware components in the actual setup.



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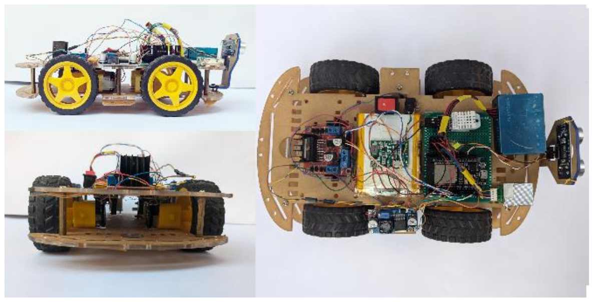

(b)

Figure 5a. Circuit diagram of the UGR; b. Images of the developed robot and hardware configuration.

4 Result and Discussion

4.1 Experimental Setup of Case Study

To test the accuracy and efficiency of the developed framework, an experimental study was conducted in a 9x12m indoor space comprising four rooms. The robot successfully navigated through the test environment, using its integration with BIM to access accurate spatial maps. This integration allowed the robot to traverse complex indoor layouts with ease. The A* algorithm, combined with drift-correction mechanisms, ensured optimized movement, achieving precise path planning and time-efficient navigation. Upon reaching designated locations, the robot began collecting real-time environmental data on temperature, humidity, PM2.5, PM10, and CO_2 levels. The results demonstrated the framework's reliability, as the robot's trajectory closely followed the planned navigation path in dynamic indoor conditions. However, since the current system relies on non-autonomous navigation, it lacks real-time path adaptation and localization. This odometry-based approach is susceptible to cumulative drift and relies on predefined paths, limiting its ability to handle unexpected obstacles or environmental changes. While effective in structured environments, its performance can be affected in dynamic settings, where real-time localization and adaptive path planning would improve overall navigation accuracy.

4.2 Results and Interpretations

The environmental data collected by the robot was continuously logged over a 24-hour period, with measurements taken every 5 minutes. As shown in Figure 6, the temperature and humidity levels are plotted on a dual-axis graph, clearly illustrating the inverse relationship between these two parameters. The general trend in the data can also be observed with 3rd-degree polynomial illustrated in the graph. The temperature showed moderate fluctuations, ranging from a minimum of 10.1°C to a maximum of 14.0°C, with an average of 12.2°C. In contrast, the humidity remained relatively stable, fluctuating between 50.0% and 72.5%, with an average of 67.6%. This automated data collection ensured accuracy and consistency, eliminating the need for manual measurements and providing a comprehensive dataset.

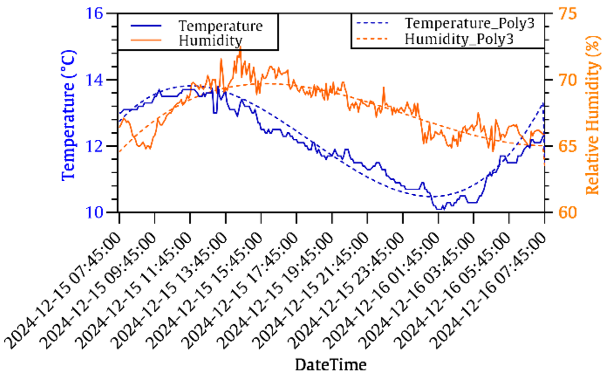

Figure 6. Recorded temperature (°C) and humidity (%) data over 24 hours.

Air quality data, including PM2.5 and PM10, are depicted in Figure 7. The graph demonstrates distinct spikes in particulate matter concentrations at specific times, likely corresponding to activities such as cleaning or movement within the test environment. Despite these occasional fluctuations, the overall air quality remained within acceptable indoor thresholds based on WHO standards. PM2.5 levels for the recorded data ranged from 13.9 to 41.6 µg/m³, with a 24-hour average of 28.7 µg/m³, slightly exceeding the WHO interim target of 25 µg/m³. PM10 levels varied between 15.6 and 47.8 µg/m³, with a 24-hour mean of 33.0 µg/m³, well within the WHO guideline limit of 50 µg/m³. The generalized trend observed in the data is shown using a 3rd-degree polynomial on the graph. These values reflect indoor air quality for the test space, where particulate matter concentrations can vary slightly throughout the day. The use of a dual-axis scale in this graph effectively highlights the differences in magnitude and trends between PM2.5 and PM10 levels, providing a clear representation of the data.

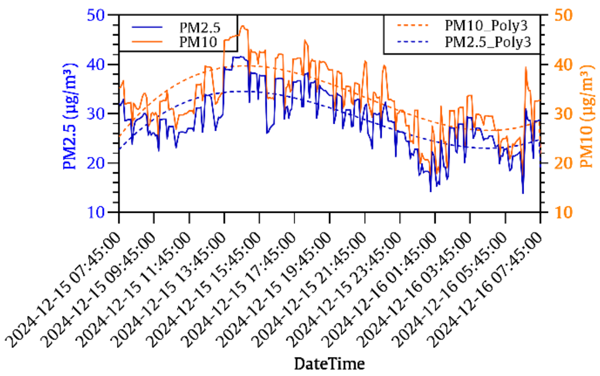

Figure 7. Recorded PM2.5 and PM10 (µg/m³) concentrations over 24 hours.

Figure 8 shows the CO_2 levels, revealing moderate fluctuation, peaking at 1022 ppm with 75% value at 719 ppm. These trends emphasize the importance of adequate ventilation in maintaining healthy indoor air quality. The CO_2 levels in collected data ranged from 446 to 1022 ppm, with an average of 666 ppm, indicating moderate fluctuations throughout the day. Though there are higher fluctuation in data; the overall trend shown on the graph confirms that CO_2 levels remained below critical thresholds, reflecting good ventilation in the test space. The observed indoor environmental data trends not only showcase the robot's ability to collect accurate and real-time data but also provide valuable insights into environmental dynamics over time.

These results highlight the potential of using a UGV for ambient data collection, particularly in retrofit building applications where installing stationary sensors can be costly and labour-intensive. A mobile robot offers a more flexible and cost-effective solution by measuring the spatial distribution of air quality, temperature and humidity across different locations. However, unlike fixed sensors that provide continuous data at a single point, the UGV collects data at intervals as it moves, which may lead to gaps in capturing sudden environmental changes. To mitigate this limitation, the sampling approach should be optimized to balance spatial coverage and data collection frequency, ensuring a more reliable analysis.

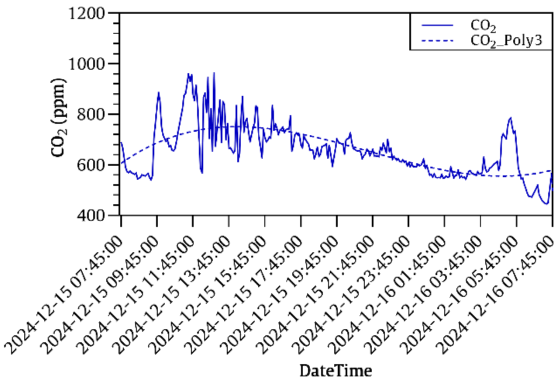

Figure 8. Recorded CO_2 levels (ppm) over 24 hours.

4.3 Limitations

While the framework exhibited promising results, several limitations exist. One notable issue is the robot's reliance on pre-uploaded updated BIM data, which can lead to navigation or data collection inaccuracies if the models are outdated or incomplete. This is certainly an important aspect to be addressed in future work for buildings without any prior BIM documentation. Additionally, the system's performance in highly dynamic or crowded environments has not been fully tested, and testing in such environments may shed light on further adaption to rapid changes or irregular conditions by improving the state-of-the-art algorithms. Another critical limitation is the need for continuous wireless internet access, as the robot depends on real-time data transmission and communication with the server for data processing and navigation updates.

The current sensor setup is limited to a small set of environmental parameters such as temperature, humidity, PM2.5, PM10, and CO_2. Expanding the range of measurable parameters by incorporating additional sensors comparing the data with that from stationary sensors installed in various spaces could provide a more holistic environmental analysis. Furthermore, the accuracy of the robot may vary, as odometry is prone to surface slippage and wheel malfunction, leading to cumulative errors over time. Future research is needed to focus on enhancing navigation algorithms, expanding sensor capabilities, and addressing the requirement for continuous internet access to ensure seamless operation in diverse and dynamic environments.

5 Conclusion

The study presents a novel framework that integrates BIM and semi-autonomous mobile robots to address the challenges of real-time ambient data collection in older buildings with limited automation infrastructure. By using BIM for spatial mapping and navigation, the proposed system enables efficient robot movement and accurate environmental monitoring. The framework demonstrated its ability to collect minimum critical indoor environmental data parameters, including temperature, humidity, particulate matter, and CO_2 levels, in a scalable and cost-effective manner. The real-time data visualization on a web platform further empowers facility managers to optimize HVAC operations, improving both energy efficiency and occupant thermal comfort. Results from the case study confirmed the system's reliability, with consistent data accuracy and efficient robot navigation, even in complex indoor layouts.

While the findings highlight the potential of this framework to transform building management practices, certain limitations must be addressed. The reliance on updated BIM models and consistent wireless connectivity poses challenges for dynamic or crowded environments. Additionally, the limited range of sensors restricts the scope of environmental analysis. Future research should focus on enhancing navigation algorithms for greater adaptability, expanding the sensor suite to cover more environmental parameters, and developing offline capabilities to mitigate connectivity issues. Despite these limitations, this study provides a solid foundation for scalable, real-time ambient data collection, contributing to sustainable and resilient building operations.

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