Mobile Autonomous System for Measuring Pollutants in Indoor Environments

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Abstract— The panorama of air quality monitoring is constantly evolving, and its importance has become increasingly fundamental even in indoor environments. Recent studies show the impact of indoor air pollutants on human health. Since individuals spend a substantial part of their lives indoors, more and more attention is paid to guaranteeing the safety and purity of indoor air to safeguard health both at home and in the workplace. In this work, the design and development of an autonomous mobile measurement system dedicated to the sampling and analysis of indoor air quality in closed environments is presented. The system consists of a rover and several sensor technologies to provide a comprehensive assessment of air quality. The system moves autonomously in the closed environment, monitoring pollutants and transmitting data via wi-fi connection to the cloud for analysis and identification of possible dangerous situations. The preliminary tests carried out include the evaluation of various pollution scenarios, such as the presence of smoke, exhaust gases, chemical pollutants, and gas leaks. Furthermore, the autonomous mobile measurement system has been validated during about 12 hours in a real indoor environment. The presented work also offers a critical analysis and interpretation of these results, illustrating the practical implications and effectiveness of the proposed system in real contexts.

Keywords—air quality, pollutants, sensors, autonomous system, mobile system, indoor monitoring.

INTRODUCTION

Air pollution is a major risk factor and continues to represent a global cause of death for millions of people. In this context, indoor air quality plays a crucial role in human health since many people spend most of their time indoors. In fact, this risk factor appears to be one of the main contributors to worsening health [1]. Currently, the risk factor is ranked among the top five environmental risks to public health [2]. However, the main risk in developed countries lies not so much in homes, as can happen in some countries around the world, but in industrial environments. Industrial buildings often contain significant sources of air pollutants and are in locations that also present problems with outdoor air quality [3].

Air quality studies are increasing given its growing importance globally. There are many factors that put human health at risk inside an enclosed space. Closed environments can collect a higher concentration of pollutants than open spaces, as, being less ventilated, they tend to accumulate pollutants over time. One statistic shows that indoor air pollutant levels can be 2 to 5 times higher than outdoor levels [4]. Furthermore, people generally spend a large part of their time indoors and the times have further extended after the SARS-CoV-2 pandemic: it is estimated that on average a person spends 90% of their time in an enclosed space [1]. Prolonged exposure speeds up the onset of any health problems. Indoor air pollutants come from various sources, such as building materials (asbestos, formaldehyde), household cleaning products, personal hygiene products, cooking, smoking, heating appliances, and even furniture. These sources release gases or particles into the air, contributing to indoor air pollution [5]. Pollutants can in fact also come from sources external to the closed place; some studies have revealed how the external environment is an important factor that cannot be neglected [6]. Until a few years ago, the main method for sampling and studying air quality involved large monitoring stations located in strategic points of the city. Only recently large monitoring stations are giving way to new, smaller, and low-cost air quality sensors. These sensors have lower accuracy than traditional monitoring stations but are more flexible and easier to maintain [7]. As regards closed spaces, only recently studies have been demonstrating the importance of continuous monitoring of air quality for safeguarding health. Many systems use a series of sensors positioned in different areas within a building; these communicate the acquired data with a gateway which in turn publishes the data on a server so that it is accessible from the outside [7]. The increasingly widespread diffusion of low energy consumption devices and compact radio connections allows for real-time data, guaranteeing the monitoring and prediction of air quality trends, in order to act in the presence of health risks [2, 7, 8]. However, to effectively cover a large area such as an industrial warehouse it is necessary to provide numerous measurement points with a significant increase in costs for these monitoring systems.

In this work, the design, development and testing of an autonomous mobile measurement system dedicated to the sampling and analysis of indoor air quality in closed environments is presented. The system consists of a rover and several sensor technologies to provide a comprehensive and dynamic assessment of air quality. The system moves autonomously in the closed environment, monitoring pollutants and transmitting data via wireless connection to the cloud for analysis and identification of possible dangerous situations. A significant advantage over fixed monitoring systems is its versatility. In environments such as factories, where machinery and configurations can change frequently, a fixed sensor could quickly become obsolete or less effective. On the contrary, the mobile system easily adapts to dynamic situations, ensuring constant and accurate monitoring even in the presence of changes in the working environment. Furthermore, this mobility allows data to be collected from different areas and at different times, providing a more complete and detailed representation of indoor air quality and its possible impacts on human health and workplace safety.

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DESIGN OF THE AUTONOMOUS MEASUREMENT ROVER

The proposed system is composed of a rover capable of moving autonomously within a closed space, equipped with sensors capable of monitoring the main pollutants and communication capabilities with the surrounding environment. Figure 1 shows a schematic diagram of the complete system. An open-source rover developed by Perlatecnica [9] was chosen and the mechanical and electronic structure was modified to add sensors capable of sampling some harmful elements in indoor spaces, an ultrasonic sensor to improve movement autonomy in closed environments and a wi-fi communication device. In particular, the data regarding the most significant pollutants in closed spaces are: PM1.0, PM2.5 and PM10 particulate matter and volatile organic compounds (VOC).

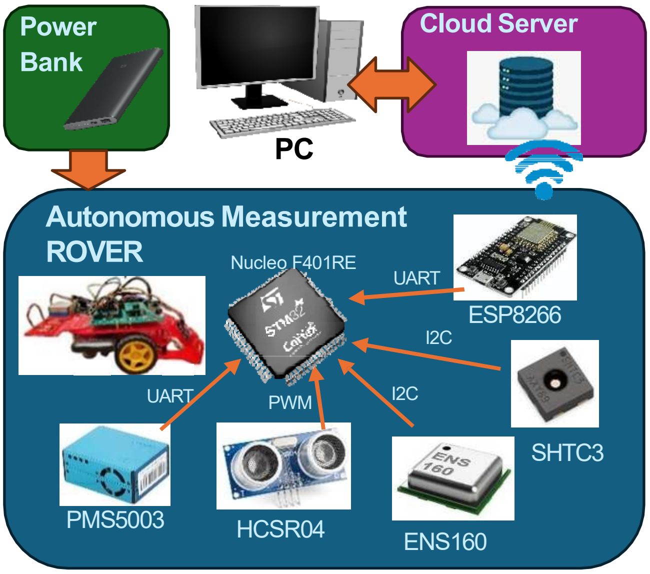

Fig. 1. Schematic bloc diagram of the mobile autonomous system.

The rover includes two DC motors, a front-mounted ultrasonic sensor, a gyroscope, an accelerometer, a rechargeable battery, the wi-fi module and the pollutants sensors (Figure 2). These components allow the rover to move autonomously, avoid obstacles and monitor its rotations and accelerations. The movement part of the rover is entrusted to the STMicroelectronics IHM12A1 driver integrated into the motherboard which controls the two DC motors. Together with the motor, a reducer is required which allows the output torque of the motor to be increased to the detriment of the maximum achievable speed. In this case a reducer with a 1:120 ratio is mounted. The algorithms useful for autonomous driving of the vehicle and the code for the operation of the sensors are executed by the STM32 microcontroller mounted on a STMicroelectronics Nucleo F401RE board. The STM32 microcontroller has an ARM®32-bitCortex®-M4 hardware architecture with 12bit ADC which makes it suitable for applications that require complex calculations and at the same time have good energy efficiency. The Nucleo board integrates the ST-Link programmer-debugger which offers a serial interface and a USB port useful not only for programming the microcontroller, but also for powering the entire board and for communicating with a computer. An HC-SR04 sensor is implemented for obstacle detection. It works based on the ultrasound principle; waves are emitted and the time they take to reach an object and come back is measured. Once the time is measured, the distance is calculated based on the speed of sound. The HC-SR04 sensor is front-mounted to maximize obstacle detection. Its technical specifications, which include a measurement range from 2 cm to 400 cm and a detection angle of approximately 30 degrees, make it ideal for autonomous navigation applications. The PMS5003 dedicated to monitoring particles suspended in the air and the ENS160 designed for the detection of volatile organic compounds (VOC) were chosen as sensors for identifying pollutants. The two sensors are connected to the main board via UART and I2C protocols respectively. The data collected by these sensors is processed and then transmitted in real time to the Cloud server through the ESP8266 wi-fi module which communicates with the microcontroller via UART communication protocol. Once the data arrives on the server, it is archived and the trend over time is shown, allowing for in-depth analysis. By implementing thresholds, the ThingSpeak server can generate an automatic alert by sending a notification via email. This timely notification allows you to take appropriate measures and address potential risk situations proactively.

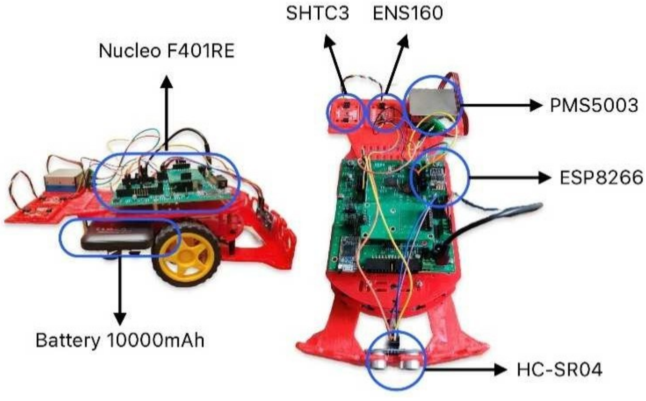

Fig. 2. Image of the proposed rover integrating sensors and electronics.

A. Sensor for the detection of particulate matter

For the detection of particulate matter, the PMS5003 was chosen, it is a nephelometer, a type of sensor capable of detecting the concentration of particles in the air with diameters greater than 0.3 µm via optical analysis. The sensor works via the principle of laser diffusion, i.e. the particles suspended in the air are irradiated and the diffused light is sampled in order to obtain the variation curve over time. It uses a fan to create a flow (approximately 0.1 L/min) of air to be conveyed inside the case and it is equipped with a laser (approximately 680 ± 10 nm) and a photodiode detector to convert the light diffused in a voltage pulse [10]. The light scattered by the particles is converted into an electrical signal and this signal is sent to an amplifier and subsequently it will then be processed according to Mie theory in the microprocessor. The digital output is then provided in units-of-diameter/units-of-volume and has two modes of operation: if there are no changes in particle concentration, values are sent every 2.3 seconds. Once a substantial change in concentration is identified, the fast mode is activated, and the sensor will read every 200-800 milliseconds. The particle size measurement range goes from a minimum of 0.3 µg to a maximum of 10 µg. The manufacturer of the PMS5003 sensors is the Plantower company, which uses two proprietary algorithms (CF1 and CF ATM) to estimate the concentrations of PM1.0, PM2.5 and PM10. However, no data relating to the calculations involved in the transformation from the numbers of sampled particles (provided as output by the sensor) to the estimate of the mass concentration (always provided as output by the sensor) are provided. Comparative studies between the PMS5003 sensor and other commercial reference sensors are reported in the literature [11]. The results show that the higher the particulate concentration, the greater the error between the sensor and the standard measuring device. PMS5003 is therefore suitable for urban-type particulate matter; in fact, several articles show non-optimal results of the sensor in the detection of particles above PM2.5 (urban particulate limit) [12, 13]. The inability of PMS sensors to detect large particles (sizes between 2.5 and 10 μm) is mainly attributed to the sampling method based on Mie theory and the limited ability to aspirate large particles into the device [14]. The error that concerns particles lower than PM2.5 derives from the company's practice of assigning a zero value to concentrations that do not reach a certain predefined threshold. In particular, some common activities such as cooking, cleaning and other particle-producing activities fall below this threshold for a sufficiently long period of time, PM2.5 concentration estimates are limited to a significantly reduced fraction of all observations [15]. Furthermore, within the article [11] and as also verified in the measurements carried out, cases appear in which PM values are highly overestimated. It is hypothesized that this is due to the presence of larger particles floating in the sensor's sampling air.

To adjust measurement problems related to the calculation of PM2.5 concentration, a specific algorithm (ALT-CF3) was used in this work which has proven to outperform the Plantower algorithms with regards to bias and precision. The results suggest that Plantower algorithms overestimate PM2.5 concentrations by approximately 40-50%, [15]. To obtain the PM2.5 particulate concentration, the calculations are divided by particles of different sizes (0.3-0.5 μg, 0.5-1 μg and 1-2.5 μg) and the results obtained are added. For each size range, the spherical particle with constant diameter Dp equal to the geometric mean of the range and constant density ρ is considered. We can then find the mass of the particles by applying the formula:

$$m = \rho\pi Dp^3 / 6 \qquad (1)$$

The total mass of the particles is equal to the mass of the individual particle multiplied by the number Ni of particles detected. Finally, the concentration of PM2.5 is equal to the sum of the masses of all particles in the three ranges [16]:

$$PM2.5 = aN\,1 + bN\,2 + cN\,3 \qquad (2)$$

where a, b and c are the masses of the single particle in the respective ranges and N1, N2 and N3 are the number of particles in each range. Numerically the values of a, b and c are reported in Table 1.

TABLE I. VALUES OF THE COEFFICIENTS A,B,C [65].

Bin	Dp Geom. Mean [um]	Volume [um3/100]	Mass (density =1) [ug/m3/100]
0.3-0.5 um	0.387298335	0.000304183	a=0.000304183
0.5-1 um	0.707106781	0.001851201	b=0.001851201
1-2.5 um	1.58113883	0.020697059	c=0.020697059

However, the PM2.5 value must be compared with an instrument calibrated according to regulations, for this reason a correction factor CF is often added to (2):

$$PM2.5 = CF\,(aN\,1 + bN\,2 + cN\,3) \qquad (3)$$

Several studies [17] compared data from stations calibrated according to Californian regulations to try to obtain a CF value that would allow the error in the estimate of PM2.5 to be reduced to a minimum. This value was chosen as 3, for this reason the algorithm is also called ALT-CF3 [16].

B. Sensor for the detection of volatile organic compound (VOC)

For the detection of volatile organic compounds (VOC), a module based on the ENS160 sensor was implemented within the system. It is a digital multigas sensor, based on MOX (metal-oxide) technology with four heated elements. The variations in the resistance of the heating plates to the passage of gases, allows the detection of a wide range of volatile organic substances including ethanol, toluene, hydrogen and oxidizing gases. The ENS160 also supports intelligent algorithms to process raw sensor measurements on the chip. These algorithms calculate CO2 equivalents (Carbon dioxide), TVOC (total volatile organic compound), air quality indices (AQI) and perform humidity and temperature compensation. Extreme humidity conditions (outside the range 20%-80%) can affect the output signal, especially when very precise or single gas measurements are needed. To overcome such impacts, the ENS160 is equipped with a temperature and humidity compensation algorithm, which is based on data from an external temperature and humidity sensor (SHTC3). As stated in the datasheet, the data provided by the sensor has a typical error of less than 12% in a controlled environment. The tests were performed in an environment at 25 °C with a relative humidity of 50% and pre-conditioning for at least 24 hours. No data is provided regarding the algorithms used to calculate the outputs. For CO2 data, the proportional correlation between VOC and CO2 is reversed, providing a standardized output signal in ppm CO2 equivalents from the measured VOCs.

C. Data reading and transmission to the Cloud

The board mounted on the rover is programmed using Mbed Studio, an IDE (Integrated Development Environment) designed for microcontrollers with the Mbed OS operating system. It is an open-source operating system for ARM Cortex-M boards, used in particular for the Internet of Things (IoT). The data is sent from the ESP8266 module via wi-fi connection to the cloud server. The data is sent to the microcontroller in the form of a character buffer containing the pollutant values collected in the scan. The TCP connection to the Thingspeaks server occurs using specific APIs (Application Programming Interface). An API key (apiKey) is provided in the code. This key serves as an authentication token, allowing the device to identify itself to the server. Once authentication has occurred, you can make an HTTP POST request to send data to ThingSpeak. This request is used to update a channel with data collected from sensors. Finally, if the uploaded data exceeds a certain level considered vital for human health, a script is activated that sends an alert via email to the designated address.

EXPERIMENTAL RESULTS

With the aim of evaluating correct functioning in specific health risk situations, tests aimed at simulating different application scenarios were conducted: presence of smoke and consequent potential fire threats; identification of pollution resulting from exhaust gases; evaluation of pollution levels caused by chemical products; identification of any methane gas leaks inside a home. The various tests were performed by taking measurements at regular intervals of 2.5 seconds. As regards movement within closed spaces, autonomy tests were carried out on the integrated battery with active monitoring and communication. Finally, a complete mobile monitoring test was also carried out over the maximum time span of the rover's battery life, to verify how the air quality inside a home varied over the 12 hours of autonomy.

The evaluation of the presence of smoke is a critical aspect to guarantee the safety of internal environments. The results of the tests conducted to evaluate the ability of the rover's sensors (PM2.5, PM10, CO2, TVOC and AQI) in identifying the presence of smoke are shown in Figure 3. The tests involved blowing out a candle at a distance of about one meter, simulating scenarios in which smoke could arise from potential fires. Analyzing the recorded data, spikes were observed in the charts during the moments when the candle was extinguished. The most obvious peaks were identified in the PM values, which indicate a significant increase in the concentration of particulate matter. A further observation which is exposed in this section but which can also be found in the other data collected, is the fact that the data coming from the PMS5003 sensor presents a delay of approximately 17 seconds compared to the data provided by the ENS160 sensor.

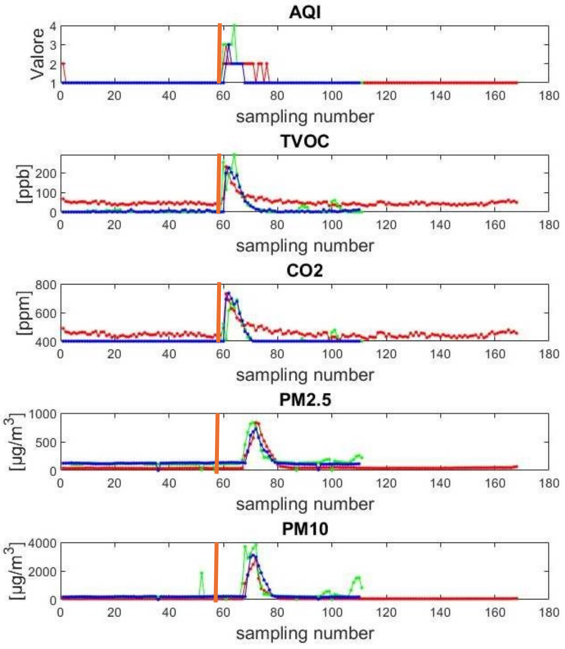

Fig. 3. Measurement data collected during different trials simulating a scenario with the presence of smoke.

In the scenario involving the presence of toxic fumes, the system was positioned approximately 1.5 meters from the exhaust of a diesel car. The objective is to evaluate the rover's ability to detect and analyze pollutants due to the combustion of hydrocarbons. During the initial start-up of the diesel car, a significant increase in AQI, TVOC and CO2 values is observed (Figure 4). These values subsequently decrease and stabilize during the operation of the car and, in particular, drop to non-hazardous levels after ventilation of the space. Unlike the sharp peaks observed in AQI, TVOC and CO2, PM values do not show a rapid increase during the ignition phase. However, the increase is more gradual. Even after prolonged ventilation, PM values remain high, underscoring the persistent nature of particulate matter in the air after exposure.

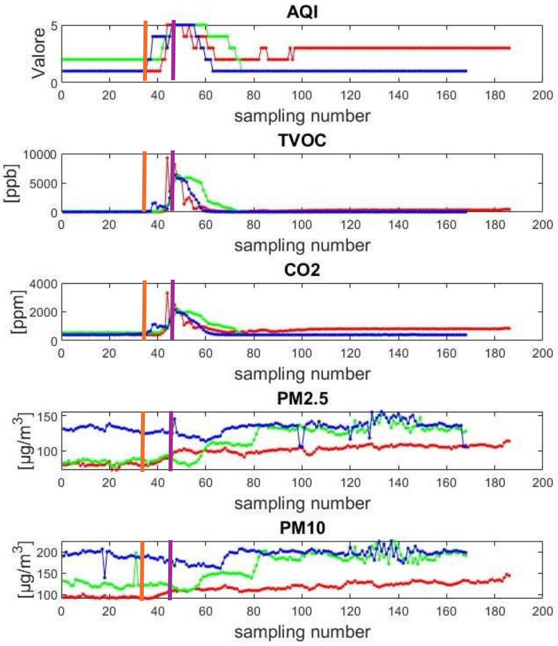

Fig. 4. Measurement data collected during different trials simulating a scenario with the presence of toxic fumes.

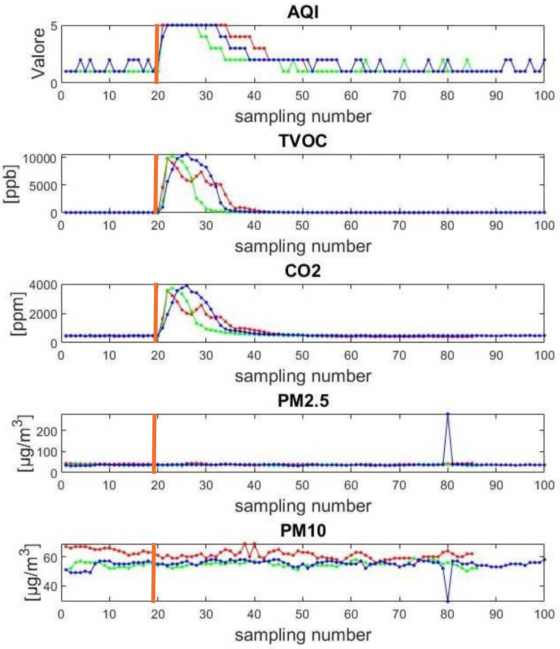

Fig. 5. Measurement data collected during different trials simulating a scenario with the presence of acetone.

The system was also tested by simulating the spill of chemical products, in this scenario the rover was positioned approximately 0.5 m from chemicals, in particular an acetone and a disinfectant with a higher concentration of isopropyl alcohol. In Figure 5 and Figure 6, the graphs both show noticeable peaks as the chemicals are brought closer to the sensors. These peaks are directly related to exposure to acetone and disinfectant, showing how the release of volatile organic compounds into the air increases. After closing the caps and ventilating, TVOC and CO2 levels gradually decrease. PM values do not show a significant increase during exposure to chemicals.

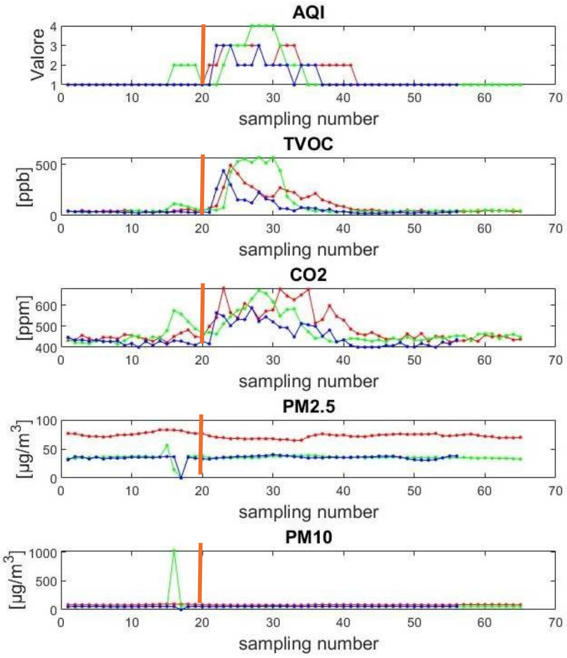

Fig. 6. Measurement data collected during different trials simulating a scenario with the presence of alcohols.

In the last application scenario aimed at identifying possible methane gas leaks inside a home, the rover was positioned approximately 1 meter from a kitchen stove, which was opened intermittently four times. The graphical representation of AQI, TVOC and CO2 values reveals distinct peaks corresponding to each kitchen stove ignition event (Figure 7). The relatively rapid decrease in values after each ignition event implies efficient dissolution of pollutants, strengthening the system's ability to detect transient gas leaks. As previously described, the absence of PM peaks suggests the ineffectiveness of this type of sensor for identifying potential gas leaks.

Finally, to evaluate the behavior of the mobile system over a period of one day, it was chosen to carry out the detection of pollutants inside a house, allowing the rover to move freely in the various environments, where four people and three animals were located. domestic. The sampling period began before dinner time, with the aim of capturing variations in air quality during the evening and night. Graph analysis shows a discernible peak in AQI, TVOC and CO2 values during dinner, reflecting a temporary decline in air quality associated with increased human activity (Figure 8). The levels remain below the absolute danger threshold, reaching a maximum AQI value of 3. The slow flattening of the graphs over the course of the night suggests that, without adequate air circulation, pollutants tend to accumulate in the interior of the environment, reinforcing the importance of periodic ventilation.

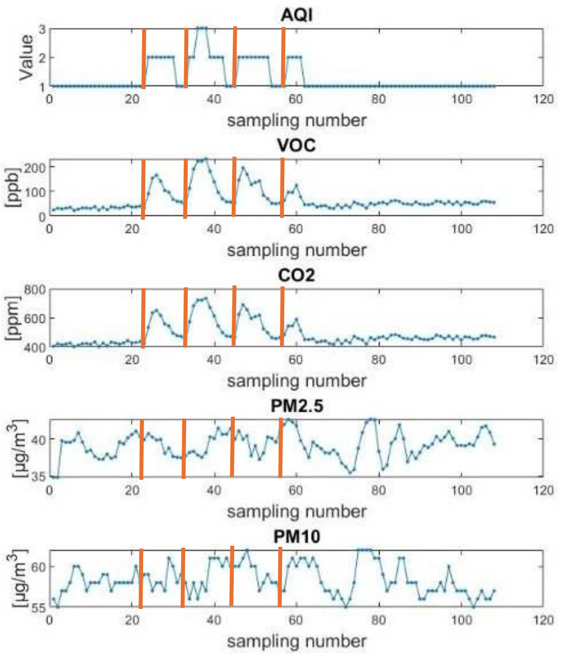

Fig. 7. Measurement data collected during different trials simulating a scenario with the presence of gas leakages.

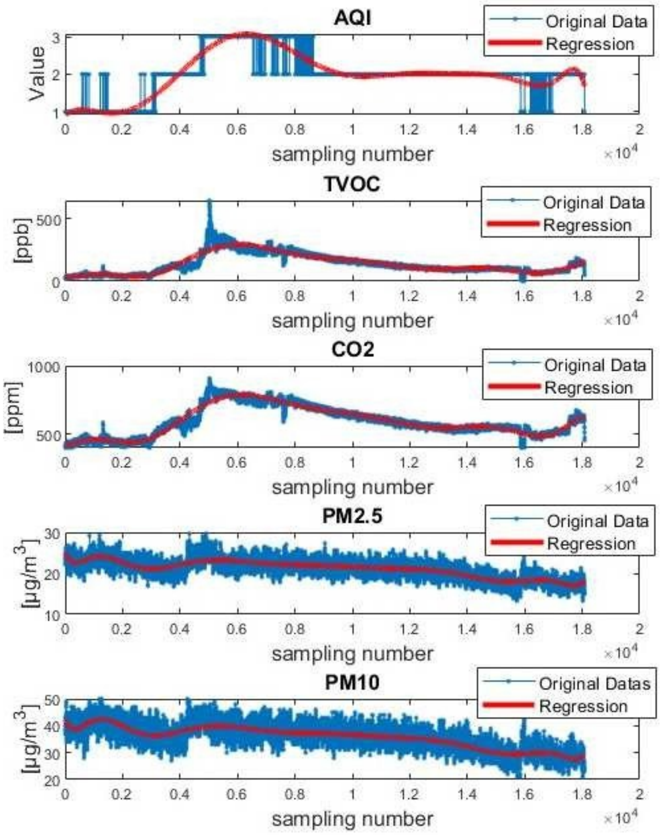

Fig. 8. Measurement data collected during about 12 hours in a real indoor environment.

CONCLUSIONS

This work presents the development and implementation of an autonomous mobile system for monitoring air quality in closed environments. The key contributions of this study are multiple. First, the feasibility of using autonomous rovers for environmental monitoring tasks is demonstrated. The integration of different sensor technologies into the rover made it possible to detect and analyze different air pollutants, providing essential data for indoor health and safety. Secondly, the system can provide valuable information on the nature and distribution of the most common pollutants within closed spaces both in terms of space and time distribution. The results underlined the importance of continuous and dynamic monitoring to avoid encountering situations that can lead to the emergence of problems in the short or long term. Examples of usage scenarios may be different: in manufacturing plants, chemical processing plants and warehouses to ensure compliance with occupational health and safety regulations; in hospitals, clinics, and laboratories to maintain air quality standards, particularly in areas such as operating rooms or isolation wards; in schools and universities to monitor indoor air quality, ensuring a safe learning environment for students and staff; in homes, particularly in areas subject to known pollutants or in the homes of people suffering from respiratory diseases.

The proposed system made it possible to recognize the most dangerous pollutants for humans and send a prompt response when the risky event occurs. The development of the autonomous mobile system has also demonstrated that it is possible to analyze air quality without the need to use highly professional and consequently expensive instruments. The use of a mobile detection system in fact allows to modify the environment or move the proposed system to another environment in a more flexible way compared to fixed systems. Furthermore, the possibility of monitoring the presence of pollutants with a mobile system could allow to evaluate a larger area with more accuracy than a fixed system equipped with a limited number of measurement points. This opens the doors to IoT integrations and leads to greater general awareness of the environment in which people spend several hours a day.

REFERENCES

[1] Francesco Lolli, Antonio Maria Coruzzolo, Samuele Marinello, Asia Traini, and Rita Gamberini. A bibliographic analysis of indoor air quality (iaq) in industrial environments. Sustainability, 14(16), 2022.

[2] Rui Pitarma, Gon¸calo Marques, and B´arbara Roque Ferreira. Monitoring indoor air quality for enhanced occupational health. Journal of medical systems, 41(2):23, 2017.

[3] James F Meadow, Adam E Altrichter, Steven W Kembel, Jeff Kline, G Mhuireach, M Moriyama, Dale Northcutt, Timothy K O'Connor, Ann M Womack, GZ Brown, et al. Indoor airborne bacterial communities are influenced by ventilation, occupancy, and outdoor air source. Indoor air, 24(1):41–48, 2014.

[4] Shun-Cheng Lee, Hai Guo, Wai-Ming Li, Lo-Yin Chan, Inter-comparison of air pollutant concentrations in different indoor environments in Hong Kong, Atmospheric Environment, 36(12), 2002.

[5] Dikaia E. Saraga, Xavier Querol, Regina M.B.O. Duarte, Noel J. Aquilina, Nuno Canha, Elena Gómez Alvarez, Milena Jovasevic-Stojanovic, Gabriel Bekö, Steigvilė Byčenkienė, Renata Kovacevic, Kristina Plauškaitė, Nicola Carslaw, Source apportionment for indoor air pollution: Current challenges and future directions, Science of The Total Environment, Volume 900, 2023.

[6] Dennis YC Leung. Outdoor-indoor air pollution in urban environment: challenges and opportunity. Frontiers in Environmental Science, 2:69, 2015.

[7] Mohamed Anis Fekih, Walid Bechkit, Herv´e Rivano, Mano¨el Dahan, Florent Renard, Lucille Alonso, and Florent Pineau. Participatory air quality and urban heat islands monitoring system. IEEE Transactions on Instrumentation and Measurement, 70:1–14, 2021.

[8] Dharmendra Singh, Meenakshi Dahiya, Rahul Kumar, and Chintan Nanda. Sensors and systems for air quality assessment monitoring and management: A review. Journal of Environmental Management, 289:112510, 2021.

[9] Perlatecnica – associazione no profit. https://www.perlatecnica.it/. (Accessed on 12/1/2024).

[10] K. Kaur and K. E. Kelly. Performance evaluation of the alphasense opc-n3 and plantower pms5003 sensor in measuring dust events in the salt lake valley, utah. Atmospheric Measurement Techniques, 16(10):2455–2470, 2023.

[11] Nicole Cowell, Lee Chapman, William Bloss, and Francis Pope. Field calibration and evaluation of an internet-of-things-based particulate matter sensor. Frontiers in Environmental Science, 9, 2022.

[12] K. K. Barkjohn, B. Gantt, and A. L. Clements. Development and application of a united states-wide correction for pm2.5 data collected with the purpleair sensor. Atmospheric Measurement Techniques, 14(6):4617–4637, 2021.

[13] Aliaksei Hauryliuk Provat K. Saha Allen L. Robinson Albert A. Presto Carl Malings, Rebecca Tanzer and R Subramanian. Fine particle mass monitoring with low-cost sensors: Corrections and long-term performance evaluation. Aerosol Science and Technology, 54(2):160–174, 2020.

[14] J. R. Ouimette, W. C. Malm, B. A. Schichtel, P. J. Sheridan, E. Andrews, J. A. Ogren, and W. P. Arnott. Evaluating the purpleair monitor as an aerosol light scattering instrument. Atmospheric Measurement Techniques, 15(3):655–676, 2022.

[15] Lance Wallace. Testing a new ldquo;decryptedrdquo; algorithm for plantower sensors measuring pm2.5: Comparison with an alternative algorithm. Algorithms, 16(8), 2023.

[16] Lance Wallace, Jianzhao Bi, Wayne R Ott, Jeremy Sarnat, and Yang Liu. Calibration of low-cost purpleair outdoor monitors using an improved method of calculating pm2. 5. Atmospheric Environment, 256:118432, 2021.

[17] Jianzhao Bi, Lance A Wallace, Jeremy A Sarnat, and Yang Liu. Characterizing outdoor infiltration and indoor contribution of pm2. 5 with citizen-based lowcost monitoring data. Environmental Pollution, 276:116763, 2021.